JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 59, No. 3, May 2024, pp. 1064–1099

doi:10.1017/S0022109023000455

Inferring Aggregate Market Expectations from the Cross Section of Stock Prices

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Abstract

We introduce a new approach to estimating long-term aggregate discount rates using the cross section of earnings and book values to explain current stock prices and extract expected market returns. The proposed discount rate measure is countercyclical. Shocks to it account for nearly half of historical market return variation; in contrast, shocks to other discount rate measures account for no more than 2%. It dominates other measures in explaining time-series variation in returns on duration-sorted portfolios and delivers out-of-sample predictability that exceeds that afforded by other expected return measures and predictive variables. It also performs well in international equity markets.

I. Introduction

Aggregate expected returns are inherently unobservable and difficult to measure. Yet measures of aggregate expected returns are crucial for studying the nature of risks in the economy, the activities that give rise to these risks, and the compensation demanded for bearing them. Poor measurement of expected returns limits our understanding of asset prices over time and across stocks. For example, time-varying yet stationary expected returns imply a mean-reverting process (Chen, Da, and Zhao (2013)). What economic factors drive this mean-reversion? What is the role of time-varying risk and time-varying risk aversion? How do these forces manifest in the prices of individual securities? These questions are difficult to

We are grateful to an anonymous referee and Thierry Foucault (the editor) for constructive and insightful comments that greatly improved the article. We also thank Geert Bekaert, Michael Brandt, Hui Guo, Michael Halling, Volkan Muslu (CFMA discussant), Jim Ohlson, Sergei Sarkissian, Ivo Welch, Robert Whitelaw, Jeff Wurgler, Nir Yehuda, Tim Zhang (AAA discussant), and conference participants at the 2017 American Accounting Association meeting and the 2019 Conference on the Convergence of Financial and Managerial Accounting Research for helpful comments and suggestions, and Yan Li and David Ng for sharing their aggregate implied cost of capital data. David Weinbaum gratefully acknowledges research support from the Harris Fellowship in Finance. All errors remain our responsibility.

answer without precise discount rate proxies. Improved measures of aggregate expected returns can also promote cash-flow and discount-rate decompositions of returns (e.g., Campbell and Shiller (1988), Campbell (1991), Vuolteenaho (2002), and Campbell and Vuolteenaho (2004), among others), and can enhance the ability of researchers to distinguish behavioral and rational economic theories of the price formation process (Bordalo, Gennaioli, La Porta, and Shleifer (2022)). Cochrane ((2011), p. 1091) describes discount-rate variation as the central organizing question in current asset pricing research and remarks, "most of the puzzles and anomalies we face amount to discount-rate variation that we do not understand." Better measures of expected returns must surely help.

In this article, we show that aggregate market return expectations can be inferred from the cross section of stock prices, earnings, and book values. Intuitively, as discount rates rise, equity values shift away from risky future earnings and toward net assets on hand. But earnings persistence matters too: When persistence is low, equity values will also depend more on assets on hand. Thus, the *relative* contributions of earnings and book values to stock prices *in the cross section* will vary with both aggregate expected returns and earnings persistence. Our approach uses the Ohlson (1999) model to disentangle the effects of earnings persistence and discount rates. Specifically, we perform monthly Theil–Sen regressions of stock prices on firm accounting fundamentals (e.g., earnings, book values) using a broad, representative cross section of U.S. stocks.[1] The theory underlying our approach not only formalizes the underlying intuition, but also predicts that long-run expected returns can be estimated directly from the parameter estimates. That is, our measure does not merely track temporal variation in discount rates, but also provides a point estimate of prevailing long-run expected returns from the estimated coefficients on earnings and book values.

We examine the equity market risk premium measured as aggregate expected returns less the yield on one-year Treasury securities. Our main results are easily summarized. First, our measure of the equity risk premium has economically sensible properties. For example, it is countercyclical: it rises during recessions and is lower during expansions. It is also strongly correlated with macroeconomic variables that reflect the business cycle, including the GDP growth rate, unemployment rate, inflation rate, industrial production growth, and aggregate volatility, and is negatively correlated with past market returns.

Second, we rely on the observation that an empirically valid discount rate measure should not only predict future returns, but also shocks to it should explain a significant fraction – about half – of the variation in realized returns (e.g., Cochrane (2011)). We compare the performance of our measure to that of other cross-sectional discount rate measures, including various implementations of the implied cost of capital (Gebhardt, Lee, and Swaminathan (2001), Ohlson and Juettner-Nauroth (2005), and Li, Ng, and Swaminathan (2013)) and the Kelly and Pruitt (2013) three-pass return predictor. We find that our measure is the only one to come close to the 50% benchmark: shocks to our discount rate measure account for 43% of the variation in historical market returns, whereas shocks to other measures

[1]As discussed below, Theil–Sen is a nonparametric alternative to the ordinary least squares (OLS) estimation methodology that provides robust parameter estimates in the presence of outliers and heteroscedasticity.

account for no more than 2%. We also construct our measure using a broad sample of international stocks and find that it performs similarly well in explaining market returns outside the United States.

Third, having established the ability of our approach to capture discount rate changes, we take it to the cross section and consider duration-sorted equity portfolios. Stock prices fall (rise) as discount rates rise (fall), and the duration of a stock's expected cash flows amplifies the effect. In fact, the discount rate change for a given month drives the monthly return spread between high- and low-duration stocks. Thus, our analysis proceeds in two stages. In the first, we run monthly cross-sectional regressions of stock returns on duration-sorted portfolio assignments. The estimated slope coefficient in these regressions reflects the return spread between high- and low-duration stocks, which is a function of the change in the discount rate over the month. In the second step, we run a time-series regression of the first-stage estimates on the various measures of discount rate changes. We find that our measure dominates others in explaining the time-series variation in the returns on duration-sorted portfolios.

Fourth, our measure of expected returns predicts aggregate stock market returns at horizons of 1–12 months. In a direct horse race, we find that it dominates the predictability of a large set of alternative variables that have been proposed in the literature, including other cross-sectional discount rate measures as well as the popular valuation ratios and business cycle variables from Welch and Goyal (2008), Robert Shiller's cyclically adjusted price-earnings ratio, and the Bordalo et al. (2022) index of long-term expected earnings growth. Out-of-sample tests have received a great deal of attention in the literature. Welch and Goyal (2008) find little evidence of out-of-sample predictability across the large number of candidate predictive variables they consider; they propose an out-of-sample R^2 statistic to gauge out-of-sample performance. The measure we propose delivers a high out-of-sample R^2 of 4.5% at the annual horizon.

We propose a new measure of long-run aggregate expected returns that performs well empirically. The approach is easy to implement, as it only requires estimation of a single first-stage cross-sectional nonparametric regression of prices on dividends, book values, and earnings. Our minimal data requirements offer the potential for an ex ante expected return measure for any market with price and basic accounting data, and indeed, we find that our measure performs well in international markets. Moreover, our measure can be estimated in real-time so that there is no look-ahead bias. Along with these benefits, we show that our measure relates in sensible ways to market and economic determinants, that shocks to it account for a large fraction of historical market return variation, that it dominates other measures in explaining time-series variation in returns on duration-sorted portfolios, and that it forecasts aggregate returns better than other well-known predictors.

Our long-run discount rate measure is derived from a cross-sectional regression of stock prices on accounting data. Because all the variables are dollar amounts, two concerns arise if one estimates the regression using OLS: outliers and heteroscedasticity. We address both issues by employing an estimation approach due to Theil (1950) and Sen (1968). The Theil–Sen (TS) estimator is a nonparametric alternative to OLS specifically designed to address concerns of outliers and heteroscedasticity. The estimation approach can be described as follows: Assuming that we need to estimate K parameters in a regression model, the TS estimator draws a random sample of K observations and solves for the parameters. In OLS terms, K observations used to estimate K parameters yield an R^2 of 100%. This procedure is repeated a large number of times, solving for the parameters with each draw, which results in a distribution for each of the K parameters. The TS estimator employs the median of each distribution as the parameter estimate.

Because our measure is based on a fundamental present value relation fitted to the cross section of stock prices, it is related to other cross-sectional measures of expected returns proposed in the literature. Polk, Thomson, and Vuolteenaho (2006) construct a cross-sectional equity premium measure based on the observation that, in the CAPM, the expected return on a stock is linearly related to its beta in the cross section. The slope of this relation is the cross-sectional price of risk, which yields the Polk et al. (2006) measure of the equity risk premium. While Polk et al. (2006) find strong empirical support for their measure over their full 1927–2002 sample, the performance of their measure deteriorates in post-1965 data. In contrast, our measure performs well over our more recent sample period of Jan. 1976 to Dec. 2018.

Another measure is that of Kelly and Pruitt (2013), who use the three-pass regression filter developed by Kelly and Pruitt (2015) to forecast aggregate market returns from the cross section of portfolio-level valuation ratios. The approach we propose outperforms the Kelly and Pruitt (2013) technique in several direct horse races.

Also related is the literature on implied cost of capital, which is defined as the discount rate that equates the price of a stock to the present value of its expected future dividends, or cash flows. For example, Pástor, Sinha, and Swaminathan (2008) use the implied cost of capital approach to test the intertemporal CAPM, Lee, Ng, and Swaminathan (2009) use it to test international asset pricing models, and Li et al. (2013) use the aggregate implied cost of capital to predict market returns. While related to our approach, these implied costs of capital approaches require analyst earnings forecasts. In addition, they require researcher-specified assumptions regarding market expectations of long-term growth rates and dividend payout rates for each firm. Our approach, in contrast, relies on a single cross-sectional regression of stock prices on book values and earnings to estimate expected market returns. Thus, our model infers market expectations from the relation between prices and current accounting variables without the need for assumptions specified by the researcher. In other words, rather than polling analysts about near-term earnings and adding assumptions about long-term growth, our approach simply polls investors, in the form of share price, on their views of recent accounting fundamentals. Moreover, our minimal data requirements offer the potential for an ex ante measure of long-run expected returns where the use of analyst forecasts is unwarranted (e.g., rapidly changing market conditions) or impossible (e.g., some international markets). Finally, we show that our measure outperforms various implementations of the implied cost of capital in several direct comparisons.

Importantly, this article does not merely provide a new measure of aggregate expected returns, it also makes a broader methodological contribution. First, we go beyond the traditional in- and out-of-sample return prediction analyses and consider whether shocks to a candidate discount rate measure explain a sufficiently large fraction of the variation in contemporaneous realized market returns. Second, we take our analysis to the cross section, and consider the returns on duration-sorted portfolios. In so doing, we tie together the literature on stock market predictability discussed above and the growing literature on equity duration (e.g., Dechow, Sloan, and Soliman (2004), Lettau and Wachter (2007), among others).

The rest of this article is organized as follows: Section II describes our methodology and data. Section III empirically validates our market risk premium measure. Section IV investigates the sources of its performance and presents alternative estimation techniques and international evidence. Section V concludes.

II. Data and Empirical Methodology

This section explains how we construct our aggregate expected return measure and describes the data we use in the article.

A. Valuation with Time-Varying Expected Returns

To develop a framework to value securities that allows for time-varying discount rates, we begin with the definition of the expected return on an asset. The expected return $E_t(r_{t+1})$ on an asset is defined as:

$$E_t(r_{t+1}) = E_t\left(\frac{P_{t+1} + D_{t+1}}{P_t}\right) - 1, \tag{1}$$

where P_t is the stock price at time t and D_t is the dividend paid at time t. By iterating equation (1) and assuming a transversality condition, it follows from the law of iterated expectations that

$$P_t = E_t\left[\sum_{\tau=1}^{\infty} \frac{D_{t+\tau}}{\prod_{k=0}^{\tau-1} E_{t+k}(1 + r_{t+k+1})}\right]. \tag{2}$$

Our objective is to develop a methodology for estimating long-run average expected returns. Following Keloharju, Linnainmaa, and Nyberg (2021), we define the time t long-run average expected return as the discount rate R_t that solves the equation:

$$P_t = E_t\left[\sum_{\tau=1}^{\infty} \frac{D_{t+\tau}}{(1 + R_t)^{\tau}}\right]. \tag{3}$$

This definition of long-run expected return is analogous to the definition of the yield to maturity on a bond or the internal rate of return on a project.

Our approach makes two assumptions that enable us to directly relate R_t to security prices and observable accounting variables. The first assumption is the clean surplus accounting relation. Clean surplus accounting requires that all gains and losses that affect book value be included in earnings (i.e., the change in book value from one period to the next equals earnings minus net dividends),

(4) $$\mathrm{BV}_t = \mathrm{BV}_{t-1} + \mathrm{NI}_t - D_t,$$

where BV_t is the book value of the equity at time t and NI_t denotes earnings for the period from $t-1$ to t. In this framework, dividends encompass all transactions between a firm and its shareholders, including stock repurchases.[2]

This assumption allows dividends to be expressed in terms of earnings and book values. Assuming transversality then makes it possible to express price as the sum of book value and the present value of future residual income, or abnormal earnings,

(5) $$P_t = \mathrm{BV}_t + \sum_{\tau=1}^{\infty} \frac{E_t\left(\mathrm{NI}^a_{t+\tau}\right)}{(1+R_t)^{\tau}},$$

where $\mathrm{NI}^a_{t+\tau}$ denotes the firm's abnormal earnings, defined as

(6) $$\mathrm{NI}^a_{t+\tau} = \mathrm{NI}_{t+\tau} - R_t \times \mathrm{BV}_{t+\tau-1}.$$

Equation (5) is known as the residual income model or the Edwards–Bell–Ohlson (EBO) valuation equation.[3] The implied cost of capital literature implements the residual income model by making use of consensus analyst forecast data (e.g., Pástor et al. (2008), Lee et al. (2009), and Li et al. (2013)).

Second, we assume that current period income carries implications for future earnings. Kormendi and Lipe (1987) were among the first to establish that security prices reflect the degree of persistence in earnings information. Dechow, Hutton, and Sloan (1999) find that a mean-reverting process provides a reasonable description of the time-series properties of abnormal earnings. However, not all earnings components have equal persistence. For example, special items are transitory (Dechow and Ge (2006)), and nonoperating income is less persistent than operating income (Fairfield, Sweeney, and Yohn (1996)). Moreover, other value-relevant information exists beyond the information captured by current accounting numbers, and this other information impounded in price anticipates future earnings (e.g., Beaver, Lambert, and Morse (1980), Collins, Kothari, Shanken, and Sloan (1994)). Thus, a description of the time-series evolution of residual income should reflect three empirical facts: mean reversion in residual income, differential persistence among earnings components, and the existence of other value-relevant information not captured by current earnings, book values, and dividends. To formalize these empirical facts, we follow Ohlson (1999) and characterize the relation between current earnings and future earnings with the following process,

[2]Clean surplus is a common assumption. For example, Vuolteenaho (2002) invokes the clean surplus relation to develop a present value identity for the book-to-market ratio, and Fama and French (2016) rely on the clean surplus relation to motivate the investment (CMA) and profitability (RMW) factors.

[3]As Lee, Myers, and Swaminathan (1999) point out, the reference to "EBO" is due to Bernard (1994). Various forms of the model can be found in Preinreich (1938), Edwards and Bell (1961), and Ohlson (1995), among others.

(7a) $$\mathrm{NI}^a_{t+1} = \omega_{11}\mathrm{NI}^a_t + \omega_{12}\mathrm{NI}_{2,t} + \gamma_1 \cdot v_t + \varepsilon_{1,t+1},$$

(7b) $$\mathrm{NI}_{2,t+1} = \omega_{22}\mathrm{NI}_{2,t} + \gamma_2 \cdot v_t + \varepsilon_{2,t+1},$$

(8) $$v_{t+1} = G \cdot v_t + \varepsilon_{3,t+1},$$

where total earnings NI_t are the sum of core earnings (denoted $\mathrm{NI}_{1,t}$ below) and transitory earnings ($\mathrm{NI}_{2,t}$), v_t is information about future abnormal earnings that is not incorporated in current abnormal earnings, $\varepsilon_{1,t}$, $\varepsilon_{2,t}$ and $\varepsilon_{3,t}$ are unpredictable mean zero disturbance terms, ω_{11}, ω_{12}, and ω_{22} are persistence parameters that are nonnegative and less than 1, and γ_1 and γ_2 are vectors of fixed constants.

This assumption is identical to Ohlson's (1999) assumption A3′, except that Ohlson (1999) assumes a constant per-period discount rate, whereas here R_t is the long-run time-t average expected return in a setting with time-varying discount rates. Although R_t varies over time, at each time t it is a fixed constant. Specifically, in equations (5) and (6), R_t is the same for all future periods τ, thus Ohlson's (1995), (1999) logic prevails.

As we show next, if equations (7a), (7b), and (8) approximate the evolution of earnings, we can infer aggregate expected returns from simple cross-sectional regressions of prices on book values, earnings (decomposed), and dividends. Our analyses involve joint tests of the functional form of the earnings-generating process and the empirical content of the resulting measure of aggregate expected returns. If equations (7a), (7b), and (8) provide a poor description of the relation between current earnings and future earnings expectations impounded in price, our measure of aggregate expected returns should not perform well in our empirical tests.

Combining equations (7a), (7b), and (8) with the residual income model formulation in equation (5) results in the following valuation relation (see Appendix A of the Supplementary Material for details):

(9) $$P_t = (1-k_t)\mathrm{BV}_t + k_t(\varphi_t \mathrm{NI}_{1,t} - D_t) + (\alpha_{1,t} + \alpha_{2,t} + k_t)\mathrm{NI}_{2,t} + \beta \cdot v_t,$$

where $\varphi_t = (1+R_t)/R_t$, $k_t = (R_t\omega_{11})/(1+R_t-\omega_{11})$, and $\alpha_{1,t}$ and $\alpha_{2,t}$ are functions of ω_{11}, ω_{12}, ω_{22}, and R_t. Note that φ_t equals a P/E multiple assuming current earnings in perpetuity (i.e., perfect persistence), whereas k_t captures the effects of an earnings trajectory that is less than perfectly persistent. For example, if earnings are perfectly persistent ($\omega_{11} = 1$), k_t equals 1. In this case, the weight on book value ($1 - k_t$) becomes 0, and stock price can be summarized as a multiple of earnings adjusted for the impact of current dividends, transitory earnings, and other information.

Equation (9) leads to a natural cross-sectional measure of long-run market expected returns. First, we regress the cross section of stock prices on book values, core earnings, other earnings, and clean-surplus net dividends. Although equation (9) describes a firm-specific relation, coefficient estimates in a cross-sectional regression capture the average of the firm-specific relations among the stocks included in the regression. Moreover, while cross-sectional differences in short-term expected returns are sizeable (e.g., Martin and Wagner (2019)), long-term discount rates vary much less across stocks (Keloharju et al. (2021)). In the second step, therefore, we recover long-run expected market returns from the first-stage coefficient estimates. We develop this approach more fully in the next section.

B. Long-Run Expected Market Return Estimation

Motivated by equation (9), we recover our measure of long-run market returns from the loadings on book value and earnings in the cross-sectional regression,

$$P_{i,t} = \alpha_t + \beta_{1,t}\mathrm{BV}_{i,t} + \beta_{2,t}\mathrm{OIAD}_{i,t} + \beta_{3,t}\mathrm{OTHINC}_{i,t} + \beta_{4,t}\mathrm{DIV}_{i,t} + \epsilon_{i,t}, \tag{10}$$

where $P_{i,t}$ is the stock price in month t, $\mathrm{BV}_{i,t}$ denotes book value of equity for the most recent quarter, $\mathrm{OIAD}_{i,t}$ denotes last-12-month (LTM) operating income after depreciation, $\mathrm{OTHINC}_{i,t} = \mathrm{NI}_{i,t} - \mathrm{OIAD}_{i,t}$ is other income (where $\mathrm{NI}_{i,t}$ is LTM net income), and $\mathrm{DIV}_{i,t}$ denotes clean surplus dividends, which we compute from book values and earnings using equation (4). As the other information variable in equation (9) is orthogonal to book values and earnings, we leave it unspecified. Doing so should not impact our parameter estimates; moreover, specifying this term incorrectly or with error (i.e., not orthogonal to earnings, book values, and dividends) will result in bias in the parameter estimates of interest if the resulting other information variable is correlated with earnings, book values, or dividends. The intercept of equation (10) therefore captures the average implications of other information for the present value of future cash flows, with the other information specific to any particular firm flowing to the residual.

Like equation (9), equation (10) separates net income into operating income and other income. We do this because other income reflects noise and transitory items. Operating income is more persistent than the items that appear below the operating income line on the income statement (e.g., Fairfield et al. (1996)). Moreover, the persistence of operating income is likely more consistent across stocks and from one cross section to the next. We therefore allow the coefficients on operating and nonoperating income to differ, following Ohlson (1999), and use the loading on operating income to construct our measure of aggregate expected returns.[4]

We estimate the parameters in equation (10) by using the TS estimator of Theil (1950) and Sen (1968). TS is a nonparametric alternative to OLS designed specifically to address issues of outliers and heteroscedasticity. These concerns arise here because all the variables in equation (10) are dollar amounts per share. The TS estimation approach proceeds as follows: The regression in equation (10) features five coefficients to be estimated. The TS estimator draws a random sample of five observations and solves for the parameters. In OLS terms, five

[4]In untabulated tests, we find that not separating net income in this fashion diminishes the performance of our approach to estimating the equity risk premium. Transitory items have attracted a great deal of attention in the value relevance literature. For example, Barth, Beaver, and Landsman (2001) and Barth, Li, and McClure (2018) show that the relation between prices and both net income and book values has steadily declined in recent decades, a phenomenon they attribute to increasing amounts of noise and transitory items that weaken the link between prices and accounting quantities.

observations are used to estimate five parameters, which yields an R^2 of 100%. We repeat this procedure 10,000 times, solving for the parameters with each draw. This results in a distribution for each of the five parameters. The TS estimator uses the median of each distribution as the final parameter estimate.[5] While our main results are based on the TS approach, in Section IV we compare market risk premium estimates based on least squares and TS. Anticipating those results, we find that the TS approach is less affected by scaling choices and that it produces higher predictive R^2s.

We obtain historical accounting data from Compustat and stock prices from CRSP. We use all common stocks listed on the NYSE, AMEX, or NASDAQ.[6] Our analysis uses quarterly financial statement data and covers the period from Jan. 1976 to Dec. 2018. The analysis is conducted using per share data.[7] We report descriptive statistics for our first-stage regression variables in Panel A of Table 1. Our sample includes 820,473 firm-month observations over the 516 months in our sample period. Thus, the average number of stocks in each cross section is 1,590. The average stock has a price of \$22.50, average book value of \$9.80, and average operating income of \$2.01 per share.

Using the TS procedure, we estimate our first-stage regression in equation (10) every month from Jan. 1976 to Dec. 2018 and report the results in Panel B of Table 1. We present the average coefficient estimates, average adjusted R^2, implied R, φ, ω_{11}, and k parameters from the Ohlson model in equation (9), and Newey–West t-statistics. Consistent with Dechow et al. (1999), book value and earnings load positively and significantly in these regressions.

Each month, we extract the aggregate expected market return in month t, R_t, from the cross-sectional regression estimates as,[8]

$$R_t = \frac{\widehat{\beta}_{2,t}}{\widehat{\beta}_{1,t} + \widehat{\beta}_{2,t} - 1} - 1. \tag{11}$$

Equation (11) follows from equation (9) by noting that,[9]

[5]Peng, Wang, and Wang (2008) and Wilcox (2010) show that TS is nearly as efficient as OLS even under ideal normality conditions. Ohlson and Kim (2015) find that the TS procedure produces better estimates than OLS in settings where variables are dollar amounts, which are plagued by outlier and heteroscedasticity issues.

[6]We eliminate financials and utilities. We also eliminate stocks with market capitalizations below \$50 million or stock prices less than \$1 per share. Finally, although Ohlson and Kim ((2015), fn. 2) recommend 100,000 (and up to 200,000) samples for each estimation, this would require 51.6 million estimations for our 516 month sample. In developing our approach, we noticed that trimming extreme observations allowed us to achieve comparable results with fewer samples drawn from each monthly cross section. We therefore trim observations at 5% and 95%.

[7]In Section IV, we obtain stronger results using gross levels instead of per share amounts in TS regressions, and also scaling by book value, or market value, of equity. Thus, our use of per share data provides a conservative test of our approach.

[8]Peng et al. (2008) show that the TS estimator is consistent in linear regression models with arbitrary error distributions. By the Slutsky theorem, it follows that $\hat{\beta}_{2,t}/\left(\hat{\beta}_{1,t} + \hat{\beta}_{2,t} - 1\right)$ is a consistent estimator of $\beta_{2,t}/\left(\beta_{1,t} + \beta_{2,t} - 1\right)$.

[9]We construct R_t from the coefficient on book value, β_1, rather than the coefficient on dividends, β_4, because β_1 is estimated much more precisely than β_4: the standard deviation of β_1 is 0.29, while the standard deviation of β_4 is 1.07.

TABLE 1

Estimated Ex Ante Expected Returns

Table 1 reports descriptive statistics for the regression variables and monthly regression parameter estimates from a first-stage regression of price per share on book value of equity per share (BVE), operating income after depreciation per share (OIAD), other earnings per share (OTHINC), and net dividends per share (DIV), calculated based on the clean surplus relation. BVE is measured as of the most recent quarter, and the remaining variables are measured over the trailing four quarters. We trim regression variables at 5% and 95% and we exclude stocks with price per share of $1 and market value of equity less than $50 million. We estimate regressions monthly, using all quarterly accounting data released by firms over the prior 3 months. In Panel B, we report the time-series average of the monthly regression estimates with *t*-statistics based on Newey–West (1987) standard errors for the full sample. R, φ, k, and ω_{11} denote parameters implied by the monthly regression estimates. R denotes the expected return, φ denotes an earnings multiplier, k denotes the weight placed on flow versus stock measures, and ω_{11} denotes earnings persistence. In Panel C, we report these statistics for NBER recession and nonrecession periods.

Panel A. Descriptive Statistics for Stage 1 Regression Variables

	Mean	Std. Dev	Min	Q1	Median	Q3	Max
PRICE	22.498	19.616	1.000	9.750	17.750	29.375	675.890
BVE	9.798	7.793	−0.106	4.136	7.819	13.287	73.098
OIAD	2.013	2.201	−2.155	0.436	1.534	3.038	21.334
OTHINC	−0.991	1.248	−15.671	−1.462	−0.668	−0.167	6.604
DIV	0.059	1.194	−6.862	−0.329	−0.006	0.569	7.200

N = 820,473 firm-month observations

Panel B. Stage 1 Regression Estimates for the Full Sample

		N	CONST	BVE	OIAD	OTHINC	DIV	R	φ	k	ω_{11}
Full sample	Estimate	516	6.677	0.301	7.243	5.125	−1.117	0.114	14.092	0.699	0.961
	t-stat.		(31.07)	(11.50)	(67.64)	(32.77)	(−12.00)	(21.61)	(14.70)	(26.76)	(265.20)

Panel C. Stage 1 Regression Estimates for Nonrecessionary (N = 455 Months) and Recessionary (N = 61 Months) Months

		N	CONST	BVE	OIAD	OTHINC	DIV	R	φ	k	ω_{11}
Nonrecession	Estimate	455	6.603	0.318	7.369	5.104	−1.140	0.108	14.797	0.682	0.959
	t-stat.		(29.69)	(11.39)	(68.02)	(29.79)	(−11.13)	(20.56)	(13.94)	(24.47)	(250.61)
Recession	Estimate	61	7.227	0.173	6.302	5.281	−0.947	0.164	8.831	0.827	0.973
	t-stat.		(9.75)	(2.52)	(19.60)	(14.83)	(−5.12)	(9.38)	(8.44)	(12.11)	(89.53)
Difference	Estimate	516	0.625	−0.145	−1.068	0.177	0.193	0.056	−5.966	0.145	0.014
(Recession − Nonrecession)	*t*-stat.		(0.81)	(−1.96)	(−3.15)	(0.45)	(0.91)	(3.07)	(−4.00)	(1.96)	(1.25)

$$
\begin{aligned}
\frac{\widehat{\beta}_{2,t}}{\widehat{\beta}_{1,t}+\widehat{\beta}_{2,t}-1}-1 &= \frac{k_t\varphi_t}{1-k_t+k_t\varphi_t-1}-1\\
&= \frac{k_t\varphi_t}{k_t\varphi_t-k_t}-1\\
&= \frac{\varphi_t}{\varphi_t-1}-1\\
&= \frac{1}{\varphi_t-1}\\
&= \frac{1}{\frac{1+R_t}{R_t}-1}\\
&= R_t.
\end{aligned}
$$

R_t averages 0.114, or long-run expected returns of 11.4% per year. This is quite close to the average annual market return over our sample period, 12.76% per year. We explore the empirical validity of this expected return measure in Section III.

We also estimate and report other parameters from equation (9). The ω_{11} parameter captures the implied persistence of current earnings. Although significantly less than 1 (Newey–West t-stat. = 10.86, unreported), ω_{11} of 0.961 implies that prices anticipate a highly persistent earnings stream. This is consistent with Chan, Karceski, and Lakonishok (2003), who find that earnings changes are nearly unforecastable.

Equation (9) predicts that the coefficients on book value and earnings will vary with both expected returns and earnings persistence. Dropping the t subscripts, the partial derivative of $(1-k)$, the weight on book value, with respect to R is $\partial(1-k)/\partial R=\left(\omega_{11}^2-\omega_{11}\right)/(1+R-\omega_{11})^2$, which is negative for constant ω_{11} less than 1. Similarly, the partial derivative of $k\varphi$, the weight on earnings, with respect to R is $\partial(k\varphi)/\partial R=-\omega_{11}^2/(1+R-\omega_{11})^2$, which is also negative. Thus, the weights on earnings and book value should both decline as expected returns increase. Viewing (9) as a weighted average of valuations based on P/B and P/E, the valuation multiples (i.e., loadings on book value and earnings) decline as risk rises. Intuitively, when value depends on highly persistent yet uncertain future earnings, as is the case when $\omega_{11}>0$, value declines as the risk in those earnings increases or investors' risk tolerance declines.

Moreover, an increase in R impacts the weight on earnings more than that on book value when ω_{11} is close to 1. Because the denominators in the partial derivatives are the same, the differential impact of a small change in R is driven by the numerator. For example, let $c=1/(1+R-\omega_{11})^2$. For $\omega_{11}=0.961$ (our empirical point estimate), $\partial(1-k)/\partial R=\left(\omega_{11}^2-\omega_{11}\right)\cdot c=-0.037c$. In contrast, $\partial(k\varphi)/\partial R=-\omega_{11}^2\cdot c=-0.924c$. Thus the weight on earnings falls at a faster rate than the weight on book value as R increases. This too makes intuitive sense: compared to the stock of value on hand, the contribution to value from a stream of risky earnings evaporates at a faster rate as risk and/or risk aversion increase.

To illustrate these relations with the data, we next separate months into recessionary and nonrecessionary periods based on NBER recession dates. We report the results in Panel C of Table 1. Of our 516 months, we have 61 recessionary months and 455 nonrecession months. Expected returns should rise during recessions as risk aversion and uncertainty about consumption increase. Consistent with this, R_t equals 16.4% in recession months but only 10.8% in nonrecession months. The difference is economically large (5.6%) and statistically significant (t-stat. = 3.07). The proposed measure is thus countercyclical. Also, as we expect, the coefficient on book value declines from 0.318 in nonrecession months to 0.173 in recession months, and the difference is statistically significant (t-stat. = −1.96).

The coefficient on operating income also declines during recessions. In nonrecession months, the coefficient on operating income averages 7.369, but only averages 6.302 in recession months. The difference is −1.068, which is statistically significant (t-stat. = −3.15). Consistent with our predictions, the decline in the earnings coefficient is much more dramatic than the decline in the book value coefficient.

C. Alternative Expected Market Return Measures and Predictive Variables

To focus on the equity risk premium, we construct expected excess returns (ExR_t) as our expected return measure, R_t, less the yield on one-year Treasury securities, collected from the Federal Reserve. To examine the robustness of our findings, and to appreciate them in a wider empirical context, we compare ExR_t to four alternative discount rate measures and to an additional set of 17 predictive variables that have been proposed in the literature.

We estimate three separate implied cost of capital measures, all of which use analyst forecasts (which could improve model performance). The first implementation follows Li et al. (2013), and estimates the implied cost of capital as the value r_e that solves

$$P_t = \sum_{k=1}^{T} \frac{\text{FE}_{t+k} \times (1 - b_{t+k})}{(1 + r_e)^k} + \frac{\text{FE}_{t+T+1}}{r_e (1 + r_e)^T}, \tag{12}$$

where FE_{t+k} and b_{t+k} are forecasts of earnings and plowback rates for year $t+k$, and $T = 15$ is the forecasting horizon. We follow Li et al. (2013) and implement equation (12) in three steps. First, we use median analyst forecasts from IBES to construct FE_{t+1} and FE_{t+2}. Second, we forecast FE_{t+3} through FE_{t+T+1} by assuming that earnings growth mean reverts exponentially fast to the long-run GDP growth rate. Third, we forecast the plowback rate b_{t+1} using the most recent dividend payout ratio, and we assume that plowback rates then mean revert linearly to the ratio of the GDP growth rate to r_e, consistent with the view that, in the steady state, competition drives returns on new investments down to the cost of equity (this also implies that any growth in earnings after T is value-irrelevant, such that the terminal value in equation (12) is the present value of a perpetuity). We then estimate the aggregate implied cost of capital ICC_t each month t as the value-weighted average of the implied costs of capital of all firms in the S&P 500 index.[10]

[10]We obtain from David Ng the implied cost of capital data used in Li et al. (2013). Our implied cost of capital estimates has a 96.7% correlation with the measure employed by Li et al. (2013) over their (shorter) sample period. Our estimation procedure for the implied cost of capital therefore closely

Besides ICC_t, we consider two additional implementations of the implied cost of capital. We follow Gode and Mohanram (2003) in implementing the Ohlson and Juettner-Nauroth (2005) model (OJN_t) and the Gebhardt et al. (2001) version of the residual income valuation model (RIV_t). The Ohlson and Juettner-Nauroth model relates current price to analyst forecasts of earnings per share for the next 2 years and a dividend per share forecast for the next year. The model assumes short-term earnings growth decays to a long-term growth rate. The Ohlson and Juettner-Nauroth model does not require assumptions about return on equity or dividends beyond year +1, and provides a closed-form solution for the cost of equity. Gebhardt et al. (2001) implement the residual income model using analyst forecasts of earnings per share for the subsequent 3 years. Implied return on equity in year three is calculated using book value per share at the beginning of year three. Book value per share is forecast using earnings per share and dividend payout assumptions with the clean surplus relation. Return on equity beyond year three is assumed to revert to (rolling 10-year) industry median by year 12. Residual income is assumed to be constant beyond year 12. We construct OJN_t and RIV_t as the value-weighted average implied costs of capital of all firms with available data.

The implied cost of capital approach makes a number of assumptions that may be problematic. For example, as Lyle and Wang (2015) point out, the implied cost of capital approach requires solving a nonlinear equation that can have more than one solution, and choosing among these solutions is arbitrary. Also, the implied cost of capital approach relies on analyst earnings forecasts, and these can be biased (e.g., La Porta (1996), Hou, Van Dijk, and Zhang (2012), and Mohanram and Gode (2013)). Furthermore, the implied cost of capital approach is sensitive to the estimation of long-term growth forecasts (e.g., Easton, Taylor, Shroff, and Sougiannis (2002), Nekrasov and Ogneva (2011)). Economically, the implied cost of capital approach uses analyst forecasts to specify the other information term in Ohlson (1995). As we argue in Section II, this term is orthogonal to currently available accounting information, thus leaving it unspecified should not impact our parameter estimates, although specifying it incorrectly could. As our approach does not make any of these assumptions, it offers the potential for improvement over the implied cost of capital approach.

We also include in our analysis the cross-sectional measure of Kelly and Pruitt (2013), who use the three-pass regression filter developed by Kelly and Pruitt (2015) to forecast aggregate market returns from the cross section of portfolio-level valuation ratios. Some of our analysis also considers the predictive variables from Welch and Goyal (2008) as additional controls: the logged dividend price ratio, the logged dividend yield, the logged earnings-to-price ratio, the logged dividend payout ratio, stock return variance, the book-to-market ratio, net equity expansion, the three-month Treasury yield, the long-term yield, the default spread, the default return spread, inflation, the investment-to-capital ratio, the long term rate of return, and the term spread. This is the data set used in Welch and Goyal (2008),

mimics theirs. We thank David Ng for graciously providing us with these implied costs of capital estimates.

updated by Amit Goyal through Dec. 2018.[11] We obtain the data from Amit Goyal's website. Finally, we include the cyclically adjusted price-earnings ratio and the index of long-term expected earnings growth, LTG_t, which we estimate each month as the value-weighted average of firm-level median estimates of long-term earnings growth forecasts from analysts across all firms in the S&P 500 index. Bordalo et al. (2022) show that LTG_t proxies for nonrational expectations of long-term fundamentals, and that it predicts errors in these expectations as well as stock returns.

D. Descriptive Statistics and Equity Risk Premium Over Time

Panel A of Table 2 provides summary statistics for ExR_t and the other discount rate measures over our sample period of Jan. 1976 to Dec. 2018. ExR_t averages 6.4% per annum and exhibits significant time series variability, with a standard deviation of 3.9%. The second row in Panel A of Table 2 provides the corresponding summary statistics for the implied cost of capital ICC_t. While ICC_t averages 6.3% per annum, which nearly equals the 6.4% average of ExR_t, with a standard deviation of only 2.5%, it exhibits much less time-series variability than ExR_t. The distributions of the other two implied cost of capital estimates, RIV_t and OJN_t, are quite similar to that of ICC_t, while the Kelly and Pruitt (2013) three-pass return predictor KP_t has a lower mean (5.6%) and much lower standard deviation (0.7%). Summary statistics on the other variables, in Panel B of Table 2, are in line with those reported in other studies.

Panel C of Table 2 presents correlations. Three findings emerge from these data. First, the correlations between ICC_t, RIV_t, and OJN_t are very high, but none of these variables has a high correlation with ExR_t. For example, the Pearson correlation between ExR_t and ICC_t is only 2% (−2% Spearman). Second, our measure has a low (in fact, negative) correlation with KP_t. Third, our measure is essentially uncorrelated with LTG_t. These findings are important because they highlight the fact that our measure of the market risk premium is potentially quite different from both other discount rate measures and from proxies for expected cash flows.

As a first test of whether ExR_t is a plausible measure of the equity risk premium, we consider its behavior over the business cycle. In Figure 1, we plot the evolution of ExR_t, along with the historical median and 2-standard-deviation bands (calculated using historical data starting in Jan. 1986). The shaded time periods in the figure indicate NBER recessions. The risk premium should rise during recessions, as both risk and risk aversion increase. Consistent with our earlier results, we find that ExR_t is indeed significantly higher in recessionary periods than in expansions.[12]

Next, we empirically validate our expected return measure.

[11]We do not include the cross-sectional premium because its time-series is incomplete (it ends in 2002). We also omit the consumption-to-wealth ratio because its construction is not out of sample (a previous version of the paper featured this variable; our results are robust to its inclusion).

[12]As indicated in Table 1, the difference is large and highly statistically significant. We also find that ExR_t is higher during recessions than its sample average (including recessions and expansions) and higher than the average over the 12 months prior to the recession.

TABLE 2

Descriptive Statistics and Correlations

Table 2 reports distribution statistics (Panels A and B) and correlations (Panel C) for alternative discount rate measures and return predictors. In Panel A, ExR denotes the expected excess return from a first-stage Theil–Sen estimation of prices on earnings, book values, and dividends. ICC denotes the implied cost of capital from Li et al. (2013). RIV denotes implied cost of capital from the residual income valuation model in Gode and Mohanram (2003). OJN denotes the implied cost of capital from the Ohlson and Juettner-Nauroth (2005) model from Gode and Mohanram (2003). KP denotes the three-pass return predictor from Kelly and Pruitt (2013). In Panel B, LTG is value-weighted long-term EPS growth forecast for the S&P 500. CAPE is Shiller's cyclically adjusted P/E ratio. The remaining variables are from Welch and Goyal (2008) and collected from Amit Goyal's website. DP denotes the logged dividend-to-price ratio. DY denotes the logged dividend yield. EP denotes the logged earnings-to-price ratio. DE denotes the logged dividend payout ratio. SVAR denotes stock return variance. BM denotes the book-to-market ratio. NTIS denotes net equity expansion. TBL denotes the 3 month treasury yield. LTY denotes the long-term yield. DFY denotes the default yield spread. DFR denotes the default return spread. INFL denotes inflation. IK denotes the investment-to-capital ratio. LTR denotes the long-term rate of return. TMS denotes the term spread. The sample period is 1976 to 2018, except for LTG, which starts in 1982.

	Mean	Std. Dev.	Q1	Median	Q3
Panel A. Distribution Statistics for Discount Rate Measures					
ExR	0.064	0.039	0.040	0.059	0.079
ICC	0.063	0.025	0.044	0.063	0.080
RIV	0.062	0.029	0.039	0.057	0.081
OJN	0.064	0.021	0.048	0.061	0.079
KP	0.056	0.007	0.051	0.057	0.060
Panel B. Distribution Statistics for Other Predictive Variables					
DP	−3.669	0.433	−4.000	−3.797	−3.331
DY	−3.663	0.434	−3.992	−3.794	−3.320
EP	−2.873	0.477	−3.149	−2.904	−2.554
CAPE	20.952	8.854	13.575	21.000	26.395
DE	−0.797	0.342	−0.976	−0.853	−0.667
SVAR	0.002	0.005	0.001	0.001	0.002
BM	0.447	0.274	0.266	0.334	0.514
NTIS	0.005	0.020	−0.010	0.009	0.019
TBL	0.045	0.036	0.012	0.048	0.063
LTY	0.067	0.030	0.045	0.064	0.085
DFY	0.011	0.005	0.008	0.010	0.013
DFR	0.000	0.015	−0.006	0.000	0.006
INFL	0.003	0.004	0.001	0.003	0.005
IK	0.036	0.003	0.034	0.035	0.038
LTR	0.007	0.031	−0.013	0.008	0.025
TMS	0.022	0.014	0.013	0.023	0.033
LTG	12.300	1.703	11.252	11.890	12.691

(continued on next page)

TABLE 2 (continued)

Descriptive Statistics and Correlations

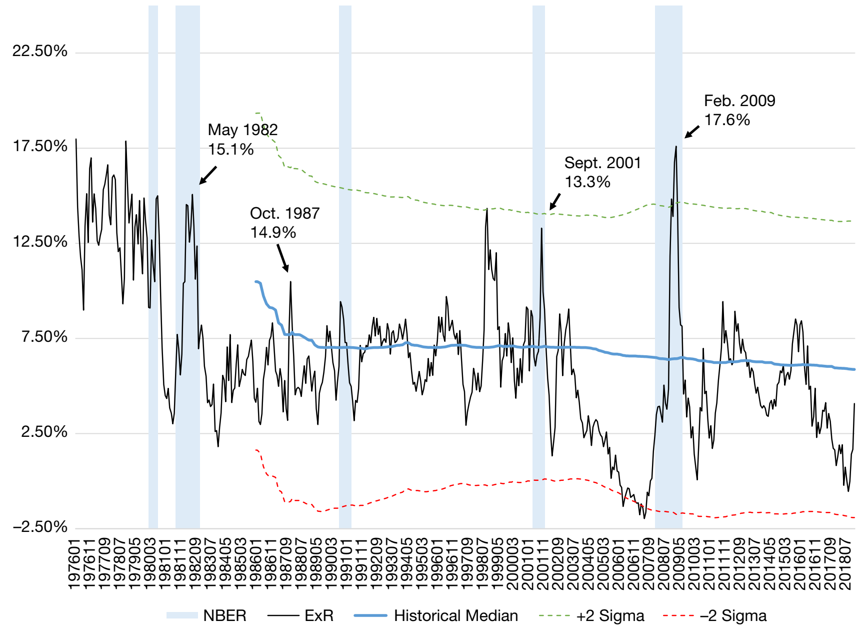
Panel C. Pearson (Above) and Spearman (Below) Correlations

	ExR	ICC	RIV	OJN	KP	LTG	CAPE	DP	DY	EP	DE	SVAR	BM	NTIS	TBL	LTY	DFY	DFR	INFL	IK	LTR	TMS
ExR		0.02	−0.06	−0.01	−0.38	0.05	−0.39	0.49	0.47	0.27	0.23	0.15	0.53	0.28	0.27	0.31	0.27	0.01	0.18	0.15	0.01	0.00
ICC	−0.02		0.90	0.98	0.12	−0.52	−0.13	−0.05	−0.06	−0.26	0.29	0.09	−0.10	−0.04	−0.67	−0.46	0.20	0.09	−0.23	−0.71	−0.05	0.70
RIV	−0.15	0.89		0.93	0.28	−0.45	0.04	−0.24	−0.24	−0.31	0.13	0.10	−0.22	−0.16	−0.75	−0.63	0.11	0.06	−0.20	−0.58	−0.06	0.56
OJN	−0.05	0.98	0.93		0.19	−0.51	−0.06	−0.14	−0.14	−0.28	0.21	0.09	−0.16	−0.05	−0.73	−0.54	0.13	0.07	−0.25	−0.68	−0.06	0.69
KP	−0.33	0.17	0.33	0.23		0.50	0.88	−0.89	−0.89	−0.77	−0.05	0.16	−0.82	−0.19	−0.65	−0.74	−0.30	−0.01	−0.38	0.10	−0.04	0.07
LTG	0.02	−0.43	−0.41	−0.45	0.30		0.62	−0.45	−0.45	−0.20	−0.25	0.02	−0.25	0.14	0.22	0.05	−0.21	−0.06	0.04	0.68	−0.01	−0.42
CAPE	−0.39	−0.06	0.14	0.01	0.88	0.47		−0.95	−0.95	−0.68	−0.26	0.01	−0.85	−0.04	−0.54	−0.67	−0.55	−0.03	−0.33	0.34	−0.05	−0.05
DP	0.44	−0.01	−0.21	−0.09	−0.86	−0.39	−0.95		1.00	0.72	0.26	−0.03	0.91	0.08	0.68	0.76	0.50	0.01	0.38	−0.18	0.04	−0.10
DY	0.43	−0.02	−0.22	−0.09	−0.87	−0.40	−0.94	0.99		0.72	0.26	−0.07	0.90	0.08	0.68	0.76	0.49	0.03	0.37	−0.18	0.05	−0.10
EP	0.22	−0.16	−0.24	−0.20	−0.86	−0.34	−0.78	0.77	0.77		−0.48	−0.20	0.81	0.14	0.66	0.62	0.12	−0.09	0.43	0.11	0.03	−0.34
DE	0.25	0.18	−0.04	0.11	−0.17	−0.06	−0.35	0.41	0.40	−0.19		0.24	0.01	−0.10	−0.06	0.10	0.46	0.14	−0.12	−0.39	0.00	0.35
SVAR	0.15	−0.04	−0.05	−0.05	0.21	0.15	0.04	−0.12	−0.15	−0.22	0.11		−0.08	−0.18	−0.10	−0.07	0.31	−0.18	−0.15	0.00	0.14	0.10
BM	0.35	0.06	−0.11	0.00	−0.82	−0.46	−0.92	0.90	0.89	0.84	0.21	−0.14		0.16	0.70	0.73	0.48	0.00	0.46	0.02	0.03	−0.22
NTIS	0.32	−0.01	−0.12	−0.02	−0.18	0.23	−0.10	0.06	0.06	0.05	0.03	−0.10	0.07		0.18	0.27	−0.28	0.02	0.15	0.02	−0.04	0.12
TBL	0.25	−0.70	−0.80	−0.76	−0.71	0.29	−0.58	0.62	0.62	0.61	0.16	−0.01	0.53	0.13		0.92	0.28	−0.05	0.46	0.40	0.03	−0.57
LTY	0.33	−0.51	−0.68	−0.57	−0.79	0.16	−0.71	0.71	0.71	0.61	0.31	0.00	0.62	0.29	0.93		0.37	0.00	0.40	0.19	0.01	−0.20
DFY	0.15	0.21	0.10	0.17	−0.34	−0.23	−0.60	0.49	0.48	0.32	0.33	0.33	0.53	−0.30	0.22	0.29		0.08	0.01	−0.18	0.10	0.06
DFR	0.02	0.09	0.08	0.08	−0.03	−0.04	−0.04	0.02	0.05	0.01	0.04	−0.14	0.03	−0.01	−0.03	0.02	0.08		−0.05	−0.09	−0.48	0.11
INFL	0.14	−0.20	−0.15	−0.20	−0.37	0.01	−0.36	0.36	0.35	0.38	−0.02	−0.04	0.37	0.13	0.38	0.38	0.10	−0.07		0.17	−0.08	−0.30
IK	0.09	−0.69	−0.55	−0.66	0.00	0.52	0.21	−0.16	−0.17	0.07	−0.38	0.10	−0.20	0.03	0.40	0.22	−0.20	−0.12	0.14		0.00	−0.58
LTR	0.01	−0.05	−0.08	−0.07	−0.03	0.01	−0.03	0.02	0.01	0.02	0.01	0.08	0.03	−0.02	0.03	0.00	0.01	−0.57	−0.07	0.01		−0.05
TMS	0.01	0.71	0.56	0.71	0.05	−0.33	−0.11	−0.01	−0.01	−0.23	0.38	0.02	0.01	0.20	−0.46	−0.13	0.16	0.15	−0.19	−0.59	−0.05	

FIGURE 1

ExR and NBER Recessions

Figure 1 depicts the time-series behavior of ExR from Jan. 1976 to Dec. 2018. ExR denotes expected market excess returns estimated from a first-stage Theil–Sen estimation of prices on earnings, book values, and dividends. The shaded time periods indicate NBER recessions. Starting in Jan. 1986, the blue horizontal curve is the rolling median of ExR based on all the prior historical data, and the two dashed curved denote the corresponding 2-standard-deviation bands.



III. Validating the Aggregate Expected Return Measure

This section validates our measure of the equity risk premium. We show that i) shocks to it account for a large fraction of historical market return variation, ii) it explains time-series variation in returns on duration-sorted portfolios, iii) it forecasts future aggregate returns, and iv) it comoves with macroeconomic variables in a sensible manner.

A. Variance Decomposition and In-Sample Stock Market Return Variation

Cochrane (2011) provides a variance decomposition that shows that discount rate variation accounts for all the variation in dividend yields. Cochrane's result suggests a validity test for our expected return measure: it should explain all the variation in dividend yields. In Appendix B of the Supplementary Material, we begin by following Cochrane (2011) and estimate regressions of long-run returns, long-run dividend growth, and long-run dividend yields, all on current dividend yields. Our results confirm Cochrane's: We find that all the variation in dividend yields reflects variation in discount rates. We then extend Cochrane's analysis by using our measure of expected returns instead of realized future returns. Again, we find that all dividend-price ratio volatility reflects discount rate variation as captured by our expected return measure.

Although discount rate variation accounts for all of the variation in dividend yields, Cochrane (2011) observes that it accounts for about half of the variation in returns (the other half corresponds to cash flow shocks). To see this, start with the Campbell and Shiller (1988) linearization of the one-period return,

$$r_{t+1} \approx k + \rho\left(p_{t+1} - d_{t+1}\right) + \Delta d_{t+1} - (p_t - d_t), \tag{13}$$

where r_t denotes log return, d_t log dividend, p_t log price, and the parameters ρ and k are defined by $\rho = 1/\left(1 + \exp\left(\overline{d_t - p_t}\right)\right)$ and $k = -\ln\rho - (1-\rho)\ln(1/\rho - 1)$, where $\overline{d_t - p_t}$ is the mean log dividend-price ratio. Denoting the shock to returns as $\epsilon^r_{t+1} = r_{t+1} - E_t(r_{t+1})$, the shock to dividend yields $\epsilon^{dp}_{t+1} = d_{t+1} - p_{t+1} - E_t\left(d_{t+1} - p_{t+1}\right)$, and the shock to dividend growth $\epsilon^{\Delta d}_{t+1} = \Delta d_{t+1} - E_t(\Delta d_{t+1})$, we have

$$\epsilon^r_{t+1} \approx -\rho\epsilon^{dp}_{t+1} + \epsilon^{\Delta d}_{t+1}. \tag{14}$$

Cochrane (2015) notes that, empirically, dividend yield shocks and dividend growth shocks are about uncorrelated, dividend growth is roughly IID with 14% standard deviation, and stock returns have a standard deviation of approximately 20%, thus cash flow news accounts for about half ($0.14^2/0.20^2 = 0.49$) of the variance in returns. Therefore, an empirically valid measure of discount rate shocks should account for roughly half of the historical variation in returns, which forms the basis of our first test.

In Panel A of Table 3, we present the results of tests of the ability of shocks to ExR_t and the other discount rate measures to explain stock market returns in sample. We use linear regressions where the dependent variable is the monthly return on the CRSP value-weighted index in excess of the one-month Treasury bill rate.

In the first regression, we proxy for discount rate news by using levels of current and prior-month discount rates, which allows us not to impose a specific representation of the prior expectation of current discount rates, allowing instead the regression to find this representation. For example, if the coefficients on current and prior discount rates are of similar magnitude but opposite signs, then discount rates are being treated by the market as if following a random walk, and if the coefficient on the prior discount rate is approximately 0, then discount rates are treated as if following a white noise process.[13] The results, in the first row of the first set of specifications in Panel A of Table 3, indicate that shocks to ExR_t explain 43.55% of the variation in market returns. The remaining sets of results show the corresponding regressions based on the other discount rate measures. In contrast to the strong explanatory power of ExR_t, these alternative measures of discount rate shocks explain less than 2% of market return variation. Our measure thus not only dominates the others but is the only one to come close to the 50% benchmark.

Next, because the coefficients on current and prior discount rates are indeed of similar magnitude but with opposite signs, the second regression in each set uses the change in the discount rate measure to proxy for discount rate shocks. The results are largely unaffected.

[13]Similarly, Lundholm and Myers (2002) proxy for unexpected earnings by using levels of current- and prior-quarter earnings.

TABLE 3

In-Sample Regressions of Excess Market Returns on Discount Rate Measures

Table 3 reports results from regressions of monthly returns on alternative discount rate measures. The dependent variable is the CRSP value-weighted index return in excess of the one-month T-Bill return. DR_t denotes the discount rate at the beginning of the month measured using one of five variables: ExR, ICC, RIV, OJN, or KP. ExR denotes the expected excess return from a first-stage Theil–Sen estimation of prices on earnings, book values, and dividends. ICC denotes the implied cost of capital from Li et al. (2013). RIV denotes implied cost of capital from the residual income valuation model in Gode and Mohanram (2003). OJN denotes the implied cost of capital from the Ohlson and Juettner-Nauroth (2005) model from Gode and Mohanram (2003). KP denotes the three-pass return predictor from Kelly and Pruitt (2013). NCF denotes cash flow news for the month from a vector autoregression model following Campbell and Vuolteenaho (2004). LTG is value-weighted long-term EPS growth forecast for the S&P 500. ΔDR denotes the change in DR over the month. The sample period is 1976 to 2018 except for LTG, which starts in 1982.

Panel A. Regressions of Excess Returns on Discount Rates and Cash Flow News

DR=	CONST	DR_{t+1}	DR_t	ΔDR	NCF	ΔLTG	ADJ RSQ (%)
ExR	0.009	−1.960	1.909				43.55
	(3.14)	(−19.75)	(19.40)				
	0.006			−1.932			43.46
	(3.88)			(−19.90)			
	0.006			−1.504	0.388		59.08
	(4.75)			(−17.09)	(14.03)		
	0.006			−2.172		0.034	50.54
	(4.23)			(−19.84)		(5.74)	
	−0.001		0.109				0.75
	(−0.22)		(2.21)				
ICC	0.001	−0.918	0.991				1.90
	(0.28)	(−3.17)	(3.42)				
	0.006			−0.955			1.92
	(3.21)			(−3.33)			
	0.006			−1.462	0.577		40.65
	(4.22)			(−6.50)	(18.32)		
	0.006			−2.075		0.043	11.33
	(3.27)			(−4.96)		(5.43)	
	−0.001		0.106				0.17
	(−0.11)		(1.37)				
RIV	0.003	−0.861	0.903				0.98
	(0.56)	(−2.53)	(2.66)				
	0.006			−0.883			1.13
	(3.20)			(−2.62)			
	0.006			−1.816	0.593		41.17
	(4.23)			(−6.87)	(18.71)		
	0.006			−2.354		0.046	10.53
	(3.26)			(−4.52)		(5.77)	
	0.001		0.074				−0.07
	(0.24)		(0.81)				
OJN	0.004	−0.487	0.523				1.23
	(0.84)	(−2.68)	(2.90)				
	0.006			−0.508			1.37
	(3.17)			(−2.85)			
	0.006			−0.652	0.560		38.31
	(4.10)			(−4.62)	(17.56)		
	0.006			−1.070		0.045	9.42
	(3.28)			(−3.85)		(5.68)	
	0.002		0.073				0.04
	(0.35)		(1.10)				
KP	0.032	3.945	−4.411				0.86
	(2.04)	(1.81)	(−2.03)				
	0.006			4.149			0.51
	(3.13)			(1.91)			
	0.006			4.865	0.554		36.71
	(4.02)			(2.80)	(17.16)		
	0.006			1.862		0.046	6.52
	(3.15)			(0.82)		(5.59)	
	0.034		−0.495				0.42
	(2.15)		(−1.77)				

Panel B. Multivariate Regressions of Returns on Discount Rate Change Measures

CONST	ΔExR	ΔICC	ΔRIV	ΔOJN	ΔKP	NCF	ΔLTG	ADJ RSQ (%)
0.006	−1.933	−1.335	−0.113	1.758	1.957			44.06
(3.86)	(−19.51)	(−2.50)	(−0.63)	(2.79)	(1.20)			
0.006	−1.403	−0.584	0.010	−0.134	2.979	0.413		60.12
(4.74)	(−15.34)	(−1.29)	(0.07)	(−0.24)	(2.15)	(14.35)		
0.006	−2.127	−0.708	0.593	−0.273	1.599		0.033	50.71
(4.20)	(−18.84)	(−1.08)	(0.73)	(−0.92)	(0.96)		(5.45)	
0.006	−1.614	−0.149	−0.510	−0.137	2.743	0.358	0.020	61.78
(4.86)	(−14.76)	(−0.26)	(−0.70)	(−0.52)	(1.87)	(11.30)	(3.72)	

One potential concern with these tests is that they omit news about fundamentals. To address this concern, we estimate news about fundamentals in two ways. First, we follow Campbell and Shiller (1988) and Campbell (1991), who use equation (13) and solve forward iteratively subject to the terminal condition that the price-dividend ratio is nonexplosive to derive the return decomposition

$$(15) \qquad r_{t+1} - E_t(r_{t+1}) = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j},$$

where the first term, $N_{\text{CF},t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}$, denotes cash flow news and the second, $N_{\text{DR},t+1} = (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j}$, denotes discount rate news. Our implementation of this decomposition follows the VAR methodology in Campbell and Vuolteenaho (2004): We first estimate expected returns and discount rate shocks by assuming that the data are generated by a first-order VAR model and then use realized returns and equation (15) to back out cash flow news.[14]

The third regression in each set of results reported in Panel A of Table 3 controls for cash flow shocks. The change in ExR_t remains strongly significant after controlling for $N_{\text{CF},t}$. The performance of the other measures improves substantially with the inclusion of $N_{\text{CF},t}$, but none of the R^2s is nearly as strong as that of the corresponding regression that features ExR_t.[15]

The second way in which we estimate news about fundamentals is through revisions in the index of long-term expected earnings growth, LTG_t. This analysis is motivated by the finding in Bordalo et al. (2022) that analysts appear to revise long-term growth forecasts based on fundamental news. The fourth regression in each set of results therefore includes ΔLTG_t. Consistent with the view that ΔLTG_t reflects news about fundamentals, we find that it is positively associated with contemporaneous market returns. Including ΔLTG_t does not change our conclusions: shocks to ExR_t remain significant and continue to outperform other discount rate shock measures.

The fifth regression in each set of results includes only the discount rate from the end of the prior month, thus omitting the current discount rate. Therefore, these specifications are standard in-sample predictive regressions. Several results emerge from this analysis. First, ExR_t is a significant predictor of aggregate stock market excess returns. Of course, omitting discount rate shocks and cash flow news reduces the R^2 because a lot of return movement is not forecastable. Nonetheless, the degree of predictability is rather strong, even at the monthly forecasting horizon, with a t-statistic on ExR_t of 2.21 and a corresponding R^2 of 0.75%.[16] Second, the effect is

[14]Following Campbell and Vuolteenaho (2004), the VAR model uses four state variables: the excess market return, the term spread, the S&P500 price-to-earnings ratio, and the small stock value spread.

[15]In untabulated results, we find that the change in ExR_t remains strongly significant after controlling for $N_{\text{DR},t}$, while shocks to the other measures become insignificant. By construction, $N_{\text{CF},t}$ and $N_{\text{DR},t}$ together explain nearly 100% of market return variation, thus we do not control for both at the same time.

[16]At the monthly frequency, the serial correlation in ExR_t equals 0.92. To account for the finite-sample bias in the estimated coefficients due to persistence in ExR_t, we implement the Stambaugh (1999) correction and find that Stambaugh bias has little effect: the correction produces an estimate for the

economically important. To gauge economic significance, we use the descriptive statistics in Table 2. A 1-standard deviation increase in ExR_t predicts an increase in aggregate excess returns of 0.43% in the next month ($0.039 \times 0.109 = 0.0043$). Third, the forecasting ability of ExR_t dominates that afforded by the alternative discount rate measures.[17] Appendix C of the Supplementary Material presents additional evidence of in-sample predictability (based on both monthly and annual horizons, and controlling for the other predictive variables), and we consider out-of-sample tests in Section III.C.

Finally, in Panel B of Table 3, we show the results of a horse race between shocks to ExR_t and to the other discount rate measures. After controlling for both ExR_t and news about fundamentals, none of the other measures remains significant (with the right sign).

Overall, the results in Table 3 highlight the empirical content of ExR_t in both levels and changes. Having established that ExR_t provides a valid measure of discount rate shocks, we turn to the cross section, and investigate the ability of ExR_t to explain the returns on duration-sorted equity portfolios.

B. Returns on Duration-Sorted Portfolios

A growing literature examines the relation between duration and the cross section of stock returns. Briefly, Dechow et al. (2004) develop a measure of the duration of individual stocks that is based on cash flow forecasts. They find that stocks with high duration have low returns relative to stocks with low duration. Gormsen (2021) shows that the declining equity term structure inverts during bad economic times. Lettau and Wachter (2007), (2011) argue for a duration-based explanation of the value premium. Gonçalves (2021) uses cash-flow duration to explain the profitability and investment premiums. We use the returns on duration-sorted equity portfolios to compare different measures of discount rate shocks.

To understand our approach, consider the Macaulay duration for a bond,

$$D = \frac{\sum_{t=1}^{T} t \times \left(\text{CF}_t/(1+r)^t\right)}{P}, \tag{16}$$

where D denotes duration, CF_t time-t cash flow, r yield to maturity, and P price. Ignoring convexity and higher-order effects, bond returns are a simple function of duration and changes in yields:

coefficient on ExR_t of 0.106 (t-stat. 2.14). Thus Stambaugh bias accounts for less than 3% of the magnitude of the predictive coefficient in the regression.

[17] The Kelly and Pruitt (2013) measure does not perform well in these tests. Our in-sample results involve quantities that are time-t measurable. In contrast, the measure in Kelly and Pruitt (2013) is not time-t measurable in their in-sample analysis: the first stage of their 3-stage approach regresses book-to-market ratios on next period returns using the full-time series, including subsequent realizations. In addition, Kelly and Pruitt (2013) use logs of returns and log book-to-market ratios, and they use gross returns. We do obtain a similar in-sample R^2 to that in Kelly and Pruitt (2013) (15.7% vs. 18.1%) over their sample period when we use log gross returns and a first-stage regression using the full time-series of data.

$$\text{(17)} \qquad \frac{\Delta P}{P} \approx -\frac{D}{1+r}\Delta r.$$

As equation (17) indicates, stock prices fall as discount rates rise, and the duration of a stock's expected cash flows amplifies the effect. We can infer the sign and relative magnitude of discount rate changes from the spread in returns across portfolios sorted on duration. Such a return spread provides an independent measure of the discount rate change for a given month, and we exploit this insight to validate ExR_t and the other measures of the market risk premium.

Our approach, then, is as follows: Every month, we sort stocks into quintiles based on their durations and estimate cross-sectional regressions of stock returns on the portfolio assignments (scaled to range from 0 to 1). The estimated slope coefficient in these regressions captures the return spread between high- and low-duration stocks, similar to the mimicking portfolio of the equity term premium in Gormsen (2021). From equation (17), it is a function of the change in the long-run discount rate, provided that such shocks are common across stocks. We then run time-series regressions of the first-stage slope estimates on various measures of discount rate changes.

We follow Weber (2018) and Gormsen (2021) and use the implied equity duration (IED) measure from Dechow et al. (2004) to proxy for equity duration. Dechow et al. (2004) extend the measure of duration in equation (16) to equities by splitting the summation term into a 10-year finite forecasting period and a terminal value, forecasting the finite-period cash flows by forecasting return on equity and growth in equity, assuming that the terminal value is paid out as a level perpetuity, and inferring its value from the observed stock price. For robustness, we also report results based on four other variables that may proxy for duration. The first is the earnings-to-price ratio (EP). Dechow et al. (2004) show that there is a negative relation between EP and IED, and that EP can proxy for duration in firms with low growth in equity and persistent return on equity. The second is the book-to-market ratio (BTM), which Dechow et al. (2004) show is also negatively related to IED, and which can be a good duration proxy for firms with low growth in equity and rapidly mean reverting return on equity. The third is the ratio of cash flow from operations to price (CFOP), which intuition suggests is related to duration (firms with relatively stronger current cash flow from operations likely also have shorter durations). The fourth is the expected long-term earnings growth (LTG) of a stock, computed as the median of long-term analyst growth forecasts. La Porta (1996) shows that high-LTG stocks underperform low-LTG stocks, Bordalo et al. (2022) find that aggregate LTG_t predicts the return spread between high- and low-LTG stocks, and Gormsen and Lazarus (2023) use LTG as the basis for their measure of equity duration. Because LTG is positively related to duration, we investigate whether discount rate shocks explain the return spread on LTG-sorted portfolios.

Panel A of Table 4 shows the results of the second-stage time-series regression – returns on duration-sorted portfolios on discount rate changes – using IED as the duration variable. As expected from equation (17), the coefficient on ΔExR_t is negative. It is also highly significant, with a t-statistic of -4.37. Among the alternative measures of discount rate shocks, two are significant in univariate regressions (ΔICC_t and ΔOJN_t), however only ΔExR_t remains significant in the

TABLE 4

Regressions of Duration-Sorted Portfolio Returns on Discount Rate Measures

Table 4 presents time-series regressions of returns to duration-sorted portfolios on discount rate change measures. In each monthly cross section, stocks are sorted into quintile portfolios based on one of five equity cash flow duration proxies: Implied Equity Duration (IED), earnings to price (EP), book to market (BTM), cash flow from operations to price (CFOP), or analyst forecasts of long-term EPS growth (LTG). ΔExR denotes the change in expected market returns from a first-stage Theil–Sen estimation of prices on earnings, book values, and dividends. ΔICC denotes the change in implied cost of capital from Li et al. (2013). ΔRIV denotes change in implied cost of capital from the residual income valuation model in Gode and Mohanram (2003). ΔOJN denotes change in the implied cost of capital from the Ohlson and Juettner-Nauroth (2005) model from Gode and Mohanram (2003). ΔKP denotes the change in the three-pass return predictor from Kelly and Pruitt (2013). Changes in discount rate measures should be positively related to BTM, CFOP, and EP (long in low-duration stocks) but negatively related to IED (long in high-duration stocks). The sample period is 1976 to 2018, except for LTG, which starts in 1982. The numbers in parentheses are *t*-statistics.

Duration Variable	Constant	ΔExR	ΔICC	ΔRIV	ΔOJN	ΔKP	ADJ RSQ (%)
Panel A. IED							
	0.024	−1.041					3.40
	(6.60)	(−4.37)					
	0.024		−1.700				1.12
	(6.57)		(−2.61)				
	0.024			−0.597			0.35
	(6.56)			(−1.68)			
	0.024				−1.724		0.66
	(6.56)				(−2.10)		
	0.024					−0.054	−0.19
	(6.58)					(−0.07)	
	0.023	−0.997	−1.987	−0.029	1.045	0.576	3.53
	(6.59)	(−4.08)	(−1.50)	(−0.06)	(0.61)	(0.72)	
Panel B. EP							
	0.001	0.885					2.59
	(0.39)	(3.83)					
	0.001		0.926				0.22
	(0.33)		(1.46)				
	0.001			0.037			−0.19
	(0.30)			(0.11)			
	0.001				0.662		−0.06
	(0.32)				(0.83)		
	0.001					−0.429	−0.13
	(0.29)					(−0.56)	
	0.001	0.920	2.002	−0.417	−1.373	−0.871	2.66
	(0.37)	(3.87)	(1.55)	(−0.95)	(−0.82)	(−1.12)	
Panel C. BTM							
	−0.045	0.484					0.81
	(−14.04)	(2.28)					
	−0.045		1.049				0.45
	(−14.03)		(1.82)				
	−0.045			0.483			0.27
	(−14.01)			(1.55)			
	−0.045				0.999		0.17
	(−14.01)				(1.38)		
	−0.045					−0.032	−0.19
	(−14.02)					(−0.05)	
	−0.045	0.449	1.323	0.243	−1.037	−0.336	0.63
	(−14.00)	(2.06)	(1.12)	(0.60)	(−0.67)	(−0.47)	
Panel D. CFOP							
	0.001	0.720					1.89
	(0.16)	(3.30)					
	0.000		1.144				0.53
	(0.12)		(1.93)				
	0.000			0.119			−0.17
	(0.09)			(0.37)			
	0.000				0.690		−0.03
	(0.10)				(0.92)		
	0.000					−0.633	−0.05
	(0.07)					(−0.88)	
	0.001	0.747	2.781	−0.321	−2.204	−0.989	2.60
	(0.14)	(3.35)	(2.30)	(−0.78)	(−1.40)	(−1.35)	

(continued on next page)

TABLE 4 (continued)

Regressions of Duration-Sorted Portfolio Returns on Discount Rate Measures

Panel E. LTG

	−0.004	−1.647					13.17
	(−1.59)	(−8.26)					
	−0.004		−3.185				4.78
	(−1.57)		(−4.82)				
	−0.004			−1.146			1.48
	(−1.34)			(−2.77)			
	−0.004				−3.563		3.12
	(−1.56)				(−3.91)		
	−0.004					−2.036	0.77
	(−1.40)					(−2.11)	
	−0.005	−1.484	−2.970	0.195	1.525	−0.709	14.36
	(−1.74)	(−7.12)	(−2.47)	(0.35)	(0.88)	(−0.77)	

multivariate regression that includes all five measures of discount rate changes. The results using EP, BTM, CFOP, and LTG as duration variables, in Panels B–E of Table 4, are similar. The signs of the coefficients flip in Panels B–D because those duration variables are inverse measures of duration. Overall, these results show that our discount rate measure ExR_t dominates the others in explaining time-series variation in returns on duration-sorted portfolios.

The preceding sections show that shocks to ExR_t explain a significant fraction of the time-series variation in aggregate returns as well as the returns on duration-sorted portfolios. These tests provide a novel way of comparing discount rate measures. Next, we turn to return prediction, and show that ExR_t also fares well in more standard predictability tests.

C. Out-of-Sample Predictability

This section investigates the ability of ExR_t to predict returns out of sample. We assess out-of-sample performance based on the out-of-sample R^2 statistic, which allows us to examine how ExR_t and the full set of 21 alternative discount rate measures and predictive variables perform out of sample relative to a simple historical average.

1. Empirical Procedure

We continue to use linear regressions where the dependent variable is the excess return on the CRSP value-weighted index. Our out-of-sample forecasts are based on rolling regressions that use data available through the time at which the forecasts are made. We divide our sample period into a 20-year initial estimation period (1976–1995) and a forecast evaluation period (1996–2018). To evaluate a predictive variable X_t, at each time τ in the evaluation period, we regress excess stock returns through time τ on the lagged predictive variable. The time-τ out-of-sample forecast of the $\tau+1$ return based on predictive variable X_t is then computed using the estimated coefficients from this OLS regression. We proceed in this manner through the end of the forecast evaluation period, thus generating a series of out-of-sample forecasts for each predictive variable.[18] Following Campbell and

[18]The out-of-sample tests use fitted values from rolling regressions as return predictors rather than ExR_t itself. This is because ExR_t is the time-t long-run expected market excess return. It is not a forecast

Thompson (2008) and Welch and Goyal (2008), we use a rolling historical average of excess market returns through time τ as the benchmark forecasting model. This corresponds to the case of no predictability, as it amounts to imposing the restriction that the coefficient on X_t is 0 in the predictive regression of returns on X_t.

For each predictive variable X_t, we compute the out-of-sample R^2 statistic, R^2_{OS}, to measure the reduction in mean squared error for the predictive model that uses variable X_t relative to the benchmark rolling mean return model,

$$R^2_{\mathrm{OS}} = 1 - \frac{\mathrm{MSE}(X_t)}{\mathrm{MSE}_B}, \tag{18}$$

where $\mathrm{MSE}(X_t)$ is the mean squared error of the predictive model based on variable X_t and MSE_B is the mean squared error of the benchmark average return model.

If a variable performs better than the simple historical average in the sense that it produces out-of-sample forecasts that are closer to future realized excess returns in a mean squared error sense, then its out-of-sample R^2 will be positive. Also, one predictive variable outperforms another if the out-of-sample R^2 of the former exceeds that of the latter.

To test whether a predictive variable has a positive and statistically significant out-of-sample R^2, we follow Li et al. (2013): we test the null hypothesis that $R^2_{\mathrm{OS}} \leq 0$ against the alternative that $R^2_{\mathrm{OS}} > 0$ by using the adjusted mean squared prediction error statistic of Clark and West (2007). We obtain the corresponding p-value from a one-sided t-statistic, based on the standard normal distribution.

2. Main Results

To begin, Figure A1 in the Supplementary Material shows plots of the difference between the cumulative sum of squared errors from the mean return benchmark model and the cumulative sum of squared errors from ExR_t and the various other predictive variables. We find that ExR_t performs well in this framework, and that ICC_t and the Kelly and Pruitt (2013) discount rate measure also do well. However, the other predictive variables, such as the traditional valuation ratios and the index of long-term expected earnings growth LTG_t, perform poorly in this graphical test.

Table 5 presents monthly and annual out-of-sample R^2 statistics for each predictive variable, along with p-values based on the adjusted mean squared prediction error statistic of Clark and West (2007). We find an out-of-sample return forecasting R^2 for ExR_t of 0.79% (p-value 0.037) at the monthly frequency. The other predictive variables fail to generate statistically significantly positive out-of-sample R^2s. The degree of predictability that ExR_t produces is economically important. To gauge the economic significance of a predictive R^2 of 0.79% at the monthly frequency, we can follow the heuristic calculation in Cochrane (2005) and Kelly and Pruitt (2013). The Sharpe ratio S^* earned by an active investor who trades so as to exploit the predictive information in ExR_t is given by

of expected excess returns over the next month or year. We also use fitted values for the alternative return predictors, thus all predictive variables are treated consistently. This follows the approach used in prior literature, for example, Li et al. (2013) also employ fitted values from rolling regressions when they investigate the out-of-sample performance of ICC_t.

TABLE 5

Out-of-Sample Return Prediction

Table 5 reports results from out-of-sample forecasting tests for return predictors. ExR denotes the expected excess market return from a first-stage Theil–Sen estimation of prices on earnings, book values, and dividends. ICC denotes the implied cost of capital from Li et al. (2013). RIV denotes implied cost of capital from the residual income valuation model in Gode and Mohanram (2003). OJN denotes the implied cost of capital from the Ohlson and Juettner-Nauroth (2005) model from Gode and Mohanram (2003). KP denotes the three-pass return predictor from Kelly and Pruitt (2013). LTG is value-weighted long-term EPS growth forecast for the S&P 500. CAPE is Shiller's cyclically adjusted P/E ratio. The remaining variables are from Welch and Goyal (2008) and collected from Amit Goyal's website. DP denotes the logged dividend-to-price ratio. DY denotes the logged dividend yield. EP denotes the logged earnings-to-price ratio. DE denotes the logged dividend payout ratio. SVAR denotes stock return variance. BM denotes the book-to-market ratio. NTIS denotes net equity expansion. TBL denotes the 3-month treasury yield. LTY denotes the long-term yield. DFY denotes the default yield spread. DFR denotes the default return spread. INFL denotes inflation. IK denotes the investment-to-capital ratio. LTR denotes the long-term rate of return. TMS denotes the term spread. The table reports the out-of-sample R^2 statistics (R^2_{OS}) for monthly and annual return forecasts and the associated p-values based on the Clark and West (2007) adjusted mean squared prediction error statistic. The sample period is 1976 to 2018, except for LTG, which starts in 1982.

	MONTHLY		ANNUAL	
	R^2_{OS} (%)	p-Value (%)	R^2_{OS} (%)	p-Value (%)
ExR	0.79	3.70	4.53	5.92
ICC	−0.04		1.51	22.00
RIV	−0.42		−1.14	
OJN	−0.55		−2.86	
KP	−0.16		1.84	23.06
DP	−0.45		−6.76	
DY	−0.42		−7.14	
EP	−0.68		−9.09	
CAPE	−0.55		−8.05	
DE	−1.45		−3.50	
SVAR	1.07	17.71	−0.62	
BM	−0.25		−3.67	
NTIS	−1.62		−10.86	
TBL	−0.64		−2.80	
LTY	−0.65		−7.29	
DFY	−0.85		0.43	32.90
DFR	−1.49		−1.32	
INFL	−0.42		0.27	28.69
IK	0.04	32.25	−4.62	
LTR	−0.17		−0.95	
TMS	−0.37		3.29	8.36
LTG	0.13	18.80	−26.82	

$$S^* = \sqrt{\frac{S_0^2 + R^2_{\mathrm{OS}}}{1 - R^2_{\mathrm{OS}}}}, \tag{19}$$

where S_0 is the Sharpe ratio earned by a buy-and-hold investor. Using data back to 1871, Campbell and Thompson (2008) estimate a monthly buy-and-hold Sharpe ratio of 0.108. At the monthly frequency, therefore, an out-of-sample return forecasting R^2 of 0.79% implies that an investor using the information in ExR_t to form optimal portfolios could improve their Sharpe ratio relative to a buy-and-hold investor by 30%.

The annual out-of-sample R^2 for ExR_t is 4.53% (p-value 0.059). None of the other predictive variables produces an out-of-sample R^2 that comes close. The implied cost of capital ICC_t yields an insignificant annual out-of-sample R^2 of 1.51% (p-value 0.220). The other two implied cost of capital measures, RIV_t and OJN_t, have negative out-of-sample R^2s. The Kelly and Pruitt (2013) predictor yields an annual out-of-sample R^2 of 1.84%, which is also not statistically significant. All the traditional predictive variables have insignificant (and often negative) out-of-sample R^2s, in line with the poor out-of-sample results reported by Welch and Goyal

(2008). Consistent with our findings in Figure A1 in the Supplementary Material, the index of long-term expected earnings growth LTG_t does not predict returns out of sample.[19]

Overall, the results of these out-of-sample tests show that ExR_t is a strong predictor of future returns. ExR_t is the only predictive variable that produces statistically significant and positive out-of-sample R^2s at both the annual and the monthly frequencies.

D. Determinants of ExR_t

As a brief analysis of the economic determinants of our risk premium measure ExR_t, we estimate in Table 6 regressions of ExR_t on its own lag, market variables, and macroeconomic variables. We first examine these variables one by one, then include all the variables jointly.

The market variables are consistent with our expectations. ExR_t is negatively related to past market returns. Thus, increases in expected returns produce low returns during period t and high expected returns at the end of period t. ExR_t is positively related to recent return volatility, consistent with high expected returns in periods of high uncertainty. In untabulated tests, we also study the intertemporal relation between risk and return using ExR_t and the alternative measures of expected returns, and using ex ante measures of expected market volatility. ExR_t has a positive association with expected return volatility, confirming a positive risk–return tradeoff consistent with economic theory. In contrast, the alternative measures do not.

The macroeconomic variables are all significantly correlated with our equity premium measure. ExR_t is negatively related to GDP growth, the Chicago Fed National Activity Index (CFNAI), and industrial production growth. In contrast, ExR_t is positively related to changes in unemployment and to inflation. All these relations convey a similar message: expected returns are broadly countercyclical – they are lower when economic measures indicate robust economic activity. Finally, ExR_t is negatively related to consumer confidence, but the relation is not statistically significant.

We report two multivariate specifications in the last two rows of Table 6. The first omits lagged ExR_t. While both capital market variables remain significant, the specification reveals substantial overlap in the information carried by the macroeconomic variables: only GDP growth, changes in unemployment, and inflation retain statistical significance. The final specification includes lagged ExR_t, which subsumes all the explanatory power of the economic variables. In this case, the excess market return remains highly significant (CFNAI is also statistically significantly related to ExR_t).[20]

[19]The final difference in Figure A1 in the Supplementary Material between the squared prediction error for the various predictive variables and that for the benchmark model is sign-identical with the out-of-sample R^2 in Table 5. In Appendix C of the Supplementary Material, we do confirm the Bordalo et al. (2022) result that LTG_t is a strong predictor of market returns in sample.

[20]To better understand the correlations between ExR_t and macroeconomic series, we also examine the systematic component in firm-level earnings in untabulated tests. We form an aggregate seasonally

TABLE 6

Determinants of ExR

Table 6 reports results from regressions of ExR on its lagged value, capital market variables (MKT-RF, VOL), economic variables (ΔGDP, ΔUNEMPL, INFL, CFNAI, ΔINDPRO) and a sentiment variable (ΔCONSCONF). ExR denotes annual expected excess returns as of the end of the month inferred from a first-stage Theil–Sen estimation of prices on earnings, book values, and dividends, MKT-RF denotes the monthly excess return of the CRSP value-weighted portfolio over the 1-month T-bill for the most recent month, VOL denotes the monthly variance computed from daily excess CRSP value-weighted index returns over the most recent month, ΔGDP denotes the most recent realization of quarterly GDP growth, ΔUNEMPL denotes the change in unemployment for the most recent month, INFL denotes the change in the consumer price index for the most recent month, CFNAI denotes the value of the Chicago Fed National Activity Index for the most recent month, ΔINDPRO denotes the change in industrial production for the most recent month, and ΔCONSCONF denotes the change in the University of Michigan Consumer Confidence Index for the most recent month. The sample period is 1976 to 2018.

	Intercept	ExR(*t*−1)	MKT-RF	VOL	ΔGDP	ΔUNEMP	INFL	CFNAI	ΔINDPRO	ΔCONSCONF	ADJ RSQ (%)	MONTHS
Coefficient	0.005	0.919									85.81	515
t-stat.	(3.99)	(55.76)										
Coefficient	0.065		−0.123								1.73	516
t-stat.	(37.55)		(−3.17)									
Coefficient	0.060			1.361							2.36	516
t-stat.	(31.63)			(3.67)								
Coefficient	0.069				−0.171						1.58	516
t-stat.	(29.36)				(−3.05)							
Coefficient	0.064					0.207					1.76	516
t-stat.	(37.50)					(3.20)						
Coefficient	0.058						1.901				3.00	516
t-stat.	(26.76)						(4.11)					
Coefficient	0.064							−0.004			0.88	516
t-stat.	(37.26)							(−2.36)				
Coefficient	0.065								−0.505		0.57	516
t-stat.	(36.49)								(−1.99)			
Coefficient	0.061									−0.025	−0.09	500
t-stat.	(37.13)									(−0.76)		
Coefficient	0.058		−0.075	1.214	−0.173	0.147	2.033	0.001	−0.298	0.022	11.10	500
t-stat.	(18.39)		(−1.93)	(3.02)	(−2.79)	(2.09)	(4.61)	(0.29)	(−0.67)	(0.67)		
Coefficient	0.005	0.942	−0.217	−0.113	−0.009	−0.031	−0.144	−0.003	0.229	−0.016	91.76	500
t-stat.	(4.11)	(69.33)	(−17.91)	(−0.91)	(−0.45)	(−1.42)	(−1.04)	(−2.65)	(1.68)	(−1.59)		

Overall, these results reveal that ExR_t is strongly related to economic uncertainty, business cycle variables, and macroeconomic conditions. Furthermore, the final specification shows that lagged ExR_t appears to summarize and subsume most of the information in the other variables, consistent with ExR_t tracking macroeconomic conditions. The evidence indicates that the equity risk premium is countercyclical.

IV. Further Interpretation and Discussion

In this section, we first explore the economic mechanism that leads ExR_t to predict returns. We next investigate the robustness of our main results by considering alternative estimation techniques and data from international markets.

A. Sources of Predictability

The previous sections show that we can infer aggregate market return expectations from the cross section of stock prices, earnings, and book values. The resulting measure predicts market returns in- and out-of-sample and outperforms numerous other predictors on multiple dimensions. Why is it that our approach performs so well?

The intuition for our approach is that, as discount rates rise, equity values shift away from risky future earnings and toward net assets on hand. However, earnings persistence matters too: When persistence is low, equity values will also depend more on assets on hand. Thus, the *relative* contributions of earnings and book values to stock prices *in the cross section* will vary with both aggregate expected returns and earnings persistence.

This suggests that our approach is successful because it disentangles the effects of earnings persistence and discount rates. To test this hypothesis, we run the cross-sectional regressions in equation (10), and we present in the first three rows of Table 7 the results of simple in-sample predictive regressions of market excess returns on i) the coefficient on book value (β_1), ii) the coefficient on operating income (β_2), and iii) both β_1 and β_2.

Consistent with the view that disentangling discount rates and earnings persistence is important in constructing a measure of expected market returns, these specifications do not have predictive ability: the coefficients on book value and operating income are insignificant. This is expected because all three specifications combine expected returns and earnings persistence in the loadings on book value and earnings.

differenced earnings (SDE) series. Each month, we average firm-specific SDEs for all observations with quarters ending in the most recent 3 months. We match aggregate SDE with firm-specific SDE based on the month that the fiscal quarter ends. We then match firm-quarter observations with ExR_t as of the beginning of the quarter (because ExR_t is a forward-looking measure). We estimate firm-specific regressions of SDE on aggregate SDE, ExR_t, and their interaction for all stocks. We find a systematic component in firm SDE. The interaction term is significant, indicating that firm SDE is especially sensitive to aggregate SDE when expected returns as of the beginning of the period are high. High ExR_t is thus driven at least in part by high risk in the form of a higher systematic component in earnings.

TABLE 7

Sources of Predictability

Table 7 presents regressions of 12 month ahead excess market returns on Theil–Sen estimates of book value (β_1), earnings (β_2), and the estimated persistence parameter ω_{11}. The numbers in parentheses are t-statistics based on Hodrick (1992) standard errors. The sample period is 1976 to 2018.

	Constant	β_1	β_2	ω_{11}	ADJ RSQ (%)
Estimate	1.158	−0.101			3.27
t-stat.	(35.48)	(−1.41)			
Estimate	1.308		−0.025		3.68
t-stat.	(11.83)		(−1.72)		
Estimate	1.331	−0.097	−0.024		6.68
t-stat.	(12.00)	(−1.35)	(−1.66)		
Estimate	0.706		−0.028	0.652	6.23
t-stat.	(1.38)		(−1.94)	(1.22)	

While we employ equation (9) to solve for R_t, we can also use it to solve for ω_{11}. Specifically, in equation (9), $\varphi_t = (1+R_t)/R_t$ and $k_t = (R\omega_{11})/(1+R-\omega_{11})$. It therefore follows that

$$
\begin{aligned}
\frac{\widehat{\beta}_{2,t}}{\widehat{\beta}_{1,t}+\widehat{\beta}_{2,t}} &= \frac{k_t\varphi_t}{1-k_t+k_t\varphi_t} \\
&= \left(\frac{1+R_t}{R_t}\cdot\frac{R_t\omega_{11}}{1+R_t-\omega_{11}}\right)\Big/\left(1-\frac{R_t\omega_{11}}{1+R_t-\omega_{11}}+\frac{1+R_t}{R_t}\cdot\frac{R_t\omega_{11}}{1+R_t-\omega_{11}}\right) \\
&= \left(\frac{\omega_{11}(1+R_t)}{1+R_t-\omega_{11}}\right)\Bigg/\left(1+\frac{\omega_{11}}{1+R_t-\omega_{11}}\right) \\
&= \frac{\omega_{11}(1+R_t)}{1+R_t-\omega_{11}}\cdot\frac{1+R_t-\omega_{11}}{1+R_t} \\
&= \omega_{11}.
\end{aligned}
$$

Therefore, we can use the loadings on book value and earnings to measure the persistence parameter ω_{11}.

Note that, from equation (9), if ω_{11} equals 0, then the loading on book value is 1, and the loading on earnings is 0. The coefficient on book value carries no information about discount rates in this case: R_t can only be inferred from our approach when earnings are priced (i.e., when the coefficient β_2 on earnings is greater than 0). In this sense, β_2 is the primary variable that carries information about R_t. We test this in the fourth specification in Table 5, where we run predictive regressions of returns on β_2, controlling for ω_{11}. We find that β_2 indeed explains future returns after controlling for ω_{11}.

B. The Theil–Sen Estimator

As we explain in Section II, we estimate the parameters in equation (10) by using the TS estimator of Theil (1950) and Sen (1968), which is a nonparametric alternative to OLS designed to address issues of outliers and heteroscedasticity. These are potential concerns in our setting because the variables in equation (10) are dollar amounts per share. In this section, we explore alternative scaling approaches and compare the predictive ability of OLS and TS estimates of ExR_t for various

TABLE 8

Out-of-Sample Performance of Alternative Specifications

Table 8 reports the in-sample (IS) and out-of-sample (OOS) R^2 statistics for annual return forecasts using alternative specifications. SCALAR refers to alternative scaling variables used in the estimation. SHARES denotes shares outstanding at the end of the month from CRSP. MVE denotes market value of equity at the end of the month from CRSP. BVE denotes book value of equity from the most recent quarterly earnings announcement from COMPUSTAT. NONE denotes the use of levels (no scalar). For SHARES, and NONE, LEAST SQUARES denotes ordinary least squares. For the others, estimating occurs using levels data with scaling achieved through weighted least squares. The sample includes 516 monthly observations from 1976 to 2018.

	THEIL_SEN		LEAST_SQUARES	
SCALAR	IS R^2 (%)	OOS R^2 (%)	IS R^2 (%)	OOS R^2 (%)
SHARES	4.95	4.53	1.95	−3.90
NONE	7.61	7.40	7.69	8.26
MVE	8.14	8.31	0.70	−0.13
BVE	8.32	8.53	0.87	−13.07

choices of scaling variables. We use four different scaling variables and estimate both OLS and TS regressions in each case. We thus obtain $4 \times 2 = 8$ different versions of ExR_t, and we test the predictive ability of each.

Table 8 reports the results. The first scaling variable is shares outstanding (at the end of the month, from CRSP), which is the scaling variable we use in the main results in the rest of the article. We also show the results with no scaling (thus using levels), scaling with market value of equity (at the end of the month, from CRSP), and scaling with book value of equity (from the most recent quarterly earnings announcement, from COMPUSTAT).

Both the in-sample and the out-of-sample R^2s based on the TS approach are remarkably stable across scaling variables, consistent with the view that the TS estimator is less affected by the scaling choices made by the researcher. On the other hand, the performance of the OLS-based measures is quite sensitive to scaling choices, with in-sample R^2s ranging from 0.7% to 7.69%, and out-of-sample R^2s ranging from −13.07% to 8.26%. Further, the TS based estimates of ExR_t generally yield higher in- and out-of-sample R^2s in predictive regressions.

C. International Evidence

Next, we extend our results to international equity markets. We obtain accounting data and exchange rates from Compustat Global, index returns from Datastream, and historical interest rates from the Monetary and Financial Statistics database maintained by the OECD. We focus on three regions: the United Kingdom, Japan, and continental Europe. While the United Kingdom and Japan are the two largest equity markets outside the United States, we also collect stocks from France, Germany, Italy, and Switzerland, and form an aggregate market for continental Europe.

In contrast to our primary results, for these tests, we use annual financial statement data to ensure we have enough observations to estimate our first stage, cross-sectional stock price model. December is the most common month of the fiscal year-end in the United Kingdom and continental Europe, so we only use firms with a December fiscal year end in those two regions. In Japan, the most common

TABLE 9

International Evidence

Table 9 reports results on the performance of ExR (the expected excess return inferred from a first-stage regression of prices on earnings, book values, and dividends) outside the United States. This analysis includes the United Kingdom, Japan, and continental Europe (France, Germany, Italy, and Switzerland). Panel A reports regression parameter estimates from a first-stage regression of price per share on book value of equity per share (BVE), operating income after depreciation per share (OIAD), other earnings per share (OTHINC), and net dividends per share (DIV) calculated based on the clean surplus relation. All the variables are based on annual financial statement data and we estimate the regressions annually. R denotes the expected return implied by the regression estimates. Panel B presents the results of regressions where the dependent variable is the aggregate excess return from month $t+4$ to $t+15$ (inclusive) relative to the financial statement data date. ExR_t denotes ExR at the beginning of month $t+4$, ExR_{t+1} denotes ExR at the end of month $t+15$, and ΔExR denotes the change in ExR over the period. The sample period is 1991 to 2018. The numbers in parentheses are t-statistics.

Panel A. First Stage Regression Estimates

	DV = Price 3 Months After Year End					
	Continental Europe		UK		Japan	
Variable	Estimate	t-Stat.	Estimate	t-Stat.	Estimate	t-Stat.
Intercept	6.324	(3.05)	0.148	(5.22)	0.794	(5.06)
BV	0.483	(6.53)	0.501	(6.04)	0.390	(10.08)
OIAD	7.354	(9.04)	6.202	(13.06)	4.417	(13.23)
OTHINC	−4.794	(−5.38)	−2.020	(−4.21)	−1.289	(−4.17)
DIV	0.389	(1.29)	0.514	(3.02)	−1.563	(−1.74)
R	9.1%	(5.91)	9.5%	(5.72)	19.7%	(9.45)
Avg. Obs.	774		503		704	

Panel B. Market Return Regressions

Exchg	Constant	ExR_{t+1}	ExR_t	ΔExR	ADJ RSQ (%)
Europe	0.094	−1.608	1.040		37.40
	(1.91)	(−3.24)	(2.21)		
	0.068			−1.310	38.37
	(1.89)			(−4.15)	
	0.014		1.234		13.59
	(0.29)		(2.26)		
UK	0.053	−1.334	1.301		49.03
	(1.82)	(−4.38)	(4.26)		
	0.052			−1.317	51.05
	(2.16)			(−5.30)	
	0.014		0.790		12.02
	(0.38)		(2.13)		
Japan	0.122	−1.746	1.243		51.49
	(1.79)	(−5.22)	(3.92)		
	0.030			−1.468	48.86
	(0.91)			(−5.08)	
	−0.055		0.423		0.57
	(−0.65)		(1.07)		

fiscal year end is March, coinciding with the fiscal year end of the Japanese government.

We match financial statement data with stock prices 3 months later (i.e., end of the following March for the United Kingdom and continental Europe and end of the following June for Japan). We convert all stock prices and financial statement data from the reporting currency to the British pound (Compustat Global's "universal" currency). For prices and balance sheet data, we use exchange rates as of the date of the observation. For income statement items and our dividend measure, we use the average exchange rate over the year. We estimate 28 cross-sectional regressions from 1991 to 2018. We report the results from these annual cross-sectional price-level regressions in Panel A of Table 9.

Each year and for each region, we extract the aggregate expected return for the region from the cross-sectional regression estimates summarized in Panel A of

Table 9, and we construct ExR_t by subtracting the long-term interest rate. In each region, we then relate aggregate excess returns (converted to British pounds) from month $t+4$ to $t+15$ (inclusive) relative to the financial statement data date to the contemporaneous surprise in ExR_t (from the beginning of month $t+4$ to the end of month $t+15$). To construct aggregate excess returns for continental Europe, we compute the simple average of the excess index returns for the four countries we examine.

Panel B of Table 9 reports the results from regressing annual excess returns on the surprise in ExR_t. We again begin by proxying for news in ExR_t by using beginning and ending levels of ExR_t. Our earlier U.S.-based finding that shocks to ExR_t explain close to half of the time-series variation in market returns comes through clearly in all three international regions: shocks to ExR_t explain 37.40% of the variation in market returns in Europe, 49.03% in the United Kingdom, and 51.49% in Japan. The results are similar when we use the change in ExR_t to proxy for discount rate news. Our measure thus comes remarkably close to the 50% benchmark not only in the United States, but also in major international markets.

The last regression in each region shown in Panel B of Table 9 omits the ending level of ExR_t, yielding an annual in-sample predictive regression. The degree of predictability is substantial in continental Europe and the UK, with t-statistics on ExR_t of 2.26 for Europe and 2.13 for the UK, and adjusted R^2s of 13.59% for Europe and 12.02% for the UK. In the case of Japan, the coefficient on ExR_t is also positive, but we lose statistical significance.[21]

Overall, we conclude that the empirical performance of ExR_t in both levels and changes is quite similar in the United States and in major markets outside the United States.

V. Conclusion

This article introduces a new measure of long-run expected market returns that is based on the cross section of stock prices. The intuition for our measure is straightforward. As discount rates rise, equity values shift away from risky future earnings and toward net assets on hand. But earnings persistence matters too: when persistence is low, equity values will also depend more on assets on hand. Thus, the *relative* contributions of earnings and book values to stock prices *in the cross section* will vary with both aggregate expected returns and earnings persistence. Our approach disentangles the effects of earnings persistence and discount rates.

Several important findings emerge from our analysis. First, our measure possesses economically sensible properties: it is countercyclical, rising during recessions and falling during expansions, and is strongly correlated with macroeconomic variables that reflect the business cycle. Second, shocks to it account for nearly half of the variation in historical market returns. In contrast, shocks to other discount rate measures account for less than 2%. Third, it dominates other discount rate measures in explaining the returns on duration-sorted portfolios. Because

[21]The research design employed here avoids overlapping return windows: we use annual financial statement data for firms with a common fiscal year end to predict annual returns over windows that do not overlap.

returns to duration-sorted portfolios depend on the contemporaneous discount rate change, this result validates our measure. Fourth, it delivers out-of-sample predictability that exceeds that afforded by other expected return measures and popular predictive variables. Fifth, it also performs well in international equity markets.

But this article does more than provide a new measure of long-run market expected returns: it also makes a broader contribution by introducing a novel way of comparing long-run discount rate measures. We argue that the level of such measures should not only predict future returns, but also that changes in such measures should explain a significant fraction – about half – of the variation in historical market returns. We show that our measure is the only one to come close to the 50% benchmark. Having established that our measure produces a valid proxy for both discount rate levels and changes, we take it to the cross section and consider duration-sorted portfolios, thus tying the stock return predictability literature and the literature on equity duration.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000455.

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