On the Stock Market Variance-Return or Price Relations: A Tale of Fear and Euphoria

HUI GUO, QIAN LIN AND YU-JOU PAI *

FIRST DRAFT: MARCH 2018

THIS DRAFT: OCTOBER 31, 2019

Stock market variance-return or price relations are sometimes negative and sometimes positive. We explain these puzzling findings using a model with two ("fear" and "euphoria") variances. In the model, conditional equity premium depends positively on fear variance and negatively on euphoria variance. Market prices, which correlate negatively with discount rates, decrease with fear variance and increase with euphoria variance. Because market variance is the sum of fear and euphoria variances, its relation to conditional equity premium or market prices can be negative or positive, depending on the relative importance of two variances. Our empirical results support model's main implications.

JEL: C6, E2, and G1.

Keywords: Stock Market Variance, Investment-Specific Technology, Fear and Euphoria, Conditional Equity Premium, and Anomalies.

* Hui Guo is from the Lindner College of Business at the University of Cincinnati (guohu@mail.uc.edu). Qian Lin is from the School of Economics and Management at Wuhan University (linqian@whu.edu.cn). Yu-Jou (Abby) Pai is from the Lindner College of Business at the University of Cincinnati (paiyu@mail.uc.edu). The paper formerly circulated under the title "On the Stock Market Variance-Return or Price Relations: A Tale of two variances." We are grateful to Hengjie Ai, Colin Campbell, Hung-Kun Chen, Jiakai Chen, Wen-I Chuang, David Hirshleifer, Victor Huang, Ye Li, Joon Ho Kim, Qianqiu Liu, Dimitris Papanikolaou, Ghon Rhee, Mehmet Saglam, Ivan Shaliastovich, Tray Spilker, Chi-Yang Tsou, Harald Uhlig, Wenyu Wang, Ingrid Werner, Robert Whitelaw, Chen Xue, Tong Yu, and seminar and conference participants at the University of Cincinnati, the University of Hawaii, National Taiwan University, Zhongnan University of Economics and Law, Dongbei University of Finance and Economics, the 2019 Midwest Finance Association Meeting, and the 2019 American Finance Association PhD Student Poster Session for comments and suggestions. We thank Dimitris Papanikolaou at Northwestern University for providing the industry classification data, David Ng at Cornell University for the implied cost of capital data, and Buhui Qiu at the University of Sydney for the average options-implied variance data.

Shiller (1981) challenges the efficient market hypothesis by showing that dividends are too smooth to account for excessive variations in stock market prices. Subsequent studies, e.g., Campbell and Cochrane (1999) and Bansal and Yaron (2004), have modified rational expectations asset pricing models by allowing the time-varying equity premium instead of cash flows to be the main culprit of stock market fluctuations. Recent models, however, fail to account for dynamics of the conditional equity premium and stock market prices. Specifically, these models stipulate that when perceived variance increases, (1) the required equity premium rises and (2) stock market prices fall. Neither implication, however, is supported by data.

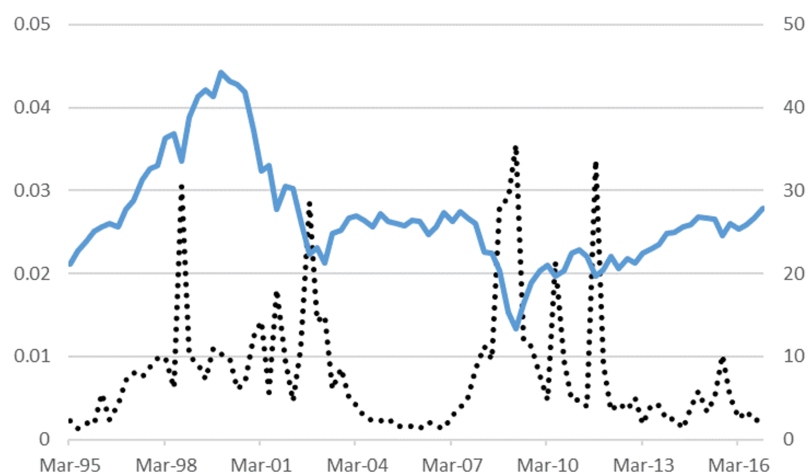


Figure 1. . Stock Market Variance (Dashed Line) and Price-Earnings Ratio

Numerous empirical studies, e.g., Campbell (1987), French, Schwert, and Stambaugh (1987), and Guo and Whitelaw (2006), have investigated the first implication, i.e., the stock market variance-return relation, and found mixed evidence, ranging from positive to insignificant or even negative. Few studies have examined the second implication, i.e., the stock market variance-price relation. In an important exception, Schwert (1989) documents that *relations between stock volatility with either dividend or earnings yield are sometimes positive and sometimes negative* (pp.1134) over the 1859 to 1987 period. As Figure 1 shows, this intriguing finding continues to hold true in the recent sample. The relation between stock market variance and the price-earnings ratio is positive during the dotcom bubble period but is negative during the subprime mortgage crisis period. Figure 2 illustrates a similar relation between consumption (nondurable goods and services) variance and the price-earnings ratio. In this paper, we attempt to explain these two puzzles, i.e., unstable stock market variance-return relation and variance-price relation, using a consumption-based asset pricing model.

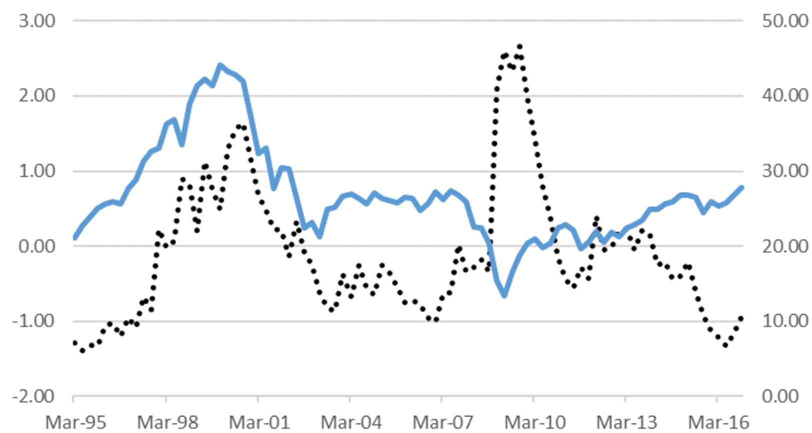


Figure 2. . Standardized Consumption Variance (Dashed Line) and Price-Earnings Ratio

We hypothesize two types of variances that resonate with the wisdom that *fear and euphoria are dominant forces*, as keenly acknowledged by the former Fed Chairman Alan Greenspan. In our model, while VIX, the options-implied volatility of S&P 500 index and a measure of stock market variance, is fear gauge, we propose another volatility as euphoria gauge.

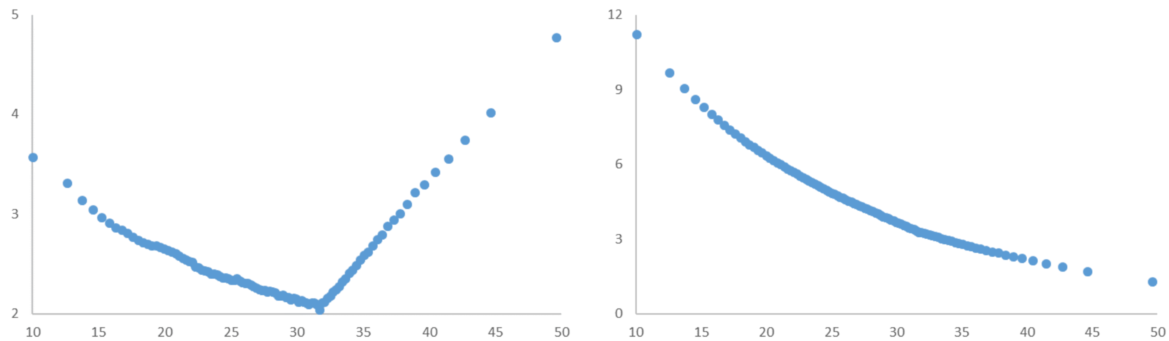
Specifically, we consider two standard economic risks, disembodied technological (DT) shocks and investment-specific technological (IST) shocks, in a variant of Bansal and Yaron (2004)'s long-run risk model. DT shocks, which affect productivity of both consumption-goods producers and investment-goods producers, are the main driving force of economic fluctuations in classical real business cycle models, e.g., Cooley (1995). Relatively recent studies emphasize that IST shocks, which affect productivity of only investment-goods producers, also play a crucial role in explaining economic growth and business cycles. In particular, Justiniano, Primiceri, and Tambalotti (2010, 2011) and others find that a positive IST shock increases output but reduces current consumption. This is because the positive IST shock improves investment opportunities and prompts households to save and invest more in physical capital by reducing current consumption in exchange for more future consumption. By contrast, a positive DT shock increases both output and current consumption.

DT shocks have a positive risk price due to their positive correlation with current consumption growth. In addition, the stock market loads positively on DT shocks because of their positive effects on output and dividends. Therefore, in our model, the conditional equity premium depends positively on the variance of DT shocks. DT variance is a measure of fear because an increase in DT variance raises the conditional equity premium and lowers stock market prices. This is the traditional view of the stock market risk-return relation.

As in Papanikolaou (2011), IST shocks have a negative risk price because they generate a tradeoff of current consumption with future consumption. The stock market loads positively on IST shocks because of their positive effects on output and dividends. Therefore, the conditional equity premium depends negatively on the variance of IST shocks. IST variance is a measure of euphoria because an increase in IST variance lowers the conditional equity premium and raises stock market prices. This is our key new insight on the stock market risk-return relation.

We illustrate main theoretical results in Figures 3(a) and 3(b). Figure 3(a) shows that the conditional stock market variance is a V-shaped function of the price-dividend ratio in model simulation. For example, stock market variance-price relation was positive during the dotcom bubble period because IST or euphoria variance was the main source of economic uncertainty. The relation was negative during the subprime mortgage crisis period because DT or fear variance was the dominant component of stock market variance. Figure 3(b) shows that consistent with the present-value relation, the conditional equity premium decreases monotonically with the price-dividend ratio. Figures 3(a) and 3(b) together imply that the relation between the conditional equity premium and market variance can be positive, negative, or insignificant in finite samples. For example, stock market returns were low following the dotcom bubble and were high following the subprime mortgage crisis.

We link euphoria variance to IST shocks that determine long-term economic prospects and investment opportunities. Merton (1973) points out that *one should interpret the*



(a) Conditional Market Variance (b) Conditional Equity Premium

Figure 3. . Relation between Conditional Market Variance or Conditional Equity Premium (in Percentage, Vertical Axis) and Price-Dividend Ratio (Horizontal Axis) in Simulated Data

effects of a changing interest rate ... in the way economists have generally done in the past: namely, as a single (instrumental) variable representation of shifts in the investment opportunity set. Consistent with this conjecture, long-term Treasury bond prices depend only on IST shocks in our model, and euphoria variance is proportional to the long-term Treasury bond variance. In addition, because stocks with more loadings on euphoria variance have higher prices, the value-weighted average stock variance correlates closely with euphoria variance. We find that in the U.S. data, both model-implied euphoria variance measures correlate closely with the variance of IST proxies advocated in existing empirical studies, e.g., Papanikolaou (2011) and Kogan and Papanikolaou (2013, 2014). Moreover, all three euphoria variance measures lend strong empirical support to our model's main implications.

First, while the relation between stock market variance and prices is weak in the univariate regression, it becomes significantly negative when we control for euphoria variance that correlates positively with stock market prices.[1] The two variances jointly account for up to 60% variation of scaled market price measures, compared with 2% for

[1]Because stock market variance is a linear function of euphoria variance and fear variance in our model, it becomes a proxy for fear variance when we control for its correlation with euphoria variance as in bivariate regressions. We focus mainly on this specification because it is consistent with the notion that VIX, a measure of stock market variance, is preferred fear gauge in Wall Street.

stock market variance alone. Second, while the stock market variance-return relation is weak in the univariate regression, it becomes significantly positive when we control for euphoria variance that correlates negatively with the conditional equity premium. Expected excess returns on individual stocks are also linear functions of market variance and euphoria variance, and loadings on these variances explain the cross-section of expected excess stock returns. Last, the risk-free rate correlates negatively with market variance and positively with euphoria variance in multivariate regressions. This implication provides a potential explanation for high risk-free rates during the dotcom bubble period and for low risk-free rates during the subprime mortgage crisis period.

Several empirical studies document a positive stock market variance-return relation when controlling for the variance of a hedging risk factor. Our simple model provides a unified explanation for these findings. Following Merton (1973)'s conjecture, Scrugg (1998) uses Treasury bond returns as a proxy for the hedging risk factor. This finding is particularly interesting because it allows us to link traditional investment opportunity measure to various empirical measures of IST shocks—a key implication of our model. Guo and Whitelaw (2006) use the scaled stock market price as a control variable because it is a linear function of stock market variance and euphoria variance in our model. Guo and Savickas (2008) use the value-weighted average idiosyncratic variance. Guo, Savickas, Wang, and Yang (2009) use the variance of the value premium that is a direct measure of IST shocks in Papanikolaou (2011). In addition, we find similar results using other IST proxies proposed by Kogan and Papanikolaou (2013, 2014).

In a closely related study, Segal, Shaliastovich, and Yaron (2015) consider a variant of the long-run risk model in which good (bad) variance correlates positively (negatively) with stock market prices. Good variance is uncertainty of positive economic news and bad variance is uncertainty of negative economic news. In their model, the conditional equity premium depends positively on both good and bad variances, and the direct impact of both variances on stock market prices is negative. The relation between good variance and stock market prices is positive because these authors argue for a positive relation between good variance and expected economic growth. That is, Segal et al. (2015) use the interplay between cash flows and variances to explain the unstable stock market variance-price relation.[2] We complement their argument by showing that the interplay between the conditional equity premium and variances also contributes to the unstable stock market variance-price relation.

Guo (2004) argues that stock market variance is a U-shaped function of the scaled stock market price using a limited stock market participation model. In his model, shareholders' liquidity condition is the main driver of financial market dynamics. While positive (negative) shocks to shareholders' liquidity conditions increase (decrease) stock market prices, both types of shocks increase stock market variance. For example, the subprime mortgage crisis arguably originated from negative liquidity shocks that raised stock market variance and depressed stock market prices (e.g., Brunnermeier and Pedersen (2009) and He and Krishnamurthy (2013)). Similarly, the dotcom bubble may be the ramification of positive liquidity shocks. Guo (2004), however, does not decompose market variance into fear and euphoria components.

Martin (2017) derives a lower bound on the equity premium in terms of a volatility index. Gao and Martin (2019) show that the volatility index does not explain the stock market valuation during the dotcom bubble period and attribute this episode to investor sentiment or euphoria. Mispricing is certainly a viable explanation for euphoria. Our model and empirical findings shed new light on its economic origins.

The remainder of the paper is organized as follows. We develop the theoretical model in Section I and present simulation results to illustrate the model's main implications in Section II. We discuss the data in Section III and report empirical results in Section IV. We offer some concluding remarks in Section V.

I. The Model

A. Preference and Aggregate Consumption Dynamics

The representative agent has the Epstein and Zin (1989) recursive utility function $U_t = \left[(1-\delta)C_t^{\frac{1-\gamma}{\theta}} + \delta\left(\mathbb{E}_t[U_t^{1-\gamma}]\right)^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}}$, where $0 < \delta < 1$ is the time discount factor, $\gamma > 0$ is the relative risk aversion coefficient, $\psi > 0$ is the elasticity of intertemporal

[2]Similarly, using a regime-switching model with learning, David and Veronesi (2013) show that both stock market prices and variance increase when good news on economic growth is correlated with an increase in uncertainty.

substitution or EIS, and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$.

Aggregate consumption dynamics are as follows

$$
\begin{aligned}
\Delta c_{t+1} &= \mu_c + x_t + \sigma_{g,t}\eta_{t+1} - \psi_x \sigma_{x,t} e_{t+1}, \\
x_{t+1} &= \rho x_t + \varphi_e \sigma_{x,t} e_{t+1}, \\
\sigma^2_{g,t+1} &= \sigma^2_g + v_g(\sigma^2_{g,t} - \sigma^2_g) + \sigma_1 z_{1,t+1}, \\
\sigma^2_{x,t+1} &= \sigma^2_x + v_x(\sigma^2_{x,t} - \sigma^2_x) + \sigma_2 z_{1,t+1} + \sigma_3 z_{2,t+1}.
\end{aligned} \tag{1}
$$

Δc_{t+1} is the log consumption growth rate with the unconditional mean μ_c. x_t is the expected log consumption growth rate that has zero mean and follows a persistent AR(1) process. Many authors, e.g., Greenwood, Hercowitz, and Krusell (1997) and Fisher (2006), argue that IST shocks are an important determinant of long-run economic growth. Following this literature, we interpret e_{t+1}, the innovation in x_{t+1}, as the IST shock which correlates positively with expected consumption growth or $\varphi_e > 0$. A positive IST shock also reduces the current consumption, i.e., $\psi_x > 0$. These relations are consistent with both theoretical results and empirical findings in Justiniano et al. (2010, 2011) and Papanikolaou (2011). For example, Papanikolaou (2011) shows in his Figure 3 that following a positive IST shock, consumption falls on the impact and increases persistently afterwards in both data and model.[3]

We interpret η_{t+1} as a DT shock that affects only current consumption, and it may also capture other shocks that have short-term effects on consumption. $\sigma_{g,t}$ and $\sigma_{x,t}$ are the conditional variances of DT shocks and IST shocks, respectively. Both $\sigma_{g,t}$ and $\sigma_{x,t}$ follow AR(1) processes with the unconditional means σ^2_g and σ^2_x and with homoscedastic shocks $z_{1,t+1}$ and $z_{2,t+1}$, respectively. The term $\sigma_2 z_{1,t+1}$ captures the potential correlation between $\sigma_{g,t}$ and $\sigma_{x,t}$. The shocks, η_{t+1}, e_{t+1}, $z_{1,t+1}$, and $z_{2,t+1}$ have i.i.d. standard normal distributions. Below, we discuss model's main theoretical

[3]Using a general equilibrium model, Papanikolaou (2011) shows that IST shocks have a negative risk price because a positive IST shock reduces current consumption. By contrast, Garlappi and Song (2017) argue that under some alternative parameterizations, a positive IST shock increases current consumption and has a positive risk price. The empirical evidence is also mixed. Papanikolaou (2011) and Kogan and Papanikolaou (2013, 2014) find that IST shocks have a negative risk price, while Garlappi and Song (2016) document a positive risk price for IST shocks. We shed new light on this growing literature by allowing for heteroscedastic DT and IST shocks and investigating their effects on the time-varying equity premium.

results and delegate their detailed deviations to the online Appendix.

B. Pricing kernel

Using the log-linear approximation of Campbell and Shiller (1988), we can write the log return on the claim to aggregate consumption as

$$r_{a,t+1} = k_0 + k_1 z_{t+1} - z_t + \Delta c_{t+1}, \tag{2}$$

where $z_t = \ln(P_t/C_t)$ is the log price-consumption ratio, $\bar{z} = \mathbb{E}[z_t]$, $k_0 = \ln(e^{\bar{z}} + 1) - \frac{\bar{z}e^{\bar{z}}}{e^{\bar{z}}+1}$, and $k_1 = \frac{e^{\bar{z}}}{e^{\bar{z}}+1} < 1$. Unless otherwise indicated, we use uppercase letters for original variables and lowercase letters for their logs. From Epstein and Zin (1989), the log pricing kernel is

$$m_{t+1} = \ln M_{t+1} = \theta \ln \delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta - 1) r_{a,t+1}. \tag{3}$$

The Euler equation for any asset i is $\mathbb{E}_t[M_{t+1}R_{i,t+1}] = 1$. We log-linearize the Euler equation for the claim to aggregate consumption, $R_{a,t+1}$, and derive the log price-consumption ratio as a linear function of state variables: $z_t = A_0 + A_1\sigma^2_{g,t} + A_2\sigma^2_{x,t} + A_3 x_t$, where $A_1 = \frac{(1-\gamma)^2}{2\theta(1-k_1 v_g)}$, $A_2 = \frac{[\theta k_1 A_3 \varphi_e + (\gamma-1)\psi_x]^2}{2\theta(1-k_1 v_x)}$, and $A_3 = \frac{1-\frac{1}{\psi}}{1-k_1\rho}$. Then the shock to the log pricing kernel is

$$\begin{aligned} m_{t+1} - \mathbb{E}_t[m_{t+1}] &= k_1(\theta-1)(A_1\sigma_1 + A_2\sigma_2)z_{1,t+1} + k_1(\theta-1)A_2\sigma_3 z_{2,t+1} \\ &\quad + [\gamma\psi_x + k_1\varphi_e \frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}]\sigma_{x,t}e_{t+1} - \gamma\sigma_{g,t}\eta_{t+1}. \end{aligned} \tag{4}$$

The price of DT shocks, γ, is unambiguously positive. The risk price of IST shocks, $-\gamma\psi_x - k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}$, has two components. The first component $-\gamma\psi_x$ reflects the concern about current consumption. It is negative because a positive IST shock lowers the current consumption. The second component $-k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}$ relates to the concern about future consumption because a positive IST shock increases expected future consumption. It is positive if $\gamma > \frac{1}{\psi}$ or households prefer early resolution of uncertainty and is negative if $\gamma < \frac{1}{\psi}$ or households prefer late resolution of uncertainty.

In a general equilibrium model, Papanikolaou (2011) assumes $\gamma < \frac{1}{\psi}$ by setting

$\gamma = 1.1$ and $\psi = 0.3$ in the calibration. These parameter choices reflect the balance of two concerns. First, DT shocks contribute little to the equity premium. IST shocks can generate a sizable equity premium if stock market prices decline following a positive IST shock. This is because a positive IST shock, which lowers current consumption, can lead to a substantial increase in the risk-free rate if the elasticity of intertemporal substitution is low. Second, a negative risk price for IST shocks is needed to generate a positive value premium because growth stocks are more susceptible to IST shocks than are value stocks. Papanikolaou (2011) notes that $\gamma < \frac{1}{\psi}$ is a sufficient but not necessary condition for IST shocks to have a negative risk price.

In our consumption-based model, we follow Bansal and Yaron (2004) and assume $\gamma > \frac{1}{\psi}$. The price of IST shocks is negative in our calibration because its first component dominates its second component in magnitude. As in Bansal and Yaron (2004), DT shocks generate a sizable equity premium because we assume time-varying uncertainties and a relatively large relative risk-aversion coefficient. That is, our explanation for the equity premium puzzle is different from that in Papanikolaou (2011) who assumes homoscedastic shocks.

Segal (2019) allows for time-varying uncertainties in a general equilibrium model and assume $\gamma > \frac{1}{\psi}$. He shows that investment sector total factor productivity (TFP) shocks help explain the value premium as in Papanikolaou (2011) and consumption sector TFP shocks help explain the equity premium puzzle as in Bansal and Yaron (2004). Note that investment (consumption) sector TFP shocks are closely related to IST (DT) shocks but they are not the same things. In addition, as in Segal et al. (2015), Segal (2019) assumes that variance of investment sector TFP shocks correlates positively with future economic growth. These setups allow Segal (2019) to address how *shocks* to uncertainties affect the aggregate economy and asset prices. In contrast, we focus on the relation between *levels* of uncertainties and stock market prices or the conditional equity premium.

Our consumption-based model offers the new insight that IST variance correlates negatively with the conditional equity premium. Given our compelling empirical evidence, it will be interesting to investigate whether such an economic mechanism exists in general equilibrium models and under what conditions. Because IST shocks induce the tradeoff between current and future consumption and we assume a relatively large elasticity of intertemporal substitution, we suspect that results should be qualitatively similar in general equilibrium models.

C. Stock Market Returns

The log dividend growth rate of the stock market portfolio is

$$\Delta d_{t+1} = \mu_d + \phi x_t + \pi_\eta \sigma_{g,t} \eta_{t+1} + \pi_e \sigma_{x,t} e_{t+1}. \tag{5}$$

As in Bansal and Yaron (2004), the dividend growth rate depends positively on x_t. It also depends positively on DT and IST shocks because they both improve productivity and thus increase output and dividends. For example, Kogan and Papanikolaou (2014) argue that a positive DT shock and a positive IST shock increase the profitability of consumption-goods producers and investment-goods producers, respectively. Similarly, Bansal, Kiku, and Yaron (2012) also assume that technological shocks have positive effects on dividends.

Log-linearizing the stock market return, we have $r_{m,t+1} = k_{0,m} + k_{1,m} z_{m,t+1} - z_{m,t} + \Delta d_{t+1}$, where $z_{m,t} = \ln(P_{m,t}/D_t)$ is the log price-dividend ratio, $\bar{z}_m = \mathbb{E}[z_{m,t}]$, $k_{0,m} = \ln(e^{\bar{z}_m} + 1) - \frac{\bar{z}_m e^{\bar{z}_m}}{e^{\bar{z}_m}+1}$, and $k_{1,m} = \frac{e^{\bar{z}_m}}{e^{\bar{z}_m}+1} < 1$. The log stock market price-dividend ratio is a linear function of state variables:

$$z_{m,t} = A_{0,m} + A_{1,m}\sigma_{g,t}^2 + A_{2,m}\sigma_{x,t}^2 + A_{3,m}x_t, \tag{6}$$

where $A_{1,m} = \frac{(\gamma - \frac{1}{\psi})(1-\gamma) + (\pi_\eta - \gamma)^2}{2(1-k_{1,m}v_g)}$, $A_{2,m} = \frac{1}{1-k_{1,m}v_x}\big[(\theta - 1)(k_1 v_x - 1)A_2 + \frac{1}{2}(\gamma\psi_x + {} + k_1\varphi_e \frac{\frac{1}{\psi}-\gamma}{1-k_1\rho} + k_{1,m}A_{3,m}\varphi_e + \pi_e)^2\big]$, and $A_{3,m} = \frac{\phi - \frac{1}{\psi}}{1-k_{1,m}\rho}$.

The conditional equity premium is a linear function of DT and IST variances

$$\begin{aligned} \mathbb{E}_t[r_{m,t+1} - r_t^f] \;&=\; c_0 - \frac{1}{2}\sigma_{m,t}^2 + \gamma\pi_\eta\sigma_{g,t}^2 \\ &\quad - [\gamma\psi_x + k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}](k_{1,m}A_{3,m}\varphi_e + \pi_e)\sigma_{x,t}^2, \end{aligned} \tag{7}$$

where c_0 is a generic constant term and its exact formula is provided in the online appendix. In equation (7), $-\frac{1}{2}\sigma_{m,t}^2$ is the Jensen's inequality adjustment term. The coefficient $\gamma\pi_\eta$ is positive or the conditional equity premium depends positively on $\sigma_{g,t}^2$.

Note that $-[\gamma\psi_x + k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}]$ is the risk price of IST shocks. $(k_{1,m}A_{3,m}\varphi_e + \pi_e)$ is positive if $A_{3,m} > 0$ or $\phi > \frac{1}{\psi}$, a standard assumption in long-run risk models. If the risk price of IST shocks is negative and $\phi > \frac{1}{\psi}$, the conditional equity premium depends negatively on $\sigma^2_{x,t}$. That is, under standard parameterizations, variances of DT shocks and IST shocks have opposite effects on the conditional equity premium: An increase in $\sigma^2_{g,t}$ ($\sigma^2_{x,t}$) increases (decreases) the conditional equity premium.

The present-value relation implies a close link between stock prices and discount rates. The coefficient on DT variance in equation (6) is negative and decreases with $\gamma\pi_\eta$, the coefficient on DT variance in equation (7), when γ is relatively large, e.g., greater than 2 for $\psi = 1.5$ and $\pi_\eta = 2.2$ as in the calibration. Intuitively, an increase in $\sigma^2_{g,t}$ raises the conditional equity premium and thus lowers stock market prices. Similarly, the coefficient on IST variance in equation (6) is positive if the coefficient on IST variance in equation (7),$-[\gamma\psi_x + k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}](k_{1,m}A_{3,m}\varphi_e + \pi_e)$, is negative and large in magnitude. That is, an increase in IST variance lowers the conditional equity premium and thus raises stock market prices.[4] To highlight their different effects on stock market prices, we dubs $\sigma^2_{g,t}$ fear variance and $\sigma^2_{x,t}$ euphoria variance.

The conditional market variance is a function of DT and IST variances

$$\sigma^2_{m,t} = c_0 + (k_{1,m}A_{3,m}\varphi_e + \pi_e)^2\sigma^2_{x,t} + \pi^2_\eta\sigma^2_{g,t}. \tag{8}$$

Equation (8) shows that the conditional market variance is a measure of fear variance when we control for its correlation with euphoria variance. VIX, a measure of the conditional stock market volatility in our model, is the standard fear gauge in Wall Street. Extant empirical studies have intensively investigated the relation between expected stock market variance and returns. In addition, market variance and IST variance are more reliably available in data than is DT variance. For these reasons, we use equation (8) to substitute DT variance out by stock market variance in our model's main implications. For example, combining equations (6) and (8), we rewrite the log

[4]The coefficients in equation (6) are not linear functions of their counterparts in equation (7). This is mainly because the discount rate equals the sum of the equity premium and the risk-free rate. Because the risk-free rate is very smooth in both data and our model, the conditional equity premium is the main determinant of the price-dividend ratio.

stock market price-dividend ratio

$$z_{m,t} = c_0 + a\sigma^2_{m,t} + b\sigma^2_{x,t} + A_{3,m}x_t, \tag{9}$$

where $a = \frac{A_{1,m}}{\pi^2_\eta}$ and $b = A_{2,m} - \frac{A_{1,m}}{\pi^2_\eta}(k_{1,m}A_{3,m}\varphi_e + \pi_e)^2$. The coefficient on market variance in equation (9) has the same (negative) sign as the coefficient on DT variance in equation (6). That is, market variance is a proxy for DT variance when we control for its correlation with IST variance. Similarly, The coefficient on IST variance in equation (9) has the same (positive) sign as that in equation (6) because $A_{1,m}$ is negative.

We also rewrite the conditional equity premium as a linear function of stock market variance and euphoria variance

$$\mathbb{E}_t[r_{m,t+1} - r^f_t] = c_0 + \alpha\sigma^2_{m,t} + \beta\sigma^2_{x,t}, \tag{10}$$

where $\alpha = -\frac{1}{2} + \frac{\gamma}{\pi_\eta}$ and $\beta = -[\gamma\psi_x + k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}](k_{1,m}A_{3,m}\varphi_e + \pi_e) - \frac{\gamma}{\pi_\eta}(k_{1,m}A_{3,m}\varphi_e + \pi_e)^2$. The coefficient on market variance in equation (10) has the same sign as the coefficient on fear variance in equation (7) except for the Jensen's inequality adjustment term $-\frac{1}{2}\sigma^2_{m,t}$. Similarly, the coefficient β in equation (10) is negative if the coefficient on euphoria variance in equation (7) is negative.

D. Individual Stock or Portfolio Returns

An individual stock differs from the market portfolio in two ways. First, it has different loadings on systemic risks. Second, it has idiosyncratic risk. Specifically, the log dividend growth rate of stock p is

$$\Delta d_{p,t+1} = \mu_d + \phi_p x_t + \pi_{\eta,p}\sigma_{g,t}\eta_{t+1} + \pi_{e,p}\sigma_{x,t}e_{t+1} + \pi_p z_{p,t+1}, \tag{11}$$

where $z_{p,t+1}$ is an i.i.d. homoscedastic idiosyncratic shock.

Using the log-linear approximation for the stock return, we have $r_{p,t+1} = k_{0,p} + k_{1,p}z_{p,t+1} - z_{p,t} + \Delta d_{p,t+1}$, where $z_{p,t} = \ln\frac{P_{p,t}}{D_{p,t}}$, $\bar{z}_p = \mathbb{E}[z_{p,t}]$, $k_{0,p} = \ln(e^{\bar{z}_p} + 1) - \frac{\bar{z}_p e^{\bar{z}_p}}{e^{\bar{z}_p}+1}$, and $k_{1,p} = \frac{e^{\bar{z}_p}}{e^{\bar{z}_p}+1} < 1$. The log price-dividend ratio is

$$z_{p,t} = A_{0,p} + A_{1,p}\sigma^2_{g,t} + A_{2,p}\sigma^2_{x,t} + A_{3,p}x_t, \tag{12}$$

where $A_{1,p} = \frac{(\gamma-\frac{1}{\psi})(1-\gamma)+(\pi_{\eta,p}-\gamma)^2}{2(1-k_{1,p}v_g)}$, $A_{2,p} = \frac{1}{1-k_{1,p}v_x}\big[(\theta-1)(k_1 v_x-1)A_2+\frac{1}{2}((\theta-1)k_1 A_3\varphi_e+\gamma\psi_x + k_{1,p}A_{3,p}\varphi_e + \pi_{e,p})^2\big]$, and $A_{3,p} = \frac{\phi_p-\frac{1}{\psi}}{1-k_{1,p}\rho}$.

The conditional stock variance is

$$\sigma_{p,t}^2 = c_0 + (k_{1,p}A_{3,p}\varphi_e + \pi_{e,p})^2\sigma_{x,t}^2 + \pi_{\eta,p}^2\sigma_{g,t}^2. \tag{13}$$

The conditional stock risk premium is

$$\begin{aligned}\mathbb{E}_t[r_{p,t+1} - r_t^f] &= c_0 - \frac{1}{2}\sigma_{p,t}^2 + \gamma\pi_{\eta,p}\sigma_{g,t}^2 \\ &\quad -[\gamma\psi_x + k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}](k_{1,p}A_{3,p}\varphi_e + \pi_{e,p})\sigma_{x,t}^2. \end{aligned} \tag{14}$$

In equation (14), the stock risk premium increases with $\pi_{\eta,p}$, the loading of stock p on DT shocks. If the IST risk price $-\gamma\psi_x - k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}$ is negative, the risk premium decreases with $\pi_{e,p}$, the stock loading on IST shocks. In a similar vein, in equation (12), the coefficient $A_{1,p}$ decreases with $\pi_{\eta,p}$ when $\pi_{\eta,p} < \gamma$, indicating that stocks with high loadings on DT shocks have low prices. The coefficient $A_{2,p}$ increases with $\pi_{e,p}$ if $-\gamma\psi_x - k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}$ is negative and $\phi_p > \frac{1}{\psi}$, indicating that stocks with high loadings on IST shocks have high prices. We can also write the risk premium as a linear function of stock market variance and euphoria variance:

$$\mathbb{E}_t[r_{p,t+1} - r_t^f] = c_0 + \alpha_p\sigma_{m,t}^2 + \beta_p\sigma_{x,t}^2, \tag{15}$$

where $\alpha_p = \frac{\gamma\pi_{\eta,p}-\frac{1}{2}\pi_{\eta,p}^2}{\pi_\eta^2}$ and $\beta_p = -[\gamma\psi_x+k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}](k_{1,p}A_{3,p}\varphi_e+\pi_{e,p}) - \frac{\gamma\pi_{\eta,p}-\frac{1}{2}\pi_{\eta,p}^2}{\pi_\eta^2}(k_{1,m}A_{3,m}\varphi_e+\pi_e)^2 - \frac{1}{2}(k_{1,p}A_{3,p}\varphi_e + \pi_{e,p})^2$.

E. The Risk-Free Rate

Using the Euler equation $\mathbb{E}_t[M_{t+1}R_t^f] = 1$ and equation (8), we have the risk-free rate

$$r_t^f = c_0 + \frac{1}{\psi}x_t + \frac{c}{\pi_\eta^2}\sigma_{m,t}^2 + [d - \frac{c}{\pi_\eta^2}(k_{1,m}A_{3,m}\varphi_e + \pi_e)^2]\sigma_{x,t}^2, \tag{16}$$

where $c = -\frac{1}{2}[\gamma + \frac{\gamma}{\psi} - \frac{1}{\psi}], d = -[(\theta-1)(k_1 v_x - 1)A_2 + \frac{1}{2}((\theta-1)k_1 A_3 \varphi_e + \gamma\psi_x)^2]$. The risk-free rate depends on euphoria and fear (or market) variances because of the precautionary saving effect.

F. Long-Term Real Treasury Bonds and Euphoria Variance

In our model, the long-term *real* Treasury bond is affected by IST shocks but not by DT shocks. As a result, its conditional variance is a linear function of euphoria variance. We illustrate this point using a perpetual bond that pays \$1 every period. Using the log-linear approximation method proposed by Campbell and Shiller (1988), we have the log bond return

$$r_{b,t+1} = \ln \frac{P_{b,t+1} + 1}{P_{b,t}} = k_{0,b} + k_{1,b} z_{b,t+1} - z_{b,t}, \tag{17}$$

where $P_{b,t}$ is the bond price, $z_{b,t} = \ln P_{b,t}$, $\bar{z}_b = \mathbb{E}[z_{b,t}]$, $k_{0,b} = \ln(e^{\bar{z}_b} + 1) - \frac{\bar{z}_b e^{\bar{z}_b}}{e^{\bar{z}_b}+1}$, and $k_{1,b} = e^{\bar{z}_b}/(e^{\bar{z}_b} + 1) < 1$. The log bond price is a linear function of state variables:

$$z_{b,t} = A_{0,b} + A_{1,b}\sigma^2_{g,t} + A_{2,b}\sigma^2_{x,t} + A_{3,b} x_t, \tag{18}$$

where $A_{1,b} = \frac{(\gamma - \frac{1}{\psi})(1-\gamma)+\gamma^2}{2(1-k_{1,p} v_g)}$, $A_{2,b} = \frac{1}{1-k_{1,p} v_x}\left[\frac{1-\theta}{2\theta}(\theta k_1 A_3 \varphi_e + (\gamma-1)\psi_x)^2 + \frac{1}{2}((\theta-1)k_1 A_3 \varphi_e + \gamma\psi_x + k_{1,p} A_{3,p}\varphi_e)^2\right]$, and $A_{3,b} = \frac{-\frac{1}{\psi}}{1-k_{1,p}\rho}$. The realized bond return is

$$\begin{aligned} r_{b,t+1} \;=\; & c_0 + (k_{1,b} v_g - 1)A_{1,b}\sigma^2_{g,t} + (k_{1,b} v_x - 1)A_{2,b}\sigma^2_{x,t} + (k_{1,b} A_{3,b}\rho - A_{3,b})x_t \\ & + (k_{1,b} A_{1,b}\sigma_1 + k_{1,b} A_{2,b}\sigma_2) z_{1,t+1} + k_{1,b} A_{2,b}\sigma_3 z_{2,t+1} + k_{1,b} A_{3,b}\varphi_e \sigma_{x,t} e_{t+1}. \end{aligned} \tag{19}$$

The conditional bond variance is a linear function of euphoria variance:

$$Var_t[r_{b,t+1}] = c_0 + (k_{1,b} A_{3,b}\varphi_e)^2 \sigma^2_{x,t}. \tag{20}$$

G. Model's Main Implications

Our model has several novel implications for understanding stock market variance-return or price relations. First, the stock market variance-price relation is unstable because in equation (6) the stock market price-dividend ratio depends negatively on fear variance, i.e., $A_{1,m} < 0$, and positively on euphoria variance, i.e., $A_{2,m} > 0$. The relation is negative when stock market variance comprises mainly fear variance and is positive when euphoria variance is the dominant component. However, equation (9) shows that the *partial* relation between the stock market price-dividend ratio and variance is negative, i.e., $a = \frac{A_{1,m}}{\pi_\eta^2} < 0$, when we control for euphoria variance which correlates positively with the stock market price-dividend ratio in bivariate regressions.

Second, the stock market variance-return relation is unstable because in equation (7) the conditional equity premium correlates positively with fear variance, i.e., $\gamma\pi_\eta > 0$, and negatively with euphoria variance, i.e., $-[\gamma\psi_x + k_1\varphi_e\frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}](k_{1,m}A_{3,m}\varphi_e + \pi_e) < 0$. The relation is positive when stock market variance comprises mainly fear variance and negative when euphoria variance is the dominant component. However, equation (10) shows that the *partial* relation between the conditional equity premium and market variance is positive, i.e., $\alpha = -\frac{1}{2} + \frac{\gamma}{\pi_\eta} > 0$, when we control for euphoria variance which correlates negatively with the conditional equity premium in bivariate regressions. Moreover, market variance and euphoria variance jointly forecast excess stock market returns because they capture dynamics of the conditional equity premium.

Third, equation (16) shows that both stock market variance and euphoria variance are important determinants of the risk-free rate.

Forth, the model suggests that we can measure euphoria variance in two ways. First, equation (20) shows that variance of long-term *real* Treasury bonds is a linear function of euphoria variance. Second, a stock with larger $\pi_{e,p}$, the loading on IST shocks, has a higher price (equation (12)) and its variance also has a closer correlation with $\sigma_{x,t}^2$ (equation (13)). Therefore, a price- or value-weighted average stock variance is a proxy for $\sigma_{x,t}^2$ or euphoria variance.

Last, taking the unconditional expectation of equation (15), we have

$$\mathbb{E}[r_{p,t+1} - r_t^f] = c_0 + \alpha_p E[\sigma_{m,t}^2] + \beta_p E[\sigma_{x,t}^2]. \tag{21}$$

Equation (21) shows that loadings on stock market variance α_p and loadings on euphoria variance β_p help explain the cross-section of expected excess stock returns. In the next section, we illustrate these implications using simulated data.

II. Model Simulation

Table 1 reports the parameter values that we choose for the model at the monthly frequency. For comparison, most parameter values are identical to those adopted in Bansal et al. (2012) when applicable with following exceptions. First, ψ_x is a new parameter in our model. It equals 0.0389 or a one standard deviation increase in IST shocks reduces the contemporaneous consumption by $\mathbb{E}[\psi_x \sigma_{x,t}] = 0.0389 * 0.006 * \sqrt{12} = 0.08\%$ per year. The effect is similar to the point estimate of about 0.10% in a year reported in Figure 3 of Justiniano et al. (2010).[5] This parameter value is sufficient to generate a negative risk price for IST shocks, $-\gamma\psi_x - k_1\varphi_e \frac{\frac{1}{\psi}-\gamma}{1-k_1\rho}$, which decreases with ψ_x.

A. Calibration

Table 1— Configuration of Model Parameters

Preferences	δ	γ	ψ			
	0.9989	10	1.5			
Consumption	μ_c	ρ	φ_e	ψ_x	σ_g	σ_x
	0.0015	0.975	0.001	0.0389	0.0015	0.006
	v_g	v_x	σ_1	σ_2	σ_3	
	0.999	0.999	0.000006	0	0.000006	
Dividends	μ_d	ϕ	π_e	π_η	π_p	
	0.0015	2.2	3	2.2	0.005	

Note: The table reports the parameter values used in the model.

Second, π_e, another new parameter capturing the effect of IST shocks on the dividend growth rate, equals 3. One standard deviation increase in IST shocks increases the contemporaneous dividend by $\mathbb{E}[\pi_e \sigma_{x,t}] = 3 * 0.006 * \sqrt{12} = 6.24\%$ per year. When we take into account that dividends are levered, this parameter value is consistent with the point estimate of about 2.2% increase in output in a year following a one standard deviation increase in IST shocks reported in Figure 3 of Justiniano et al. (2010).

[5] Justiniano et al. (2010) report the effect using quarterly data and we convert it into annual data by multiplying it by 2.

Third, DT shocks cause a strong positive correlation between aggregate consumption and dividends. Bansal et al. (2012) assume an idiosyncratic shock to aggregate dividends to dampen the correlation to matches its data counterpart. Because IST shocks have opposite effects on aggregate consumption and dividends, we do not need the idiosyncratic shock in our model.

Fourth, the unconditional volatility is 0.006 for IST shocks, σ_x, and is 0.0015 for DT shocks, σ_g. This calibration is consistent with the empirical finding by Justiniano et al. (2011) that IST shocks are more volatile than DT shocks.

Fifth, the volatility of volatility (σ_1 and σ_3) is 0.000006, compared with 0.0000028 in Bansal et al. (2012). Because euphoria variance and fear variance have opposite effects on the equity premium, using Bansal et al. (2012)'s volatility of volatility calibration generates a somewhat smaller equity premium, although it does not affect our main results qualitatively.

Sixth, because IST shocks affect the dividend growth process directly, we adopt a smaller value for π_η (2.2 in our model versus 2.6 in Bansal et al. (2012)) and a smaller value for ϕ (2.2 in our model versus 2.5 in Bansal et al. (2012)) so that the volatility of the dividend growth rate in simulated data matches that in actual data.

Last, Bansal et al. (2012) consider only one variance process, and we assume that euphoria variance and fear variance follow different stochastic processes. We assume that the two variances are uncorrelated by setting the parameter σ_2 to zero, as in Papanikolaou (2011). Allowing for moderate correlation between IST variance and DT variance does not qualitatively change our main results.

B. Aggregate Quantities and Asset Prices

In Table 2, we report the summary statistics of the consumption growth rate, the dividend growth rate, stock market returns, the stock market price-dividend ratio, and the risk-free rate in annual frequency. The column under the title “Data” reproduces the Bansal et al. (2012) estimation from the actual data spanning the 1930 to 2008 period with 79 annual observations. For each simulation, we generate 1,948 monthly observations, discard the first 1,000 observations, and convert the remaining 948 observations into 79 annual observations. We conduct 10,000 simulations and report the distribution of the summary statistics in columns under the title “Model”. The

Table 2— Consumption, Dividend, and Asset Returns

	Data	Model					
Moment	Estimate	Median	2.5%	5%	95%	97.5%	Pop
$E[\Delta c]$	1.93	1.80	0.99	1.15	2.43	2.59	1.80
$\sigma(\Delta c)$	2.16	3.21	1.84	1.99	5.20	5.60	3.56
$AC1(\Delta c)$	0.45	-0.01	-0.26	-0.22	0.19	0.23	0.00
$AC2(\Delta c)$	0.16	-0.01	-0.26	-0.22	0.20	0.24	0.00
$AC3(\Delta c)$	-0.10	-0.01	-0.26	-0.22	0.19	0.23	0.00
$AC4(\Delta c)$	-0.24	-0.01	-0.26	-0.22	0.19	0.23	0.00
$AC5(\Delta c)$	-0.02	-0.01	-0.25	-0.22	0.19	0.23	0.00
$VR6(\Delta c)$	0.84	0.89	0.45	0.51	1.48	1.62	1.00
$E[\Delta d]$	1.15	1.79	-1.32	-0.74	4.40	4.96	1.80
$\sigma(\Delta d)$	11.05	12.92	8.25	8.80	18.69	19.88	13.84
$AC1(\Delta d)$	0.21	-0.01	-0.25	-0.20	0.18	0.22	0.00
$VR6(\Delta d)$	0.59	0.91	0.48	0.53	1.46	1.59	1.02
$Corr(\Delta c, \Delta d)$	0.55	0.54	0.17	0.23	0.80	0.83	0.54
$E[R]$	7.66	7.11	3.77	4.32	10.55	11.37	7.29
$\sigma(R)$	20.28	16.16	11.35	11.99	22.36	23.79	17.13
$AC1(R)$	0.02	-0.02	-0.24	-0.21	0.17	0.21	0.00
$E[p-d]$	3.36	3.31	2.76	2.86	3.56	3.61	3.27
$\sigma(p-d)$	0.45	0.17	0.09	0.10	0.31	0.34	0.29
$AC1(p-d)$	0.87	0.89	0.71	0.75	0.96	0.96	0.97
$E[R^f]$	0.57	1.32	-0.28	0.03	1.83	1.87	1.14
$\sigma(R^f)$	2.86	0.46	0.22	0.25	0.83	0.91	0.79
$AC1(R^f)$	0.65	0.94	0.78	0.82	0.98	0.98	0.98

Note: The table reports summary statistics of the consumption growth rate, Δc; the dividend growth rate, Δd; the stock market return, R; the log price-dividend ratio, $p-d$; and the risk-free rate, R^f. E is the mean; σ is the standard deviation; ACi is the ith-order autocorrelation coefficient; $VR6$ is the variance ratio of six-year growth rate to six times one-year growth rate; and $Corr$ is the correlation coefficient. The column under the name "Data" reproduces annual estimates from the 1930 to 2008 period reported in Bansal et al. (2012) and Beeler and Campbell (2012). The column under the name "Model" reports the distribution of annual estimates from 10,000 simulated samples of 79 years each. "Pop" reports annual estimates from a long simulated sample of 100,000 years.

column "Pop" reports the summary statistics from the simulation of 100,000 annual observations.

In our model, the expected consumption growth rate is persistent. This specification generates a positive autocorrelation in consumption growth, as in Bansal and Yaron (2004). On the other hand, a positive IST shock lowers current consumption and increases future consumption. This assumption generates a negative autocorrelation in consumption growth. Overall, Table 2 shows that the median autocorrelations are negative but small in magnitude. Beeler and Campbell (2012) emphasize that consumption follows a mean-reverting process in the data, with negative third- to fifth-order autocorrelations. Moreover, Beeler and Campbell (2012) report that the variance ratio of 6-year consumption growth to 1-year consumption growth is 0.84.

The key statistics of actual consumption data are within the 95% interval of simulated data except for the first-order autocorrelation of 0.45. The strong first-order autocorrelation is partly due to the time-aggregation bias pointed out by Working (1960). In addition, Kroencke (2017) argues that it also reflects the fact that the Bureau of Economic Analysis filters the consumption expenditure data. In a similar vein, Guo and Pai (2019) find that the autocorrelation is much weaker in unrevised real-time consumption data than in revised consumption data commonly used in empirical studies, including Bansal et al. (2012) and Beeler and Campbell (2012). With these caveats in mind, simulated consumption matches actual consumption reasonably well.

Table 2 shows that the model does a reasonably good job in explaining main statistical properties of dividends, stock market returns, the log stock market price-dividend ratio, and the risk-free rate. Their summary statistics from the data are within the 95 percent interval of simulated data except that as in Bansal et al. (2012), the standard deviations of the risk-free rate and the log price-dividend ratio are somewhat smaller in simulated data than in actual data.

C. Stock Market Variance-Price Relation

This subsection illustrates the relation between stock market variance and the log stock market price-dividend ratio. For comparison with empirical findings that are based on the quarterly sample spanning the 1963Q1 to 2016Q4 period, we use 216 quarterly observations in each simulated sample. Specifically, we generate a monthly

Table 3— Price-Dividend Ratio and Variances in Simulated Data

	Median	10%	30%	70%	90%	Pop	Scaler
Panel A: Stock Market Variance							
VMKT	-7.205	57.329	21.486	-36.702	-86.125	-0.333	1
	(-0.587)	(5.293)	(1.749)	(-2.942)	(-7.227)	(-39.200)	1
R^2	12.870	0.477	4.503	26.556	50.586	8.031	0.01
Panel B: Euphoria Variance							
VG	4.509	-2.136	2.091	6.896	10.876	3.067	100
	(3.779)	(-1.456)	(1.560)	(6.377)	(10.789)	(41.977)	1
R^2	21.708	0.974	8.037	39.867	63.553	7.811	0.01
Panel C: Stock Market Variance and Euphoria Variance							
VMKT	-2.268	-2.253	-2.263	-2.273	-2.283	-2.086	100
	(-4.879)	(-2.529)	(-3.675)	(-6.508)	(-10.063)	(770.050)	100
VG	2.569	2.553	2.563	2.575	2.585	19.483	1000
	(5.228)	(2.772)	(4.012)	(6.860)	(9.972)	(151.655)	100
R^2	99.981	99.937	99.969	99.989	99.995	99.991	0.01
Panel D: Stock Market Variance and Value-Weighted Average Stock Variance							
VMKT	-7.691	-5.554	-6.713	-8.875	-10.784	-4.471	100
	(-34.303)	(-18.645)	(-27.306)	(-43.263)	(-60.458)	(-394.924)	1
VWASV	8.759	6.185	7.570	10.212	12.521	4.105	100
	(34.031)	(18.545)	(26.902)	(42.974)	(60.211)	(322.695)	1
R^2	97.172	91.185	95.649	98.167	99.033	95.703	0.01

Note: The table reports the OLS estimation results of regressing the stock market price-dividend ratio on contemporaneous variances for simulated data. We generate 10,000 simulated samples and report their distributions. The column "Pop" reports the results obtained from 100,000 simulated quarterly observations. VMKT is stock market variance, VG is euphoria variance, and VWASV is value-weighted average stock variance. t-values are reported in parentheses. The coefficient and the t-value of stock market variance are sorted from the highest to the lowest. All other statistics are sorted from the lowest to the highest. The column "Scaler" indicates the actual values of the statistics reported in a row are the reported values time the scaler in that row. For example, the scaler for R^2 is 0.01, indicating that it is reported in percentage.

sample of 1,648 observations, discard the first 1,000 observations, and convert the remainder into 216 quarterly observations. We generate 10,000 simulated samples and report their distributions in Table 3. The column "Pop" reports the results obtained from 100,000 simulated quarterly observations.

In Panel A of Table 3, we report the ordinary least squares (OLS) estimation results of regressing the log stock market price-dividend ratio on a constant and concurrent conditional stock market variance. Leading asset pricing models stipulate a negative variance-price relation, and we sort the coefficient on stock market variance and its t-value from high to low. The R^2 is sorted from low to high. The simulation results illustrate that the univariate stock market variance-price relation is unstable in our model. The coefficient is positive in over 30% of simulated samples, while the median coefficient is negative. In addition, the median t-value and the median R^2 are -0.587 and 12.87%, respectively, indicating that on average the variance-price relation is weak.

In our model, the stock market variance-price relation is sometimes negative because the stock market price-dividend ratio depends negatively on fear variance. The relation is sometimes positive because as we show in Panel B of Table 3, the stock market price-dividend ratio correlates positively with euphoria variance. When market variance comprises mainly fear variance, stock market prices are relatively low and decrease with market variance. When euphoria variance is the dominant component, stock market prices are relatively high and increase with market variance. Overall, as Figure 3(a) shows, market variance is a V-shaped function of the stock market price-dividend ratio. Bansal et al. (2012)'s model stipulates a negative relation between the stock market price-dividend ratio and future stock market variance. In contrast with this implication, Beeler and Campbell (2012) show that the relation is rather weak in U.S. data. Their finding, however, is consistent with our modified long-run risk model.

In Equation (9), the stock market price-dividend ratio is a linear function of stock market variance, euphoria variance, and expected dividend growth. In particular, the coefficient on stock market variance is negative when we control for euphoria variance that correlates positively with stock market prices. To illustrate this point, in Panel C of Table 3, we report the OLS estimation results of regressing the stock market price-dividend ratio on stock market variance and euphoria variance. The coefficient on stock market variance is always negative and the coefficient on euphoria variance is always positive. In addition, the R^2 is close to 100%, indicating that, consistent with Shiller (1981)'s findings, expected dividend growth has negligible explanatory power for stock market prices in our calibration. This result also suggests the time-varying conditional equity premium, which is a linear function of stock market variance and euphoria variance, accounts for most of stock market price variation in the model. In the next subsection, we show that the unstable stock market variance-price relation reflects the unstable stock market variance-return relation.

D. Stock Market Variance-Return Relation

In our model, the conditional equity premium depends positively (negatively) on fear (euphoria) variance. When stock market variance comprises primarily fear (euphoria) variance, stock market prices are low (high) and the variance-return relation is positive (negative). We illustrate these results using two figures. Figure 3(b) shows that conditional equity premium decreases monotonically with the stock market price-dividend ratio, while stock market variance is a V-shaped function of the price-dividend ratio in Figure 3(a). Therefore, our model suggests that the stock market variance-return relation is positive (negative) when stock market prices are low (high). Yu and Yuan (2011) find that the stock market risk-return relation is positive when investor sentiment is low and is weak or negative when investor sentiment is high. Because investor sentiment moves closely to the scaled stock market price, their findings are consistent with our model's implication.

In the empirical analysis, researchers often use realized equity premium as a proxy for the conditional equity premium. Following this specification, we use the expected market variance $\sigma_{m,t}^2$ based on information at time t to forecast the time $t+1$ excess market return $r_{m,t+1}$, and report the OLS regression results in Panel A of Table 4. The coefficient on conditional market variance, VMKT, is negative in over 30% of simulated samples but has a positive median, indicating an unstable stock market variance-return relation. In panel B, we report the OLS regression results of forecasting one-quarter-ahead excess stock market returns using conditional euphoria variance, VG. The coefficient on VG is negative in over 50% of simulated samples.

In Panel C of Table 4, we include both stock market variance and euphoria variance as the predictive variables. The coefficient on market variance (euphoria variance) is

Table 4— Excess Stock market Returns and Variances in Simulated Data

	Median	10%	30%	70%	90%	Pop
Panel A: Stock Market Variance						
VMKT	0.577	-4.461	-1.322	2.551	5.845	0.859
	(0.167)	(-1.192)	(-0.389)	(0.730)	(1.555)	(7.989)
R^2	0.227	0.008	0.076	0.539	1.399	0.077
Panel B: Euphoria Variance						
VG	-12.771	38.981	7.462	-33.867	-71.727	-3.855
	(-0.345)	(1.018)	(0.209)	(-0.895)	(-1.698)	(-3.785)
R^2	0.248	0.009	0.079	0.578	1.420	0.018
Panel C: Stock Market Variance and Euphoria Variance						
VMKT	9.329	-1.970	4.673	14.828	24.606	4.133
	(1.112)	(-0.238)	(0.575)	(1.645)	(2.440)	(21.327)
VG	-104.825	17.694	-52.230	-163.844	-269.035	-36.383
	(-1.126)	(0.198)	(-0.592)	(-1.684)	(-2.480)	(-19.788)
R^2	1.133	0.205	0.608	1.849	3.207	0.504
Panel D: Stock Market Variance and Value-Weighted Average Stock Variance						
VMKT	31.642	-4.837	15.650	51.183	90.259	8.922
	(1.122)	(-0.184)	(0.590)	(1.662)	(2.482)	(20.176)
VWASV	-35.496	6.099	-17.440	-58.211	-102.337	-7.977
	(-1.096)	(0.196)	(-0.573)	(-1.637)	(-2.457)	(-18.791)
R^2	1.135	0.187	0.607	1.859	3.349	0.559

Note: The table reports the OLS estimation results of regressing one-quarter-ahead excess stock market returns on stock variances for simulated data. We generate 10,000 simulated samples and report their distributions. The column "Pop" reports the results obtained from 100,000 simulated quarterly observations. VMKT is stock market variance, VG is euphoria variance, and VWASV is value-weighted average stock variance. t-values are reported in parentheses. R^2 is reported in percentage.

positive (negative) in most simulated samples. In addition, the coefficients, t-values, and R^2 are substantially larger in magnitude than their univariate regression counterparts reported in panels A and B. The difference reflects an omitted variables problem. In simulated data, the median coefficient of correlation between market variance and euphoria variance is 87%, although they have opposite effects on future market returns. As a result, in the univariate regressions, the estimated coefficient on the market variance (euphoria variance) is biased downward (upward) toward zero.

Because of the strong correlation between the stock market price-dividend ratio and the conditional equity premium, the results in Table 3 essentially illustrate the stock market variance-return relation using an ex-ante equity premium measure. Noticeably, the ex-ante equity premium measure allows us to estimate the stock market variance-return relation more precisely than does the ex-post equity premium measure used in Table 4. That is, using scaled stock market prices provides a more powerful test of the stock market risk-return tradeoff than using realized excess market returns. The reason is that, as Elton (1999) points out, the realized excess stock market return is a poor proxy for the conditional equity premium because the latter accounts for a relatively small fraction of variation in the former.

E. Uncertainties and the Risk-Free Rate

In Table 5, we illustrate the relation between the risk-free rate and variances stipulated in equation (16). Panel A reveals a negative relation between the risk-free rate and stock market variance. Panel B shows that the simple relation between the risk-free rate and euphoria variance is unstable. When we use both variances as the explanatory variables in panel C, the coefficients on stock market variance and euphoria variance are negative and positive, respectively. Moreover, the median R^2 is 94%, indicating that uncertainties account for most of the risk-free rate variation in our model.

F. Value-Weighted Average Stock Variance

To illustrate the implications for the cross-section of stock returns, we construct 125 portfolios that have different loadings on systematic risks in equation (11). Specifically, ϕ_p takes one of five possible values [1.4, 1.8, 2.2, 2.6, 3.0], $\pi_{\eta,p}$ takes one of five possible values [1.4, 1.8, 2.2, 2.6, 3.0], and $\pi_{e,p}$ takes one of five possible values [1,9, 2.3, 2.7, 3.1,

Table 5— The Risk-Free Rate and Variances in Simulated Data

	Median	10%	30%	70%	90%	Pop
Panel A: Stock Market Variance						
VMKT	-0.330	0.057	-0.156	-0.508	-0.803	-0.552
	(-4.391)	(0.750)	(-2.140)	(-7.300)	(-12.597)	(-95.703)
R^2	25.154	1.052	9.793	44.832	68.888	34.156
Panel B: Euphoria Variance						
VG	0.022	4.727	1.758	-1.807	-4.892	-0.461
	(0.026)	(5.157)	(1.967)	(-2.013)	(-5.454)	(-7.964)
R^2	9.972	0.398	3.377	21.227	43.645	0.303
Panel C: Stock Market Variance and Euphoria Variance						
VMKT	-1.552	-1.411	-1.502	-1.590	-1.630	-1.640
	(-45.723)	(-25.944)	(-36.013)	(-58.059)	(-82.125)	(-2421.912)
VG	14.457	13.059	13.946	14.847	15.297	12.442
	(40.015)	(23.298)	(31.841)	(50.455)	(69.519)	(1897.623)
R^2	94.372	86.416	91.804	96.249	97.877	99.015
Panel D: Stock Market Variance and Value-Weighted Average Stock Variance						
VMKT	-4.845	-3.568	-4.264	-5.551	-6.653	-3.179
	(-31.929)	(-17.946)	(-25.763)	(-39.390)	(-53.290)	(-425.995)
VG	5.189	3.657	4.477	6.061	7.408	2.634
	(29.978)	(16.815)	(24.004)	(36.890)	(49.436)	(314.120)
R^2	96.088	87.734	96.369	94.041	97.303	96.364

Note: The table reports the OLS estimation results of regressing the risk-free rate on contemporaneous stock variances for simulated data. We generate 10,000 simulated samples and report their distributions. The column "Pop" reports the results obtained from 100,000 simulated quarterly observations. VMKT is stock market variance, VG is euphoria variance, and VWASV is value-weighted average stock variance. t-values are reported in parentheses. R^2 is reported in percentage.

3.5]. We assume π_p, the volatility of the idiosyncratic risk is 0.005 for all portfolios. The average values of ϕ_p, $\pi_{\eta,p}$, and $\pi_{e,p}$ equal those of the market portfolio.

Stocks with larger $\pi_{e,p}$ have higher price-dividend ratios and closer correlation with euphoria variance, ceteris paribus. Therefore, a value-weighted average stock variance (VWASV) has a stronger correlation with euphoria variance than with fear variance. In our simple setup, we do not have a formal specification for the cross-sectional distribution of market capitalizations. Specifically, some high tech companies, e.g., Apple, Amazon, Google, Facebook, and Microsoft, have extremely large market capitalizations. As a proximation, we use the squared price-dividend ratio as the weight in simulated data.

Of 10,000 simulated samples, the median coefficient of correlation between VWASV and euphoria variance is 95%, compared with only 38% for the correlation between VWASV and fear variance. By contrast, equal-weighted average stock variance has similar correlation (around 50%) with euphoria and fear variances. More importantly, Panel D of Tables 3, 4, and 5 show that the explanatory power of VWASV for the log price-dividend ratio, the equity premium, and the risk-free rate, respectively, is qualitatively similar to that of euphoria variance.

G. The Cross-Section of Stock Returns

Equation (21) shows that loadings on stock market variance and euphoria variance help explain the cross-section of expected excess stock returns. To illustrate this implication, we run the Fama and MacBeth (1973) regression using the 125 portfolios discussed in the preceding subsection. In the first stage, for each portfolio, we run a time-series forecasting regression of its excess returns on conditional stock market variance and euphoria variance as in equation (15). In the second stage, we run the cross-sectional regression of portfolio returns on their loadings on stock market variance $\hat{\alpha}_p$ and loadings on euphoria variance $\hat{\beta}_p$. The estimated risk prices of loadings $\hat{\alpha}_p$ and $\hat{\beta}_p$ are positive because they equal unconditional means of stock market variance and euphoria variance, respectively. We illustrate these points in Table 6. In panel A, the risk prices of loadings on stock market variance, VMKT, and euphoria variance, VG, are both positive in most simulated samples. The median R^2 is 78%, suggesting that stock market variance and euphoria variance account for a significant portion of

Table 6— Cross-Section of Expected Excess Returns in Simulated Data

	Median	10%	30%	70%	90%	Pop	Scaler
Panel A: Stock Market Variance and Euphoria Variance							
Const	0.332	-0.047	0.174	0.552	0.983	-0.111	0.01
	(1.922)	(-0.255)	(1.006)	(2.868)	(4.234)	(-1.100)	1
VMKT	1.199	-0.709	0.568	1.867	3.127	6.438	0.001
	(2.148)	(-1.072)	(1.054)	(2.952)	(3.898)	(30.043)	1
VG	0.057	-0.141	-0.013	0.125	0.244	0.387	0.001
	(1.084)	(-2.159)	(-0.239)	(2.193)	(3.366)	(15.071)	1
R^2	77.532	37.098	65.333	84.886	90.801	99.674	0.01
Panel B: Stock Market Variance and Value-Weighted Average Stock Variance							
Const	0.333	-0.046	0.177	0.552	0.989	-0.189	0.01
	(1.946)	(-0.241)	(1.021)	(2.909)	(4.262)	(-1.909)	1
VMKT	4.812	-2.744	2.332	7.517	12.563	26.422	0.001
	(2.169)	(-1.077)	(1.093)	(2.961)	(3.900)	(31.536)	1
VWASV	1.042	-1.100	0.337	1.781	3.125	5.731	0.001
	(1.777)	(-1.530)	(0.580)	(2.716)	(3.725)	(24.130)	1
R^2	77.484	36.683	65.312	84.915	90.864	99.666	0.01

Note: The table reports the Fama and MacBeth (1973) regression results for simulated data. In the first stage, for each portfolio, we run a time-series forecasting regression of its returns on conditional stock market variance and euphoria variance. In the second stage, we run the cross-sectional regression of portfolio returns on their loadings on stock market variance and euphoria variance. The table reports the estimated risk prices of loadings on variances. t-values are reported in parentheses. VMKT is stock market variance, VG is euphoria variance, and VWASV is value-weighted average stock variance. The column "Scaler" indicates the actual values of the statistics reported in a row are the reported values time the scaler in that row. For example, the scaler for R^2 is 0.01, indicating that it is reported in percentage. We generate 10,000 simulated samples and report their distributions. The column "Pop" reports the results obtained from 100,000 simulated quarterly observations.

variation in the cross-section of stock returns in our model. Panel B shows that results are almost identical when we use VWASV as a proxy for euphoria variance.

III. Data

We briefly discuss the main variables used in the empirical analysis and provide details of data construction in the online appendix. We use quarterly data spanning the 1963Q1 to 2016Q4 period unless otherwise indicated. Daily and monthly stock return data are from the Center of Research in Security Prices (CRSP), annual accounting data are from Compustat, and analysts earnings forecast data are from I/B/E/S. We obtain the Fama-French 5 factor portfolio return data from Kenneth French at Dartmouth College, the aggregate earnings-price ratio data from Robert Shiller at Yale University, and industry classification data from Dimitris Papanikolaou at Northwestern University.

We follow Boudoukh, Michaely, Richardson, and Roberts (2007) to construct the dividend-price ratio and the net payout-price ratio. We employ two methods to calculate corporate dividend payments: (1) the CRSP stock market indices with and without the dividend distribution and (2) the CRSP dividend payments (CRSP item DIVAMT). We define corporate net payout as the difference between dividend payments and equity issuance that we compute using the monthly change in the number of shares outstanding. We use several dividend reinvestment assumptions, including no reinvestment, the risk-free rate, and the market rate at the end of each month. We get similar results from all these alternative methods. For brevity, we use the dividend payments inferred from CRSP dividend payments data and assume zero-reinvestment to construct the dividend-price ratio and the net payout-price ratio.

We construct three sets of proxies for euphoria variance that are related to IST shocks. First, Papanikolaou (2011) shows that the spread in equity returns between investment-goods producers and consumption-goods producers (IMC) correlates strongly with standard IST shock measures such as the relative price of new equipment. The advantage of IMC is that it is available at a higher (daily) frequency, and we can construct its conditional variance more precisely using realized variance. In addition, Kogan and Papanikolaou (2013, 2014) argue that stocks with higher investment-capital ratios, Tobin's Q, price-earnings ratios, market-to-book equity ratios, market betas, idiosyncratic volatilities, and IMC betas are more sensitive to IST shocks. The high-minus-low spreads in equity returns on portfolios sorted by these characteristics are also proxies for IST shocks. Kogan and Papanikolaou (2013) document a strong comovement among the IST proxies. We construct the average and the first principle component of the eight IST proxies as two additional IST measures. We use the realized variances of the ten IST measures as proxies for euphoria variance. Second, our model suggests that VWASV is a proxy for euphoria variance. Last, in our model, variance of real Treasury bonds is a linear function of euphoria variance. We obtain options-implied nominal Treasury bond volatility, TYVIX, from Chicago Board Options Exchange (CBOE). Because inflation is stable over the 2003Q1 to 2016Q4 period over which TYVIX is available to us, we use TYVIX as an additional measure of euphoria variance.

To construct the daily IMC spread, we use industry classification data to sort stocks into two portfolios, investment-goods producers and consumption-goods producers. We calculate the daily value-weighted portfolio returns, and IMC is the difference in returns between the two portfolios. To construct daily high-minus-low portfolio spreads, we first sort stocks into two portfolios using the median NYSE market cap as the breaking point. Within each size portfolio, we sort stocks equally into three portfolios by each of the aforementioned seven characteristics. If the characteristic uses accounting data that have release delays, we form the portfolios at the end of June of year $t+1$ and hold the portfolios for a year. Otherwise, we form the portfolios at the end of December of year t and hold the portfolios for a year.[6] We construct daily portfolio returns using the value weight. We then construct a high-minus-low hedging portfolio for each characteristic. For example, we construct the return differences between high and low Tobin's Q portfolios for both small and big stocks and use their simple average as a proxy for IST shocks.

We construct quarter t realized variance of each daily IST measure as a proxy for euphoria variance:

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 + 2 \sum_{i=1}^{N_t} r_{i,t} r_{i+1,t}, \tag{22}$$

[6]Results are similar for monthly rebalanced portfolios or independently sorted portfolios.

where $r_{i,t}$ is the ith day excess return, N_t is the number of daily returns in quarter t, and the second term is the correction of serial correlation in daily returns. For the first principle component of the eight IST proxies, we do not include the second term because it generates negative realized variance in some quarters. Kogan and Papanikolaou (2013) document a strong comovement among the IST proxies. We document a strong comovement among their variances (untabulated). Because of their strong comovement, we also use the average and the first principle component of the ten standardized IST-based euphoria variance measures as additional euphoria variance measures.

To construct VWASV, we first construct quarterly realized variance of individual stocks using equation (22) and then aggregate them using the value weight.[7] Because options-implied variance is a better measure of conditional variance than is realized variance, we use value-weighted options-implied variance for VWASV after 1996. Consistent with the model implication, we document a strong relation between VWASV and IST-based euphoria variance measures. The coefficient of correlation of VWASV with the 12 IST-based euphoria variance measures ranges from 59% to 79% over the 1963Q1 to 2016Q4 period, with an average of 69%. Our model also suggests that bond variance is a proxy for euphoria variance. Consistent with this conjecture, we find a strong relation between TYVIX and the 12 IST-based euphoria variance measures, with an average correlation coefficient of 65% over the 2003Q1 to 2016Q4 period. Similarly, TYVIX is closely correlated to VWASV, with a correlation coefficient of 78%. For brevity, these results are not tabulated.

We use equation (22) to construct realized stock market variance as a proxy for conditional stock market variance. We use options-implied market variance VOX or VIX obtained from CBOE after 1986.

Following Pastor, Sinha, and Swaminathan (2008), we use the implied cost of capital (ICC) as a proxy for the conditional equity premium to test the stock market variance-return relation. To ensure that our results are not sensitive to any particular ICC measure, we use common stocks traded on NYSE, AMEX, and Nasdaq to construct

[7]Results are qualitatively similar albeit somewhat weaker if we use the squared price-dividend ratio as the weight. This is because many public companies, especially high-tech companies, do not pay dividends in recent sample period.

five commonly used ICC measures proposed by Pastor et al. (2008), Gebhardt, Lee, and Swaminathan (2001), Easton (2004), Ohlson and Juettner-Nauroth (2005), and Gordon and Gordon (1997). We also obtain the Li, Ng, and Swaminathan (2013) ICC measure from David Ng at Cornell University. I/B/E/S publishes monthly consensus forecasts on the third Thursday of each month. We impose a minimum reporting lag of three months to make sure that earnings forecasts are made based on publicly available accounting information.

For brevity, we do not report the summary statistics of these variables here and provide them in the online appendix.

IV. Empirical Results

In this section, we investigate model's main implications using actual data.

A. Forecasting Excess Stock Market Returns

Panel A of Table 7 reports the univariate regression results of forecasting one-quarter-ahead excess stock market returns with stock market variance VMKT and three euphoria variance measures, AVEV, VWASV, and TYVIX. AVEV is the average of ten standardized IST-based euphoria variance measures.[8] Over the 1963Q2 to 2016Q4 period, stock market variance, VMKT, correlates positively and significantly with future excess stock market returns at the 5% level. By contrast, the correlation is negative for all euphoria variance measures albeit statistically insignificant.

In panel B of Table 7, we include both stock market variance and a euphoria variance measure as forecasting variables. Consistent with our model's prediction, we find that the two variances have substantially stronger forecasting power for excess stock market returns in bivariate regressions than in univariate regressions.[9] The coefficient on VMKT is always significantly positive at the 1% level, and the coefficients on euphoria

[8]In the online appendix, we show that results are qualitatively similar for all ten IST-based euphoria variance measures and their first principle component.

[9]The results that market variance and TYVIX jointly forecast market returns are consistent with the results reported in Scrugg (1998), who argue that Treasury bond returns are a proxy for a hedging risk factor. In particular, he shows that while the stock market variance-return relation in insignificant in the univariate regression, it becomes significantly positive when controlling for the covariance between stock market returns and Treasury bond returns as an additional determinant of the conditional equity premium.

Table 7—Forecasting Excess Stock Market Returns Using Variances

	Panel A		Panel B			Panel C		
Variable	All Variance	R^2	Euphoria Variance	Market Variance	R^2	MSER	ENC_NEW Statistics	5% BSCV
VMKT	2.799**	3.707						
	(2.054)							
AVEV	-0.898	0.347	-2.715***	4.765***	8.679	0.913	13.586	2.370
	(-1.481)		(-4.339)	(4.453)				
VWASV	-0.065	-0.440	-2.096***	8.979***	13.473	0.825	21.880	2.330
	(-0.168)		(-4.063)	(6.849)				
TYVIX	-24.718	5.722	-53.546***	4.658***	17.143	0.771	8.849	2.629
	(-1.495)		(-2.798)	(5.699)				

Note: The table reports the OLS estimation results of forecasting one-quarter-ahead excess stock market returns using variances. VMKT is stock market variance. AVEV is the average of ten standardized IST-based euphoria variance measures. VWASV is the value-weighted average stock variance. TYVIX is the options-implied Treasury bond variance. TYVIX is available over the 2003Q1 to 2016Q4 period and the other variance measures are available over the 1963Q1 to 2016Q4 period. Panel A reports the univariate regression results. Panel B reports the bivariate regression results with stock market variance and a euphoria variance measure as the forecasting variables. Panel C reports the out-of-sample forecast results. For TYVIX, we use the 2003Q1 to 2009Q4 period for the initial in-sample estimation and make the out-of-sample forecast recursively for the 2010Q1 to 2016Q4 period using an expanding sample. For the other euphoria variance measures, we use the 1963Q1 to 1989Q4 period for initial in-sample estimation and make the out-of-sample forecast recursively for the 1990Q1 to 2016Q4 period using an expanding sample. MSER is the mean squared forecasting errors ratio of the forecasting model to a benchmark model in which the conditional equity premium equals average equity premium in historical data. ENC_NEW is the encompassing test proposed by Clark and McCracken (2001). t-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

variance are always significantly negative at the 1% level. The coefficients and t-values are substantially larger in magnitude than their univariate counterparts reported in panel A for both market variance and euphoria variance. In addition, the R^2 is much higher in bivariate regressions than in corresponding univariate regressions. The difference reflects the omitted variables problem. The coefficient of correlation between market variance and euphoria variance measures is positive, ranging between 30% to 70%, while they have opposite effects on the conditional equity premium. If we omit euphoria variance (market variance) in the forecast regression, the coefficient on market variance (euphoria variance) is downward (upward) biased toward zero.[10]

In panel C of Table 7, we investigate the out-of-sample predictive power of stock market variance and euphoria variance. For TYVIX, we use the 2003Q1 to 2009Q4 period for the initial in-sample estimation and make the out-of-sample forecast for the 2010Q1 to 2016Q4 period using an expanding sample. For the other euphoria variance measures, we use the 1963Q1 to 1989Q4 period for initial in-sample estimation and make the out-of-sample forecast for the 1990Q1 to 2016Q4 period using an expanding sample. We use two standard measures to gauge the out-of-sample performance. MSER is the mean squared forecasting errors ratio of the forecasting model to a benchmark model in which the conditional equity premium equals average equity premium in historical data. ENC_NEW is the encompassing test proposed by Clark and McCracken (2001). We find that stock market variance and euphoria variance jointly have significant out-of-sample forecasting power for excess market returns.

The three euphoria variance measures contain similar information about the conditional equity premium. Untabulated results show that both AVEV and TYVIX lose their predictive power when we control for VWASV in multivariate regressions. Because TYVIX is available for a short sample period, we use AVEV and VWASV as euphoria variance measures in the remainder of the paper.

[10]The multicollinearity problem cannot explain our findings because it inflates standard errors and does not increases R^2. As a further robustness check, we orthogonalize market variance by euphoria variance and vice versa, and find that the orthogonalized market variance or euphoria variance has significant predictive power for excess market returns (untabulated).

B. ICC as a Measure of the Conditional Equity premium

We follow Pastor et al. (2008) and use ICC as a proxy for the conditional equity premium to investigate the stock market variance-return relation. Panel A of Table 8 investigates the relation between ICC and market variance. Consistent with Pastor et al. (2008)'s finding, the relation is positive and statistically significant at the 10% level using their ICC measure, PSS, over the extended sample period. We find similar results using the Li et al. (2013) ICC measure, LNS, which is very similar to PSS. For the other ICC measures, the relation is positive albeit insignificant.

In Panel B of Table 8, we add AVEV as an additional explanatory variable. All ICC measures correlate positively and significantly with market variance at least at the 10% level. Their correlation with AVEV is significantly negative at the 5% level. The adjusted R^2 is also substantially higher than its counterpart reported in Panel A. The results are qualitatively similar when we use VWASV as a proxy for euphoria variance in Panel C. Therefore, the relatively weak relation between ICC and market variance documented in panel A reflects the omitted variables problem: Both stock market variance and euphoria variance are significant determinants of the implied cost of capital.

If ICC is a measure of the conditional equity premium, it may forecast excess stock market returns. Consistent with this conjecture, Li et al. (2013) show that their ICC measure have significant market return predictive power. In the online appendix we replicate their main finding that LNS correlates positively and significantly with the one-quarter-ahead excess stock market return at the 5% level. The other ICC measures also correlate positively with future excess stock market returns; however, the relation is statistically insignificant at the 5% level. To investigate whether the forecasting power of ICC reflects its correlation with market variance and euphoria variance, we decompose ICC into two components by regressing it on market variance and euphoria variance, as in Table 8. The fitted component of ICC measures correlates positively and significantly with future stock market returns, while the residual component has negligible predictive power. Therefore, ICC forecasts market returns because of its correlations with market variance and euphoria variance.

Table 8— Implied Cost of Capital and Stock Market Variance

	PSS	GLS	Easton	OJ	GG	AICC	LNS
Panel A: Stock Market Variance							
VMKT	0.161*	0.137	0.075	0.110	0.145	0.125	0.225**
	(1.787)	(1.593)	(0.820)	(1.393)	(1.510)	(1.428)	(2.217)
R^2	5.060	3.149	0.283	1.815	3.239	2.529	4.694
Panel B: Stock Market Variance and Average of Euphoria Variance Measures							
AVEV	-0.148**	-0.184**	-0.154**	-0.144**	-0.184**	-0.163**	-0.184**
	(-2.279)	(-2.517)	(-2.117)	(-2.286)	(-2.463)	(-2.362)	(-2.012)
VMKT	0.277**	0.282***	0.196*	0.222**	0.289**	0.253**	0.371**
	(2.519)	(2.576)	(1.701)	(2.189)	(2.524)	(2.303)	(2.648)
R^2	12.453	14.041	6.472	8.311	13.055	10.999	9.980
Panel D: Stock Market Variance and Value-Weighted Average Stock Variance							
VWASV	-0.116***	-0.146***	-0.122***	-0.109***	-14.935***	-0.129***	-0.122*
	(-3.415)	(-4.332)	(-3.058)	(-3.129)	(-4.566)	(-3.707)	(-1.923)
VMKT	0.522***	0.596***	0.455***	0.451***	0.612***	0.529***	0.599***
	(3.885)	(4.398)	(3.090)	(3.408)	(4.472)	(3.872)	(2.812)
R^2	19.683	25.114	12.911	13.989	24.022	19.490	12.446

Note: The table reports the OLS estimation results of regressing the implied cost of capital on contemporaneous stock market variance and euphoria variance measures. PSS, GLS, Easton, OJ, and GG are the implied cost of capital measures constructed following Pastor et al. (2008), Gebhardt et al. (2001), Easton (2004), Ohlson and Juettner-Nauroth (2005), and Gordon and Gordon (1997), respectively. AICC is the average of these five ICC measures. LNS is the ICC measure used in Li et al. (2013). LNS is available over the 1981Q1 to 2011Q4 period, GLS and AICC are available over the 1982Q1 to 2016Q4 period, and the other ICC measures are available over the 1981Q1 to 2016Q4 period. VMKT is stock market variance. AVEV is the average of ten standardised IST-based euphoria variance measures. VWASV is the value-weighted average stock variance. *t*-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

C. *Stock Market Variance and Prices*

Equation (12) shows that the log price-dividend ratio depends on the expected long-run growth rate of cash flows, market variance, and euphoria variance. Following Sadka (2007), we use realized real earnings growth in the following 20 quarters as a proxy for the expected cash flows: FEG=$\sum_{i=0}^{20} k_{1,m}^{i}[\Delta e_{t+1+i}]$, where $k_{1,m} = 0.996^3$ for quarterly data. By contrast with extant asset pricing models, Panel A of Table 9 shows that the relations between market variance and scaled stock market prices are rather weak.

In panel B of Table 9, we add AVEV as an additional explanatory variable. The scaled stock market prices correlate negatively with market variance, and the correlation is statistically significant at least at the the 10% level. The three scaled stock market prices correlate positively and significantly with AVEV at the 1% level. The adjusted R^2 ranges from 19% to 51%, indicating that market variance and euphoria variance jointly account for a substantial portion of variation in stock market prices. Panel C shows that results are similar or stronger for VWASV, with the adjusted R^2 of up to about 60%. In addition, consistent with Shiller (1981)'s finding, we show that FEG has weak explanatory power for stock market prices.

In our model, the price-dividend ratio correlates with market variance and euphoria variance because these variances are the determinants of the conditional equity premium. To investigate this implication, we decompose the stock market price into two components by regressing it on market variance and euphoria variance. The online appendix shows that the fitted component correlates negatively and significantly with one-quarter-ahead excess stock stock market returns, while the predictive power is negligible for the residual component.

D. *Explaining the Cross-Section of Expected Excess Stock Returns*

We use the Fama and MacBeth (1973) cross-sectional regression to test whether loadings on stock market variance and loadings on euphoria variance account for the cross-section of expected stock returns. Specifically, we first regress excess returns of each test portfolio on lagged stock market variance and lagged euphoria variance, and use the estimated loadings in the second-stage cross-sectional regressions. Because both stock market variance and euphoria variance are persistent and have measurement

Table 9— Scaled Stock Market Prices and Variances

	PD	PPO	PE
Panel A: Stock Market Variance			
VMKT	4.411	7.486	-4.015
	(0.377)	(1.181)	(-0.380)
FEG	0.058	0.025	0.045
	(0.292)	(0.412)	(0.245)
R^2	-0.328	1.660	-0.569
Panel B: Stock Market Variance and Average of Euphoria Variance Measures			
AVEV	0.342***	0.247***	0.276***
	(8.366)	(5.473)	(6.726)
VMKT	-20.671*	-10.655***	-24.260***
	(-1.837)	(-2.040)	(-2.185)
FEG	0.033	0.007	0.025
	(0.210)	(0.238)	(0.163)
R^2	27.905	51.148	19.080
Panel C: Stock Market Variance and Value-Weighted Average Stock Variance			
VWASV	18.072***	14.965***	13.184***
	(6.525)	(5.046)	(5.219)
VMKT	-48.463***	-36.296***	-42.586***
	(-4.523)	(-4.759)	(-3.857)
FEG	0.077	0.040	0.059
	(0.468)	(1.262)	(0.369)
R^2	24.571	59.108	13.461

Note: The table reports the OLS estimation results of regressing scaled stock market prices on contemporaneous stock market variance and euphoria variance. PD is the price-dividend ratio. PPO is the ratio. PE is the price-earnings ratio. VMKT is stock market variance. AVEV is the average of ten standardized IST-based euphoria variance measures. VWASV is the value-weighted average stock variance. FEG is the earnings growth in the following 10 years. Data span the 1963Q1 to 2016Q4 period. *t*-value is reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10— Cross-Section of Portfolio Returns and Variances

	Constant	Euphoria Variance	Market Variance	R^2
Panel A: 175 Value-weighted double-sorted Portfolios				
AVEV	0.027***	0.842***	0.002**	67.814
	(4.995)	(3.668)	(2.022)	
VWASV	0.030***	0.020***	0.003***	72.697
	(5.210)	(3.435)	(2.372)	
Panel B: 175 Equal-weighted double-sorted Portfolios				
AVEV	0.026***	1.328***	0.004***	76.754
	(4.546)	(5.604)	(3.548)	
VWASV	0.032***	0.029***	0.005***	81.950
	(5.310)	(5.402)	(3.759)	

Note: The table reports the Fama and MacBeth (1973) cross-sectional regression results for two sets of test portfolios. We first sort stocks equally into five portfolios by market capitalization, and then within each size portfolio we sort stocks equally into five portfolios by each of the seven characteristics: the investment-capital ratio, Tobin's Q, the price-earnings ratio, idiosyncratic volatility, IMC beta, the book-to-market equity ratio, and market beta. We use the value weighted 175 portfolios in panel A and the equal-weighted 175 portfolios in panel B. VMKT is stock market variance. We use two proxies of euphoria variance. is the average of ten standardized IST-based euphoria variance measures. VWASV is the value-weighted average stock variance. The data span the 1963Q1 to 2016Q4 period. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

errors, we include two lags of market variance and two lags of euphoria variance in the first-stage regression, and the loadings used in the second stage are the sum of the coefficients on two lags of stock market variance or two lags of euphoria variance. Results are qualitatively similar when we include one lag of stock market variance and one lag of euphoria variance.

We use two sets of test portfolios. We first sort stocks equally into five portfolios by market capitalization, and then within each size portfolio, we sort stocks equally into five portfolios based on each of the seven characteristics: the investment-capital ratio, Tobin's Q, the price-earnings ratio, idiosyncratic volatility, IMC beta, the book-to-market equity ratio, and market beta. We use equal or value weights to construct 175 portfolios.[11] In panel A of Table 10, we report the Fama and MacBeth (1973) regression results for the 175 value-weighted double-sorted portfolios. The risk price of loadings on euphoria variance is positive and significant at the 1% level for both AVEV and VWASV. The risk price of loadings on market variance is significantly positive at the 1% level. The cross-sectional R-squared ranges from 68% to 73%, which are comparable to the median R-squared in simulated data reported in Table 6. Panel B shows that results are similar for the 175 equal-weighted doubt-sorted portfolios.

E. Risk-Free Rate and Variances

We investigate the relation between the risk-free rate and variances in Table 11. Panel A reports the univariate regression results. While the risk-free rate correlates negatively with market variance, its correlations with euphoria variance measures AVEV and VWASV are positive. Nevertheless, the relation is statistically insignificant in all cases. Panel B reports the estimation results of the bivariate regression. The negative relation between stock market variance and the risk-free rate becomes statistically significant at the 1% level when in conjunction with VWASV and at the 10% level when in conjunction with AVEV. Moreover, the relation between the risk-free rate and euphoria variance is significantly positive at the 1% level for VWASV and at the 10% for AVEV. These findings are consistent with the simulation results reported in Table 5.

[11] We obtain from Kenneth French at Dartmouth College the 32 triple-sorted portfolios formed on market capitalization, operation profit, and total asset growth and the 32 triple-sorted portfolios formed on market capitalization, book-to-market equity ratios, and total asset growth. In the online appendix, we show that results are qualitatively similar for these two sets of portfolios.

Table 11— Stock Variances and the Risk-Free Rate

	Panel A		Panel B		
	Variance	R^2	Euphoria Variance	Market Variance	R^2
VMKT	-0.068 (-1.201)	0.683			
AVEV	0.000 (0.789)	0.257	0.001* (1.769)	-0.134* (-1.708)	3.464
VWASV	0.010 (0.477)	-0.259	0.071*** (3.087)	-0.288*** (-2.923)	7.625

Note: The table reports the OLS estimation results of regressing the risk-free rate on contemporaneous stock market variance and euphoria variance. VMKT is stock market variance. AVEV is the average of ten standardized IST-based euphoria variance measures. VWASV is the value-weighted average stock variance. Data span the 1963Q1 to 2016Q4 period. *t*-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

F. Fear Variance, Euphoria Variance, and Consumption Variance

In this subsection, we investigate whether stock market variance and the value-weighted average stock variance forecast consumption variance. Guo and Pai (2019) find substantial difference between real-time consumption data and revised consumption data. For robustness, we estimate conditional consumption (nondurable goods and services) variance using the GARCH (1,1) model for both measures over the 1985Q1 to 2018Q4 period. Their correlation coefficient is 69% (untabulated). We standardize log real-time consumption variance and log revised consumption variance, and use their average as the consumption variance measure. We use log stock market variance, LVMKT, and log value-weighted average stock variance, LVWASV, as the forecasting variables.

Table 12— Forecasting Consumption Variance

Panel A: One-Quarter Ahead			Panel B: Four-Quarter Ahead		
LVMKT	LVWASV	R^2	LVMKT	LVWASV	R^2
0.477***		0.168	2.090***		0.253
(3.803)			(3.458)		
	0.648***	0.185		2.725***	0.255
	(4.295)			(3.542)	
0.217	0.424**	0.191	1.145*	1.538**	0.277
(1.343)	(2.221)		(1.857)	(2.022)	
Panel C: Six-Quarter Ahead			Panel D: Eight-Quarter Ahead		
LVMKT	LVWASV	R^2	LVMKT	LVWASV	R^2
3.054***		0.270	3.745***		0.257
(3.626)			(3.757)		
	3.864***	0.255		4.431***	0.212
	(3.363)			(3.098)	
1.873**	1.923*	0.288	2.815***	1.514	0.261
(2.232)	(1.697)		(2.610)	(1.026)	

Note: The table reports the OLS estimation results of forecasting consumption variance over the 1985Q1 to 2016Q4 period. LVMKT is stock market variance. LVWASV is the value-weighted average stock variance. We use the Newey-West standard errors to construct t-values reported in parentheses. We use 1, 4, 6, and 8 lags for one, four, six, and eight-quarter-ahead consumption variance forecasts. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 12 shows that both LVMKT and LVWASV have significant predictive power in univariate regressions. Both variables are significant at least at the 10% level in bivariate regressions for four-quarter-ahead and six-quarter-ahead consumption variances. In addition, while LVWASV has stronger predictive power at short horizons, LVMKT has stronger predictive power at long horizons. Overall, our preliminary results suggest that fear variance and euphoria variance are important determinants of consumption variance.

V. Conclusion

The log price-dividend ratio is approximately a linear function of expected future discount rates and expected future dividend growth rates. The time-varying equity premium has become the central organizing question in rational expectations asset pricing paradigm since Shiller (1981)'s seminal finding that the dividend component accounts for little variation in stock market prices. The price-dividend ratio plays a pivotal role in modern asset pricing models of the time-varying equity premium because of the mechanical link between these two variables. Few studies, however, have attempted to address *formally* the fundamental asset pricing question that Shiller (1981) raised four decades ago: What are the economic origins of fluctuations in stock market prices? In this paper, we try to fill the gap by investigating empirically and theoretically the relation between stock market prices and systematic risks that are determinants of the conditional equity premium and stock market prices in rational expectations asset pricing models.

A positive relation between the conditional stock market variance and return is the key building block of extant asset pricing models. To address Shiller (1981)'s excess volatility puzzle, these models assume that the conditional stock market variance, which is the sole determinant of the conditional equity premium, is also the main driver of variation in stock market prices. By contrast with these models' conjecture of a negative stock market price-variance relation, we show that the relation is sometimes positive and sometimes negative. The finding corroborates extensive empirical evidence of an unstable stock market variance-return relation.

We provide a novel theoretical explanation for these puzzling empirical findings. Stock market variance has two components, euphoria variance and fear variance. The conditional equity premium depends positively on fear variance but negatively on euphoria variance. Because stock market variance is the sum of the two variances, its relation with the conditional equity premium can be positive, negative, or insignificant, depending on the relative importance of its two components. The unstable stock market variance-return relation implies an unstable relation between stock market variance and prices: The relation is positive (negative) when euphoria (fear) variance is the dominant component. Nevertheless, our model suggests that fear variance and euphoria variance jointly explain fluctuations in stock market prices and the conditional equity premium. Our empirical evidence strongly supports these implications.

Fear variance and euphoria variance resonate with the conventional wisdom that fear and euphoria are dominant forces in the stock market. Fear and euphoria usually refer to investors' irrational behaviors or animal spirits. We suggest that they might also be explained by systematic risks. Our model provides a rich set of testable implications that can be used to explore the origins of fear and euphoria perceived by financial market participants. It sheds new light on the behavioral asset pricing theories in which investor sentiment is the main driver of stock market prices.

For example, Guo and Qiu (2018) find that commonly used sentiment measures correlate positively with euphoria variance and negatively with stock market or fear variance. In addition, the sentiment measures forecast excess market returns because of their correlation with euphoria variance and stock market variance. Their results suggest a close relation between standard investor sentiment measures and the conditional equity premium. In addition, while the existing literature, e.g., Bloom (2009), emphasizes the adverse effect of aggregate economic uncertainty on aggregate investment, Guo and Qiu (2018) find that the latter correlates positively with euphoria variance and negatively with stock market or fear variance.

Our empirical findings suggest that euphoria variance is related to investment-specific technological shocks. While more work is needed to fully understand the origins of investment-specific technological shocks, extant studies, e.g., Justiniano et al. (2011) find that they are closely related to financial market frictions. Similarly, Ludvigson, Ma, and Ng (2019) show that shocks to financial market uncertainty are an important exogenous driver of business fluctuations. A general equilibrium models with financial market frictions and a production sector will provide a better understanding of how financial market shocks influence the real economy. We leave this important question for future research.

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