Stock Market Duration*

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August 31, 2023

Abstract

At the peak of the tech bubble, only 0.57% of market valuation comes from dividends in the next year. Taking the ratio of total market value to the value of one-year dividends, we obtain a duration of 175 years. In contrast, at the height of the global financial crisis, more than 2.2% of market value is from dividends in the next year, implying a duration of 46 years. What drives market duration? We find that market participants have limited information about cash flow beyond one year. Therefore, an increase in market duration is due to a decrease in the discount rate rather than good news about long-term growth. Accordingly, market duration negatively predicts annual market return with out-of-sample R^2 of 15%, outperforming other predictors in the literature. While the price-dividend ratio reflects the overall valuation level, market duration captures the slope of the valuation term structure. We show that market duration, as a discount rate proxy, is a critical state variable that augments the price-dividend ratio in spanning the (latent) state space for stock-market dynamics.

*We thank Nick Barberis, Geert Bekaert, Jules van Binsbergen, Zhi Da, Kent Daniel, Joost Driessen, Stefano Giglio, Will Goetzmann, Benjamin Golez, Hui Guo, Bryan Kelly, Ralph Koijen, Lars Lochstoer, Alan Moreira, Riccardo Sabbatucci, Tano Santos, José Scheinkman, Jessica Wachter, and Michael Weber for in-depth discussions.

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1 Introduction

We define stock market duration as the ratio of total market capitalization to the price of dividend in the very next year (the one-year dividend strip price in Binsbergen, Brandt, and Koijen, 2012). In March 2000, market duration is 175 years, which suggests that at the peak of the dot-com bubble, the U.S. stock market derives 99.4% of value from dividends beyond the next year. Duration varies significantly over time, with a monthly standard deviation of 1.6 years in the last three decades. At the market bottom during the global financial crisis, market duration is only 46 years in March 2009 with more than 2.2% of market value from dividends paid within the next year.

What drives the relative valuation of long- vs. short-term dividends? An increase in market duration represents a steepening of the valuation term structure, with the long-term dividends commanding a higher valuation relative to dividends in the near term. While duration represents the slope, the standard price-dividend ratio captures the overall level of market valuation. What information can we extract from the dynamics of slope and level of the valuation term structure?

We find that market duration and the price-dividend ratio span the state space of equity market. Stock prices are determined by the conditional expectations of future returns and dividends, so a model of aggregate stock market requires at least two state variables for return and cash-flow dynamics (e.g., Lettau and Wachter, 2007; Binsbergen and Koijen, 2010; Kragt, de Jong, and Driessen, 2020). In other words, the lower bound of the state-space dimension is two. Our analysis shows that two is also the upper bound. Market duration and the price-dividend ratio as the two state variables contain sufficient information for forecasting returns and future dividends. Moreover, market duration is the state variable that corresponds closely to conditional expected return. We show that this strong connection between market duration and the discount rate is due to the striking difference in cash-flow predictability at short and long horizons.

Identifying state variables is an important task in asset pricing and macro finance as it lays the foundation for various research topics (e.g., Sims, 1980; Cochrane, 1991; Barberis, Shleifer, and Vishny, 1998; Campbell and Ammer, 1993; Campbell and Cochrane, 1999; Barberis, Huang, and Santos, 2001; Lettau and Ludvigson, 2001; Ang and Piazzesi, 2003; Bansal and Yaron, 2004;

Campbell and Vuolteenaho, 2004; Kaltenbrunner and Lochstoer, 2010; Lettau and Wachter, 2011; Gabaix, 2012; He and Krishnamurthy, 2013; Wachter, 2013; Kelly and Pruitt, 2013; Brunnermeier and Sannikov, 2014; Barberis, Greenwood, Jin, and Shleifer, 2015; Muir, 2017; Campbell, Giglio, Polk, and Turley, 2018; Campbell, Pflueger, and Viceira, 2020; Cieslak and Pang, 2021). Our findings show that market duration and the price-dividend ratio are the two state variables for the equity market, and market duration is particularly powerful in revealing the discount-rate dynamics. Next, we summarize the key steps of our analysis and our contributions to the literature on state-space models in asset pricing, return predictability, and cash-flow expectations.

Our analysis starts with a characterization of the equity-market state space. We explore information directly from the prices of dividend strips rather than select macro or market variables. The logarithm of dividend strip prices at different maturities scaled by the realized dividend are linear functions of state variables in an exponential-affine setup or through log-linearization (Campbell and Shiller, 1988). Therefore, this set of valuation ratios of dividend strips fully reveals the state variables as long as the number of dividend strips is at least as large as the number of state variables and the valuation ratios have linearly independent state-variable coefficients.

We find that two principal components drive the dynamics of valuation ratios of dividends at different maturities. Importantly, when forecasting market return and dividend growth, a minimum of two valuation ratios are sufficient to maximize the predictive power. While different pairs of valuation ratios possess different predictive power, the pairs with the strongest predictive power perform as well as combinations of three or more valuation ratios. Our findings suggest that the state space is two-dimensional. Next, we show that the log market duration (dr), i.e., the logarithm of total market value scaled by one-year dividend price, and the log price-dividend ratio (pd) possess a predictive power for both return and dividend growth that is at least as strong as any combination of dividend valuation ratios and thus serve as the pair of state variables.

A striking finding from our forecasting exercises is that dr alone is sufficient for forecasting returns. Augmenting dr with pd or other valuation ratios of dividend strips does not improve the predictive power. In fact, the return predictive power of dr not only subsumes that of pd

and other valuation ratios but also surpasses other predictors in the literature, such as those summarized in Goyal and Welch (2007) and more recent studies. Specifically, dr demonstrates remarkable in-sample and out-of-sample (OOS) return predictability of annual market returns, reporting substantial R^2 of 25% and 15%, respectively. The OOS R^2 is in sharp contrast to the almost zero OOS R^2 from pd. Moreover, the predictive power of dr survives Hodrick (1992) adjustment for standard errors, Stambaugh (1999) adjustment for small-sample bias, and tests for out-of-sample predictive power such as encompassing (ENC) and Clark-West (CW) tests.

These findings are critical for understanding both the discount-rate dynamics and the fluctuation of market duration. If the conditional expected return is a univariate function of dr, then we can rearrange the equation and solve dr as a univariate function of the conditional expected return, which implies that the variation in market duration is fully discount-rate driven. To analyze the connection between dr and discount rate, we set up a two-dimensional state space model. Without loss of generality, the (latent) state variables are the conditional expected return and expected dividend growth rate that follow AR(1) processes (Lettau and Wachter, 2007; Binsbergen and Koijen, 2010). dr and pd are bivariate linear functions of state variables, and vice versa.

In our model, a necessary and sufficient condition for the conditional expected return to be a univariate function of dr (and vice versa) is that the market does not contain information on cash-flow growth beyond the very next year. Intuitively, under this condition, the price of next year's dividends exhausts all the information about future cash flows, so dr, which is the log market value minus the log price of next year's dividend, teases out cash-flow information and only contains information about the discount rate, thus becoming a univariate function of the conditional expected return. Given that the expected dividend growth rate follows an AR(1) process, this condition translates into a zero autoregressive coefficient of the expected dividend growth rate: All the relevant information about future cash flows—the current expected growth rate and the history of realized shocks—is not propagated into the future beyond the next year.[1]

[1]Given a two-dimensional state space, adding more lags to the autoregressive processes of expected return and expected dividend growth is not necessary. If AP(p) or ARMA(p,q) models were required or if other (macroeconomic or market) variables feed into the dynamics of expected return and expected cash-flow growth rate, we should have found the state-space dimension to be higher than two because to span the state space, we must augment the current

To estimate the autoregressive coefficient (persistence) of the expected dividend growth rate, we use analyst forecasts to proxy for the expected cash-flow growth and estimate two econometric models of belief dynamics that take advantage of, respectively, analysts' short-term and long-term forecasts. As an alternative method, we also fit a state-space model to dividend data to estimate the persistence of expected dividend growth. The message from our findings is consistent: Cash-flow growth expectation lacks persistence. This provides an explanation of the strong connection between market duration and expected return.

We also show analytically that return prediction errors should comove with the value of autoregressive coefficient of cash-flow growth expectation. To test this prediction, we conduct rolling-window estimation. In each window, we estimate the autoregressive coefficient of the expected cash-flow growth and the forecast error from predicting returns with dr. Both the in-sample and out-of-sample forecasting errors comove with the value of the autoregressive coefficient, suggesting that when the market contains limited information about cash-flow growth beyond one year, the mapping between dr and the expected return strengthens.

In our model, a zero autoregressive coefficient of the expected cash-flow growth rate fully captures the fact that the market contains limited information about cash-flow growth beyond the very next year. The emphasis on this autoregressive coefficient is warranted within our two-dimensional state-space model, wherein the expected dividend growth rate follows a AR(1) process. While our analysis of state-space dimension supports this specification, we still go beyond our model to characterize market participants' cash-flow expectations. First, we show that dividend and earnings growth within one year are highly predictable, especially by analysts' forecasts.[2] The R^2 is 73% from forecasting the near year's growth. In contrast, cash-flow predictability beyond one year is weak. For growth from the next one to two years, the in-sample R^2 of our best prediction model is only 8%. It declines to 7% for growth between the second and third year.

Our findings on the striking difference between short- and long-term cash-flow predictability lend support to dr as a discount-rate proxy. Cochrane (2011) points out that the price-dividend

conditional expectations of next-period return and cash flow growth rate with lagged conditional expectations.

[2] This can be explained by firms offering forward guidance on near-term performances.

ratio, pd, may predict future returns if cash flows are not predictable. We show that short-term cash flows are in fact highly predictable but long-term cash flows are not. This finding then suggests that the discount-rate proxy should be market duration, dr, which captures the relative valuation of long- vs. short-term cash flows and reflects the slope of valuation term structure, rather than pd, which reflects the overall level of valuation. Consider a market timing strategy based on the return predictive power of dr. Because dr has a negative predictive coefficient, the strategy reduces market exposure when duration increases and raises market exposure when duration decreases. The strategy delivers an out-of-sample Sharpe ratio of 0.58. It bets against the valuation of long-term cash flows rather than the overall level of valuation reflected in pd.

Beyond time-varying discount rate, return predictability typically entertains an alternative interpretation based on mispricing. The profitability of dr-based market timing strategy can be explained by market participants' lack of information on long-term growth and the associated over- or under-valuation of cash flows at long horizons. Moreover, the market timing strategy also avoids betting against the valuation of short-term cash flows that market participants are informed about. When the valuation of long-term cash flows rises, the resultant increase in market duration signals exuberance, while when the valuation of long-term cash flows declines, market participants may be overly pessimistic about long-term growth. This interpretation is consistent with the emphasis in Bordalo, Gennaioli, La Porta, and Shleifer (forthcoming) on market participants' errors in forecasting long-term growth as a key driver of asset prices.

Literature. Asset prices are typically modeled as functions of state variables. One approach to selecting state variables is through economic theories (e.g., Campbell and Cochrane, 1999, Bansal and Yaron, 2004). Our paper contributes to the alternative approach of state space modeling (e.g., Duffee, 2002; Dai and Singleton, 2003). Using the valuation ratios of dividend strips, we empirically analyze the dimension of state space and provide support to the widely adopted assumption of a two-dimensional state space (e.g., Lettau and Wachter, 2007; Binsbergen and Koijen, 2010; Kragt, de Jong, and Driessen, 2020). Moreover, we show that our measure of market duration and the commonly used price-dividend ratio map out the two state variables of equity market. Our work builds upon the previous research on measuring the prices of dividend strips (Binsbergen, Brandt, and Koijen, 2012; Binsbergen, Hueskes, Koijen, and Vrugt, 2013; Binsbergen and Koijen, 2017; Cejnek and Randl, 2016, 2020; Cejnek, Randl, and Zechner, 2021; Golez and Jackwerth, 2023; Giglio, Kelly, and Kozak, forthcoming). While the literature on dividend strips focuses on characterizing the term structure of equity risk premium, our paper instead focuses on the term structure of equity valuation ratios and how to use valuation ratios to map out state variables.[3]

Our approach of extracting state variables from disaggregated valuation ratios is similar in spirit to that in Kelly and Pruitt (2013) but differs in several crucial ways. Kelly and Pruitt (2013) decompose the stock market into individual stocks and filter out state variables from the valuation ratios of individual stocks. We decompose the market by the horizon of aggregate cash flows.[4] By avoiding idiosyncratic noise in firm-level valuation ratios, we do not rely on statistical filtering to extract state variables. The valuation ratios of dividend strips, our measure of market duration, and the price-dividend ratio are already combinations of state variables. Since our two state variables can be measured in real time and directly from market prices, they are less prone to estimation errors and thus offer a more precise characterization of the state of equity market.

A frequent application of the state variables in finance literature is to predict asset returns. We contribute to the voluminous literature on return predictability by offering a novel return predictor based on a relative valuation of short- and long-term cash flows (e.g., Fama and French, 1988; Campbell and Shiller, 1988; Lettau and Ludvigson, 2001; Baker and Wurgler, 2000; Lewellen, 2004; Goyal and Welch, 2007; Cochrane, 2007; Ang and Bekaert, 2007; Lettau and Van Nieuwerburgh, 2007; Campbell and Thompson, 2008; Kelly and Pruitt, 2013; Rapach, Ringgenberg, and

[3] There is an extensive literature on the term structure of equity risk premium (e.g., Lettau and Wachter, 2007, 2011; Hansen, Heaton, and Li, 2008; Croce, Lettau, and Ludvigson, 2014; Belo, Collin-Dufresne, and Goldstein, 2015; Ai, Croce, Diercks, and Li, 2018; Backus, Boyarchenko, and Chernov, 2018; Bansal, Miller, Song, and Yaron, 2021; Gonçalves, 2021a; Gormsen, 2021; Boguth, Carlson, Fisher, and Simutin, 2022).

[4] There is a large literature on measuring the cash-flow duration for the aggregate market based on accounting information (Binsbergen, 2021; Golez and Koudijs, 2023) and for individual stocks based on accounting information (Dechow, Sloan, and Soliman, 2004; Da, 2009; Chen, 2011; Weber, 2018; Gonçalves, 2021b; Walter and Weber, 2022) or derivative prices (Gormsen and Lazarus, 2023). Our paper differs by focusing on a valuation-based duration measure rather than the term structure of corporate cash flows.

Zhou, 2016; Martin, 2017; Johnson, 2019; Chen, Da, and Huang, 2022; Kelly, Malamud, and Zhou, forthcoming; Bordalo, Gennaioli, La Porta, and Shleifer, forthcoming). The construction of our predictor is simple, and it outperforms the other predictors in the literature by different metrics. Moreover, we provide an intuitive explanation on the connection between market duration and conditional expected return based on the term structure of cash-flow predictability.

We show that short-term cash flows are highly predictable but long-term cash flows are not, and this finding has direct implications on finding the discount-rate proxy. Cochrane (2011) suggest that the price-dividend ratio predicts future returns and serves as a discount-rate proxy if cash flows are not predictable. But our findings on the striking difference in cash-flow predictability at short- vs. long horizons suggest that the proper discount-rate proxy and the state variable driving the conditional expected return should be market duration, dr. Our findings on cash flow predictability at different horizons contributes to the literature on cash-flow predictability (Larrain and Yogo, 2008; Binsbergen and Koijen, 2010; Koijen and Van Nieuwerburgh, 2011; Binsbergen, Hueskes, Koijen, and Vrugt, 2013; Chen, Da, and Zhao, 2013; Jagannathan and Liu, 2018; Pettenuzzo, Sabbatucci, and Timmermann, 2020; Golez and Koudijs, 2023; Pruitt, 2023)

Characterizing the dynamics of expected cash-flow growth rate has always been an important topic in the asset pricing literature (Bansal and Yaron, 2004; Beeler and Campbell, 2012; Belo, Collin-Dufresne, and Goldstein, 2015; Collin-Dufresne, Johannes, and Lochstoer, 2016). Recently a growing body of work focuses on analyzing market participants' expectation formation. Adam and Nagel (2022) provides an excellent summary of the latest developments.[5] Our findings are most related to Bordalo, Gennaioli, La Porta, and Shleifer (forthcoming), who document that market participants' errors in forecasting long-term growth are key to understanding asset-price fluctuations. Also related, Da and Warachka (2011) find that the disparity between long- and short-term earnings expectations drives the cross-sectional difference in average stock

[5]There is a fast-growing literature on firm-level cash flow expectations (La Porta, 1996; Dechow and Sloan, 1997; Copeland, Dolgoff, and Moel, 2004; Da and Warachka, 2011; Piotroski and So, 2012; Bordalo, Gennaioli, La Porta, and Shleifer, 2019; Bouchaud, Krüger, Landier, and Thesmar, 2019; Binsbergen, Han, and Lopez-Lira, 2022) and expectations of aggregate cash-flow growth (Chen, Da, and Zhao, 2013; Nagel and Xu, 2022; De La O and Myers, 2021; McCarthy and Hillenbrand, 2021; Charles, Frydman, and Kilic, 2023; Bordalo, Gennaioli, La Porta, OBrien, and Shleifer, 2023; Schmidt-Engelbertz and Vasudevan, 2023).

returns. Our contribution is to show that, first, there exists a striking difference in short- vs. long-term cash flow predictability, and second, such difference guides us towards finding a better discount-rate proxy, our measure of market duration. Moreover, we show that the term structure of cash-flow predictability is closely tied to the persistence of agents' cash-flow expectations. Our findings echo the recent studies on the importance of agents' perceived persistence of key state variables in explaining belief formation and asset prices (Gabaix, 2019; Wang, 2020).

2 Valuation Ratios and the State Space

We consider a dynamic economy where the information filtration is driven by a Markov process. Specifically, the state of an economy at time t is summarized by X_t, a K-by-1 vector of state variables. We assume that X_t evolves as a first-order vector autoregression

$$X_{t+1} = \Pi X_t + \sigma_X^\top \epsilon_{t+1}, \tag{1}$$

where ϵ_{t+1} is a N-by-1 vector of shocks that capture all the news at $t+1$ and are independent over time with normal distribution $N(\mathbf{0}, \Sigma)$. Note that since any higher-order vector autoregression can be written as a first-order vector autoregression by expanding the number of state variables, the AR(1) specification is without loss of generality. The autoregressive coefficients are given by Π, a constant K-by-K matrix, and σ_X is a N-by-K matrix of shock loadings.

The growth rate of dividend from t to $t+1$ has a N-by-1 shock-loading vector σ_D,

$$\ln\left(\frac{D_{t+1}}{D_t}\right) = g_t + \sigma_D^\top \epsilon_{t+1}, \tag{2}$$

where the time-varying expected dividend growth rate is given by

$$g_t = \phi^\top X_t + \overline{g} - \frac{1}{2}\sigma_D^\top \Sigma \sigma_D. \tag{3}$$

We allow the state-variable loadings, ϕ, to be any K-by-1 vector. If g_t does not depend on a state variable, the corresponding element in ϕ is zero; likewise, if a shock does not affect the growth rate of aggregate dividend, the corresponding element in σ_D is zero.

No arbitrage implies the existence of a stochastic discount factor

$$M_{t+1} = \exp\left\{-r_f - \frac{1}{2}\lambda_t^\top \Sigma \lambda_t - \lambda_t^\top \epsilon_{t+1}\right\}, \tag{4}$$

where r_f is the one-period risk-free rate and the N-by-1 vector of risk prices, λ_t, is given by

$$\lambda_t = \overline{\lambda} + \theta^\top X_t. \tag{5}$$

We do not impose any restrictions on the state-variable loadings of the risk prices in λ_t.

Let P_t^n denote the time-t price of dividend at $t+n$. The no-arbitrage pricing functional gives a recursive equation for the prices of dividend strips: for $n \geq 1$,

$$P_t^n = \mathbb{E}_t\left[M_{t+1} P_{t+1}^{n-1}\right], \tag{6}$$

with the boundary condition $P_t^0 = D_t$. The log price-dividend ratio of the dividend strip with maturity n is given by

$$s_t^n \equiv \ln\left(\frac{P_t^n}{D_t}\right) = A(n) + B(n)^\top X_t, \tag{7}$$

where $A(n)$ and $B(n)$ are deterministic functions of n given by a system of recursive equations

$$B(n) = \left(\Pi^\top - \theta\Sigma\sigma_X\right) B(n-1) + \phi - \gamma - \theta\Sigma\sigma_D. \tag{8}$$

$$\begin{aligned} A(n) =& A(n-1) + \overline{g} - \overline{r} - \left(\sigma_D + \sigma_X B(n-1)\right)^\top \Sigma\overline{\lambda} \\ &+ \frac{1}{2}\left(\sigma_D + \sigma_X B(n-1)\right)^\top \Sigma \left(\sigma_D + \sigma_X B(n-1)\right). \end{aligned} \tag{9}$$

with the initial conditions $A(0) = 0, \text{ and } B(0) = 0.$. The derivation is provided in Appendix I.

Given K log price-dividend ratios of strips, $\{s_t^{n_i} : \forall i \in \{1, 2, ..., K\}, n_i \in \{1, 2, ..., n, ...\}\}$, with a full-rank loading matrix, $\mathbf{B}\left(\{n_i\}_{i=1}^{K}\right) \equiv \left[B(n_1), B(n_2), ..., B(n_K)\right]^T$, the state space is recovered by

$$X_t = \mathbf{B}\left(\{n_i\}_{i=1}^{K}\right)^{-1} \left[s_t^{n_1} - A(n_1), \ ..., \ s_t^{n_K} - A(n_K)\right]^\top \tag{10}$$

When the rank condition fails, these valuation ratios can still recover part of the state space. Let J $(< K)$ denote the maximum number of log price-dividend ratios with linearly independent loadings $B(n)$ and $\{n_i\}_{i=1}^{J}$ denote the corresponding set of maturities. We can write (7) as follows

$$\mathbf{B}\left(\{n_i\}_{i=1}^{J}\right) X_t = \left[s_t^{n_1} - A(n_1), \ ..., \ s_t^{n_J} - A(n_J)\right]^\top. \tag{11}$$

The stock market acts as a linear mapping, i.e., $\mathbf{B}\left(\{n_i\}_{i=1}^{J}\right)$, that compresses the K-dimensional state space of X_t into a J-dimensional space generated by the log price-dividend ratios. In sum, a collection of log price-to-dividend ratios of dividend strips (partially) span the state span. For information embedded in the state variables, we analyze these valuation ratios.

Let P_t denote the total stock market capitalization (i.e., the market price of dividends across all maturities). Following the same method, we solve the log price-to-dividend ratio of the market

$$pd_t = \ln(P_t/D_t) = A + B^T X_t, \tag{12}$$

where A and B are constant defined in Appendix I. Stock market duration is defined as the log ratio of total market capitalization to the price of dividends paid in the next year.

$$\begin{aligned} dr_t \equiv \ln\left(P_t/P_t^1\right) &= \ln(P_t/D_t) - \ln\left(P_t^1/D_t\right) = pd_t - s_t^1 \\ &= A - A(1) + (B - B(1))^T X_t. \end{aligned} \tag{13}$$

Therefore, just as the valuation ratios of dividend strips, pd_t and dr_t are also driven by the state variables X_t, and, by having different coefficients of X_t, these two variables reveal different information about the state space. Next, we analyze the dimension of state space using the valuation ratios of dividend strips with different maturities, pd_t, and dr_t. After showing that the state space is two-dimension, we argue that the pair, pd_t and dr_t, span the state space and, in particular, contain sufficient information for forecasting stock market returns and cash-flow growth.

3 The Dimension of State Space

3.1 Variable construction and summary statistics

Constructing dividend strip prices. Let P_t^n denote the price of dividend paid in year n. First, we calculate P_t^{n+}, the price of dividends that are paid after the first n years. Under the risk-neutral measure,

$$P_t^{n+} = e^{-nr_f}\mathbb{E}_t^{RN}\left[\sum_{\tau=1}^{+\infty} e^{-\tau r_f} D_{t+n+\tau}\right] = e^{-nr_f}\mathbb{E}_t^{RN}\left[\mathbb{E}_{t+n}^{RN}\left[\sum_{\tau=1}^{+\infty} e^{-\tau r_f} D_{t+n+\tau}\right]\right], \tag{14}$$

where the expectation operator, $\mathbb{E}_{t+n}^{RN}[\cdot]$, was inserted under the law of iterated expectation. Note that the (ex-dividend) stock price at $t+n$ is

$$S_{t+n} = \mathbb{E}_{t+n}^{RN}\left[\sum_{\tau=1}^{+\infty} e^{-\tau r_f} D_{t+n+\tau}\right], \tag{15}$$

so we have

$$P_t^{n+} = e^{-nr_f}\mathbb{E}_t^{RN}[S_{t+n}]. \tag{16}$$

The first component, e^{-nr_f}, is ZCB_t^n, the price of a zero-coupon bond with maturity n. The second component is the risk-neutral expectation of stock price, i.e., the futures price, F_t^n (Duffie, 2001).

We construct the price of dividend strips using zero-coupon bond prices and stock index futures prices. First, we calculate P_t^1, the price of dividend paid in the next year,

$$P_t^1 = P_t - P_t^{1+}, \tag{17}$$

as the difference between the price of all dividends, i.e., the current stock price P_t, and the price of dividends paid after the next year. Following the same method, we calculate the price of dividends paid in the next six months, $P^{0.5}$ from $P_t - P_t^{0.5+}$. In our empirical analysis, we use the valuation ratios of dividend strips with maturity 1 and 0.5, i.e., $s^1 = \ln(P^1/D_t)$ and $s^{0.5} = \ln(P^{0.5}/D_t)$, and the valuation ratio of dividends paid beyond one year, $s^{1+} = \ln(P^{1+}/D_t)$. Our analysis in the previous section shows that these valuation ratios are different linear combinations of state variables.

Data and summary statistics For futures prices, we use S&P 500 index futures, which are the most actively traded stock futures. We obtain S&P 500 futures prices from Datastream.[6] We obtain the zero-coupon bond prices are obtained from the Fama-Bliss database. The return and level of the S&P 500 index are obtained from CRSP. The dividend data is from S&P Global and obtained via the updated dataset of Goyal and Welch (2007). Our final dataset is from January 1988 to December 2019. The sample starts in 1988 to have high-quality dividend data from S&P Global and, importantly, a sufficiently liquid futures market without structural changes.[7] After the market crash of October 1987, regulators overhauled several trade-clearing protocols.[8]

We construct market duration, dr_t, as the logarithm of the ratio of S&P 500 market capitalization to the price of dividends paid in the next year. The traditional price-dividend ratio is the logarithm of the ratio of S&P 500 market capitalization to the realized dividend in the last year. Table 1 reports the summary statistics of dr_t, the traditional price-dividend ratio pd_t, the valuation ratios ($s^{0.5}$, s^1, and s^{1+}), the monthly return of S&P 500 ($r^{S\&P}_{t+1/12}$ where in the subscript 1/12 denotes one month or 1/12 of a year), the annual return of S&P 500 ($r^{S\&P}_{t+1}$), and for comparison, the monthly and annual Fama-French market portfolio (MKT) annual returns in Fama and French (1993) ($r^{MKT}_{t+1/12}$ and r^{MKT}_{t+1}). Our sample includes monthly observations until 2019, i.e., before

[6]We obtain the daily settlement prices for the S&P 500 futures. For return and cash-flow prediction at the monthly frequency, we use the settlement price of the last trading day of each month. The maturities of the traded futures contracts vary over time, so to obtain futures prices with constant maturity, we apply the shape-preserving piecewise cubic interpolation to complete the futures curve. The results using linear interpolation are similar.

[7]Wang, Michalski, Jordan, and Moriarty (1994) identify structural changes of liquidity in the S&P 500 futures market in the pre-1987 period, during the market crash, and in the post-1987 period.

[8]The stock market crash in October 1987 reveals anomalous trading in the futures market that was primarily driven by portfolio insurance (Brady Report (1988)). According to the New York Stock Exchange: "In response to the market breaks in October 1987 and October 1989, the New York Stock Exchange instituted circuit breakers to reduce volatility and promote investor confidence. By implementing a pause in trading, investors are given time to assimilate incoming information and the ability to make informed choices during periods of high market volatility."

Table 1 Summary Statistics

This table reports the number of observations, mean, standard deviation, minimum, maximum, quartiles, and monthly autocorrelation (ρ) of the main variables in this paper, including our main return predictor, dr ("duration"), the price-dividend ratio pd of the S&P 500 index, the filtered series for demeaned expected returns and dividend growth following Binsbergen and Koijen (2010) μ^F and g^F, the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP, short-term dividend strip price to dividend ratio (0.5 year and 1 year) $\log(P^{0.5}/D)$ and $\log(P^1/D)$, long-term dividend strip price to dividend ratio (beyond 1 year) $\log(P^{1+}/D)$, one-month and one-year log returns of the S&P 500 index $r^{S\&P}_{t+1/12}$ and $r^{S\&P}_{t+1}$, one-month and one-year log market returns from Fama-French market portfolio $r^{MKT}_{t+1/12}$ and r^{MKT}_{t+1}, and the 1-year dividend growth rate of S&P 500 index and the Fama-French market portfolio $\log(D_{t+1}/D_t)$ and $\log(D^{MKT}_{t+1}/D^{MKT}_t)$. Our sample is monthly observations 1988:01–2019:12.

	obs	mean	std	min	25%	50%	75%	max	ρ
dr_t	384	4.027	0.494	2.952	3.727	4.044	4.208	6.632	0.919
pd_t	384	3.883	0.289	3.239	3.656	3.930	4.047	4.524	0.985
μ^F_t	384	-0.039	0.024	-0.091	-0.051	-0.041	-0.024	0.010	0.991
KP_t	383	-0.504	0.073	-0.725	-0.562	-0.482	-0.450	-0.378	0.955
$s^{0.5}_t \equiv \log(P^{0.5}/D)$	384	0.095	0.157	-0.568	0.046	0.126	0.187	0.429	0.929
$s^1_t \equiv \log(P^1/D)$	384	0.009	0.041	-0.184	-0.015	0.013	0.034	0.108	0.022
$s^{1+}_t \equiv \log(P^{1+}/D)$	384	3.863	0.297	3.204	3.629	3.913	4.030	4.521	0.985
$r^{S\&P}_{t+1/12}$	384	-0.142	0.280	-2.241	-0.210	-0.098	0.016	0.393	0.766
$r^{S\&P}_{t+1}$	384	-0.819	0.281	-2.629	-0.883	-0.768	-0.666	-0.280	0.604
$r^{MKT}_{t+1/12}$	384	0.009	0.042	-0.187	-0.016	0.014	0.036	0.108	0.051
r^{MKT}_{t+1}	384	0.096	0.159	-0.554	0.036	0.128	0.194	0.440	0.924
$\Delta d_{t+1} \equiv \log(D_{t+1}/D_t)$	384	0.059	0.070	-0.237	0.025	0.068	0.112	0.168	0.994
$\Delta d^{MKT}_{t+1} \equiv \log(D^{MKT}_{t+1}/D^{MKT}_t)$	384	0.058	0.081	-0.207	0.018	0.051	0.107	0.262	0.962
g^F_t	384	0.019	0.059	-0.233	-0.002	0.031	0.056	0.132	0.939

the extreme market fluctuations during the Covid-19 pandemic. Our baseline analysis focuses on the returns and dividends of the S&P 500 index because we construct the strip prices using the S&P 500 futures data.[9] For robustness, we also report results using Fama-French market portfolio returns and dividends. Note that we include μ^F and KP, the return predictors from Binsbergen and Koijen (2010) and Kelly and Pruitt (2013), respectively, because these variables are also constructed to extract information on state variables. To highlight our contribution, we will compare our analysis with that in Binsbergen and Koijen (2010) and Kelly and Pruitt (2013).

The mean of stock market duration dr_t is 4.027, which translates into $56 = \exp(4.027)$ years, meaning that the total market value is 56 times the valuation of dividends in the next year. dr_t has a wide range of variation, with a minimum of 2.952 (i.e., 19 years) in November 1988 right before

[9] Previous studies of return predictability, such as Ang and Bekaert (2007), also use the S&P 500 Index to represent the U.S. equity market.

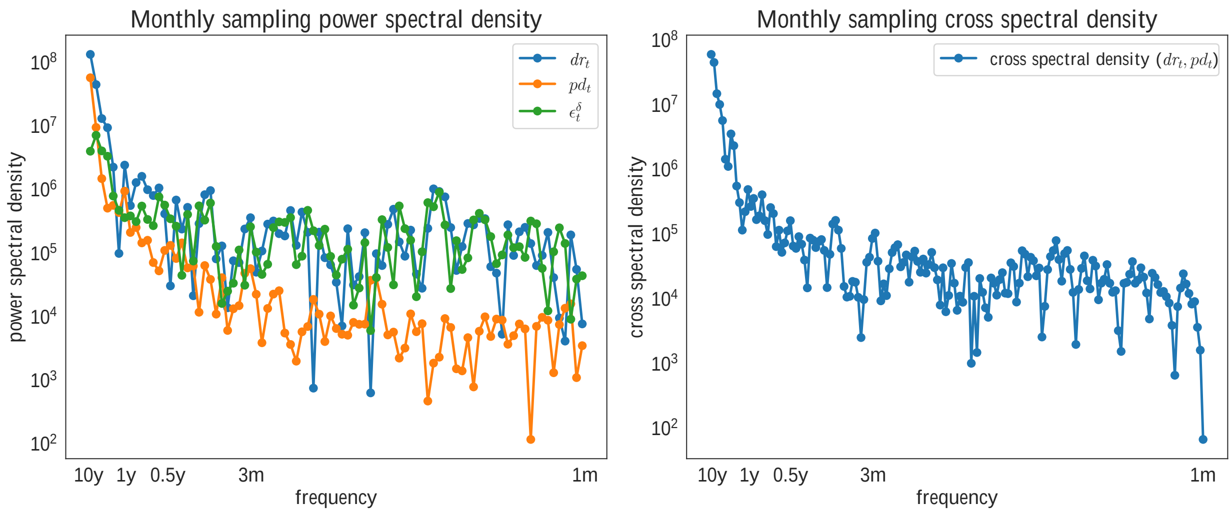
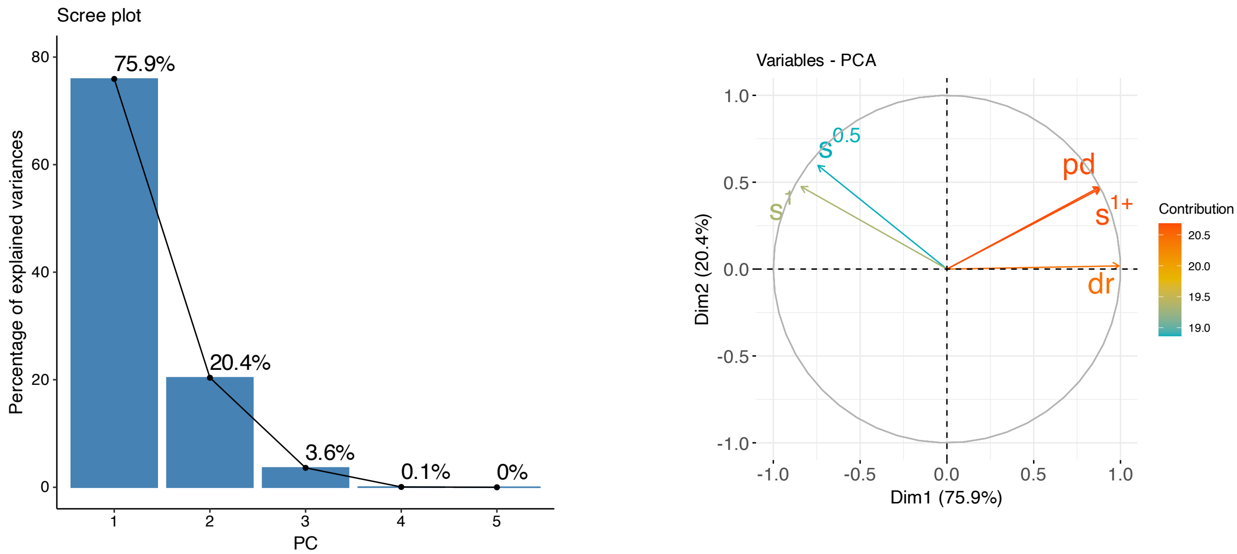


Figure 1 Spectrum and Cross-spectrum of Duration dr and Price-Dividend Ratio pd.
The left panel shows the estimated spectral densities of dr_t, pd_t, and the residuals of dr_t after projecting on pd_t (ϵ_t^{pr}). The integral of spectral density is equal to the variance. The horizontal line starts from zero and ends at π, but is labeled with the corresponding length of a cycle. The right panel shows the cross-spectral density between dr_t and pd_t. The integral of cross-spectral density is equal to the covariance.

the 1990-1991 recession and a maximum of 6.632 (i.e., 759 years) near the end of the dot-com boom (November 2000). dr_t has a lower monthly autocorrelation ("ρ") than pd_t.

dr_t and pd_t are correlated but contain distinct information. As shown in the cross-spectrum in Figure 1, the correlation of 0.87 is mainly from low-frequency movements. Panel A of Figure 1 shows the spectrum of dr_t, pd_t, and ϵ_t^{dr} (the residual from linearly projecting dr_t on pd_t). The area under the spectrum curve is the variance, so the figure provides a variance decomposition in the frequency domain. On the horizontal axis, instead of showing the frequencies from zero to π, we mark the corresponding length of the cycle for easier interpretation. Once orthogonalized to pd_t, dr_t's residual varies mainly at annual or higher frequencies. Panel B plots the cross-spectrum of dr_t and pd_t. The integral is the covariance between dr_t and pd_t. The correlation between dr_t and pd_t is mainly from low frequencies. This indicates that it is the high-frequency variation in dr_t that brings information distinct from that revealed by the traditional price-dividend ratio. Figure A.1 in the appendix shows the spectrum analysis based on daily data with similar results.

As shown in Section 2, dr_t and pd_t are essentially different combinations of state variables. Our state-space approach is closely related to Binsbergen and Koijen (2010). Binsbergen and



A. Variance Explained

B. Variable Loading

Figure 2 Principal Component Analysis of Valuation Ratios

This figure reports the PCA results for dr, pd, $s_t^{0.5}$, s_t^1, and s_t^{1+}. Panel A plots the variance explained by each principal component. Panel B plots the loading of each variable on the first two principal components.

Koijen (2010) use the realized returns and dividends to estimate a latent-state model and filter out the conditional expected return, μ_t^F, and the conditional expected dividend growth rate, g_t^F. These filtered variables are also combinations of state variables. We replicate the analysis of Binsbergen and Koijen (2010), and throughout our analysis in this paper, we compare our state-space representation via valuation ratios with the information about state space in μ_t^F and g_t^F. Kelly and Pruitt (2013) also take a state-space approach and use the cross-section of market-to-book ratios of individual stocks to extract the conditional expected return of the aggregate stock market. We have also replicated Kelly and Pruitt (2013) and include KP_t for comparison.

3.2 Analyzing the dimension of state space

We are interested in determining the dimension of the state space. Traditionally, a variety of macroeconomic and financial-market variables have been incorporated into different analytical frameworks as the state variables that generate the relevant information for asset pricing (e.g., Cieslak and Pang, 2021). For example, the market price-dividend ratio, pd_t, has been commonly selected as a state variable (Muir, 2017). However, there has been limited evidence on the dimension of state space, i.e., how many state variables are needed in an asset pricing framework. Among the theoretical studies, such as Lettau and Wachter (2007) and Binsbergen and Koijen (2010), a common assumption is that two state variables are sufficient for characterizing the stock market dynamics and, in particular, for predicting returns and cash-flow growths. In these models, these two state variables are often directly specified as the conditional expectation of return and the conditional expectation of cash-flow growth.

According to our analysis in Section 2, one way to determine the dimension of state space is to analyze the collection of valuation ratios, such as those of dividend strips, pd, and our measure of market duration dr. In Panel A of Figure 2, we report the results from principal component analysis (PCA) of dr, pd, and valuation ratios of dividend strips with maturities of six months, one year, and of dividends paid beyond one year. The first two components account for 96.3% of total variance. In correspondence with our theoretical analysis in Section 2, we show in Panel B of Figure 2 that these valuation ratios have different loadings on the two principal components, labeled as Dim1 (dimension 1) and Dim2 (dimension 2).

The results in Figure 2 indicate that the state space, mapped out by the valuation ratios, is likely to be two-dimensional, and that we may pick any two valuation ratios, for example, the pair of pd and dr, to span the state space. However, as pointed out by Kelly and Pruitt (2015), a shortcoming of PCA analysis is that the information embedded in the principal components may not be the information most relevant for objects of interest, which, in asset pricing studies, are cash-flow and return dynamics. Therefore, we also take a predictive regression approach to analyze the state space. The expected return and expected dividend growth rate are driven by the state variables. By projecting future returns and dividend growth rate on the valuation ratios, we are able to evaluate how many valuation ratios are needed to achieve the highest predictive power and thereby analyze the dimension of the underlying state space based on information relevant to cash-flow and return dynamics.

In Figure 3, we report the R^2 of predicting the annual dividend growth of the S&P 500 index

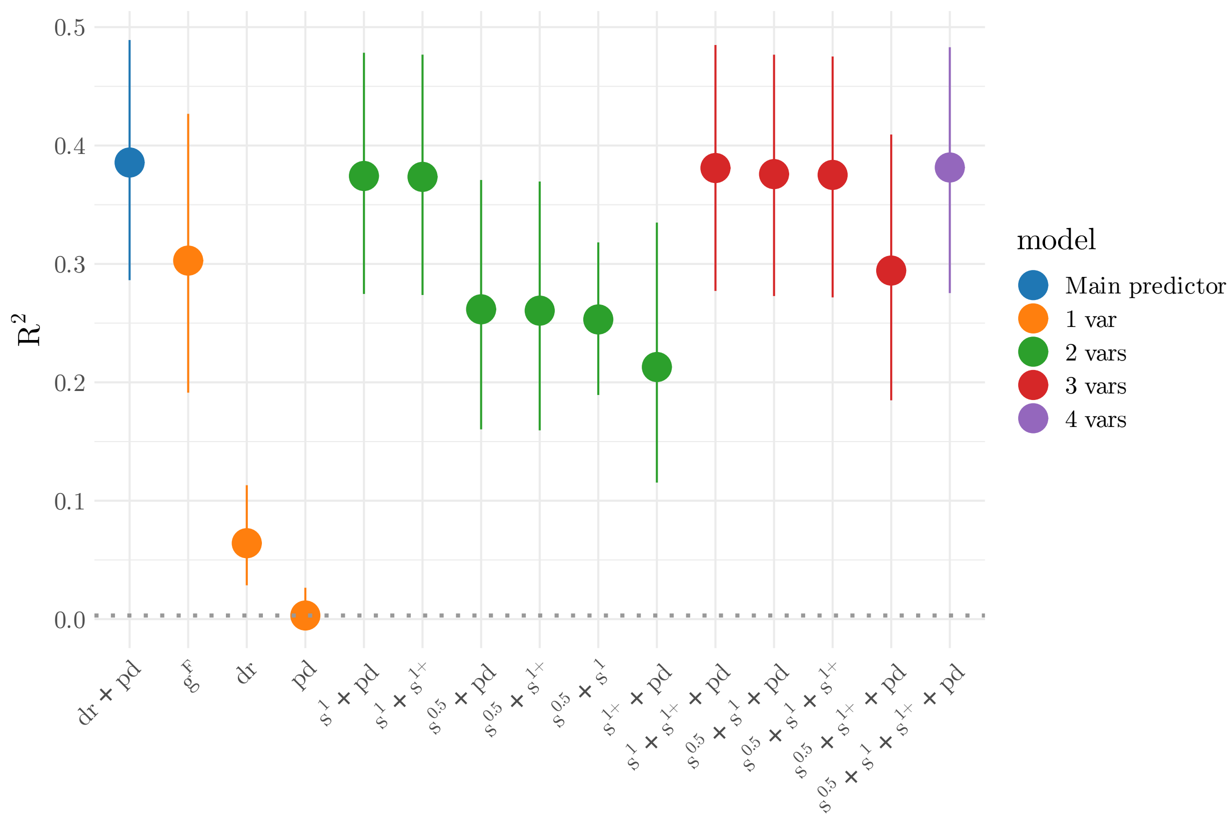


Figure 3 R^2 from Dividend Growth Predictive Regressions with Bootstrapped Confidence Interval.

This figure reports R^2 from one-year S&P 500 Index dividend growth predictive regressions with bootstrapped confidence interval. The predictors include our main predictor – a linear combination of 'duration' and 1-year dividend strip price to dividend ratio $dr + s^1$, the price-dividend ratio pd, short-term (0.5- and 1-year) dividend strip price to dividend ratio ($pd^{0.5}$ and pd^1), long-term (beyond 1-year) dividend strip price to dividend ratio (pd^{1+}), the filtered series for demeaned dividend growth following Binsbergen and Koijen (2010) g^F, the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP, and all combinations of pd, $pd^{0.5}$, pd^1 and pd^{1+}. Each bar corresponds to one separate predictive regression. The range of the bar represents 95% confidence intervals of the predictive R^2 obtained using the bootstrap method.

in the next year with different combinations of valuation ratios. We report the detailed regression results in Table A.1 in the appendix. Our predictive regression is run on monthly observations. In the first specification, the predictors include dr and pd, which achieve the highest adjusted R^2. In the next specification, for comparison, we show the forecasting performance of g^F, the predictor from Binsbergen and Koijen (2010) who develop a latent state model and filter out the conditional expectation of growth rate g^F.

In the third specification in Figure 3, we include our market duration measure dr alone. Interestingly, dr shows limited return predictive power in comparison with the combination of

dr and pd. This is surprising as one would expect that when dr increases, i.e., the stock market assigns a higher valuation to long-run dividends than the short-run dividends, the expected growth rate of dividends should rise accordingly. In the fourth specification, we show that the traditional price-to-dividend ratio also has limited cash-flow predictive power.

The weak standalone predictive power of dr and pd stands in contrast with the strong predictive power of dr and pd combined in the first specification. This again indicates that to fully capture the information embedded in the state variables, two valuation ratios are needed. In the subsequent specifications, we show that different pairs of valuation ratios exhibit different cash-flow predictive power. This shows the importance of taking a predictive regression approach in determining the dimension of state space rather than simply relying on PCA of valuation ratios. Any given pair of valuation ratios fully spans the two principal components, as indicated in the linearly independent principal-component loadings of different valuation ratios in Panel B of Figure 2. However, different pairs of valuation ratios may still contain different information about return and cash-flow dynamics.

In the last five specifications in Figure 3, we show that three or four valuation ratios do not outperform two valuation ratios in forecasting dividend growth. The adjusted R^2 we report is in-sample R^2, which does not reflect poor out-of-sample performance due to potential overfitting from adding more predictors; in other words, when competing with dr and pd, the three or four valuation ratios do not have a mechanical disadvantage due to our choice of performance metric. Overall, our results indicate that two valuation ratios (in particular, the combination of dr and pd) are the necessary minimum and sufficient for forecasting dividend growth.

Next, we examine the dimension of state space by forecasting returns. In Figure 4, we report the R^2 of predicting the annual return of S&P 500 with different combinations of price-dividend ratios. Our predictive regression is run monthly. We report the detailed regression results in Table A.2 in the appendix. The conclusion is similar to that in cash-flow prediction. Having three or more price-dividend ratios does not improve predictability relative to the best performances of combinations of two price-dividend ratios. In particular, combining dr and pd achieves the best

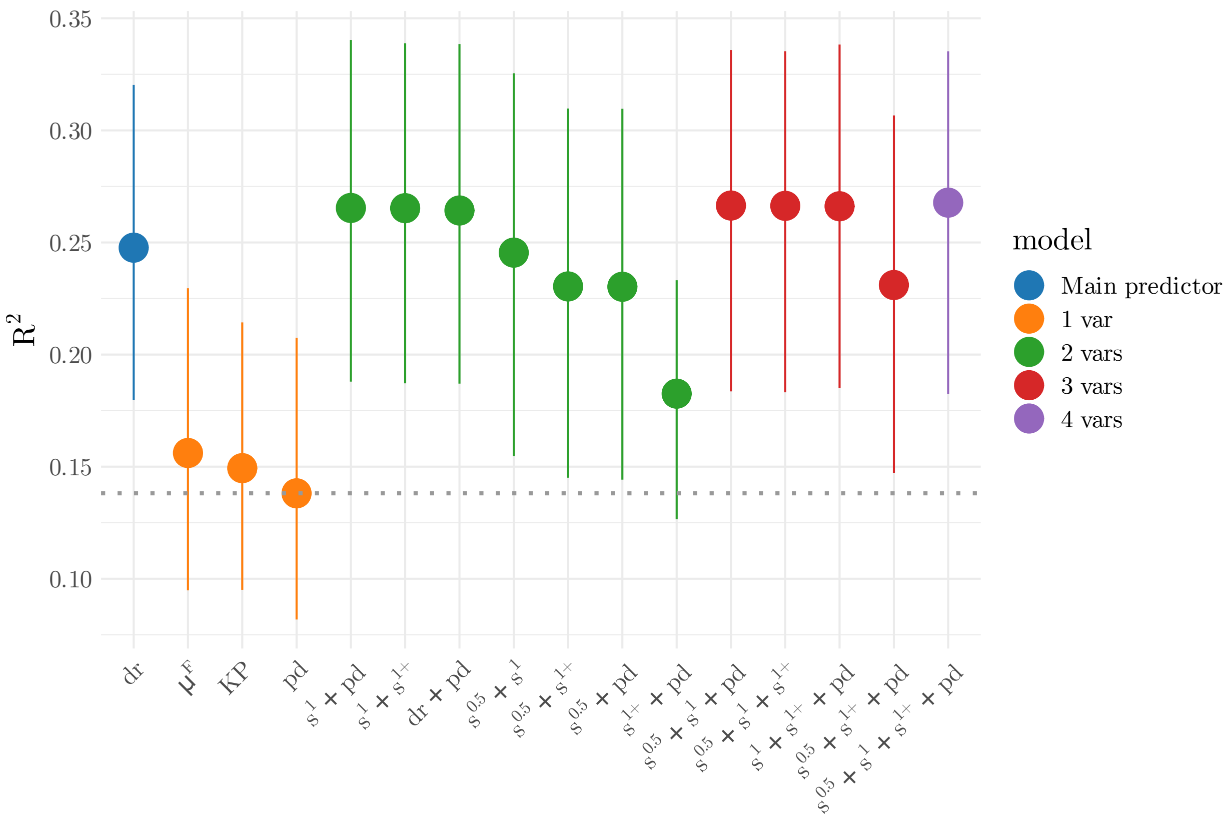


Figure 4 R^2 from Return Predictive Regressions with Bootstrapped Confidence Interval.

This figure reports R^2 from one-year S&P 500 Index return predictive regressions with bootstrapped confidence interval. The predictors include our main predictor 'duration' dr, the price-dividend ratio pd, short-term (0.5- and 1-year) dividend strip price to dividend ratio ($pd^{0.5}$ and pd^1), long-term (beyond 1-year) dividend strip price to dividend ratio (pd^{1+}), the filtered series for demeaned expected returns following Binsbergen and Koijen (2010) μ^F, the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP, and all combinations of pd, $pd^{0.5}$, pd^1 and pd^{1+}. Each bar corresponds to one separate predictive regression. The range of the bar represents 95% confidence intervals of the predictive R^2 obtained using the bootstrap method.

forecasting performance. These results again suggest that the state space is two-dimensional, and to capture the information embedded in state variables, we need dr and pd for the purposes of analyzing both return and cash-flow dynamics.

Interestingly, the predictive power of dr alone is comparable to that of two or more valuation ratios. Moreover, in the second, third, and fourth specifications in Figure 4, we find that μ^F, the return predictor in Binsbergen and Koijen (2010), KP, the return predictor in Kelly and Pruitt (2013), and the traditional price-to-dividend ratio all underperform dr in our sample period. Overall, our results suggest a close connection between dr_t and the conditional expected return. This finding is critical for understanding what drives the variation of market duration and, vice versa, what drives the expected return. We will explore this topic in the next section.

Before we move on to Section 4, we briefly discuss the rich information content of the pair dr and pd beyond forecasting return and cash-flow growth. In Table A.3 in the appendix, we report the R^2 from forecasting a variety of macroeconomic and financial-market variables with dr and pd, only dr, only pd, and for illustration purposes, dr in combination with s^1 (the log price-to-dividend ratio of one-year dividend strip), and only s^1. The pair dr and pd demonstrate the strongest and most consistent predictive power when forecasting variables related to financial intermediaries' balance-sheet capacity (with the R^2 ranging from 30% to 40%). When forecasting macroeconomic variables related to business-cycle dynamics, dr and pd have an R^2 consistently above 20%. Moreover, the R^2 from forecasting sentiment proxies is consistently above 10%. Finally, combining dr and pd outperforms other specifications.

Overall, our results suggest that dr and pd together provide not only relevant information for understanding asset-pricing dynamics but also other key objects in macro-finance. Through our analysis, we hope to demonstrate the importance of incorporating market duration, dr, as a key state variable in macro-finance studies.

4 Duration and Expected Return

A striking finding from our forecasting exercises is that market duration alone is quite sufficient for predicting returns. Augmenting dr with pd or other valuation ratios does not significantly improve the performance. Therefore, dr captures the combination of state variables that drive the conditional expected return. Next, we provide further evidence on the return predictive power of dr. As shown in Section 2, the loadings of dr on state variables depend on various parameters. We find that dr and the conditional expected return coincide in their state-variable loadings.

4.1 Univariate return prediction

We run the standard predictive regression to forecast market return in the next twelve months:

$$r_{t+1} = \alpha + \beta dr_t + \epsilon_{t+1}, \tag{18}$$

Because we use overlapping monthly data, we adopt Newey and West (1987) standard errors with 18 lags to account for the moving-average structure induced by overlap (Cochrane and Piazzesi, 2005). We also calculate Hodrick (1992) standard errors. Hodrick (1992) shows that GMM-based autocovariance correction (e.g., Newey and West, 1987) may have poor small-sample properties. Under the serial correlation in the error term, another concern is the bias induced by the persistence of the predictor.[10] While dr_t has an autocorrelation below that of the traditional price-dividend ratio, pd_t, we still report the adjusted estimate of β following Stambaugh (1999). In the appendix (Table A.4), we also report the IVX-Wald test of predictive power (Kostakis, Magdalinos, and Stamatogiannis, 2014) that explicitly accounts for the predictor persistence.

The adjusted R^2 measures in-sample fitness. Several studies raised concerns over out-of-sample performances of return predictors (Bossaerts and Hillion, 1999; Goyal and Welch, 2007). To address these issues, we report the out-of-sample R^2 and two formal tests of out-of-sample performances. We calculate out-of-sample forecasts as a real-time investor, using data up to time t in the predictive regression to estimate β, which is then multiplied by the time-t value of the predictor to form the forecast. Out-of-sample forecasting starts from December 1997, when we have at least ten years of data. Out-of-sample R^2 is

$$R^2_{OOS} = 1 - \frac{\sum_t (r_{t+1} - \hat{r}_{t+1})^2}{\sum_t (r_{t+1} - \overline{r}_t)^2},$$

where $\hat{r}_{t+1}$ is the forecast value and $\overline{r}$ is the average of twelve-month returns (the first is January-December 1998). The out-of-sample R^2 lies in the range $(-\infty, 1]$, where a negative number means

[10] The persistence of a return predictor can cause small-sample bias (Nelson and Kim, 1993; Stambaugh, 1999) and spurious regression (Ferson, Sarkissian, and Simin, 2003).

that a predictor provides a less accurate forecast than the historical mean.

We report the p-value of two out-of-sample performance tests, "ENC" and "CW". ENC is the encompassing forecast test derived by Clark and McCracken (2001), which is widely used in the literature. We test whether the predictor has the same out-of-sample forecasting performance as the historical mean and compare the value of the statistic with critical values calculated by Clark and McCracken (2001) to obtain a p-value range. Clark and West (2007) adjust the standard MSE t-test statistic to produce a modified statistic (CW) that has an asymptotic distribution well approximated by the standard normal distribution, so for CW, we report the precise p-value.

Table 2 presents the results. Column (1) shows that the market duration, dr, demonstrates a striking degree of return predictive power. The in-sample estimation generates a predictive R^2 reaching 24.8%.[11] Out-of-sample forecasts deliver an R^2 of 14.6%, significantly outperforming the historical mean as shown by the p-values of ENC and CW.[12] The predictive coefficient is also large in magnitude, indicating high volatility of the conditional expected return. A decrease of dr_t by one standard deviation adds 7.7% to the expected return. Both Newey-West and Hodrick t-statistics are significant at least at the 1% level.

Column (2) of Table 2 reports the results for pd_t. The predictive power of pd_t is much weaker than dr_t in all aspects. Its in-sample R^2 is almost half of that of dr_t and pd_t barely exhibits any out-of-sample predictive power with R^2 equal to 0.4%. In both ENC and CW tests, pd_t fails to beat the historical mean with any statistical significance. Its coefficient is smaller in magnitude than that of dr_t.A decrease in pd_t by one standard deviation leads to an increase of expected return by 5.8%, implying a less volatile expected return than the one from dr_t. The IVX-Wald test of Kostakis, Magdalinos, and Stamatogiannis (2014) in Table A.4 in the appendix also supports the significant predictive power of dr_t while rejecting the predictive power of pd_t.

Next, we compare dr_t with two return predictors that are conceptually related. Binsbergen

[11] Foster, Smith, and Whaley (1997) discuss the potential data mining issues that arise from researchers searching among potential regressors. They derive a distribution of the maximal R^2 when k out of m potential regressors are used as predictors and calculate the critical value for R^2, below which the prediction is not statistically significant. For instance, when $m = 50$, $k = 5$, and the number of observations is 250, the 95% critical value for R^2 is 0.164.

[12] In our calculation of out-of-sample R^2 starts from Dec. 1997 (after the first ten years of data). Figure A.8 in the appendix reports the out-of-sample R^2 for different start dates and compares the OOS R^2 of dr with that of pd.

Table 2 Annual Return Prediction

This table reports the results of predictive regression (equation (18)). The left-hand side variable is the return of the S&P 500 index in the next twelve months. We consider four right-hand side variables (i.e., predictors), dr_t, pd_t, filtered series for expected returns following Binsbergen and Koijen (2010) μ^F, and the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP. The β estimate is reported, followed by Newey and West (1987) t-statistic (with 18 lags), Hodrick (1992) t-statistic, the coefficient adjusted for Stambaugh (1999) bias, and the in-sample adjusted R^2. We run the regression monthly. Starting from December 1997, we form out-of-sample forecasts of return in the next twelve months by estimating the regression with data up to the current month and use the forecasts to calculate out-of-sample R^2, ENC test (Clark and McCracken, 2001), and the p-value of CW test (Clark and West, 2007). Our monthly sample is 1988:01–2019:12.

	r_{t+1}				
	(1)	(2)	(3)	(4)	(5)
dr_t	-0.156				-0.228
Hodrick t	[-3.354]				[-2.924]
Newey-West t	(-4.499)				(-3.517)
Stambaugh bias adjusted β	-0.146				
pd_t		-0.199			0.141
		[-2.367]			[1.721]
		(-2.747)			(1.209)
		-0.189			
μ_t^F			2.584		
			[2.313]		
			(2.804)		
			2.594		
KP_t				0.895	
				[2.960]	
				(2.857)	
				0.905	
N	384	384	384	384	384
R^2	0.248	0.138	0.156	0.149	0.264
OOS R^2	0.146	0.004	-0.032	0.041	0.180
ENC	2.968	0.833	0.651	2.978	5.985
$p(ENC)$	<0.05	>0.10	>0.10	<0.05	<0.01
$p(CW)$	0.022	0.200	0.303	0.031	0.021

and Koijen (2010) extract information about state variables that drive the conditional expected return and expected cash-flow growth by estimating a latent-state model. Our approach differs as we do not estimate or filter the state variables but instead rely on dr_t, pd_t, and valuation ratios of dividend strips. In particular, the construction of our preferred return predictor, dr_t, only requires the total market capitalization and the price of dividends paid in the next year, which are directly observed from the market rather than estimated. In Column (3) of Table 2, we follow the procedure in Binsbergen and Koijen (2010) to construct their return predictor, μ_t^F. While μ_t^F slightly outperforms pd_t, its predictive power is weaker than that of dr_t across different metrics.

Table 3 Correlation between Return Predictors

This table reports the correlation matrix of four main return predictors. dr is our main return predictor, "duration." pd is the price-dividend ratio of the S&P 500 index. μ^F is the filtered series for demeaned expected returns, following Binsbergen and Koijen (2010), KP is the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013). Data sample: 1988:01–2019:12.

	dr	pd	μ_F	KP
dr	1			
pd	0.873	1		
μ_F	-0.892	-0.967	1	
KP	-0.565	-0.496	0.468	1

Note that Binsbergen and Koijen (2010) conduct analysis with a time period different from ours. Our sample period is constrained by the availability and reliability of index futures data and ends before the Covid-19 era of extreme downward and upward market movements.

While Binsbergen and Koijen (2010) utilize the aggregate data of realized returns and dividend growth, Kelly and Pruitt (2013) demonstrate another filtering method that utilizes the cross-section of market-to-book ratios of individual stocks. Individual stocks' market-to-book ratio maps out the state variables that drive the aggregate market but, as we show in Appendix I.2, these valuation ratios contain noise that is orthogonal to the expected market return. Kelly and Pruitt (2013) use the method of partial least square to reduce the noise. Our approach differs as we avoid dealing with such noise. dr_t, pd_t, and the valuation ratios of dividend strips of the aggregate market differ in their loadings on the aggregate state variables but do not contain idiosyncratic noise. In our approach, the challenge is to find the valuation ratio or a combination of valuation ratios whose state-variable loadings coincide with those of the conditional expected return and thereby achieve the highest predictive power. In the next subsection, we characterize the necessary and sufficient condition for dr_t to be such a return predictor. Following the procedure in Kelly and Pruitt (2013), we construct their return predictor, denoted by KP_t. In columns (4) of Table 2, we report the prediction results. KP_t significantly outperforms pd_t but still underperforms dr_t across different metrics, such as Newey-West t-statistic, Hodrick t-statistic, in-sample R^2, out-of-sample R^2, ENC, CW, and, IVX-Wald test reported in Table A.4 in the appendix.

While these return predictors are correlated as shown in Table 3, their predictive power differs significantly with market duration outperforming the rest. In the appendix, we demonstrate the robustness of our results by repeating the analysis with different forecasting targets. In Table A.5, we replace the S&P 500 annual return with the excess S&P 500 annual return, and in Table A.6 and A.7, we consider the Fama-French market portfolio return and excess return, respectively. Finally, we also show that market duration demonstrates superior return predictive power at a monthly horizon. Our baseline results are reported in A.8, and see Table A.9 for results on predicting monthly S&P 500 excess return. Table A.10 and Table A.11 report the results on predicting the monthly Fama-French market portfolio return and excess return, respectively.

So far, we have compared the return predictive power of dr_t with that of pd_t, which together with dr_t span the state space. We also considered μ_t^F and KP_t that are conceptually related. In Figure 5 compares dr with the other predictors proposed in the literature, including the price-dividend ratio (pd), the default yield spread (dfy), the inflation rate (infl), stock variance (svar), the cross-section premium (csp), the dividend payout ratio (de), the long-term yield (lty), the term spread (tms), the T-bill rate (tbl), the default return spread (dfr), the dividend yield (dy), the long-term rate of return (ltr), the earnings-to-price ratio (ep), the book to market ratio (bm), the investment-to-capital ratio (ik), the net equity expansion ratio (ntis), the percent equity issuing ratio (eqis), the consumption-wealth-income ratio (cay), the short interests index (SII), and the option-implied lower bound of 1-year equity premium (SVIX).[13] Most predictors are studied in a return predictability survey by Goyal and Welch (2007), and others are proposed more recently, such as the short interest index, "SII" in Rapach, Ringgenberg, and Zhou (2016), and SVIX (Martin, 2017). In the comparison, we also include pd_t, μ_t^F, and KP_t from Table 2.[14]

In Figure 5, we report in-sample ("IS") R^2, out-of-sample ("OOS") R^2, the absolute values of Newey-West, and Hodrick t-statistics. dr outperforms other predictors in all aspects. Among the alternatives, KP, pd, and the book-to-market ratio ("bm") deliver the most consistent perfor-

[13]Note that the dividend yield (dy) is not the inverse of price-dividend ratio (pd) because in the denominator of dy is the lagged market value (not the current value).

[14]When constructing KP_t, we estimate the partial least square model following the procedure in Kelly and Pruitt (2013). In Figure A.5, We report the comparison of return predictive power using the authors' original parameter estimates rather than our own estimates.

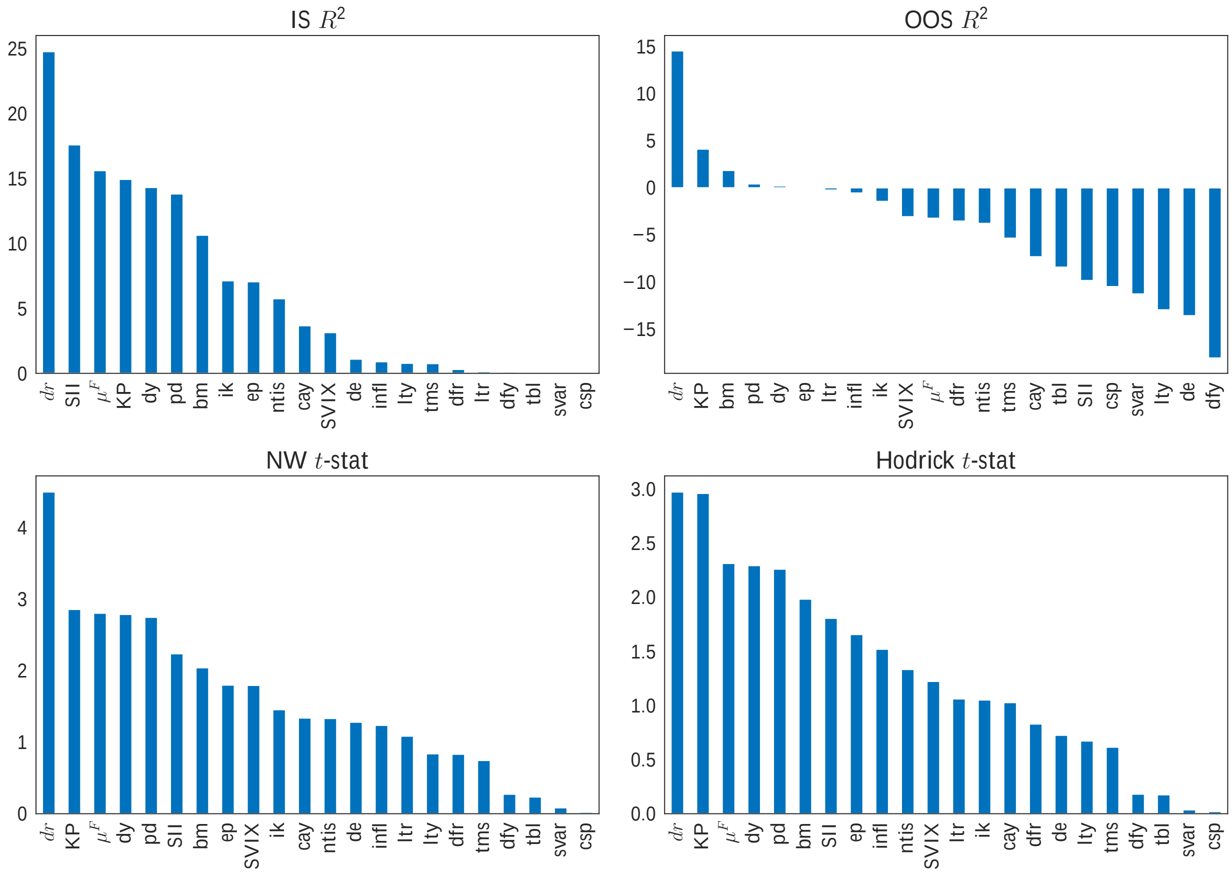


Figure 5 Comparison with Alternative Return Predictors.

This graph compares the 1-year return predictive power between dr_t and other commonly studied predictors in our sample period. Panel A reports the in-sample adjusted R^2. Panel B reports the out-of-sample R^2. Negative out-of-sample R^2 indicates that the predictive power is below the historical mean. Panel C reports the absolute values of Newey and West (1987) t-statistic (with an 18-month lag). Panel D reports the absolute values of Hodrick (1992) t-statistic. Most predictors are from Goyal and Welch (2007) and include the price-dividend ratio (pd), the default yield spread (dfy), the inflation rate (infl), stock variance (svar), the cross-section premium (csp), the dividend payout ratio (de), the long-term yield (lty), the term spread (tms), the T-bill rate (tbl), the default return spread (dfr), the dividend yield (dy), the long-term rate of return (ltr), the earnings-to-price ratio (ep), the book to market ratio (bm), the investment-to-capital ratio (ik), the net equity expansion ratio (ntis), the percent equity issuing ratio (eqis), and the consumption-wealth-income ratio (cay). SII is the short interests index from Rapach, Ringgenberg, and Zhou (2016) (1988-2014). SVIX is an option-implied lower bound of the 1-year equity premium from Martin (2017) (1996-2012). KP is the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013). BK is the filtered series for expected returns following Binsbergen and Koijen (2010).

mances across the four metrics while μ^F exhibits strong performances except for OOS R^2. The performances of other return predictors are not quite consistent across different metrics.

In Table A.12, we report the correlation between dr and these return predictors. Besides pd, μ^F, and KP, all the other return predictors with correlation above 50% or below -50%, are all valuation ratios, such as the market-to-book ratio and price-to-earnings ratio. This is consistent with the intuition in Kelly and Pruitt (2013) and our emphasis on using valuation ratios to capture information embedded in the state variables. In the appendix, we compare dr with other return predictors for alternative forecasting targets, such as S&P 500 excess annual return (Figure A.2), Fama-French market portfolio annual return (Figure A.3), and Fama-French market portfolio excess annual return (Figure A.4). In Figure A.5. Market duration exhibits the strongest predictive power across the four metrics and such performance is consistent across all forecasting targets.

4.2 A two-dimensional state space model

The findings on return predictability are critical for understanding the structure of both the conditional expected return and market duration. Next, we show that the conditional expected return is a univariate function of dr (and vice versa) when the market does not contain information on future cash-flow growth beyond the next year. Intuitively, under this condition, the price of next year's dividends exhausts all information about future cash-flow growth, so dr, which is the logarithm of market value minus the logarithm of the price of next year's dividend, teases out cash-flow information and only contains information about the discount rate.

Stock prices are determined by the conditional expectations of future returns and dividends over different horizons (Campbell and Shiller, 1988). Therefore, a model of the aggregate stock market requires at least two state variables that capture the conditional expected return and dividend growth; in other words, the lower bound of the state-space dimension is two. Our analysis so far shows that two is also the upper bound. Guided by our findings in Section 3, we simplify the general model in Section 2 by specifying a two-dimensional state space. As in Lettau and Wachter (2007) and Binsbergen and Koijen (2010), one state variable drives the conditional expectation of dividend growth rate, and the second state variable drives the conditional expected return through price of risk. Specifically, g_t is given by

$$g_t = z_t + \overline{g} - \frac{1}{2}\sigma_D^{\top}\Sigma\sigma_D, \tag{19}$$

where z_t has the following law of motion

$$z_{t+1} = \rho_z z_t + \sigma_z^\top \epsilon_{t+1} \,. \tag{20}$$

The second state variable, y_t, with a law of motion

$$y_{t+1} = \rho_y y_t + \sigma_y^\top \epsilon_{t+1} \,, \tag{21}$$

drives the price of risk λ_t, so equation (5) becomes

$$\lambda_t = \overline{\lambda} + y_t, \tag{22}$$

and the stochastic discount factor (SDF) is given by

$$M_{t+1} = \exp\left\{-r_f - \frac{1}{2}\lambda_t^2(\sigma_\lambda^\top \Sigma \sigma_\lambda)^2 - \lambda_t \sigma_\lambda^\top \epsilon_{t+1}\right\}. \tag{23}$$

In a two-dimensional state space where one state variable, z_t, is assigned to drive the expected dividend growth rate, the price of risk, λ_t, must be unidimensional, driven by y_t, and accordingly, shocks enter into the SDF as a scalar, i.e., the linear combination given by σ_λ. Any shock can be priced. The price of risk for the n-th shock is $\lambda_t \sigma_\lambda(n)$, where $\sigma_\lambda(n)$ is the n-th element of σ_λ.

As in Section 2, the N-by-1 shock vector ϵ_{t+1} contains all information at $t+1$. The variables' shock loadings may differ, for example, $\sigma_z \neq \sigma_y$. z_t and y_t can be correlated through their overlapping exposure to shocks. Also note that, in comparison with the general model in Section 2, the state-variable loadings of g_t and λ_t, i.e., ϕ and λ_t are set to one. This simplification can be done as g_t and λ_t load on one state variable, z_t and y_t, respectively.

In Appendix I, we solve the log price-dividend ratio of the aggregate market

$$pd_t = A_{pd} + B_{pd} y_t + C_{pd} z_t, \tag{24}$$

where A_{pd}, B_{pd}, and C_{pd} are constant. And the log price-dividend ratio of dividend strip that matures in one year,

$$s_t^1 = A_1 + B_1 y_t + C_1 z_t. \tag{25}$$

Therefore, market duration is

$$dr_t = pd_t - s_t^1 = A_{pd} - A_1 + (B_{pd} - B_1)y_t + (C_{pd} - C_1)z_t, \tag{26}$$

where $B_{pd} \neq B_{pd} - B_1$ and $C_{pd} \neq C_{pd} - C_1$. Since dr_t and pd_t have different loadings on z_t and y_t, we can solve z_t and y_t from dr_t and pd_t. Therefore, market duration and the traditional price-dividend ratio span the state space. In particular, dr_t and pd_t contain all the necessary information for forecasting return and dividend growth as we show in Section 3.

Proposition 1 (Spanning) *The state variables are functions of dr_t and pd_t, and vice versa.*

In Appendix I, we show $C_{pd} = 1/(1 - \kappa_1 \rho_z)$ and $C_1 = 1$ and obtain the following result.

Proposition 2 (Discount rate and duration) *The conditional expected return is a function of y_t*

$$\mathbb{E}_t[r_{t+1}] = A_{er} + B_{er} y_t, \tag{27}$$

where A_{er} and B_{er} are constant. Under $\rho_z = 0$, $\mathbb{E}_t[r_{t+1}]$ is a univariate function of dr_t and vice versa.

When ρ_z, the autoregressive coefficient of expected dividend growth rate z_t, is zero, we have $dr_t = A_{pd} - A_1 + (B_{pd} - B_1)y_t$ as the exposure of market duration to z_t is muted. As y_t drives the conditional expected return, dr_t and $\mathbb{E}_t[r_{t+1}]$ become univariate functions of one another under $\rho_z = 0$. Market participants' information at time t about future dividends is summarized by z_t which determines the expected dividend growth rate from t to $t + 1$. Therefore, if z_t lacks persistence, the market participants do not have information about dividend beyond $t + 1$. By construction, dr_t teases out information about dividend growth up to $t + 1$ by deducting s_t^1 from pd_t, so, intuitively, it contains only the information about the discount rate or expected return under $\rho_z = 0$.

4.3 The persistence of cash-flow growth expectation

We estimate ρ_z, the persistence of expected dividend growth, using two approaches. For our main analysis, we use analyst forecasts to proxy for the market participants' expectations of cash-flow growth and estimate the persistence of the expected growth rate with two econometric models. For robustness, we also fit the latent state model given by (19) and (20) to the data on realized dividends and obtain an alternative estimate of ρ_z.

Our model does not require investors to have rational expectations. As a matter of fact, even if the data-generating processes differ from equations (19) and (20) in our model, as long as agents in this economy take these equations as the stochastic processes that govern the aggregate dividends, our results on stock and dividend strip valuation hold. Therefore, to estimate ρ_z, the persistence of the expected dividend growth rate, we examine market participants' subjective expectations—the analyst forecasts obtained from IBES.

A large literature has demonstrated that analyst forecasts reflect analysts' beliefs as their compensation are tightly linked to forecast precision, and that analyst forecasts are likely to represent the market participants' beliefs more broadly (e.g., Mikhail, Walther, and Willis, 1999; Cooper, Day, and Lewis, 2001; Bradshaw, 2004). Admittedly, analyst forecasts may be distorted due to various incentive and institutional frictions (e.g., Gu and Wu, 2003; Malmendier and Shanthikumar, 2007, 2014). However, the bias is contained as long as such frictions do not vary over time systematically in a way that correlates with the analysts' true beliefs. Moreover, we will supplement our estimate of ρ_z based on analyst forecasts with an alternative estimate from a standard filtering approach applied to the state space model given by equation (19) and (20).

Recent studies using analysts' cash-flow expectations have made substantial progress in explaining a variety of phenomena in asset pricing.[15] Moreover, our focus on the persistence of

[15] For example, Bordalo, Gennaioli, La Porta, and Shleifer (2019) find that analyst forecasts of firms' long-term earnings growth overreact to news about firm fundamentals, leading to predictable cross-sectional return variations. De La O and Myers (2021) show that analyst short-term earnings forecasts, aggregated to the S&P 500 index level, explain a substantial share of the price-dividend ratio's variation. Nagel and Xu (2022) propose a model where agents form their subjective beliefs of future cash flow growth based on their experienced growth. Such beliefs give rise to a sizable and strongly counter-cyclical equity premium. Bordalo, Gennaioli, La Porta, and Shleifer (forthcoming) incorporate analyst forecasts of short- and long-term earnings of the S&P 500 index into a standard dividend discount

Table 4 Summary Statistics: Cash Flow Growth Forecasts

This table reports the number of observations, mean, standard deviation, minimum, maximum, quartiles, and monthly autocorrelation (ρ) of various measures of cash flow growth expectations. $\mathbb{E}_t^A \Delta e_{t,t+1}$, $\mathbb{E}_t^A \Delta e_{t+1,t+2}$, and $\mathbb{E}_t^A \Delta e_{t+2,t+3}$ are forecasts of 1-year earnings growth for fiscal year 1, 2, and 3 provided by IBES Global Aggregate (IGA). IGA Δe_t and Compustat Δe_t are the actual 1-year earnings growth from IGA and Compustat, respectively. $\mathbb{E}_t^A \Delta e_{t,t+1}$ and LTG_t are forecasts of 1-year and long-term earnings growth that we self-aggregate from the IBES Unadjusted US Summary Statistics File. Data sample: 1988:01–2019:12.

	obs	mean	std	min	25%	50%	75%	max	ρ
$\mathbb{E}_t^A \Delta e_{t,t+1}$	384	0.103	0.096	-0.167	0.056	0.103	0.154	0.425	0.897
$\mathbb{E}_t^A \Delta e_{t+1,t+2}$	384	0.134	0.043	-0.069	0.104	0.127	0.157	0.269	0.830
$\mathbb{E}_t^A \Delta e_{t+2,t+3}$	384	0.130	0.036	0.052	0.100	0.122	0.159	0.217	0.953
IGA $\Delta e_{t,t+1}$	384	0.072	0.135	-0.380	-0.008	0.092	0.148	0.425	0.929
Compustat $\Delta e_{t,t+1}$	384	0.068	0.481	-2.175	-0.042	0.122	0.187	2.190	0.976
LTG_t	384	0.125	0.018	0.093	0.115	0.120	0.129	0.187	0.986

agents' growth expectation is related to the theoretical and empirical works of Gabaix (2019) and Wang (2020), who highlight the importance of agents' perceived persistence of key state variables in generating patterns of under and over-reaction in belief formation and asset prices.[16]

As the coverage of dividend forecasts started in 2003 in IBES and is too short for our analysis, we follow the literature and instead proxy the analysts' expectation of dividend growth with their earnings forecasts (available since 1976). The following accounting identity connects the earnings and dividends: $D_t = \text{Earnings}_t \times (1 - \text{plowback rate}_t)$. As documented by Pástor, Sinha, and Swaminathan (2008) and Chen, Da, and Zhao (2013), the plowback rate is quite stable in the near term. Therefore, the near-term growth rates of dividends are empirically close to those of earnings: for $k = 1,\ 2,$ and 3 years,

$$\Delta d_{t+k} \equiv \ln\left(\frac{D_{t+k}}{D_{t+k-1}}\right) \approx \Delta e_{t+k} \equiv \ln\left(\frac{\text{Earnings}_{t+k}}{\text{Earnings}_{t+k-1}}\right). \tag{28}$$

Note that Δd_{t+k} is the one-year growth rate from $t+k-1$ to $t+k$. For example, for $k = 2$, Δd_{t+2} is the dividend growth rate from $t+1$ to $t+2$. The same notation applies to earnings and earnings

model with a constant discount rate, which generates a "synthetic" index price that closely resembles the actual price and exhibits strong 'excess' volatility.

[16] Gabaix (2019) and Wang (2020) emphasize the deviation of "perceived" persistence from the true persistence of the data-generating process; however, since our model in Section 2 does not require rationality, we do not explicitly contrast the subjective and true persistence.

growth expectations. Taking the analyst's expectations, $\mathbb{E}_t^A(\cdot)$, on both sides, we can proxy the expected dividend growth using the expected earnings growth:

$$\mathbb{E}_t^A(\Delta d_{t+k}) \approx \mathbb{E}_t^A(\Delta e_{t+k}) \approx \ln\left(\frac{\mathbb{E}_t^A\left(\text{Earnings}_{t+k}\right)}{\mathbb{E}_t^A\left(\text{Earnings}_{t+k-1}\right)}\right), \tag{29}$$

where, for $k = 1$, $\mathbb{E}_t^A\left(\text{Earnings}_{t+k-1}\right) = \text{Earnings}_t$ is the realized dividend in the current year.[17]

IBES Global Aggregates (IGA) provides a forecast of aggregate earnings growth for the S&P 500 index based on firm-level earnings forecasts. The aggregation procedure weighs individual companies by their market capitalization.[18] To transform earnings forecasts to forecasts of growth rates, IGA takes the procedure given by equation (29). The IGA data is available at a weekly frequency. We consider both weekly and monthly frequencies. For monthly frequency, we take the last weekly observation of each month. At time t, analysts' forecasts of earnings are available at three horizons: one, two, and three years, i.e., $\mathbb{E}_t^A(Earnings_{t+1})$, $\mathbb{E}_t^A(Earnings_{t+2})$, and $\mathbb{E}_t^A(Earnings_{t+3})$. Moreover, since IGA does not aggregate firm-level long-term growth (LTG) forecasts. We follow the same aggregation procedure to create an index-level LTG forecast that will allow us to estimate ρ_z with alternative methods. The firm-level LTG forecasts are obtained from the IBES Unadjusted US Summary Statistics File. Table 4 provides summary statistics of various cash flow growth expectations at the monthly frequency.

Next, we map the expectations of cash-flow growth to the model counterparts and derive a system of equations that can be used to estimate ρ_z. First, we acknowledge that the analyst forecasts may not perfectly capture market participants' expectations by adding a noise term between analysts' expectation and the market participants' expectation: For $k = 1, 2, 3$,

$$\mathbb{E}_t^A(\Delta e_{t+k}) = \mathbb{E}_t(\Delta e_{t+k}) + \varepsilon_{t,k}^A, \tag{30}$$

[17]We switch the order of $\mathbb{E}_t^A(\cdot)$ and $\ln(\cdot)$, assuming Jensen's inequality terms are negligible for the purpose of estimating the persistence of growth expectation. This is in line with the model in Section 2: The growth rates are log-normally distributed, so the ignored terms contain constant variances, which do not drive the variation of $\mathbb{E}_t^A(\Delta d_{t+k})$ over time, and thus, do not affect the estimates of ρ_z.

[18]To deal with the fact that companies have different fiscal year-end, IGA calendarizes all company-level data to a December calendar year before aggregation. This approach follows the Compustat rule. Please refer to "Thomson Reuters Datastream IBES Global Aggregates Reference Guide" for more detail.

where $\mathbb{E}_t(\cdot)$, is the market participants' expectation. Equations (19) imply

$$\begin{aligned}
\mathbb{E}_t^A(\Delta e_{t+1}) &= g + z_t + \varepsilon_{t,1}^A \\
\mathbb{E}_t^A(\Delta e_{t+2}) &= g + \mathbb{E}_t(z_{t+1}) + \varepsilon_{t,2}^A = g + \rho_z z_t + \varepsilon_{t,2}^A \\
\mathbb{E}_t^A(\Delta e_{t+3}) &= g + \mathbb{E}_t(z_{t+2}) + \varepsilon_{t,3}^A = g + \rho_z^2 z_t + \varepsilon_{t,3}^A.
\end{aligned}$$

Using the first equation to substitute out z_t in the second and third equations, we obtain a system:

$$\underbrace{\begin{bmatrix} \mathbb{E}_t^A(\Delta e_{t+2}) \\ \mathbb{E}_t^A(\Delta e_{t+3}) \end{bmatrix}}_{\equiv \mathbf{y}_t^A} = (1-\rho_z)\, g + \rho_z \underbrace{\begin{bmatrix} \mathbb{E}_t^A(\Delta e_{t+1}) \\ \mathbb{E}_t^A(\Delta e_{t+2}) \end{bmatrix}}_{\equiv \mathbf{x}_t^A} + \underbrace{\begin{bmatrix} \varepsilon_{t,1}^A - \rho_z \varepsilon_{t,0}^A \\ \varepsilon_{t,2}^A - \rho_z \varepsilon_{t,1}^A \end{bmatrix}}_{\equiv \epsilon_t}. \tag{31}$$

Therefore, we estimate ρ_z by regressing $\mathbf{y}_t^A$ on $\mathbf{x}_t^A$. The identification assumption is that under the econometricians' belief, the expectation of the disturbance ϵ_t is zero conditional on $\mathbf{x}_t^A$. The deviations of analysts' expectations from market participants' expectations are allowed to be correlated across the starting dates of annual dividend growth, i.e., t, $t+1$, and $t+2$.[19]

We estimate equation (31) with both monthly (column 1 and 3) and weekly observations (column 2 and 4) of analyst forecasts. The results are reported in Table 5, Panel A. In column (1) and (2), our estimation includes both equations in (31), while in Column (3) and (4), we only include the first equation, i.e., only using forecasts at one- and two-year horizons for better data quality. Across the specifications, the estimate $\hat{\rho}_z$ is statistically indistinguishable from zero.

Next, we consider an alternative way to estimate ρ_z by exploring the relationship between forecasts of short-term and long-term earnings growth (LTG). IBES provides firm-level forecasts of the annualized average growth rate of earnings over the next three to five years and has been adopted in the recent literature on expectation formation (e.g., La Porta, 1996 and Bordalo, Gennaioli, La Porta, and Shleifer, 2019). Given the autoregressive structure in equation (20), the

[19]The identification of ρ_z is robust to the correlation between these errors and ϵ_t in the model in Section 2, i.e., the structural shocks to realized dividend, market participants' beliefs on cash-flow dynamics, and their price of risk.

Table 5 The Persistence of Expected Cash-Flow Growth from Analyst Forecasts

This table reports the estimates of ρ_z, the autoregressive coefficient of expected cash-flow growth, based on equation (31). The estimation uses aggregate earnings growth forecasts of the S&P 500 Index obtained from IGA. Columns (1) and (3) report the estimates of ρ_z using monthly data, while columns (2) and (4) report the estimates of ρ_z using weekly data. columns (1) and (2) use earnings growth forecasts for 1,2 and 3 years ahead to estimate the two-equation system (31), while Columns (3) and (4) only use earnings growth forecasts for 1 and 2 years ahead to estimate the first equation in (31). t-statistics based on Driscoll-Kraay standard errors with autocorrelation of up to 18 lags are reported in parentheses. Data sample: 1988:01–2019:12.

	(1)	(2)	(3)	(4)
$(1-\rho_z)g$	0.122	0.129	0.141	0.133
	(16.906)	(13.995)	(15.536)	(16.745)
ρ_z	0.015	0.028	-0.071	-0.073
	(0.381)	(0.690)	(-1.379)	(-1.295)
N	1887	768	384	943
R^2	0.001	0.003	0.025	0.028
Sample	Monthly	Weekly	Monthly	Weekly
Periods	Y1:Y3	Y1:Y3	Y1:Y2	Y1:Y2

Table 6 The Persistence of Expected Cash-Flow Growth from LTG Forecasts

This table reports the estimates of ρ_z^{LT}, the regression coefficient in

$$\log(1 + LTG_t) = \text{const} + \rho_z^{LT}\mathbb{E}_t^A[\Delta e_{t+1}] + \varepsilon_t,$$

where LTG_t is the long-term growth forecasts (LTG) of the S&P 500 Index, self-aggregated from stock-level LTG forecasts from the IBES Unadjusted Summary File. The short-term forecast, $\mathbb{E}_t^A[\Delta e_{t+1}]$, is the IGA 1-year earnings growth forecast (IGA $\mathbb{E}_t^A[\Delta e_{t+1}]$). t-statistics based on Newey-West standard errors with autocorrelation of up to 18 lags are reported in parentheses. Our monthly observations are from 1988:01 to 2019:12.

	(1)
	$\log(1 + LTG_t)$
Intercept	0.116
	(28.615)
$\mathbb{E}_t^A[\Delta e_{t+1}]$	0.017
	(0.711)
N	384
R^2	0.011

expected growth rate from period n to $n+1$ depends on the expected growth rate over the very next period via a coefficient ρ_z^n. If ρ_z is zero, then such a coefficient is zero, which implies that the average growth rate over three years and beyond does not depend on the expected growth rate over the next year. Therefore, we regress monthly observations of LTG forecast on $\mathbb{E}_t^A[\Delta e_{t+1}]$, and denote the regression coefficient by ρ_z^{LT}. Our estimate of ρ_z^{LT} is statistically indistinguishable

Table 7 The Persistence of Expected Cash-Flow Growth from the State-Space Model

This table reports the estimation results of 1) the unrestricted state-space model given by equations (19) and (20) in Section 2, 2) the restricted state-space model (i.e., $\rho_z = 0$), and for comparison, 3) the MA(1) model ($\Delta d_{t+1} = g + \sigma_D \varepsilon_{t+1} + \chi \sigma_D \varepsilon_t$), and 4) the AR(1) model ($\Delta d_{t+1} = g + \gamma \Delta d_t + \sigma_D \varepsilon_{t+1}$) of the dividend growth ratres. Panel A uses the annual (non-overlapping) dividend growth of the S&P 500 index, and Panel B uses the annual (non-overlapping) dividend growth of the Fama-French market portfolio. The log likelihood ("LogL"), AIC, and BIC are reported. t-stats are in the squared bracket.

	$\hat{\rho}_z$	$\hat{g}$	$\hat{\sigma}_d$	$\hat{\sigma}_z$	$\hat{\chi}$	$\hat{\gamma}$	LogL	AIC	BIC
Panel A: S&P 500									
Unrestricted	0.26	0.06	0.00	0.11			74.44	-140.88	-128.97
	[0.94]	[3.01]	[0.00]	[1.70]					
Restricted		0.06	0.08	0.08			71.36	-136.72	-127.79
		[4.68]	[0.00]	[0.00]					
MA(1)		0.06	0.10		0.41		76.41	-146.82	-137.89
		[3.38]	[13.45]		[6.11]				
AR(1)		0.04	0.11			0.26	74.50	-142.99	-134.06
		[3.64]	[14.90]			[3.51]			
Panel B: MKT									
Unrestricted	-0.08	0.06	0.00	0.15			43.96	-79.92	-69.8
	[-0.06]	[3.86]	[0.00]	[0.12]					
Restricted		0.06	0.11	0.11			43.67	-81.34	-73.8
		[3.62]	[0.10]	[0.10]					
MA(1)		0.06	0.15		-0.09		44.00	-82.00	-74.4
		[3.94]	[6.99]		[-1.02]				
AR(1)		0.06	0.15			-0.08	43.96	-81.93	-74.39
		[3.89]	[6.98]			[-0.87]			

from zero. Consistent with our findings in Table 5, this implies that the persistence of cash-flow growth expectation is low.

Our final method to estimate ρ_z is to directly estimate the state-space model given by equations (19) and (20) with the realized dividend data. Using the standard Kalman filter, we obtain estimates of ρ_z. For comparison, we report results for both the S&P 500 index and the Fama-French market portfolio ("MKT").[20] Since the model is set up at annual frequency, we use the annual (non-overlapping) dividend growth data. The sample spans 1926 to 2019.[21] The results are reported in Table 7, where Panel A and B are for S&P 500 and MKT, respectively. In the row "Unrestricted" of Panel A and B of Table 7, the estimates of $\hat{\rho}_z$ are statistically indistinguishable

[20] We obtain dividend data for the Fama-French market portfolio from the CRSP NYSE/NYSEMKT/Nasdaq Value-Weighted Market Index.

[21] We also used the longest available S&P 500 dividend series starting from 1872 and obtained similar results. The results are available upon request.

Table 8 Time-varying ρ_z Estimates

This table reports the summary statistics of the rolling-window estimates of ρ_z using weekly observations, where each rolling window spans three years. In each window, we estimate ρ_z following equation (31), using aggregate earnings growth forecasts of the S&P 500 Index obtained from IGA. Data sample: 1988:01–2019:12.

	count	mean	std	min	25%	50%	75%	max	ρ
$\hat{\rho}_{z,t}$	384	0.025	0.157	-0.260	-0.066	0.001	0.074	0.791	0.975

from zero.[22] The restricted model with $\rho_z = 0$ generates similar likelihood and information criteria, indicating that allowing ρ_z to be a free parameter does not significantly improve the model fitness. We also estimate MA(1) and AR(1) models for comparison and find that the estimates of the autoregressive coefficient, i.e., χ and γ for MA(1) and AR(1), respectively, are statistically indistinguishable from zero. In sum, the state-space approach delivers a similar message as the estimation based on analyst forecasts: The persistence of growth expectation is close to zero.

In the last exercise, we conduct a rolling-window estimation of ρ_z following the method in Table 5. A rolling window contains three years of weekly observations.[23] The summary statistics of the rolling-window estimates are reported in Table 8. Naturally, the model of agents' belief formation may adjust over time, so the estimate of $\hat{\rho}_z$ fluctuates. Overall, the results are similar to those in Table 5, and in particular, the mean and median of the $\hat{\rho}_z$ series are close to zero. Our findings suggest that the expected cash-flow growth rate lacks persistence (ρ_z is close zero), which in our model implies a one-to-one mapping between market duration, dr, and expected return. In the next proposition, we characterize more tightly the connection between the value of ρ_z and return predictability. The proof is in the appendix.

Proposition 3 (ρ_z and return forecast errors) *Let v_{t+1} denote the forecast error when predicting r_{t+1} using dr_t as the predictor and ρ_z denote the autoregressive coefficient of expected cash flow growth z_t in equation (20). If $\rho_z > 0$, then v_{t+1} is positive. If $\rho_z < 0$, then v_{t+1} is negative.*

[22] The Kalman filter assumes that the shocks to realized and expected dividend growth are uncorrelated. In the appendix, we demonstrate the robustness of our estimate of ρ_z by considering different values of the correlation, from -0.9 to 0.9, while fixing the volatility of realized-dividend shock at the estimate in Panel A. The estimated ρ_z barely moves with the value of shock correlations in $[-0.9, 0.9]$ as shown in Figure A.7.

[23] The results are similar if we use alternative window lengths from one to five years (available upon request). Our sample period is 1988–2019. The first estimate of ρ_z uses three years of IGA data starting in 1985.

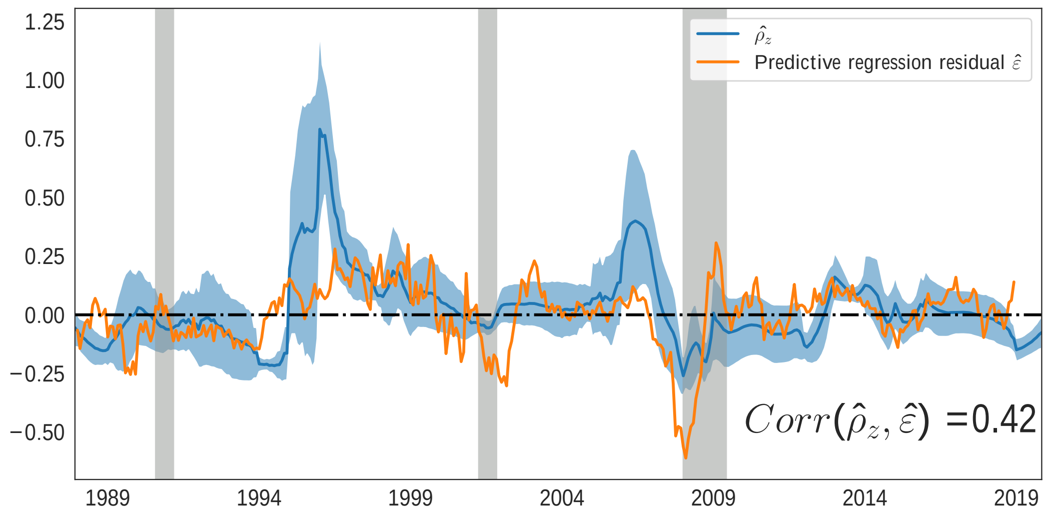


Figure 6 Rolling Estimate of Expected Growth Persistence and Return Prediction Errors

This figure plots the rolling estimate of the autoregressive coefficient of expected cash flow growth, $\hat{\rho}_{z,t}$, and the return prediction errors using market duration (dr_t) as the predictor. $\hat{\rho}_{z,t}$ is estimated using analyst forecasts of S&P 500 aggregate earnings in rolling regressions with a three-year window. This figure also plots the predictive residuals (denoted by ε_t) from the rolling-sample predictive regressions. The correlation between the two time series is also reported on the graph. Our monthly sample is 1988:01–2019:12.

The proposition implies that in a subsample where the estimate of ρ_z is positive (negative), we would expect the return forecasting error to be positive (negative). In Figure 6, we plot the rolling-window estimate of ρ_z estimates against the return forecasting residuals (denoted by ε_t) from the corresponding rolling window with dr_t as the predictor. The two time series trace each other closely, with a correlation of 0.42.[24] This provides further evidence of the connection between return predictability and the lack of persistence in expected cash-flow growth.

As implied by equation (20), under $\rho_z = 0$, the time-t expectation of growth from $t+2$ onward is a constant so the market does not contain information about cash-flow growth beyond the next year. Market duration dr is the log price-dividend ratio minus the valuation ratio of the one-year dividend strip, which, by construction, teases out market information about near-term growth embedded in the valuation ratio of the one-year dividend strip and thus leaves only

[24] In Figure A.6 in the appendix, we plot $\rho_{z,t}$ against the out-of-sample forecast errors and obtain a similarly positive correlation. We also regress the rolling-window return prediction errors, both in-sample and out-of-sample, on the rolling-window estimate of ρ_z and find a positive regression coefficient (see Table A.13 in the appendix).

Table 9 One-year Dividend and Earnings Growth Prediction

This table reports the results of dividend and earnings growth prediction. The dependent variables are the 1-year-ahead realized earnings growth from IGA (columns 1-3), realized dividend growth from Bloomberg (columns 4-6), and realized earnings growth from Compustat (columns 7-9). The independent variables are analyst forecasts of one-year earnings growth from IGA ($\mathbb{E}_t^A(\Delta e_{t+1})$), duration dr, and the price-dividend ratio pd. t-statistics are calculated based on Newey-West standard errors with 18 lags and are reported in parentheses. Data sample: 1988:01–2019:12.

	IGA Δe_{t+1}			Δd_{t+1}			Compustat Δe_{t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.056	-0.426	-0.328	0.028	-0.312	-0.295	0.122	0.478	0.394
	(-4.127)	(-1.357)	(-2.413)	(1.300)	(-1.526)	(-1.663)	(0.814)	(0.374)	(0.352)
$\mathbb{E}_t^A(\Delta e_{t+1})$	1.204		1.119	0.326		0.204	-0.591		-0.963
	(20.101)		(15.193)	(2.537)		(2.824)	(-0.629)		(-1.067)
dr_t		-0.248	-0.110		-0.181	-0.156		-0.333	-0.452
		(-2.328)	(-2.625)		(-3.535)	(-4.188)		(-1.129)	(-2.016)
pd_t		0.385	0.187		0.285	0.249		0.238	0.409
		(2.354)	(2.599)		(2.782)	(3.095)		(0.405)	(0.958)
N	372	372	372	372	372	372	372	372	372
R^2	0.731	0.199	0.769	0.193	0.386	0.454	0.014	0.053	0.086

information about the discount rate. Next, we step outside of our model given by equations (19) and (20) and consider more broadly whether the market contains information about long-term growth.

4.4 Cash-flow growth predictability: Short horizon vs. long horizon

We characterize market information about cash-flow growth at different horizons. In Table 9, we show strong predictability of near-term growth. In Column (1), we simply regress the realized one-year growth rate of aggregate earnings from firms covered by IGA on the ex ante analysts' forecast. The R^2 is 0.73, so analysts and market participants in general are able to forecast near-term cash-flow growth very well. In Column (2), we use our pair of state variables, dr and pd, to forecast cash-flow growth and obtain a R^2 of 0.20. Combining the information in dr and pd with the analysts' forecast in Column (3), the in-sample prediction R^2 rises to 0.77. In the other columns of Table 9, we replace the forecasting target. Naturally, cash-flow predictability declines in the other cases because the predictor (IGA analyst forecast, in particular) targets the earnings growth of IGA-covered firms rather than that of all firms covered by Bloomberg database (Col-

Table 10 Weaker Earnings Growth Predictability beyond One Year

This table reports results of regressions that predict earnings growth at various horizons. The dependent variables are realized earnings growth from IGA of next year (columns 1-3), between the first and second years (columns 4-6), and between the second and third years (columns 7-9). The independent variables are analysts' forecasts of one-year earnings growth from IGA (IGA $\mathbb{E}_t^A(\Delta e_{t+1})$), the self-aggregated long-term earnings growth forecasts (LTG_t) of the S&P 500 Index, the market duration dr and the price-dividend ratio pd_t. t-statistics calculated based on Newey-West standard errors with 18 lags are reported in parentheses. Data sample: 1988:01–2019:12.

	IGA $\Delta e_{t,t+1}$			IGA $\Delta e_{t+1,t+2}$			IGA $\Delta e_{t+2,t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.053	-0.426	-0.309	0.325	-0.063	-0.037	0.185	0.513	0.496
	(1.360)	(-1.357)	(-2.786)	(2.446)	(-0.211)	(-0.141)	(1.596)	(1.577)	(1.685)
IGA $\mathbb{E}_t^A(\Delta e_{t+1})$	1.222		1.174	0.030		-0.047	-0.319		-0.274
	(20.312)		(15.749)	(0.192)		(-0.348)	(-2.594)		(-1.947)
LTG_t	-0.889		-1.344	-2.155		-2.295	-0.711		-0.295
	(-3.171)		(-3.092)	(-2.186)		(-1.578)	(-0.768)		(-0.234)
dr_t		-0.248	-0.077		-0.144	-0.103		0.096	0.068
		(-2.328)	(-1.568)		(-2.878)	(-2.319)		(1.449)	(1.215)
pd_t		0.385	0.189		0.181	0.207		-0.216	-0.166
		(2.354)	(2.797)		(1.690)	(2.351)		(-1.666)	(-1.399)
N	372	372	372	360	360	360	348	348	348
R^2	0.74	0.20	0.78	0.08	0.08	0.14	0.07	0.07	0.11

umn 4-6) or that of all Compustat firms (Column 7-9). Overall, our findings suggest that market participants are informed of near-term cash-flow growth. One explanation is that firms tend to provide forward guidance on their earnings outlook, increasingly so in recent years.

Next, we examine the predictability of cash-flow growth at longer horizons. So far, our analysis of growth expectation has been based on the autoregressive model given by equations (19) and (20), and the focus has been on ρ_z, the persistence parameter, and its connection with the return predictive power of market duration dr. In this model, we have the time-t expected growth from $t+1$ to $t+2$, $\mathbb{E}_t[z_{t+2}] = \rho_z \mathbb{E}_t[z_{t+1}] = \rho_z^2 z_t$, so market information about long-term growth is contained in the expected growth rate over the next period. In the following exercises, we expand the set of potential predictors of long-term growth. In particular, we consider the LTG forecast, the aggregated long-term growth forecast over three to five years.

In Table 10, we first predict earnings growth over the next year from Column (1) to (3), and consistent with our findings in Table 9, predictability is strong, which suggests that market participants are informed of short-term growth. In Columns (4) to (6), we use the same variables to predict earnings growth from $t+1$ to $t+2$ and find predictability declines dramatically. Comparing Columns (1) and (4), the predictive R^2 declines from 0.74 to 0.08. Our forecasting exercise in Columns (7) to (9) delivers the same message. The predictability of growth over an even longer horizon, i.e., from $t+2$ to $t+3$, is even weaker. In Figure A.9 in the appendix, we report the results of alternative predictive models that take advantage of more valuation ratios (and potentially richer information embedded in the state space). Our conclusion remains robust.

Overall, our findings suggest that market participants are not informed of long-term growth, but regarding short-term growth, market information, whether from analysts' forecast or our state variables, is quite rich. These results on the term structure of cash-flow predictability shed light on the strong connection between market duration dr and expected return. By construction, dr deducts the valuation ratio of the one-year dividend strip from the price-dividend ratio pd and thereby teases out market information about near-term growth.

One may form a market timing strategy guided by our findings on dr as a return predictor. Specifically, when market duration increases, the strategy shorts the market, and when market duration decreases, the strategy adds to the long position. This strategy bets against the market valuation of long-duration cash flows. An out-of-sample R^2 of 14.6% in Column (1) of Table 2 implies that the Sharpe ratio of this market timing strategy is 0.58, which is much higher than the Sharpe ratio from other return predictors, for example, 0.37 in Campbell and Thompson (2008). In the appendix, we show how to calculate the Sharpe ratio based on the out-of-sample R^2.

5 Conclusion

We define market duration as the ratio of total market capitalization to the market value of dividends paid in the very next year. An increase in market duration implies the valuation of long-term cash flows increases relative to that of short-term cash flows. Therefore, market duration (dr) represents the slope of the valuation term structure, while the traditional price-dividend ratio (pd) represents the level. After establishing the connection between state variables and valuation ratios of dividend strips, we demonstrate that the state space is two-dimensional. Through return and cash-flow predictions, we find that dr and pd span the state space and may serve as a pair of state variables for asset pricing and in macro-finance studies in general.

Our findings not only establish market duration as a key state variable of important applications but also shed light on what drives market duration. We find a tight link between market duration and expected return. dr exhibits strong return predictive power, outperforming other predictors. Such a connection between dr and discount rate emerges when market information on long-term cash flows is limited, and empirically, we document the supporting evidence of a sharp decline of cash-flow predictability once the forecasting horizon goes beyond one year.

Cochrane (2011) point out how return predictability emerges from the lack of cash-flow predictability and the price-dividend ratio should forecast future returns. We find that cash flows in the near term are in fact highly predictable, but cash flows over the long term are not. Therefore, our measure of market duration is a better return predictor than the price-dividend ratio. Our findings support a market timing strategy of betting against market duration. When the valuation of long-term cash flows rises relative to that of near-term cash flows of which market participants are more informed of, it is likely due to a lower discount rate or exuberance over long-term growth (Bordalo, Gennaioli, La Porta, and Shleifer, forthcoming).

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Appendix I: Derivation

I.1 Solving the valuation ratios

The price-dividend ratio of dividend strip with maturity n, $P_{n,t}/D_t$, satisfies the following recursive equation

$$\frac{P_{n,t}}{D_t} = \mathbb{E}_t \left[M_{t+1} \frac{D_{t+1}}{D_t} \frac{P_{n-1,t+1}}{D_{t+1}} \right]. \tag{32}$$

We conjecture that

$$\ln \left(\frac{P_{n,t}}{D_t} \right) = A(n) + B(n)^T X_t. \tag{33}$$

Substituting this expression and expressions of stochastic discount factor and dividend growth into the recursive equation, we have

$$\begin{aligned}
&\exp \left\{ A(n) + B(n)^\top X_t \right\} \\
=&\mathbb{E}_t \left[\exp \left\{ -r_f - \frac{1}{2} \lambda_t^\top \Sigma \lambda_t - \lambda_t^\top \epsilon_{t+1} + g_t + \sigma_D^\top \epsilon_{t+1} + A(n-1) + B(n-1)^\top X_{t+1} \right\} \right] \\
=&\mathbb{E}_t \left[\exp \left\{ g_t - r_f - \frac{1}{2} \lambda_t^\top \Sigma \lambda_t + A(n-1) + B(n-1)^\top \Pi X_t + (\sigma_D - \lambda_t + \sigma_X B(n-1))^\top \epsilon_{t+1} \right\} \right] \\
=& \exp \left\{ g_t - r_f - \frac{1}{2} \lambda_t^\top \Sigma \lambda_t + A(n-1) + B(n-1)^\top \Pi X_t \right. \\
&\left. + \frac{1}{2} (\sigma_D - \lambda_t + \sigma_X B(n-1))^\top \Sigma (\sigma_D - \lambda_t + \sigma_X B(n-1)) \right\} \\
=& \exp \left\{ g_t - r_f + A(n-1) + B(n-1)^\top \Pi X_t - (\sigma_D + \sigma_X B(n-1))^\top \Sigma \lambda_t \right. \\
&\left. + \frac{1}{2} (\sigma_D + \sigma_X B(n-1))^\top \Sigma (\sigma_D + \sigma_X B(n-1)) \right\}
\end{aligned} \tag{34}$$

The coefficients on X_t should match $B(n)$ on the left hand side, so we have

$$B(n) = \left(\Pi^\top - \theta \Sigma \sigma_X \right) B(n-1) + \phi - \theta \Sigma \sigma_D - \gamma. \tag{35}$$

The constants must sum up to $A(n)$ on the left hand side, so we have

$$\begin{aligned}
A(n) =& A(n-1) + \overline{g} - \overline{r} - (\sigma_D + \sigma_X B(n-1))^\top \Sigma \overline{\lambda} + \\
& \frac{1}{2} (\sigma_D + \sigma_X B(n-1))^\top \Sigma (\sigma_D + \sigma_X B(n-1)).
\end{aligned} \tag{36}$$

The fact that $P_t^0 = D_t$ implies the boundary conditions, $A(0) = B(0) = 0$, which pins down a solution of $A(n)$ and $B(n)$.

Finally, we solve the log price-to-dividend ratio of the aggregate stock market. We conjecture

$$pd_t = \ln(P_t/D_t) = A + B^T X_t, \tag{37}$$

and proceed to solve A and B. Following Campbell and Shiller (1988), we log-linearize the stock market return

$$
\begin{aligned}
r_{t+1}^{mkt} =& \kappa_0 + \kappa_1 pd_{t+1} - pd_t + \Delta d_{t+1} \\
=& \kappa_0 - (1-\kappa_1) A - B^\top (\mathbf{I} - \kappa_1 \Pi) X_t + g_t + (\kappa_1 \sigma_X B + \sigma_D)^\top \epsilon_{t+1}
\end{aligned}
\tag{38}
$$

Under the no arbitrage condition, we have

$$
1 = \mathbb{E}_t \left[M_{t+1} \exp(r_{t+1}^{mkt}) \right]. \tag{39}
$$

We follow the same method of matching undetermined coefficients in the analysis of dividend strip valuation ratios and solve

$$
A = \frac{1}{1-\kappa_1} \left[\overline{g} - \overline{r} + \kappa_0 - (\kappa_1 \sigma_X B + \sigma_D)^\top \Sigma \overline{\lambda} + \frac{1}{2} (\kappa_1 \sigma_X B)^\top \Sigma (\kappa_1 \sigma_X B) + (\kappa_1 \sigma_X B)^\top \Sigma \sigma_D \right] \tag{40}
$$

$$
B = \left(\mathbf{I} - \kappa_1 \Pi^\top - \kappa_1 \theta \Sigma \sigma_X \right)^{-1} (\phi - \theta \Sigma \sigma_D - \gamma). \tag{41}
$$

I.2 Valuation ratios from the cross section

Consider an individual stock i. The dividend dynamics of firm i depend not only on the aggregate state variables, X_t, but also on the firm i-specific state variables, $Z_{i,t}$, that is K_i-dimensional and independent from X_t. Without loss of generality, we assume that $Z_{i,t}$ evolves as a first-order vector autoregression

$$
Z_{i,t+1} = \Omega Z_{i,t} + \sigma_{i,Z}^\top \upsilon_{i,t+1}, \tag{42}
$$

where $\upsilon_{i,t+1}$ is a N_i-by-1 vector of i-specific news that has a normal distribution $N(\mathbf{0}, \Sigma_i)$ and is independent over time and independent from the aggregate shocks ϵ_{t+1}. We use subscript i to differentiate firm i from the aggregate variables (without subscript i) and other firms (with subscript $j \neq i$).

The dividend growth rate of firm i loads on the aggregate and idiosyncratic shocks

$$
\ln \left(\frac{D_{i,t+1}}{D_{i,t}} \right) = g_{i,t} + \sigma_{i,D}^\top \epsilon_{t+1} + \sigma_{i,\upsilon}^\top \upsilon_{i,t+1}, \tag{43}
$$

where the expected dividend growth rate is given by

$$
g_{i,t} = \phi_i^\top X_t + \delta_i^\top Z_{i,t} + \overline{g}_i - \frac{1}{2} \sigma_{i,D}^\top \Sigma \sigma_{i,D} - \frac{1}{2} \sigma_{i,\upsilon}^\top \Sigma_i \sigma_{i,\upsilon}, \tag{44}
$$

which loads on the aggregate state variables, X_t, and firm i-specific state variables, $Z_{i,t}$.

The ratio of firm i's dividend strip price, $P_{i,t}^n$, to firm i's current dividend is

$$
\frac{P_{i,t}^n}{D_{i,t}} = \exp \left\{ A_i(n) + B_i(n)^\top X_t + C_i(n)^\top Z_{i,t} \right\}, \tag{45}
$$

where $A_i(n)$, $B_i(n)$, and $C_i(n)$ are firm i-specific, deterministic functions of n given by the recursive equations

$$B_i(n) = \left(\Pi^\top - \theta\Sigma\sigma_X\right) B_i(n-1) + \phi_i - \gamma - \theta\Sigma\sigma_{i,D}. \tag{46}$$

$$C_i(n) = \Omega^\top C_i(n-1) + \delta_i \tag{47}$$

$$A_i(n) = A_i(n-1) + \overline{g}_i - \overline{r} - (\sigma_{i,D} + \sigma_X B_i(n-1))^\top \Sigma\overline{\lambda} + \frac{1}{2}(\sigma_{i,D} + \sigma_X B_i(n-1))^\top \Sigma (\sigma_{i,D} + \sigma_X B_i(n-1)) + \frac{1}{2}(\sigma_{i,v} + \sigma_{i,Z} C_i(n-1))^\top \Sigma_i (\sigma_{i,v} + \sigma_{i,Z} C_i(n-1)). \tag{48}$$

with the initial conditions

$$A_i(0) = 0, \; B_i(0) = 0, \; \text{and} \; C_i(0) = 0. \tag{49}$$

The price of firm i's stock, $P_{i,t}$, is the sum of all its dividend strips

$$\frac{P_{i,t}}{D_{i,t}} = \sum_{n=1}^{+\infty} \frac{P_{i,t}^n}{D_{i,t}} = \sum_{n=1}^{+\infty} \exp\left\{A_i(n) + B_i(n)^\top X_t + C_i(n)^\top Z_{i,t}\right\}. \tag{50}$$

In Appendix I, we use the log-linearization method of Campbell and Shiller (1988) to solve an approximate exponential-affine form, so the log price-to-dividend ratio of stock i is

$$\ln\left(\frac{P_{i,t}}{D_{i,t}}\right) \approx A_i + B_i^\top X_t + C_i^\top Z_{i,t}. \tag{51}$$

Because $Z_{i,t}$ is independent from X_t, recovering the state space X_t using individual stocks' price-to-dividend ratio brings in noise. In a forecasting context, Kelly and Pruitt (2013) deal with this issue using partial least square, which is a method to compress the cross-section of valuation ratios into signals (about the state variables) that are most relevant for the forecasting targets.

I.3 Solving the two-dimensional state space model

We conjecture that the market price-dividend ratio is exponential-affine in the state variables, so the log ratio is

$$pd_t = \ln(S_t/D_t) = A + By_t + Cz_t.$$

Next, we use the log-linearization of Campbell and Shiller (1988), i.e.,

$$r_{t+1} = \kappa_0 + \kappa_1 pd_{t+1} - pd_t + \Delta d_{t+1},$$

and substitute this log market return into the no-arbitrage condition

$$\mathbb{E}_t\left[M_{t+1}\exp\{r_{t+1}\}\right] = 1.$$

to obtain

$$\mathbb{E}_t\left[\exp\left\{-r_f - \frac{1}{2}\lambda_t^2(\sigma_\lambda^\top\Sigma\sigma_\lambda)^2 - \lambda_t\sigma_\lambda^\top\epsilon_{t+1} + \kappa_0 + \kappa_1 pd_{t+1} - pd_t + \Delta d_{t+1}\right\}\right] = 1 \tag{52}$$

Using the conjecture of pd_t and pd_{t+1} and the specification of g_t and Δd_{t+1}, we obtain

$$\mathbb{E}_t\left[\exp\left\{ -r_f - \frac{1}{2}\lambda_t^2(\sigma_\lambda^\top\Sigma\sigma_\lambda)^2 - \lambda_t\sigma_\lambda^\top\epsilon_{t+1} + \kappa_0 - A - By_t - Cz_t + z_t + \overline{g} - \frac{1}{2}\sigma_D^\top\Sigma\sigma_D + \sigma_D^\top\epsilon_{t+1} \right.\right.$$
$$\left.\left. +\kappa_1 A + \kappa_1 B(\rho_y y_t + \sigma_y^\top\epsilon_{t+1}) + \kappa_1 C(\rho_z z_t + \sigma_z^\top\epsilon_{t+1}) \right\}\right] = 1 \tag{53}$$

For the conjecture of pd_t functional form to hold, the coefficient on z_t is zero, so we obtain

$$C = \frac{1}{1-\kappa_1\rho_z} \tag{54}$$

Collecting all terms with shocks at $t+1$ and using the moment-generating function, we obtain

$$\mathbb{E}_t\left[\exp\left\{-\lambda_t\sigma_\lambda^\top\epsilon_{t+1} + \sigma_D^\top\epsilon_{t+1} + \kappa_1 B\sigma_y^\top\epsilon_{t+1} + \kappa_1 C\sigma_z^\top\epsilon_{t+1}\right\}\right] = \exp\left\{\frac{1}{2}\lambda_t^2(\sigma_\lambda^\top\Sigma\sigma_\lambda)^2\right. \tag{55}$$
$$\left. -(\sigma_D + \kappa_1 B\sigma_y + \kappa_1 C\sigma_z)^\top\Sigma\sigma_\lambda\lambda_t + \frac{1}{2}(\sigma_D + \kappa_1 B\sigma_y + \kappa_1 C\sigma_z)^\top\Sigma(\sigma_D + \kappa_1 B\sigma_y + \kappa_1 C\sigma_z)\right\}$$

Substituting this expression into the no-arbitrage condition, we obtain

$$\exp\left\{-r_f + \kappa_0 - A - By_t - Cz_t + z_t + \overline{g} - \frac{1}{2}\sigma_D^\top\Sigma\sigma_D - (\sigma_D + \kappa_1 B\sigma_y + \kappa_1 C\sigma_z)^\top\Sigma\sigma_\lambda(\overline{\lambda} + y_t)\right.$$
$$\left. +\kappa_1 A + \kappa_1 B\rho_y y_t + \kappa_1 C\rho_z z_t + \frac{1}{2}(\sigma_D + \kappa_1 B\sigma_y + \kappa_1 C\sigma_z)^\top\Sigma(\sigma_D + \kappa_1 B\sigma_y + \kappa_1 C\sigma_z)\right\} = 1 \tag{56}$$

For the conjecture of pd_t functional form to hold, the coefficient on y_t is zero, so we obtain

$$B = -\frac{(\sigma_D + \kappa_1 C\sigma_z)^\top\Sigma\sigma_\lambda}{1 + \kappa_1\sigma_y^\top\Sigma\sigma_\lambda - \kappa_1\rho_y} \tag{57}$$

Finally, all the constant terms should add up to zero, so we obtain

$$A = \frac{\overline{g} - r_f + \kappa_0 - \frac{1}{2}\sigma_D^\top\Sigma\sigma_D + \frac{1}{2}(\sigma_D + \kappa_1 B\sigma_y + \kappa_1 C\sigma_z)^\top\Sigma(\sigma_D + \kappa_1 B\sigma_y + \kappa_1 C\sigma_z - 2\sigma_\lambda\overline{\lambda})}{1-\kappa_1} \tag{58}$$

In the main text, to clarify the notations, we use A_{pd}, B_{pd}, and C_{pd} to denote A, B, and C above, respectively.

Next, we solve the time-t log price-dividend ratio of the dividend strip that matures at $t+1$. The no-arbitrage condition dictates

$$\mathbb{E}_t\left[M_{t+1}\frac{D_{t+1}}{P_t^1}\right] = 1, \tag{59}$$

or equivalently

$$\mathbb{E}_t\left[M_{t+1}\frac{D_{t+1}}{D_t}\frac{D_t}{P_t^1}\right] = \mathbb{E}_t\left[M_{t+1}\exp\left\{g_t + \sigma_D^\top\epsilon_{t+1} - s_t^1\right\}\right] = 1, \tag{60}$$

so we obtain

$$\mathbb{E}_t\left[\exp\left\{-r_f-\frac{1}{2}\lambda_t^2(\sigma_\lambda^\top\Sigma\sigma_\lambda)^2-\lambda_t\sigma_\lambda^\top\epsilon_{t+1}+g_t+\sigma_D^\top\epsilon_{t+1}-s_t^1\right\}\right]=1. \tag{61}$$

We conjecture

$$s_t^1=A_1+B_1y_t+C_1z_t.$$

Substituting this conjecture, the specification of g_t, and the specification of λ_t into the no-arbitrage condition, we obtain

$$\mathbb{E}_t\left[\exp\left\{-r_f-\frac{1}{2}(\overline{\lambda}+y_t)^2(\sigma_\lambda^\top\Sigma\sigma_\lambda)^2-(\overline{\lambda}+y_t)\sigma_\lambda^\top\epsilon_{t+1}+z_t+\overline{g}-\frac{1}{1}\sigma_D^\top\Sigma\sigma_D+\sigma_D^\top\epsilon_{t+1}-A_1-B_1y_t-C_1z_t\right\}\right]=1.$$

Using the moment-generating function to simplify the expression, we obtain

$$\exp\left\{-r_f+z_t+\overline{g}-A_1-B_1y_t-C_1z_t-\sigma_\lambda^\top\Sigma\sigma_D(\overline{\lambda}+y_t)\right\}=1. \tag{62}$$

For the conjecture of s_t^1 functional form to hold, the coefficient of z_t and the coefficient of y_t must be zero, so we obtain

$$C_1=1, \tag{63}$$

and

$$B_1=-\sigma_\lambda^\top\Sigma\sigma_D. \tag{64}$$

Finally, the constant terms add up to zero, so we obtain

$$A_1=\overline{g}-r_f-\sigma_\lambda^\top\Sigma\sigma_D\overline{\lambda} \tag{65}$$

Finally, we solve the conditional expected market return. First, we start with $\mathbb{E}_t[r_{t+1}]=\kappa_0+\kappa_1\mathbb{E}_t[pd_{t+1}]-pd_t+g_t$. Using the expression of pd_{t+1}, pd_t, and g_t, and the specifications of law of motion of z_t and y_t, we obtain

$$\mathbb{E}_t[r_{t+1}]=\kappa_0-(1-\kappa_1)A+\overline{g}-\frac{1}{2}\sigma_D^\top\Sigma\sigma_D-(1-\kappa_1\rho_y)By_t. \tag{66}$$

We collect the constant terms into A_{er} and define the coefficient of y_t to be B_{er}.

I.4 Proof of Proposition 3 on ρ_z and return forecasting errors

Proof. We know that the expected return is a function of the price of risk y_t:

$$\mathbb{E}_t[r_{t+1}]=A_{er}+B_{er}y_t,$$

and that

$$dr_t=A_{pd}-A_1+(B_{pd}-B_1)y_t+(C_{pd}-C_1)z_t.$$

Combining the two equations, we have

$$\mathbb{E}_t[r_{t+1}] = A_{er} + \frac{B_{er}}{B_1 - B_{pd}}\left[dr_t - A_{pd} + A_1 - (C_{pd} - C_1)z_t\right] \tag{67}$$

$$= \text{const.} + \frac{B_{er}}{B_1 - B_{pd}}\left[dr_t - (C_{pd} - C_1)z_t\right] \tag{68}$$

If $\rho_z = 0$, $\mathbb{E}_t[r_{t+1}] = \text{const.} + \frac{B_{er}}{B_1 - B_{pd}} dr_t$. The forecast error is a white noise independent of time-t variables:

$$v_{t+1} = r_{t+1} - \mathbb{E}_t[r_{t+1}] = \epsilon_{t+1}.$$

However, if $\rho_z \neq 0$ but the investor still uses equation (68) to forecast $t+1$ return, the forecast error is then

$$v_{t+1} = r_{t+1} - \left[\text{const.} + \frac{B_{er}}{B_1 - B_{pd}} dr_t\right] = r_{t+1} - \left[\mathbb{E}_t[r_{t+1}] + \frac{B_{er}(C_{pd} - C_1)}{B_1 - B_{pd}} z_t\right]$$
$$= \epsilon_{t+1} - \frac{B_{er}(C_{pd} - C_1)}{B_1 - B_{pd}} z_t = \epsilon_{t+1} - \frac{B_{er}}{B_1 - B_{pd}}\left(\frac{1}{1 - \kappa_1 \rho_z} - 1\right) z_t.$$

The correlation between $\hat{\rho}_{z,t}$ and v_{t+1} is therefore

$$Corr(\rho_{z,t}, v_{t+1}) = -\frac{B_{er}}{B_1 - B_{pd}} Corr\left(\rho_{z,t}, \left(\frac{1}{1 - \kappa_1 \rho_{z,t}} - 1\right) z_t\right)$$

Based on our findings on return predictability, dr_t negatively predicts future returns. Therefore, the coefficient of dr_t in equation (68), $\frac{B_{er}}{B_1 - B_{pd}}$, is negative. Under this condition, we obtain

$$\text{sgn}\left(Corr(\rho_{z,t}, v_{t+1})\right) = \text{sgn}\left(Cov\left(\rho_{z,t}, \left(\frac{1}{1 - \kappa_1 \rho_{z,t}} - 1\right) z_t\right)\right)$$
$$= \text{sgn}\left(\mathbb{E}\left(\frac{\kappa_1 \rho_{z,t}^2 z_t}{1 - \kappa_1 \rho_{z,t}}\right) - \mathbb{E}\left(\rho_{z,t}\right)\mathbb{E}\left(\frac{\kappa_1 \rho_{z,t} z_t}{1 - \kappa_1 \rho_{z,t}}\right)\right)$$

As demonstrated by the rolling estimation results in Table 8 in Section 4.3, $\rho_{z,t}$ on average is close to zero (see also Table 8, we have $\mathbb{E}\left(\hat{\rho}_{z,t}\right) \approx 0$. Using 1-year earnings growth forecasts from IBES Global Aggregate (IGA) as a proxy for z_t and $\kappa_1 = 0.98$, we calculate the estimate of $\mathbb{E}\left(\frac{\kappa_1 \hat{\rho}_{z,t}^2 z_t}{1 - \kappa_1 \hat{\rho}_{z,t}}\right)$ in our sample to be 0.005626 with p-value < 0.01, which implies

$$\text{sgn}\left(Corr(\rho_{z,t}, v_{t+1})\right) = \text{sgn}\left(\mathbb{E}\left(\frac{\kappa_1 \rho_{z,t}^2 z_t}{1 - \kappa_1 \rho_{z,t}}\right)\right) > 0.$$

■

I.5 Deriving the Sharpe ratio of market-timing strategy

Following Campbell and Thompson (2008), we assume that the excess return can be decomposed as follows:

$$r_{t+1} = \mu + x_t + \varepsilon_{t+1}$$

where μ is the unconditional mean. The predictor x_t has mean 0 and variance σ_x^2, independent from the error term ε_{t+1}. For simplicity, we assume that the mean-variance investor has a relative risk aversion coefficient $\gamma = 1$. When using x_t to time the market, the investor allocates

$$\alpha_t = \frac{\mu + x_t}{\sigma_\varepsilon^2}$$

to the risky asset and on average earns an excess return of

$$\mathbb{E}\left(\alpha_t r_{t+1}\right) = \mathbb{E}\left(\frac{\left(\mu + x_t\right)\left(\mu + x_t + \varepsilon_{t+1}\right)}{\sigma_\varepsilon^2}\right) = \frac{\mu^2 + \sigma_x^2}{\sigma_\varepsilon^2}$$

The variance of the market-timing strategy is

$$\mathrm{Var}\left(\alpha_t r_{t+1}\right) = \mathrm{Var}\left[\frac{\left(\mu + x_t\right)\left(\mu + x_t + \varepsilon_{t+1}\right)}{\sigma_\varepsilon^2}\right]$$

The (squared) market-timing Sharpe ratio s_1^2 can be written as

$$s_1^2 = \frac{\left[\mathbb{E}\left(\alpha_t r_{t+1}\right)\right]^2}{\mathrm{Var}\left(\alpha_t r_{t+1}\right)} = A \cdot \frac{\mu^2 + \sigma_x^2}{\sigma_\varepsilon^2}$$

where A is a constant that depends on $Var\left[\left(\mu + x_t\right)\left(\mu + x_t + \varepsilon_{t+1}\right)\right]$ and $(\mu^2 + \sigma_x^2)/\sigma_\varepsilon^2$.

Given the buy-and-hold Sharpe ratio s_0,

$$s_0^2 = \frac{\mu^2}{\sigma_x^2 + \sigma_\varepsilon^2}$$

and the predictive regression R^2,

$$R^2 = \frac{\sigma_x^2}{\sigma_x^2 + \sigma_\varepsilon^2},$$

we obtain the relationship between the buy-and-hold and market-timing Sharpe ratios as

$$s_1^2 = A \cdot \frac{\mu^2 + \sigma_x^2}{\sigma_\varepsilon^2} = A \cdot \frac{\mu^2 + \sigma_x^2}{\left(\sigma_x^2 + \sigma_\varepsilon^2\right)\left(1 - R^2\right)} = A \cdot \frac{s_0^2 + R^2}{1 - R^2}$$

When the predictor has no predictive power, we know that $R^2 = 0$ and $s_0 = s_1$. We therefore pin down the constant $A = 1$ and obtain

$$s_1 = \sqrt{\frac{s_0^2 + R^2}{1 - R^2}}. \tag{69}$$

Using data back to 1871, Campbell and Thompson (2008) obtain a long-term estimate of the market buy-and-hold Sharpe ratio ("s_0") of 0.37 (annualized). If a mean-variance investor uses the information from dr to construct a market-timing strategy, with an out-of-sample R^2 of 14.6%, she would obtain a Sharpe ratio ("s_1") of 0.58, representing a 54.7% improvement over the Sharpe ratio achieved by the buy-and-hold approach.

Appendix II: Additional Tables and Figures

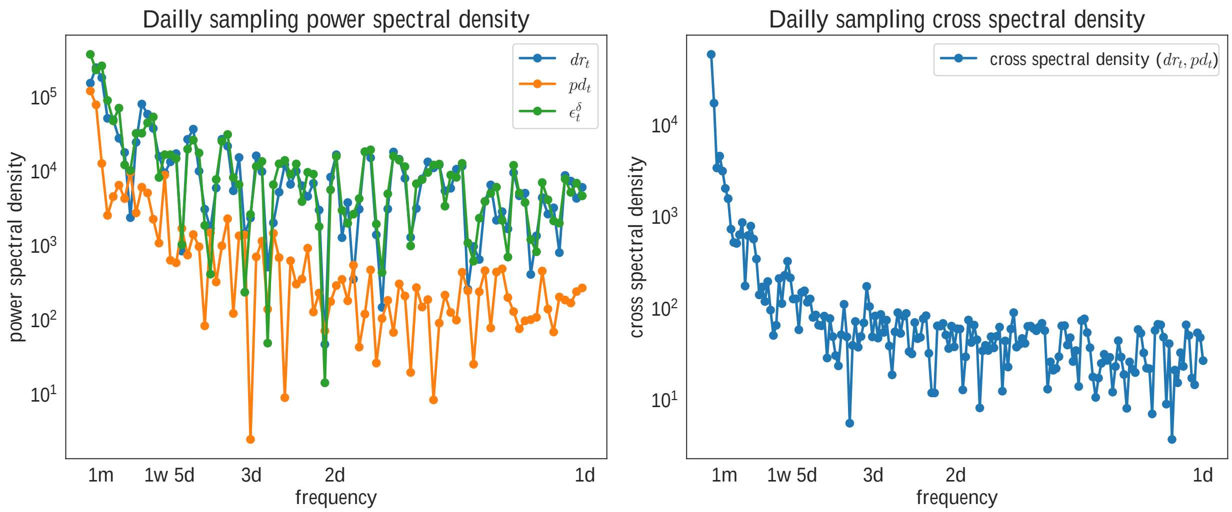


Figure A.1 Spectrum and Cross-spectrum of dr and pd (Daily Frequency).

The left panel shows the estimated spectral densities of dr_t, pd_t, and the residuals of dr_t after projecting on pd_t (ϵ_t^{pr}). The integral of spectral density is equal to the variance. The horizontal line starts from zero and ends at π, but is labeled with the corresponding length of a cycle. The right panel shows the cross-spectral density between dr_t and pd_t. The integral of cross-spectral density is equal to the covariance.

Table A.1 Predicting One-year Dividend Growth Using Different Combinations of Scaled Dividend Prices

This table reports results from one-year dividend growth predictive regressions of the S&P 500 Index. The predictors are various combinations of scaled dividend prices, which include our main predictor dr, the price-dividend ratio pd, short-term (0.5- and 1-year) dividend strip price to dividend ratio ($pd^{0.5}$ and pd^{1}), long-term (beyond 1-year) dividend strip price to dividend ratio (pd^{1+}), Each column corresponds to one separate predictive regression. Data sample: 1988:01–2019:12.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	$\log(D_{t+1}/D_t)$												
dr	-0.04				0.02			0.09		-0.18***	-0.18***		
	(0.03)				(0.04)			(0.06)		(0.06)	(0.06)		
pd				0.07			0.10		7.70		0.28**		0.11*
				(0.07)			(0.07)		(5.60)		(0.12)		(0.06)
$pd^{0.5}$		-0.02	0.14**	0.14**	0.14*							-0.04	-0.04
		(0.03)	(0.06)	(0.06)	(0.08)							(0.03)	(0.03)
s^1		0.17***				0.18***	0.18***	0.27**				0.26***	0.26***
		(0.06)				(0.06)	(0.06)	(0.11)				(0.07)	(0.07)
pd^{1+}			0.07			0.10			-7.48	0.28**		0.11*	
			(0.06)			(0.06)			(5.41)	(0.12)		(0.06)	
Intercept	0.21	0.07***	-0.09	-0.10	0.09	-0.29	-0.30	-0.27	-0.96	-0.28	-0.31	-0.35	-0.36
	(0.19)	(0.02)	(0.21)	(0.22)	(0.11)	(0.24)	(0.25)	(0.22)	(0.88)	(0.23)	(0.24)	(0.22)	(0.22)
N	372	372	372	372	372	372	372	372	372	372	372	372	372
R^2	0.06	0.27	0.26	0.26	0.20	0.37	0.37	0.36	0.21	0.38	0.38	0.41	0.41
	$\log(D_{t+1}/D_t)$												
dr	0.10*		-0.26***	-0.25***		-0.21***	-0.23***	-0.16***		-0.23***	-0.24***	-0.25***	-0.24***
	(0.05)		(0.07)	(0.07)		(0.05)	(0.06)	(0.04)		(0.04)	(0.05)	(0.06)	(0.07)
pd		3.81		0.37***	1.90		0.33***	2.05	0.36		0.35***	0.71	2.25
		(4.26)		(0.11)	(3.56)		(0.12)	(3.37)	(2.96)		(0.10)	(2.76)	(3.39)
$pd^{0.5}$	-0.04	0.10**	-0.03	-0.04					-0.04	-0.04	-0.04	-0.04	
	(0.03)	(0.04)	(0.02)	(0.02)					(0.03)	(0.03)	(0.03)	(0.03)	
s^1	0.35***				0.16***	-0.02	-0.05**		0.25***	0.03	0.02		-0.08
	(0.11)				(0.04)	(0.05)	(0.02)		(0.06)	(0.05)	(0.05)		(0.05)
pd^{1+}		-3.65	0.36***		-1.76	0.30***		-1.74	-0.25	0.34***		-0.34	-1.87
		(4.11)	(0.11)		(3.43)	(0.10)		(3.25)	(2.86)	(0.09)		(2.66)	(3.22)
Intercept	-0.34*	-0.54	-0.33*	-0.37*	-0.49	-0.28	-0.31	-0.50	-0.39	-0.34	-0.37*	-0.41	-0.52
	(0.20)	(0.68)	(0.20)	(0.21)	(0.58)	(0.24)	(0.24)	(0.55)	(0.48)	(0.21)	(0.21)	(0.45)	(0.54)
N	372	372	372	372	372	372	372	372	372	372	372	372	372
R^2	0.40	0.29	0.42	0.43	0.38	0.38	0.38	0.39	0.41	0.42	0.42	0.42	0.39

Table A.2 Predicting One-year Returns Using Different Combinations of Scaled Dividend Prices

This table reports results from one-year return predictive regressions of the S&P 500 Index. The predictors are our main predictor dr, and various combinations of scaled dividend prices, which include the price-dividend ratio pd, short-term (0.5- and 1-year) dividend strip price to dividend ratio ($pd^{0.5}$ and pd^{1}), long-term (beyond 1-year) dividend strip price to dividend ratio (pd^{1+}), Each column corresponds to one separate predictive regression. Data sample: 1988:01–2019:12.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	r_{t+1}												
dr	-0.16***												
	(0.04)												
pd		-0.20**			-0.14*		-0.09	7.54		-0.07	1.44	-1.41	-5.40
		(0.10)			(0.08)		(0.10)	(8.81)		(0.11)	(6.81)	(7.65)	(7.44)
$pd^{0.5}$			-0.14**	0.18**	0.18**				-0.13*	-0.13*	0.16**		-0.12
			(0.07)	(0.09)	(0.09)				(0.07)	(0.07)	(0.08)		(0.08)
s^{1}			0.49***			0.23**	0.23**		0.43**	0.43**		0.24***	0.50***
			(0.12)			(0.10)	(0.10)		(0.18)	(0.18)		(0.06)	(0.15)
pd^{1+}				-0.13*		-0.09		-7.53	-0.07		-1.54	1.29	5.22
				(0.07)		(0.09)		(8.55)	(0.11)		(6.59)	(7.41)	(7.19)
Intercept	0.73***	0.87**	0.05	0.76***	0.77***	0.47	0.48	-0.11	0.31	0.32	0.58	0.62	0.89
	(0.13)	(0.36)	(0.05)	(0.26)	(0.27)	(0.36)	(0.38)	(1.24)	(0.44)	(0.46)	(1.01)	(1.15)	(1.20)
N	372	372	372	372	372	372	372	372	372	372	372	372	372
R^2	0.25	0.14	0.31	0.23	0.23	0.26	0.26	0.18	0.32	0.32	0.22	0.26	0.33

Table A.3 Forecasting Macroeconomic Variables with Market Duration and Valuation Ratios

This table reports the R^2 of predicting one-year-ahead macroeconomic variables using predictors (dr, pd, and s^1) that contain information about the underlying state variables. The macroeconomic variables are divided into four categories. 1) Macroeconomic: nominal GDP Growth, Industrial Production Growth ("IP Growth"), Chicago Fed National Activity Index ("CFNAI"), Unemployment Rate, Real Consumption Growth, Total Business Inventories, Nonresidential Fixed Investment (nominal), Residential Fixed Investment (nominal), and GDP Deflator are all from FRED database. 2) Financial: Term Spread and Default Spread ("Baa-Aaa") are from FRED; Gilchrist-Zakrajšek credit spread (GZ Credit Spread) is from Gilchrist and Zakrajšek (2012); CAPE is the cyclically adjusted price-to-earnings ratio from Robert Shiller's website; cay is from Lettau and Ludvigson (2001). 3) Intermediary: Broker/Dealer leverage ("B/D Leverage") is from Adrian, Etula, and Muir (2014); Broker/Dealer 1(5) year average CDS spreads ("B/D 1(5) Year Avg. CDS") is from Gilchrist and Zakrajšek (2012); ROA of banks ("ROA Banks") is from FRED. 4) Uncertainties: CBOE 1-month VIX index ("VIX") and Chauvet and Piger (2008)'s smoothed U.S. recession probabilities estimates for given month ("CP Recession") are from FRED; Economics policy uncertainties ("EPU") is from Baker, Bloom, and Davis (2016); Survey of Professional Forecasters recession probability estimates ("SPF Recession") is from the Philadelphia Fed. 5) Sentiments: Sentiment Index (both raw and orthogonalized against several macro variables), Number of IPOs ("IPO #") and close-end fund NAV discount ("Close-end Discount") are all from Baker and Wurgler (2006).

	$dr + pd$	dr	pd	$dr + s^1$	s^1
Macroeconomic:					
GDP Growth	0.222	0.061	0.000	0.224	0.178
IP Growth	0.202	0.062	0.001	0.203	0.167
Unemployment Growth	0.335	0.062	0.001	0.325	0.229
Real Consumption Growth	0.241	0.019	0.121	0.241	0.208
Business Inventories Growth	0.383	0.114	0.000	0.377	0.304
Nonres. Fixed Investment Growth	0.366	0.055	0.005	0.361	0.240
CPI Growth	0.311	0.227	0.311	0.302	0.071
Financial:					
Baa-Aaa	0.081	0.044	0.008	0.081	0.078
GZ Credit Spread	0.321	0.318	0.218	0.321	0.259
Term Spread	0.122	0.001	0.039	0.120	0.023
CAPE	0.474	0.300	0.465	0.478	0.062
cay	0.072	0.042	0.069	0.071	0.008
Intermediary:					
B/D Leverage	0.313	0.290	0.296	0.308	0.151
B/D 1 Year Avg. CDS	0.284	0.052	0.106	0.284	0.283
B/D 5 Year Avg. CDS	0.393	0.020	0.231	0.393	0.383
ROA Banks	0.403	0.080	0.275	0.388	0.002
Uncertainties:					
VIX	0.145	0.134	0.068	0.144	0.131
EPU	0.049	0.002	0.005	0.047	0.022
CP Recession	0.063	0.030	0.004	0.063	0.059
SPF Recession	0.194	0.017	0.008	0.191	0.109
Sentiments:					
Sentiment Index	0.131	0.131	0.099	0.131	0.094
Sentiment Index (orth.)	0.113	0.109	0.102	0.113	0.062
IPO #	0.144	0.142	0.093	0.144	0.120
Close-end Discount	0.123	0.109	0.119	0.118	0.054

Table A.4 Kostakis, Magdalinos, and Stamatogiannis (2014) IVX-Wald Test

This table reports test results on the predictive coefficient β in Table (2). IVX-Wald is the Wald statistic from Kostakis, Magdalinos, and Stamatogiannis (2014) to test $H_0 : \beta = 0$ against $H_1 : \beta \neq 0$. p-value of the IVX-Wald test is shown in the parentheses. The test is designed to be robust to the persistence of the predictor. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	dr_t	pd_t	μ_t^F	KP_t
IVX-Wald	9.29***	1.56	2.77*	5.74**
p-value	(0.002)	(0.212)	(0.096)	(0.017)

Table A.5 Annual Excess Return Prediction

This table reports the results of predictive regression (equation (18)). The left-hand side variable is the excess return of the S&P 500 index in the next twelve months. We consider four right-hand side variables (i.e., predictors), dr_t, pd_t, filtered series for expected returns following Binsbergen and Koijen (2010) μ^F, and the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP. The β estimate is shown followed by Newey and West (1987) t-statistic (with 18 lags), Hodrick (1992) t-statistic, the coefficient adjusted for Stambaugh (1999) bias, and the in-sample adjusted R^2. We run the regression monthly. Starting from December 1997, we form out-of-sample forecasts of return in the next twelve months by estimating the regression with data up to the current month and use the forecasts to calculate out-of-sample R^2, ENC test (Clark and McCracken, 2001), and the p-value of CW test (Clark and West, 2007). Data sample: 1988:01–2019:12.

	r^e_{t+1}				
	(1)	(2)	(3)	(4)	(5)
dr_t	-0.146				-0.228
Hodrick t	[-3.178]				[-2.945]
Newey-West t	(-3.867)				(-3.571)
Stambaugh bias adjusted β	-0.136				
pd_t		-0.180			0.161
		[-2.168]			[1.820]
		(-2.262)			(1.286)
		-0.170			
μ^F_t			2.293		
			[2.033]		
			(2.205)		
			2.303		
KP_t				0.827	
				[2.715]	
				(2.429)	
				0.837	
N	384	384	384	384	384
R^2	0.219	0.114	0.124	0.128	0.241
OOS R^2	0.098	-0.040	-0.096	0.005	0.138
ENC	1.924	0.296	0.021	2.175	4.539
$p(ENC)$	<0.10	>0.10	>0.10	<0.05	<0.05
$p(CW)$	0.058	0.379	0.493	0.072	0.028

Table A.6 Annual Return Prediction: Fama-French Market Return

This table reports the results of predictive regression (equation (18)). The left-hand side variable is the market return in the next twelve months from Fama-French. We consider four right-hand side variables (i.e., predictors), dr_t, pd_t, filtered series for expected returns following Binsbergen and Koijen (2010) μ^F, and the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP. The β estimate is shown followed by Newey and West (1987) t-statistic (with 18 lags), Hodrick (1992) t-statistic, the coefficient adjusted for Stambaugh (1999) bias, and the in-sample adjusted R^2. We run the regression monthly. Starting from December 1997, we form out-of-sample forecasts of return in the next twelve months by estimating the regression with data up to the current month and use the forecasts to calculate out-of-sample R^2, ENC test (Clark and McCracken, 2001), and the p-value of CW test (Clark and West, 2007). Data sample: 1988:01–2019:12.

	r_{t+1}^{MKT}				
	(1)	(2)	(3)	(4)	(5)
dr_t	-0.154				-0.222
Hodrick t	[-3.233]				[-2.772]
Newey-West t	(-4.464)				(-3.511)
Stambaugh bias adjusted β	-0.144				
pd_t		-0.198			0.133
		[-2.302]			[1.608]
		(-2.706)			(1.129)
		-0.188			
μ_t^F			2.486		
			[2.327]		
			(2.656)		
			2.496		
KP_t				0.794	
				[2.223]	
				(2.689)	
				0.805	
N	384	384	384	384	384
R^2	0.236	0.134	0.141	0.128	0.251
OOS R^2	0.144	0.022	-0.023	-0.001	0.181
ENC	3.083	0.963	0.598	2.483	6.163
$p(ENC)$	<0.05	>0.10	>0.10	<0.05	<0.01
$p(CW)$	0.017	0.166	0.321	0.048	0.019

Table A.7 Annual Return Prediction: Fama-French Market Excess Return

This table reports the results of predictive regression (equation (18)). The left-hand side variable is the market excess return in the next twelve months from Fama-French. We consider four right-hand side variables (i.e., predictors), dr_t, pd_t, filtered series for expected returns following Binsbergen and Koijen (2010) μ^F, and the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP. The β estimate is shown followed by Newey and West (1987) t-statistic (with 18 lags), Hodrick (1992) t-statistic, the coefficient adjusted for Stambaugh (1999) bias, and the in-sample adjusted R^2. We run the regression monthly. Starting from December 1997, we form out-of-sample forecasts of return in the next twelve months by estimating the regression with data up to the current month and use the forecasts to calculate out-of-sample R^2, ENC test (Clark and McCracken, 2001), and the p-value of CW test (Clark and West, 2007). Data sample: 1988:01–2019:12.

	$r_{t+1}^{MKT,e}$				
	(1)	(2)	(3)	(4)	(5)
dr_t	-0.144				-0.222
Hodrick t	[-3.060]				[-2.791]
Newey-West t	(-3.745)				(-3.503)
Stambaugh bias adjusted β	-0.134				
pd_t		-0.179			0.153
		[-2.108]			[1.704]
		(-2.199)			(1.202)
		-0.169			
μ_t^F			2.192		
			[2.075]		
			(2.057)		
			2.203		
KP_t				0.725	
				[2.044]	
				(2.251)	
				0.735	
N	384	384	384	384	384
R^2	0.206	0.108	0.109	0.105	0.225
OOS R^2	0.099	-0.018	-0.081	-0.037	0.140
ENC	2.000	0.376	-0.047	1.700	4.656
$p(ENC)$	<0.10	>0.10	>0.10	<0.10	<0.05
$p(CW)$	0.047	0.349	0.485	0.120	0.027

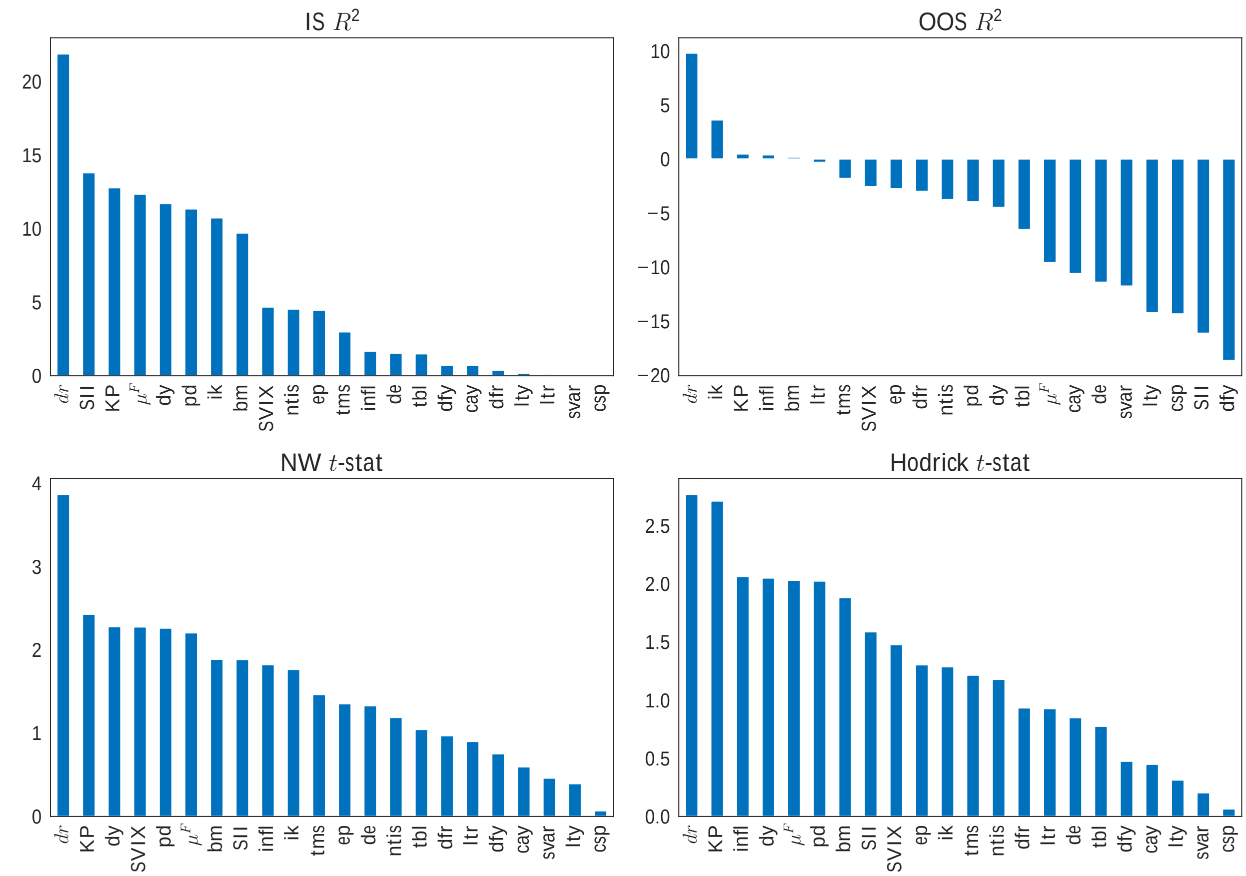


Figure A.2 Comparison with Alternative Return Predictors: Excess Return.

This graph compares the 1-year return predictive power between dr_t and other commonly studied predictors in our sample period. Panel A reports the in-sample adjusted R^2. Panel B reports the out-of-sample R^2. Negative out-of-sample R^2 indicates that the predictive power is below the historical mean. Panel C reports the absolute values of Newey and West (1987) t-statistic (with an 18-month lag). Panel D reports the absolute values of Hodrick (1992) t-statistic. Most predictors are from Goyal and Welch (2007) and include the price-dividend ratio (pd), the default yield spread (dfy), the inflation rate (infl), stock variance (svar), the cross-section premium (csp), the dividend payout ratio (de), the long-term yield (lty), the term spread (tms), the T-bill rate (tbl), the default return spread (dfr), the dividend yield (dy), the long-term rate of return (ltr), the earnings-to-price ratio (ep), the book to market ratio (bm), the investment-to-capital ratio (ik), the net equity expansion ratio (ntis), the percent equity issuing ratio (eqis), and the consumption-wealth-income ratio (cay). SII is the short interests index from Rapach, Ringgenberg, and Zhou (2016) (1988-2014). SVIX is an option-implied lower bound of the 1-year equity premium from Martin (2017) (1996-2012). KP is the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013). BK is the filtered series for expected returns following Binsbergen and Koijen (2010).

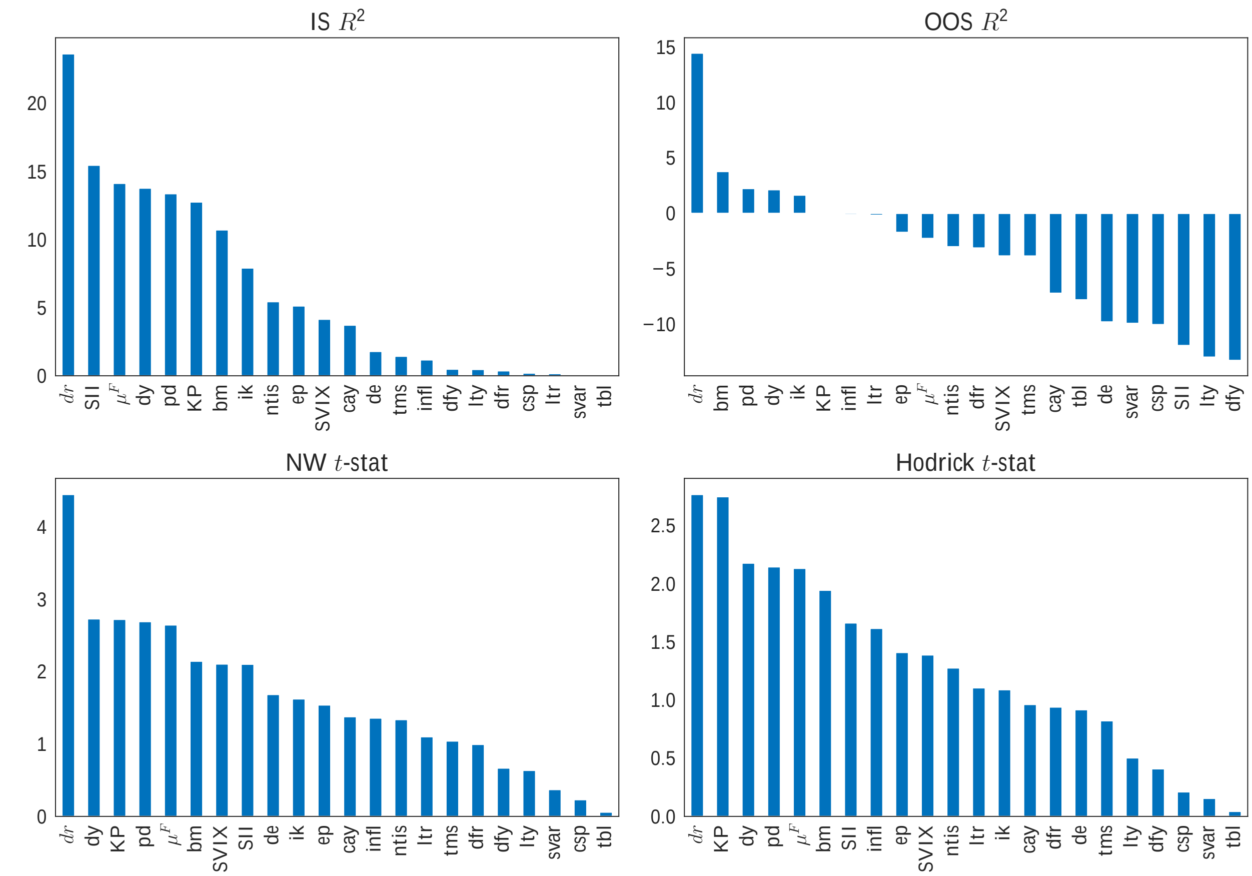


Figure A.3 Comparison with Alternative Return Predictors: Fama-French Market Return.

This graph compares the 1-year return predictive power between dr_t and other commonly studied predictors in our sample period. Panel A reports the in-sample adjusted R^2. Panel B reports the out-of-sample R^2. Negative out-of-sample R^2 indicates that the predictive power is below the historical mean. Panel C reports the absolute values of Newey and West (1987) t-statistic (with an 18-month lag). Panel D reports the absolute values of Hodrick (1992) t-statistic. Most predictors are from Goyal and Welch (2007) and include the price-dividend ratio (pd), the default yield spread (dfy), the inflation rate (infl), stock variance (svar), the cross-section premium (csp), the dividend payout ratio (de), the long-term yield (lty), the term spread (tms), the T-bill rate (tbl), the default return spread (dfr), the dividend yield (dy), the long-term rate of return (ltr), the earnings-to-price ratio (ep), the book to market ratio (bm), the investment-to-capital ratio (ik), the net equity expansion ratio (ntis), the percent equity issuing ratio (eqis), and the consumption-wealth-income ratio (cay). SII is the short interests index from Rapach, Ringgenberg, and Zhou (2016) (1988-2014). SVIX is an option-implied lower bound of the 1-year equity premium from Martin (2017) (1996-2012). KP is the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013). BK is the filtered series for expected returns following Binsbergen and Koijen (2010).

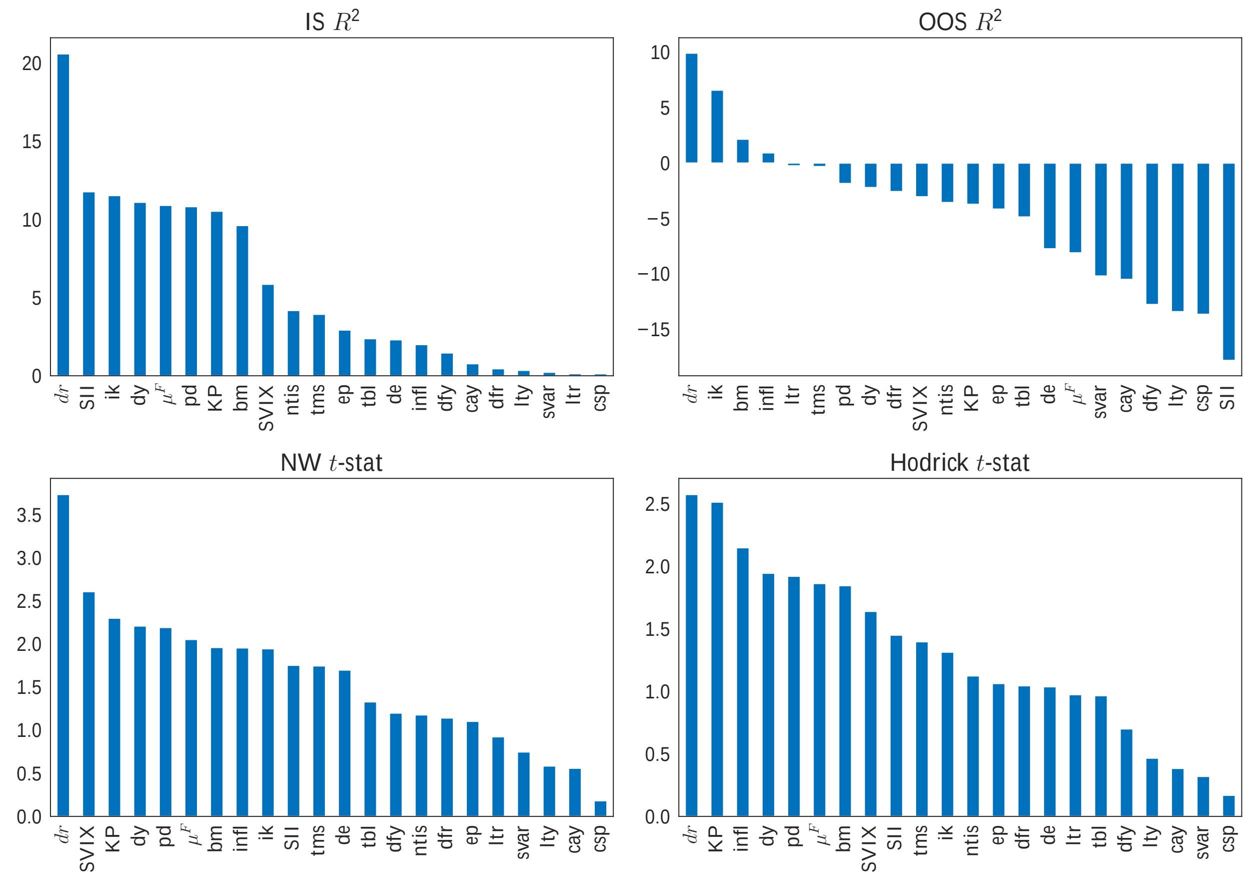


Figure A.4 Comparison with Alternative Return Predictors: Fama-French Market Excess Return.

This graph compares the 1-year return predictive power between dr_t and other commonly studied predictors in our sample period. Panel A reports the in-sample adjusted R^2. Panel B reports the out-of-sample R^2. Negative out-of-sample R^2 indicates that the predictive power is below the historical mean. Panel C reports the absolute values of Newey and West (1987) t-statistic (with an 18-month lag). Panel D reports the absolute values of Hodrick (1992) t-statistic. Most predictors are from Goyal and Welch (2007) and include the price-dividend ratio (pd), the default yield spread (dfy), the inflation rate (infl), stock variance (svar), the cross-section premium (csp), the dividend payout ratio (de), the long-term yield (lty), the term spread (tms), the T-bill rate (tbl), the default return spread (dfr), the dividend yield (dy), the long-term rate of return (ltr), the earnings-to-price ratio (ep), the book to market ratio (bm), the investment-to-capital ratio (ik), the net equity expansion ratio (ntis), the percent equity issuing ratio (eqis), and the consumption-wealth-income ratio (cay). SII is the short interests index from Rapach, Ringgenberg, and Zhou (2016) (1988-2014). SVIX is an option-implied lower bound of the 1-year equity premium from Martin (2017) (1996-2012). KP is the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013). BK is the filtered series for expected returns following Binsbergen and Koijen (2010).

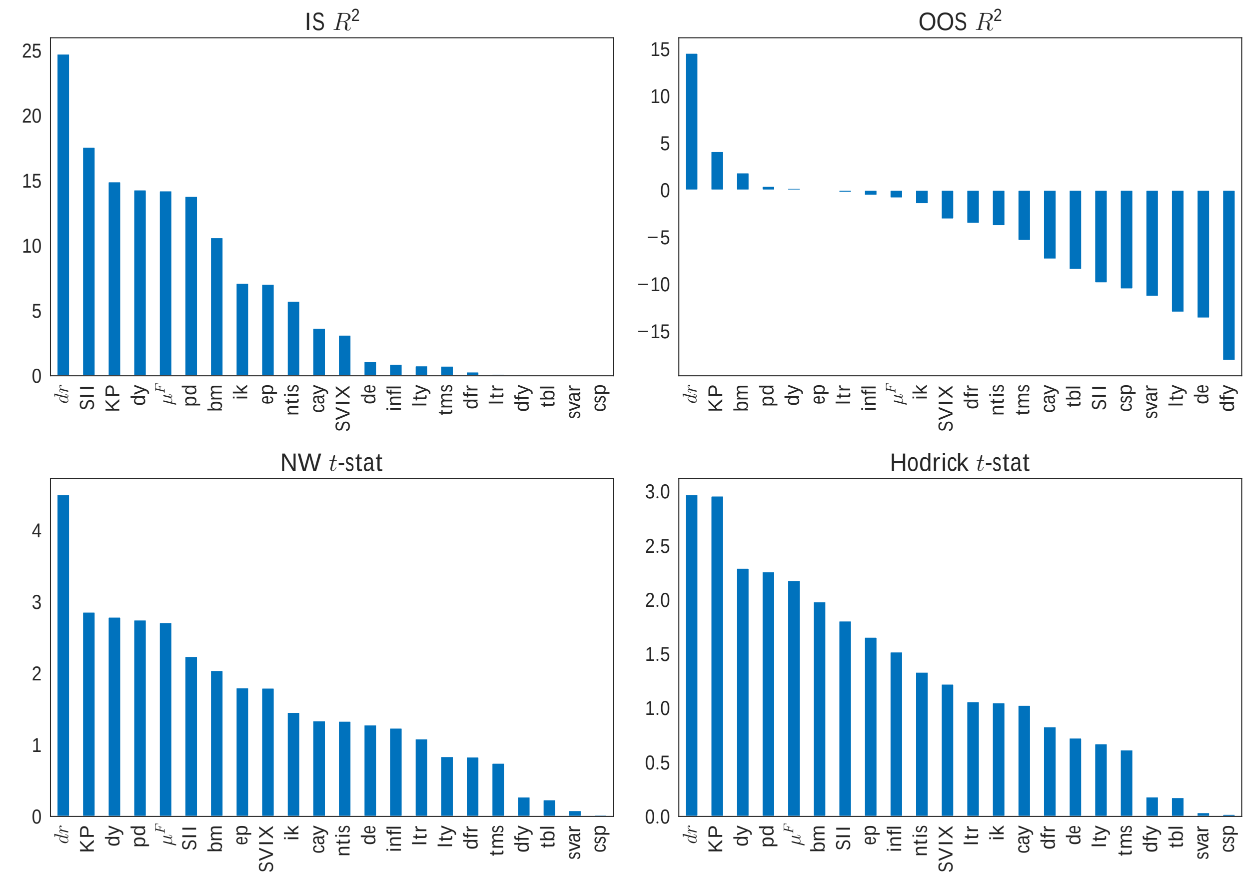


Figure A.5 Comparison with Alternative Return Predictors.

This graph compares the 1-year return predictive power between dr_t and other commonly studied predictors in our sample period. Panel A reports the in-sample adjusted R^2. Panel B reports the out-of-sample R^2. Negative out-of-sample R^2 indicates that the predictive power is below the historical mean. Panel C reports the absolute values of Newey and West (1987) t-statistic (with an 18-month lag). Panel D reports the absolute values of Hodrick (1992) t-statistic. Most predictors are from Goyal and Welch (2007) and include the price-dividend ratio (pd), the default yield spread (dfy), the inflation rate (infl), stock variance (svar), the cross-section premium (csp), the dividend payout ratio (de), the long-term yield (lty), the term spread (tms), the T-bill rate (tbl), the default return spread (dfr), the dividend yield (dy), the long-term rate of return (ltr), the earnings-to-price ratio (ep), the book to market ratio (bm), the investment-to-capital ratio (ik), the net equity expansion ratio (ntis), the percent equity issuing ratio (eqis), and the consumption-wealth-income ratio (cay). SII is the short interests index from Rapach, Ringgenberg, and Zhou (2016) (1988-2014). SVIX is an option-implied lower bound of the 1-year equity premium from Martin (2017) (1996-2012). KP is the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013). BK is the filtered series for expected returns following Binsbergen and Koijen (2010).

Table A.8 One-month Return Prediction

This table reports the results of predictive regression (equation (18)). The left-hand side variable is the return of the S&P 500 index in the next month. We consider four right-hand side variables (i.e., predictors), dr_t, pd_t, filtered series for expected returns following Binsbergen and Koijen (2010) μ^F, and the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP. The β estimate is reported, followed by Hodrick (1992) t-statistic, OLS t-statistic, the coefficient adjusted for Stambaugh (1999) bias, and the in-sample adjusted R^2. We run the regression monthly. Starting from December 1997, we form out-of-sample forecasts of return in the next twelve months by estimating the regression with data up to the current month and use the forecasts to calculate out-of-sample R^2, ENC test (Clark and McCracken, 2001), and the p-value of CW test (Clark and West, 2007). Data sample: 1988:01–2019:12

	$r_{t+1/12}$				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.056	0.067	0.017	0.018	0.036
	[3.031]	[2.163]	[4.198]	[1.203]	[0.893]
	(3.302)	(2.385)	(4.158)	(1.251)	(1.130)
dr_t	-0.012				-0.017
Hodrick t	[-2.529]				[-1.427]
Newey-West t	(-2.826)				(-2.034)
pd_t		-0.015			0.011
		[-1.891]			[0.530]
		(-2.090)			(0.751)
μ_t^F			0.211		
			[2.224]		
			(2.401)		
KP_t				0.019	
				[0.656]	
				(0.680)	
R^2	0.021	0.011	0.015	0.001	0.022
OOS R^2	0.015	0.004	0.007	-0.012	0.005
ENC	2.678	1.122	1.673	-0.676	2.384
$p(ENC)$	<0.05	>0.10	<0.10	>0.10	<0.10
$p(CW)$	0.018	0.179	0.122	0.325	0.129

Table A.9 One-month Excess Return Prediction

This table reports the results of predictive regression (equation (18)). The left-hand side variable is the excess return of the S&P 500 index in the next month. We consider four right-hand side variables (i.e., predictors), dr_t, pd_t, filtered series for expected returns following Binsbergen and Koijen (2010) μ^F, and the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP. The β estimate is reported, followed by Hodrick (1992) t-statistic, OLS t-statistic, the coefficient adjusted for Stambaugh (1999) bias, and the in-sample adjusted R^2. We run the regression monthly. Starting from December 1997, we form out-of-sample forecasts of return in the next twelve months by estimating the regression with data up to the current month and use the forecasts to calculate out-of-sample R^2, ENC test (Clark and McCracken, 2001), and the p-value of CW test (Clark and West, 2007). Data sample: 1988:01–2019:12

	$r^e_{t+1/12}$				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.051	0.059	0.013	0.014	0.026
	[2.757]	[1.878]	[3.328]	[0.901]	[0.644]
	(3.016)	(2.080)	(3.316)	(0.938)	(0.814)
dr_t	-0.011				-0.018
Hodrick t	[-2.394]				[-1.504]
Newey-West t	(-2.684)				(-2.134)
pd_t		-0.014			0.014
		[-1.687]			[0.670]
		(-1.873)			(0.944)
μ^F_t			0.188		
			[1.967]		
			(2.137)		
KP_t				0.015	
				[0.514]	
				(0.535)	
R^2	0.019	0.009	0.012	0.001	0.021
OOS R^2	0.012	0.001	0.003	-0.013	0.003
ENC	2.338	0.670	1.060	-0.766	2.233
$p(ENC)$	<0.05	>0.10	>0.10	>0.10	<0.10
$p(CW)$	0.038	0.283	0.228	0.302	0.159

Table A.10 One-month Return Prediction: Fama-French MKT Return

This table reports the results of predictive regression (equation (18)). The left-hand side variable is the return of the S&P 500 index in the next month. We consider four right-hand side variables (i.e., predictors), dr_t, pd_t, filtered series for expected returns following Binsbergen and Koijen (2010) μ^F, and the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP. The β estimate is reported, followed by Hodrick (1992) t-statistic, OLS t-statistic, the coefficient adjusted for Stambaugh (1999) bias, and the in-sample adjusted R^2. We run the regression monthly. Starting from December 1997, we form out-of-sample forecasts of return in the next twelve months by estimating the regression with data up to the current month and use the forecasts to calculate out-of-sample R^2, ENC test (Clark and McCracken, 2001), and the p-value of CW test (Clark and West, 2007). Data sample: 1988:01–2019:12

	$r^{MKT}_{t+1/12}$				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.056	0.067	0.017	0.018	0.037
	[2.833]	[2.086]	[4.070]	[1.117]	[0.891]
	(3.207)	(2.332)	(4.029)	(1.185)	(1.125)
dr_t	-0.012				-0.017
Hodrick t	[-2.354]				[-1.330]
Newey-West t	(-2.742)				(-1.945)
pd_t		-0.015			0.011
		[-1.819]			[0.488]
		(-2.044)			(0.697)
μ^F_t			0.208		
			[2.091]		
			(2.306)		
KP_t				0.018	
				[0.588]	
				(0.626)	
R^2	0.019	0.011	0.014	0.001	0.021
OOS R^2	0.012	0.003	0.005	-0.014	0.003
ENC	2.227	0.876	1.275	-1.009	1.869
$p(ENC)$	<0.05	>0.10	<0.10	>0.10	>0.10
$p(CW)$	0.034	0.220	0.171	0.220	0.176

Table A.11 One-month Return Prediction: Fama-French MKT excess Return

This table reports the results of predictive regression (equation (18)). The left-hand side variable is the excess return of the S&P 500 index in the next month. We consider four right-hand side variables (i.e., predictors), dr_t, pd_t, filtered series for expected returns following Binsbergen and Koijen (2010) μ^F, and the single predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013) KP. The β estimate is reported, followed by Hodrick (1992) t-statistic, OLS t-statistic, the coefficient adjusted for Stambaugh (1999) bias, and the in-sample adjusted R^2. We run the regression monthly. Starting from December 1997, we form out-of-sample forecasts of return in the next twelve months by estimating the regression with data up to the current month and use the forecasts to calculate out-of-sample R^2, ENC test (Clark and McCracken, 2001), and the p-value of CW test (Clark and West, 2007). Data sample: 1988:01–2019:12

	$r^{MKT,e}_{t+1/12}$				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.051	0.059	0.013	0.013	0.027
	[2.576]	[1.810]	[3.221]	[0.828]	[0.646]
	(2.926)	(2.034)	(3.208)	(0.880)	(0.816)
dr_t	-0.011				-0.018
Hodrick t	[-2.228]				[-1.402]
Newey-West t	(-2.602)				(-2.042)
pd_t		-0.014			0.013
		[-1.621]			[0.623]
		(-1.830)			(0.885)
μ^F_t			0.185		
			[1.844]		
			(2.049)		
KP_t				0.014	
				[0.453]	
				(0.484)	
R^2	0.017	0.009	0.011	0.001	0.019
OOS R^2	0.010	0.000	0.001	-0.014	0.001
ENC	1.903	0.443	0.699	-1.082	1.718
$p(ENC)$	<0.10	>0.10	>0.10	>0.10	>0.10
$p(CW)$	0.065	0.340	0.297	0.205	0.209

Table A.12 Correlations with Other Return Predictors

This table shows the correlations of alternative return predictors with both dr_t and pd_t from 1988 to 2019. μ^F is the filtered demeaned expected return following Binsbergen and Koijen (2010). KP is a predictive factor extracted from 100 book-to-market and size portfolios from Kelly and Pruitt (2013). Most alternative predictors are from Goyal and Welch (2007) that include the default yield spread (dfy), the inflation rate (infl), stock variance (svar), the cross-section premium (csp), the dividend payout ratio (de), the long-term yield (lty), the term spread (tms), the T-bill rate (tbl), the default return spread (dfr), the dividend yield (dy, log difference between current-period dividend and lagged S&P 500 index price), the long-term rate of return (ltr), the earnings-to-price ratio (ep), the book to market ratio (bm), the investment-to-capital ratio (ik), the net equity expansion ratio (ntis), the percent equity issuing ratio (eqis), and the consumption-wealth-income ratio (cay). SII is the short interests index from Rapach, Ringgenberg, and Zhou (2016) (1988-2014). SVIX is an option-implied lower bound of 1-year equity premium from Martin (2017) (1996-2012). ZCB1Y is the one-year zero-coupon bond yield from Fama-Bliss.

	dr	pd
pd	0.873	1.000
μ^F	-0.892	-0.967
KP	-0.565	-0.496
SII	0.047	-0.015
SVIX	0.055	-0.304
bm	-0.778	-0.826
cay	-0.364	-0.377
csp	0.345	0.428
de	-0.245	-0.463
dfr	-0.024	0.005
dfy	-0.078	-0.273
dr	1.000	0.873
dy	-0.879	-0.990
ep	-0.558	-0.453
ik	0.664	0.657
infl	-0.100	-0.074
ltr	-0.000	-0.056
lty	-0.368	-0.425
ntis	-0.074	0.076
svar	0.149	-0.053
tbl	-0.175	-0.243
tms	-0.255	-0.217

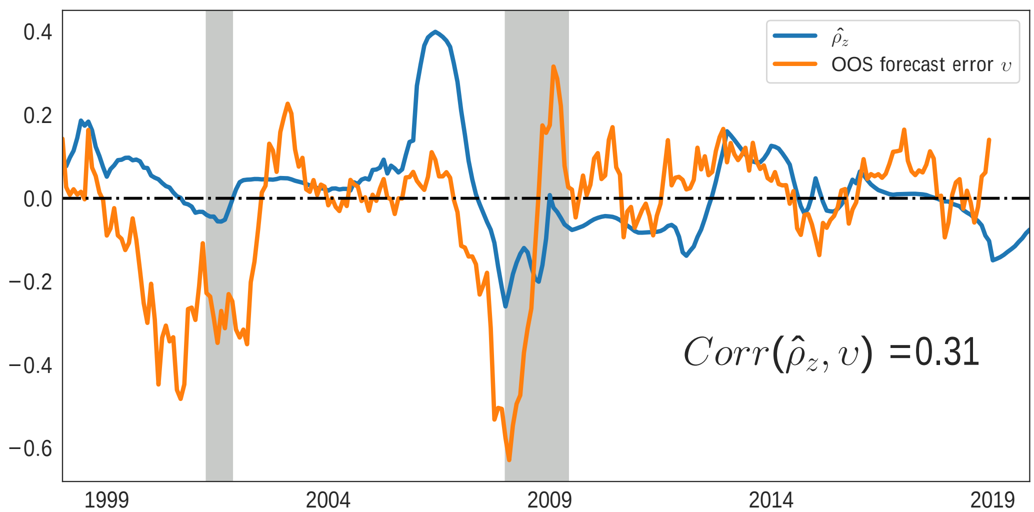


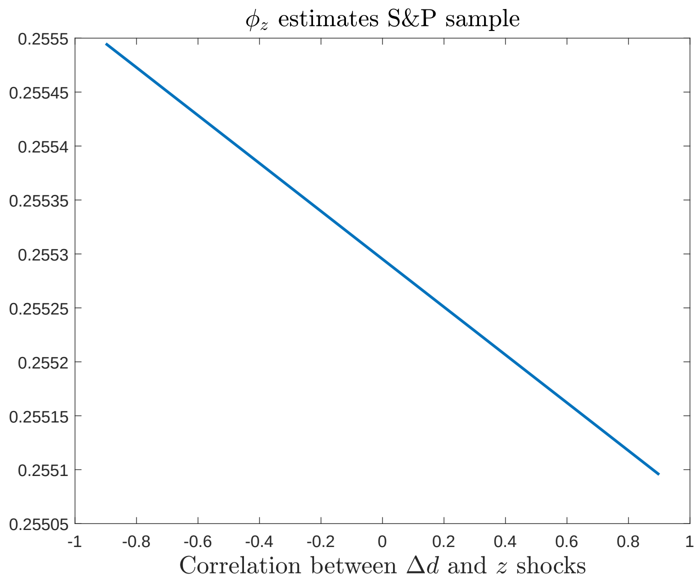
Figure A.6 Rolling Estimate of Expected Growth Persistence and Return Prediction Errors: OOS

This figure plots the rolling estimate of the autoregressive coefficient of expected cash flow growth, $\hat{\rho}_{z,t}$, and the return prediction errors using market duration (dr_t) as the predictor. $\hat{\rho}_{z,t}$ is estimated using analyst forecasts of S&P 500 aggregate earnings in rolling regressions with a three-year window. This figure also plots the out-of-sample forecast errors $\hat{v}_t$, which is calculated as the difference between the realized one-year S&P 500 return and the one-period-ahead return forecast using dr_t as the predictor. The first out-of-sample forecast starts in 1998. The correlation between the two time series is also reported on the graph. Our monthly sample is 1988:01–2019:12.

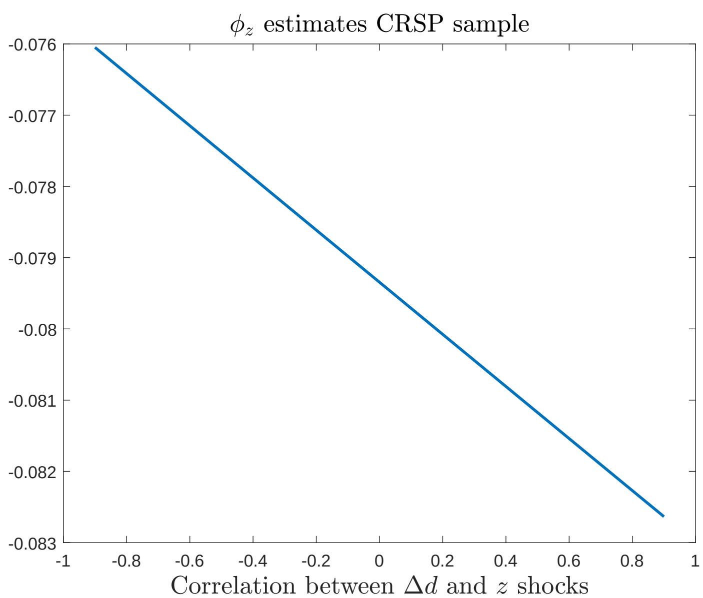
Table A.13 Time-varying ρ_z and Return Predictability

This table reports results from regressions that link return predictability from Duration (dr_t) to the time-varying expected cash-flow growth persistence ($\hat{\rho}_z$). The dependent variables are in-sample residuals (ε_t) from return predictive regressions (Column 1) and out-of-sample return forecast errors (Column 2). The independent variable is the time-varying expected cash-flow growth persistence ($\hat{\rho}_z$), estimated in three-year rolling windows. t-statistics calculated based on Newey-West standard errors with 18 lags are reported in parentheses. Data sample: 1988:01–2019:12.

	$\hat{\varepsilon}_t$	v_t
Intercept	-0.011	-0.046
	(-1.127)	(-4.076)
$\hat{\rho}_{z,t}$	0.556	0.469
	(5.143)	(4.599)
N	252	252
R^2	0.173	0.094



A. S&P 500 dividend



B. MKT dividend

Figure A.7 ρ_z Estimates from the State-Space Model with Correlated Shocks. This figure reports the expected dividend growth autoregressive coefficient ρ_z point estimates in unrestricted state-space models as in Section 2 with different correlations of Δd and z shocks. The correlations of Δd and z shocks range from -0.9 to 0.9 and the volatility of Δd shock is calibrated to the estimated $\hat{\sigma}_D$ from the state-space model with uncorrelated shocks. Panel A uses the annual dividend growth (non-overlapping) of the S&P 500 index, and Panel B uses the annual dividend growth (non-overlapping) of the Fama-French market portfolio.

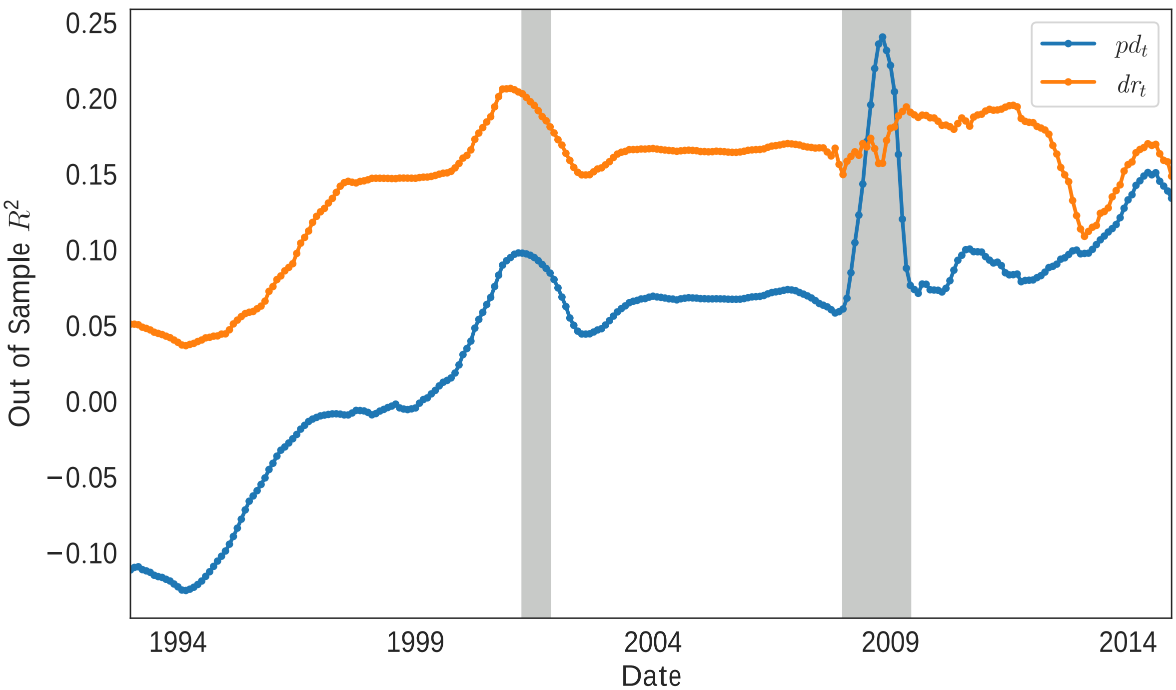
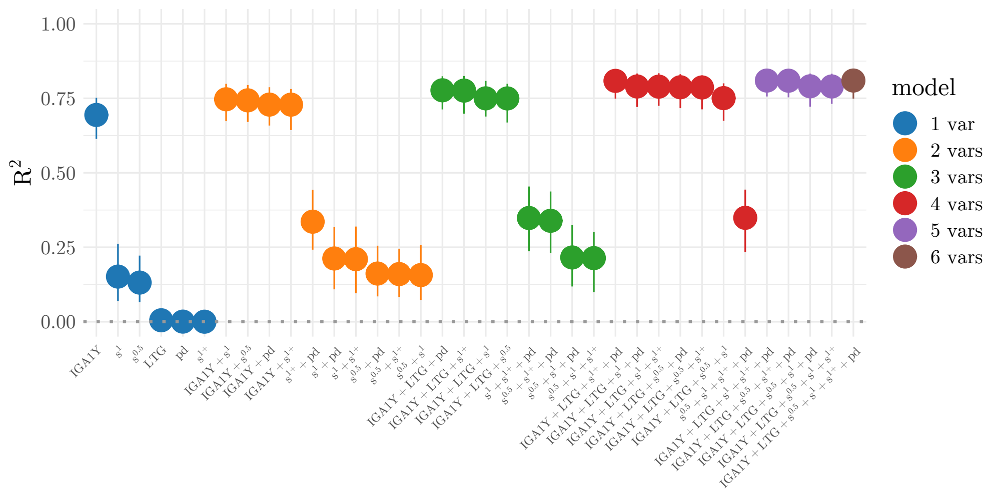
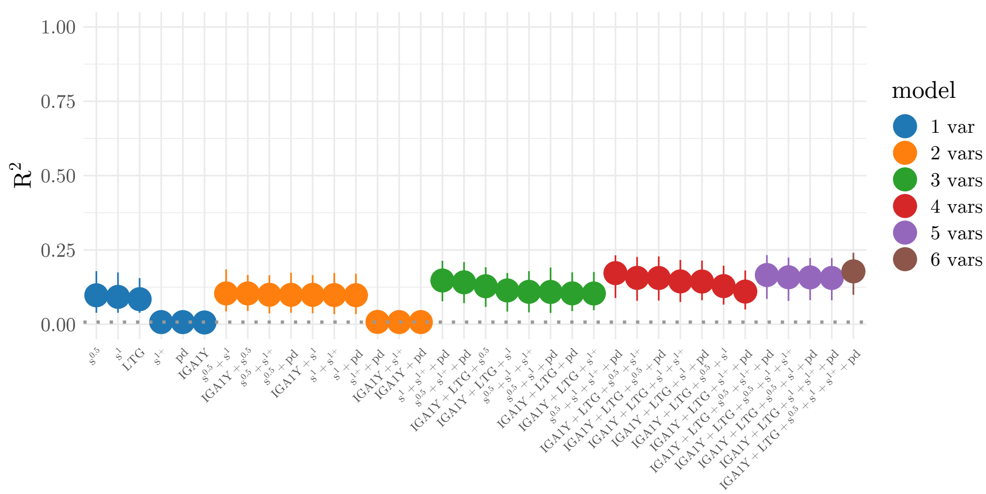


Figure A.8 Out-of-sample R^2 by Sample Split Date.

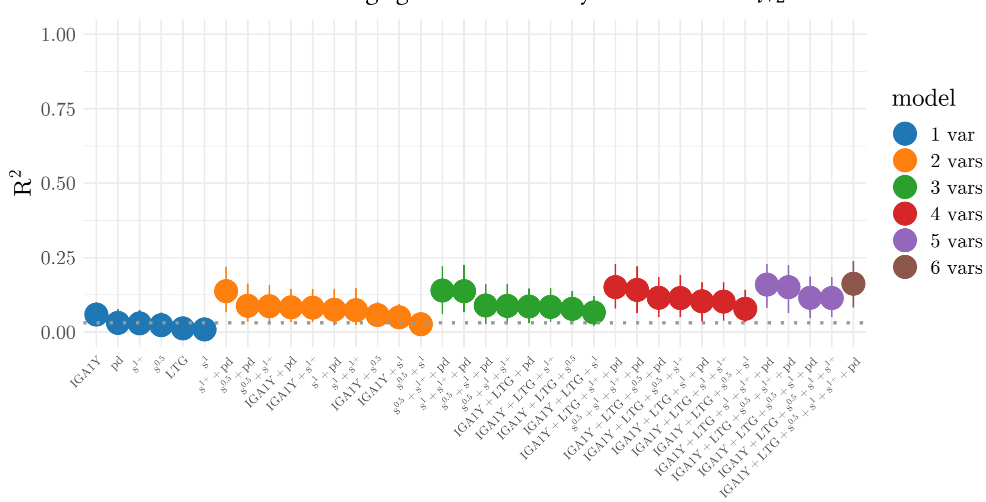
This graph reports the out-of-sample R^2 of 1-year return prediction with different sample split dates. The first and last out-of-sample split dates are Jan 1993 and Jun 2015, respectively.



A. IGA one-year earnings growth Δe_{t+1}



B. IGA earnings growth between years 1 and 2 Δe_{t+2}



C. IGA earnings growth between years 2 and 3 Δe_{t+3}

Figure A.9 R^2 from Earnings Growth Predictive Regressions at Various Horizons with Bootstrapped Confidence Interval.