Equity Yields, Investor Expectations, and the Prediction of Dividend Growth

Hang Dong*

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I develop a state-space model that leverages equity yields to forecast dividend growth rates. By integrating proprietary over-the-counter (OTC) dividend swap data with synthetic equity yields from Giglio et al. (2024), I construct an extended dataset to model dividend growth expectations. Unlike the present-value approach of Binsbergen and Koijen (2010), which relies on price-dividend ratios, I propose equity yields—derived from dividend futures—as superior predictors given their forward-looking nature and closer alignment with near-term economic conditions. Our model demonstrates strong in-sample accuracy across major indexes, including the S&P 500, Euro Stoxx 50, Nikkei 225, and FTSE 100, and outperforms the present-value method in out-of-sample tests, particularly during economic downturns, owing to its enhanced ability to capture investor sentiment through the fixed maturity characteristic of dividend derivatives. In the U.S., it predicts one-year-ahead dividend growth out of sample with an R^2 of up to 16.5% over the past 28 years. By applying a state-space model to extract investor expectations from equity yields for forecasting dividend growth, my findings highlight the critical role of investor expectations in dividend forecasting and provide empirical evidence for dividend growth predictability, particularly during economically turbulent years.

Keywords: dividend futures, equity yields, Kalman filter, dividend growth

∗Hang Dong is with the Terry College of Business at the University of Georgia. E-mail: hang.dong@uga.edu. The author declares that no funding was received for this research and have no financial or other conflicts of interest to disclose.

Introduction

This paper investigates whether investor expectations can be leveraged to forecast key economic variables, particularly dividend growth. Dividend expectations serve as a vital indicator for both the economy and financial markets. Aggregate dividends, which represent the total distributions made by corporations to shareholders, mirror the broader economic environment, offering insights into overall economic health and corporate profitability. Beyond their economic importance, dividend expectations play a pivotal role in shaping investor behavior and market dynamics within stock markets. They impact how investors assess the value of stock market assets, as anticipated future cash flows directly influence stock prices and investment decisions.

Extensive research has explored various methods for modeling predictability, with Binsbergen et al. (2013) suggesting that equity yields constructed from dividend strip data can serve as strong predictors of dividend growth. However, the predictive power of equity yields has historically been constrained by the limited length of available dividend strip data [1]. Addressing this issue, Giglio et al. (2024) make a significant contribution by leveraging the cross-section of equity returns to estimate their affine model, enabling them to price market dividend strips without directly relying on strip data. They construct a synthetic dataset of equity yields for the U.S. market, extending back to 1974.

Building on this advancement, and with the help of proprietary over-the-counter (OTC) dividend swap data provided by a major financial institution active in the dividend strips market—spanning from their inception to 2023—I compile a comprehensive 50-year dataset of equity yields for the U.S. market. This dataset combines equity yields calculated from real dividend derivative trading data since 2003 with synthetic equity yields for earlier periods. Leveraging this unique dataset, I develop a state-space model that utilizes equity yield data to investigate the predictability of dividend growth. My approach aims to overcome historical data limitations and provide a robust framework for forecasting dividend growth across both in-sample and out-of-sample contexts.

My approach is motivated by Binsbergen and Koijen (2010), who employ a present-value framework to estimate expected returns and dividend growth rates. Their study extracts aggregate information embedded in the price-dividend (pd) ratio, successfully uncovering unobserved expected

[1] The earliest dividend futures emerged in 2002 in the OTC market for the Euro Stoxx 50 index and were later listed on an exchange in 2008. S&P 500 dividend futures began trading on exchanges in late 2015.

dividend growth and returns in-sample. However, their model exhibits only modest predictive power when applied out-of-sample, offering limited improvement over standard predictive regressions. As an alternative, I propose forecasting expected dividend growth using equity yields, defined as the logarithmic ratio of the current dividend level to a dividend strip for a specific future period. Notably, dividend strip prices are not directly observable in spot markets, as they are typically traded in futures or swap markets. Therefore, I construct equity yields using dividend futures prices.[2]

Dividend futures contracts are financial instruments that represent direct claims on future dividends to be paid in a specific year by an underlying index (or by a single stock, in the case of single-stock dividend futures). At maturity, the long position pays the predetermined futures price, while the short position delivers the dollar amount of dividends distributed by the underlying index. Unlike conventional metrics used to predict returns and dividend growth, such as the dividend-price ratio (dp) —where the index level reflects the discounted value of cash flows with an infinite maturity horizon—dividend futures have a fixed maturity tied to a specific calendar year. This unique characteristic of dividend futures allows us to extract investor expectations for a specific time horizon.

Initially introduced in the early 2000s, dividend swap contracts were exclusively traded in the over-the-counter (OTC) market before transitioning to listed futures contracts (Mixon & Onur, 2017). This shift began with the launch of Euro Stoxx 50 dividend futures on Eurex in June 2008, followed by FTSE 100 Dividend Index Futures in May 2009 and Nikkei 225 Dividend Futures on the Singapore Exchange in June 2010. Notably, the U.S. market did not introduce listed dividend futures until late 2015.

In this paper, I utilize proprietary dividend futures data provided by a major financial institution active in the dividend strips market. This institution supplied over-the-counter (OTC) markings of dividend swaps for periods preceding the official listing of each index's dividend futures, as well as dividend futures data post-listing, covering the period up to December 2023. The dataset includes these instruments for the S&P 500, Euro Stoxx 50, Nikkei 225, and FTSE 100. As a result, it offers the most extensive historical coverage available for dividend strip derivatives across these four markets, spanning the entire lifespan of these markets since these inception.

However, due to the relatively late emergence of this derivative class, the earliest dividend

[2]Spot and futures prices are linked through nominal bond yields.

futures only appeared globally in 2002. As a result, the length of available data remains limited. To address this constraint, I extend my dataset in the U.S. market by incorporating synthetic dividend strip yield data reconstructed by Giglio et al.(2024). Their approach uses a large set of cross-sectional data on equity returns to estimate an affine model, allowing them to price dividend strips without relying on actual strips data. They construct a synthetic dataset of equity yields for the U.S. market, extending back to 1974, which closely matches yields on traded strips during the overlapping period.

By combining equity yields calculated from traded dividend derivative contract pricing (available since 2003) with the synthetic yields constructed by Giglio et al. (2024) for the pre-2003 period, I create a comprehensive 50-year equity yields dataset for the U.S. market, spanning from 1974 to 2023. This augmented dataset enables a more robust analysis of the dynamics of equity yields and their relationship with other macroeconomic variables.

Leveraging this extended dataset, I first examine the relationship between the one-year equity yield and NBER-defined recession periods. I find a strong correlation between the one-year equity yields and all U.S. recessions identified by the NBER. Specifically, one-year equity yields tend to rise before and during recessions, peaking as economic conditions deteriorate, and then decline to a low point after recessions end. This pattern is particularly pronounced during the two most recent recessions—the Great Recession of 2008 and the COVID-19 recession of 2020. These findings suggest that one-year equity yields exhibit predictive properties, which I incorporate into my model to forecast dividend growth.

I then apply my state-space model to this comprehensive dataset, using the entire period of data (1974–2023) to estimate the model parameters. Using these parameters and the equity yields data, I generate forecasts of dividend growth to evaluate the model's in-sample performance. My model achieves an in-sample R^2 value of 30.08% for cash-reinvested dividend growth over the study period. In contrast, Binsbergen and Koijen (2010), who use the price-dividend (pd) ratio and a state-space model, report an in-sample R^2 value of 13.9% for cash-reinvested dividend growth over their study period of 1946–2007. While the study periods differ, their lengths are broadly comparable. My model, which incorporates the one-year equity yields as a predictor, demonstrates a notable improvement in the in-sample fit for U.S. market dividend growth compared to the approach of Binsbergen and Koijen (2010).

I also conduct the in-sample analysis for Europe, Japan, and the U.K., using equity yields calculated solely from traded dividend derivative pricing. Unlike the U.S. market, synthetic equity yield data are not available for these regions. As a result, the analysis is limited to the periods during which one-year equity yields data exist: 2002–2023 for Europe and 2004–2023 for both Japan and the U.K. For these shorter sample periods, I observe high in-sample R^2 values across these markets: 48.86% for Europe, 61.55% for Japan, and 28.40% for the U.K.

I evaluate the model's real-time forecasting capability through out-of-sample testing. By integrating traded dividend derivative contract pricing with the synthetic equity yields dataset from Giglio et al. (2024), I construct a comprehensive 50-year equity yields dataset for the U.S. market. This extended dataset ensures that the annual time series is sufficiently long to enable reliable parameter estimation and robust out-of-sample evaluation. My model's one-year-ahead expected dividend growth predictions achieve an an out-of-sample R^2 of 16.5% over the past 28 years, demonstrating its strong forecasting accuracy

This paper makes two contributions to the field:

1. I construct a state-space model using dividend futures pricing data, offering a robust alternative to existing methods for forecasting dividend growth. This approach delivers improved in-sample fit and superior out-of-sample forecasting accuracy across major markets. Building on the foundational work of Binsbergen and Koijen (2010), who modeled expected returns and dividend growth as latent processes using state-space techniques, and Binsbergen et al. (2013), who introduced equity yields and explored their predictive power for dividend growth, my study integrates equity yield data into a state-space framework to derive expected dividend growth. Specifically, I focus on forecasting one-year-ahead dividend growth, following the methodology of Binsbergen and Koijen (2010). Unlike conventional metrics such as the dividend yield[3] —which reflects discounted cash flows over an infinite horizon—dividend futures have fixed maturities tied to specific calendar years, enabling us to extract investor expectations for precise time horizon. This feature allows for a more targeted and granular understanding of market sentiment, enhancing forecasting accuracy. Using equity yields derived from dividend swap and futures data, my model demonstrates improved in-sample predictive accuracy, and significantly outperforms Binsbergen and Koijen (2010)'s

[3]Binsbergen and Koijen (2010) utilize the reciprocal price-dividend ratio

present-value model in out-of-sample tests.

2. My findings provide empirical evidence supporting the predictability of dividend growth. In out-of-sample tests for the U.S. market, my model significantly outperforms the historical mean in predicting one-year-ahead dividend growth. By relying on equity yields—which encapsulate investor expectations about future dividends—as the sole predictor, I confirm the critical role of these expectations in capturing the predictable component of dividend growth. The model demonstrates a pronounced predictive advantage during economic turmoil, successfully forecasting the Great Recession by capturing extreme market fluctuations through shifts in investor sentiment. However, it fails to predict the COVID-19 recession across the S&P 500, Euro Stoxx 50, Nikkei 225, and FTSE 100, highlighting its reliance on investor expectations and its limitations during unprecedented events. These results validate the model's potential to leverage expectations for recession prediction and underscore the predictability of dividend growth, particularly during periods of economic instability.

The paper is organized as follows: Section 1 reviews the related literature. Section 2 provides a detailed discussion of the data used in the study and their sources. In Section 3, I introduce the concept of equity yields as constructed in the original paper and demonstrate their potential as a predictor by examining their connection with NBER recessions. This section also outlines the model setup, the framework of the proposed alternative approach, and the derivation of the methodology. Section 4 discusses parameter estimation and presents the average parameter estimates across the estimation period. Section 5 presents the empirical results, evaluating both the model's in-sample and out-of-sample performance. Section 6 conducts robustness tests. Finally, Section 7 summarizes the findings.

1 Related Literature

This paper relates to two strands of literature. First, it aligns with the field of stock return and dividend growth predictability. The use of predictive regression models for forecasting stock returns is heavily influenced by the seminal work of Campbell and Shiller (1988), who formalized the relationship between stock prices, dividends, and expected returns. They introduced a log-linearized present value model and provided evidence that the log dividend-price ratio is associated with expected returns. Goyal and Welch (2008), however, examined a broad set of predictors from the literature and found that most models fail to predict returns out of sample. In contrast, Campbell and Thompson (2008) argued that imposing restrictions on predictive regressions can improve their performance, allowing them to outperform the historical average returns. Subsequent research, such as Cochrane (2008) and Pástor and Stambaugh (2009), has further explored the use of various predictive variables and regression-based approaches to forecast returns.

While stock return predictability has been extensively documented, the predictability of dividend growth has been more controversial. Cochrane (2008) argues that return predictability is more robust than dividend growth predictability, emphasizing that much of the variation in the dividend-price ratio is driven by expected returns rather than expected dividend growth. Chen (2009) examines how return and dividend growth predictability have evolved over time and finds that dividend growth predictability weakens significantly in the postwar period, though it does not entirely disappear. However, evidence from Chen et al. (2013) challenges this view by demonstrating that expected dividend growth plays a significant role in driving stock price movements, particularly over longer horizons. More recently, De La O and Myers (2021), using survey forecasts, provide additional support for the view that cash flow growth expectations explain the majority of movements in the price-dividend ratio.

Binsbergen and Koijen (2010) advance this literature by modeling expected returns and expected dividend growth as latent processes. They integrate the present-value model into a state-space framework and employ Kalman filter techniques to estimate these variables. Building on the framework developed by Binsbergen and Koijen (2010), this paper incorporates equity yield derived

from dividend futures pricing data to construct a state-space model for estimating expected dividend growth. The paper then evaluates the out-of-sample predictability of these estimates against realized values.

This paper is also related to the dividend futures literature, a field that has advanced significantly since the seminal work of Binsbergen et al. (2013). Their study introduced dividend futures as a novel class of assets and provided a framework for analyzing the term structure of the equity risk premium. This foundational work has spurred a series of important studies, offering valuable insights into the dynamics of equity risk premia across different time horizons.

A key contribution to this literature comes from Binsbergen and Koijen (2017), who document a notable deviation from traditional asset pricing models. They find that short-maturity dividend claims exhibit higher risk premia and Sharpe ratios compared to long-maturity claims and the aggregate stock market. This downward-sloping pattern of risk premia has been consistently observed across major markets, including the United States, Europe, Japan, and the United Kingdom. Subsequent research has further explored the shape and dynamics of the equity risk premium term structure. For example, Gormsen (2021) extends the single-priced risk factor model to a two-priced risk factor framework, demonstrating that the equity risk premium exhibits counter-cyclical behavior. More recently, Ulrich et al. (2023) use subjective dividend growth forecasts to construct the term structure of the dividend risk premium, finding that while its level moves counter-cyclically, its slope tends to move pro-cyclically.

Despite these advancements, challenges remain in this field. A critical issue raised by Bansal et al. (2021) is the relatively short sample of available dividend futures data, which may not fully capture the true distribution of the term structure. They argue that this limited sample could introduce a downward bias in estimating the slope of the equity term structure.

Giglio et al. (2024) address this limitation by proposing an innovative approach that uses the cross-section of equity returns to estimate an affine model, enabling them to price market dividend strips without directly relying on strip data. Instead, they construct a synthetic dataset of equity yields that closely aligns with the yields of traded strips during the overlapping period. Building on this advancement, I leverage proprietary over-the-counter (OTC) dividend swap data to compile a comprehensive 50-year dataset of U.S. equity yields, combining real dividend derivative trading data

since 2003 with synthetic estimates for earlier periods. The fixed-maturity structure of dividend futures allows us to disentangle cash flow expectations over different time horizons, offering a more precise isolation of near-term investor expectations compared to traditional dividend yield metrics, which aggregate all future cash flows. By integrating equity yields from both actual traded futures prices and the synthetic dataset of Giglio et al. (2024) into a state-space model, I enhance out-of-sample forecasting accuracy for future dividend growth. This approach not only overcomes data limitations but also provides a more refined understanding of investor expectations across different horizons.

2 Data

My analysis focuses on dividends from four major markets: the US, Europe, Japan, and the UK. Dividend futures pricing data for these markets is sourced from a leading financial institution active in the dividend strips market.

For US aggregate market, I obtain the market dividend by taking both the value weighted index with-dividend and without-dividend monthly returns from the Center for Research in Security Prices (CRSP) for the period from 1974 to 2023. The difference between these returns are used to compute the monthly dividend on this value-weighted portfolio. For the analysis of annual dividend growth, I assume that dividends paid each month are reinvested at the 30-day Treasury bill rate within the same year[4]. These data are used to compute annual aggregate dividends for my analysis, avoiding the seasonality issue inherent in dividend payments (e.g., Lettau and Ludvigson, 2005; Binsbergen and Koijen, 2010; Zhu, 2015). For Europe, Japan, and the UK, I obtain monthly return data for the Euro Stoxx 50, Nikkei 225, and FTSE 100 indices, both with and without dividend distributions, from Bloomberg. The difference between these two returns is used to calculate the monthly dividends for each index. [5]

[4]Following the literature, I use cash-reinvested dividends to compute annual dividend growth. However, for equity yield calculations, I use non-reinvested D_t, as dividend futures do not account for dividend reinvestment within the year.

[5]I focus my analysis on the overall U.S. market rather than the dividends of the S&P 500 for the following reasons: Before the launch of futures, I rely on the synthetic equity yield data provided by Giglio et al.(2024). They offer equity yield data for both the overall market and the S&P 500. However, their overall market equity yield data has undergone significantly more rigorous validation compared to that of the S&P 500. Additionally, my analysis shows that the overall market equity yield data performs substantially better in my state-space model compared to the S&P 500 equity yield data.

Equity yields, as proposed by Binsbergen et al.(2013), are used to predict dividend growth in my analysis. Analogous to bond yields, equity yields are defined as the logarithmic ratio of current level of dividends to the dividend strip price, $\frac{1}{n}log(\frac{D_t}{P_{t,n}})$. Since dividend strip assets are not directly traded in the spot market, I use dividend futures prices, which represent claims to future aggregate dividends of an index at pre-agreed price for a specified future period, to construct equity yields. [6]

Although S&P500 dividend futures are currently listed on exchanges, most historical prices originate from over-the-counter (OTC) trades and are not publicly available[7]. In this paper, I use proprietary dividend futures data provided by a major financial institution active in dividend strips market. This institution supplied their OTC markings of dividend swaps for dates prior to the official listing of each index dividend futures as well as the equivalent after the listing. [8]The dataset includes daily prices, open interest, and trading volumes for S&P 500, Euro Stoxx 50, Nikkei 225, and FTSE 100 dividend futures.

The coverage periods are as follows:

1. January 2003 to December 2023 for S&P 500
2. January 2002 to December 2023 for Euro Stoxx 50
3. January 2004 to December 2023 for Nikkei 225
4. December 2004 to December 2023 for FTSE 100

[9]

However, due to relatively late emergence of this type of derivative, even the earliest dividend futures only appeared globally in 2002. Consequently, the length of available data remains limited even today. For the US market, I extend the dataset by incorporating synthetic dividend strip yield data reconstructed by Giglio et al.(2024). This ensures that the annual time series dataset is

[6]See Binsbergen et al.(2013).

[7]S&P500 index futures was listed since November 2015.

[8]After the listing of dividend futures, daily closing prices and volume data became publicly available. The dataset I received aligns exactly with the publicly available data for each day following the listing of the respective dividend index futures across four markets. However, relying solely on the annual time series derived from this publicly available data is insufficient for reliable parameter estimation—particularly for the S&P 500, which was listed only at the end of 2015.

[9]Euro Stoxx 50 index futures was listed in June 2008; Nikkei 225 index futures was listed in June 2010; FTSE 100 index futures was listed in May 2009.

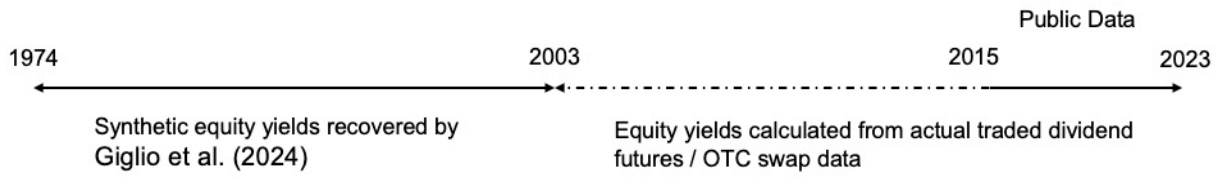


Figure 1: Data Sources for US Equity Yields

I construct a comprehensive dataset of time series for the US equity yields by integrating two primary data sources. For the period from 1974 to 2002, I utilize synthetic equity yields as published in Giglio et al.(2024). From 2003 to 2023, I incorporate equity yields derived from proprietary over-the-counter (OTC) dividend swap and futures pricing data, provided by a major financial institution active in the dividend strips market. Notably, since November 2015, S&P 500 dividend futures pricing data have been publicly available following their listing on the Chicago Mercantile Exchange (CME).

sufficiently long to enable reliable parameter estimation and robust out-of-sample evaluation of my methodology.

Giglio et al.(2024) [10]provide a dataset of aggregate market equity yields in the US, derived from an affine model without using any dividend strip data. Notably, they demonstrate that their reconstructed equity yields closely align with those calculated from actual traded dividend futures prices by comparing their results with Bansal et al. (2017) over the overlapping period[11]. The synthetic dividend strip yield data spans from January 1974 to November 2020. For my analysis, I incorporate Giglio et al.(2024)'s data prior to 2003—covering a period when the OTC market did not yet exist—resulting in a final dataset of equity yields ranging from January 1974 to December 2023. The specific composition of this dataset is more clearly illustrated in Figure 1.

[10]Giglio et al.(2024) admitted themselves that their synthetic diviend yields are not point-by-point precise, and they are inevitably subject to estimation uncertainty. However, the purpose to extend the relatively short time series of dividends strip is to enable more precise estimation of moments, compared to relying solely on the shorter observable time series of dividend strips.

[11]See Giglio et al.(2024)

For US aggregate market, I use the difference between the value weighted index with-dividend and without-dividend monthly returns to compute the monthly dividend on this value-weighted portfolio. For the analysis of annual dividend growth, I assume that dividends paid each month are reinvested at the 30-day Treasury bill rate (the risk-free rate) within the same year. Panel A of Table 1 reports the realized dividend growth rates for the U.S. aggregate market over the study period from 1974 to 2023.

Panel B presents the summary statistics for the monthly forward equity yields across all four indexes and five maturities. However, only the annual time series of equity yields and the yields with one-year maturities[12] are used in the subsequent analysis. For the U.S., I report only the monthly equity yields derived from dividend swap and futures pricing data. For further details on the synthetic equity yield dataset, refer to Giglio et al.(2024).[13] In line with Binsbergen and Koijen (2017), I find the volatilities of the yields decline monotonically with maturity for across four indexes.

3 Equity Yields and the Model

In this section, I begin by introducing the concept of equity yields and then explain how it is incorporated into the model used to derive expected dividend growth.

3.1 Equity Yields

Using dividend strip asset prices, Binsbergen et al.(2013) define equity yields, analogous to bond yields, to examine the term structure of risk premia. Based on their methodology, the forward equity yields at time t with maturity n can be calculated as the logarithmic ratio of current level of dividends to the price of n-year maturity dividend futures. This yield can further be decomposed into two components: the term structure of expected dividend growth and the term structure of risk premia:

[12] One-year equity yields are the most sensitive and arguably the most effective predictor to include in my model.
[13] See https://serhiykozak.com/#/data-code

Δd_t	
	1974-2023
Mean	0.0639
Median	0.0709
St.dev.	0.0747
Maximum	0.2677
Minimum	-0.1913

(a) Summary Statistics of Dividend Growth Rates of U.S. aggregate market, reinvested at the 30-day Treasury bill rate

Maturity in years	1y	2y	3y	4y	5y
S&P500: January 2003 – December 2023					
Mean	-0.0391	-0.0337	-0.0306	-0.0290	-0.0271
St.dev.	0.0880	0.0615	0.0442	0.0372	0.0331
Eurostoxx 50 January 2002 – December 2023					
Mean	0.0074	0.0208	0.0207	0.0201	0.0188
St.dev.	0.1293	0.1009	0.0713	0.0544	0.0439
Nikkei 225: January 2004 – December 2023					
Mean	-0.0188	-0.0185	-0.0194	-0.0180	-0.0153
St.dev.	0.0965	0.0918	0.0713	0.0582	0.0497
FTSE 100: December 2004 – December 2023					
Mean	-0.0088	0.0045	0.0098	0.0204	0.00
St.dev.	0.1082	0.0859	0.0608	0.0742	0.0742

(b) Summary Statistics of Monthly Forward Equity Yields

Table 1: Summary Statistics

Forward equity yields are calculated as $e^f_{t,n} = \frac{1}{n} ln(\frac{D_t}{F_{t,n}})$, where D_t represents the trailing sum of 12-month dividends ; $F_{t,n}$ denotes the n-year constant-maturity dividend futures prices. The difference between forward equity yields and equity yields are n-year government nominal bond yields $y_{t,n}$: $e^f_{t,n} = e_{t,n} - y_{t,n}$.

Please note that following the literature, I use cash-reinvested dividends to compute annual dividend growth. However, for equity yield calculations, I use non-reinvested D_t, as dividend futures do not account for dividend reinvestment within the year.

* From January to October 2015, the 4-year US equity yield data is unavailable. From January 2014 to October 2015, the 5-year US equity yield data is unavailable.
* From December 2014 to May 2015 the 4-year UK equity yield data is unavailable. From December 2013 to May 2015, the 5-year UK equity yield data is unavailable

$$e^f_{t,n} = \frac{1}{n} log\left(\frac{D_t}{F_{t,n}}\right) = \theta_{t,n} - g_{t,n}$$

Here, D_t represents the trailing sum of 12-month dividends at time t. $F_{t,n}$ denotes the price of an n-year constant-maturity dividend futures contracts. [14] $\theta_{t,n}$ denotes the risk premium that compensates investors for bearing dividend risk for maturity n. Finally, $g_{t,n}$ represents the average per-period expected dividend growth over the next n years:

$$g_{t,n} = \frac{1}{n} E_t\left[log(\frac{D_{t+n}}{D_t})\right]$$

For n=1 case, I have one-year forward equity yield as

$$e^f_{t,1} = log\left(\frac{D_t}{F_{t,1}}\right) = \theta_{t,1} - g_{t,1} = \mu_{t,1} - y_{t,1} - g_{t,1} \tag{1}$$

where $\mu_{t,1}$ represents the expected returns on a one-period dividend strip, defined as $\mu_{t,1} = log(\frac{D_{t+1}}{F_{t,1}})$, and $y_{t,1}$ denotes nominal one-year government bond yields. For simplicity, throughout the paper, I use μ_t and g_t to refer to the one-period-ahead expected returns ($\mu_{t,1}$), and one-period-ahead expected dividend growth ($g_{t,1}$), respectively.

Meanwhile, equity yields at time t with maturity n are defined as the logarithmic ratio of current level of dividends, D_t, to the current price of the n-year-ahead dividend strip, $P_{t,n}$

$$e_{t,n} = \frac{1}{n} log\left(\frac{D_t}{P_{t,n}}\right)$$

Under no-arbitrage condition, spot prices and futures prices of dividend strips is connected through n-year nominal government bond yields: $F_{t,n} = P_{t,n} exp(n y_{t,n})$. Therefore, I have

$$e_{t,n} = \frac{1}{n} log\left(\frac{D_t}{F_{t,n}}\right) + y_{t,n}$$

Thus, the difference between equity yields and forward equity yields is simply the nominal

[14] The constant-maturity dividend futures contracts are obtained through interpolation over different maturities. See Binsbergen et al.(2013) and Binsbergen and Koijen (2017).

government bond yield $y_{t,n}$:

$$e_{t,n} = e^f_{t,n} + y_{t,n} \tag{2}$$

For the case where $n = 1$, the following relationship connects the one-year equity yield $e_{t,1}$, the expected return on a one-period dividend strip μ_t and one-period ahead expected dividend growth g_t:

$$e_{t,1} = e^f_{t,1} + y_{t,1} = \mu_t - g_t \tag{3}$$

Equation (3) is the key relation used to derive the one-period-ahead expected dividend growth, which will be introduced in the next section. Before proceeding, I first demonstrate how my forward-looking measure of dividend expectations, equity yields, may have predictive power for economic outcomes, such as dividend growth. Specifically, I examine the correlation between equity yields and U.S. business cycles, as illustrated in Figure 2.

The grey bars represent all recession periods in the US as identified by the NBER since the availability of my equity yields dataset, starting in 1974. As depicted by the solid line in Figure 2, from January 2003 onward, monthly equity yields are calculated using actual traded dividend futures prices. Prior to this, monthly equity yields, shown by the dashed line, are sourced from the dataset provided by Giglio et al.(2024).

Both sources reveal a consistent pattern: with the exception of the March–November 2001 recession, one-year equity yields tend to rise prior to and during recession periods, subsequently declining to a low point after recessions end. This trend is particularly pronounced in the two most recent recessions—the Great Recession of 2008 and the COVID-19 recession of 2020—when equity yields were derived from actual traded futures prices. Figure 2 underscores the close relationship between the one-year equity yield, and economic conditions, suggesting it may serve as a leading indicator.

In the following sections, I will explore whether investors' expectations, as reflected in equity yields from futures prices, can be extracted to serve as a useful tool for forecasting economic variables, such as dividend growth.

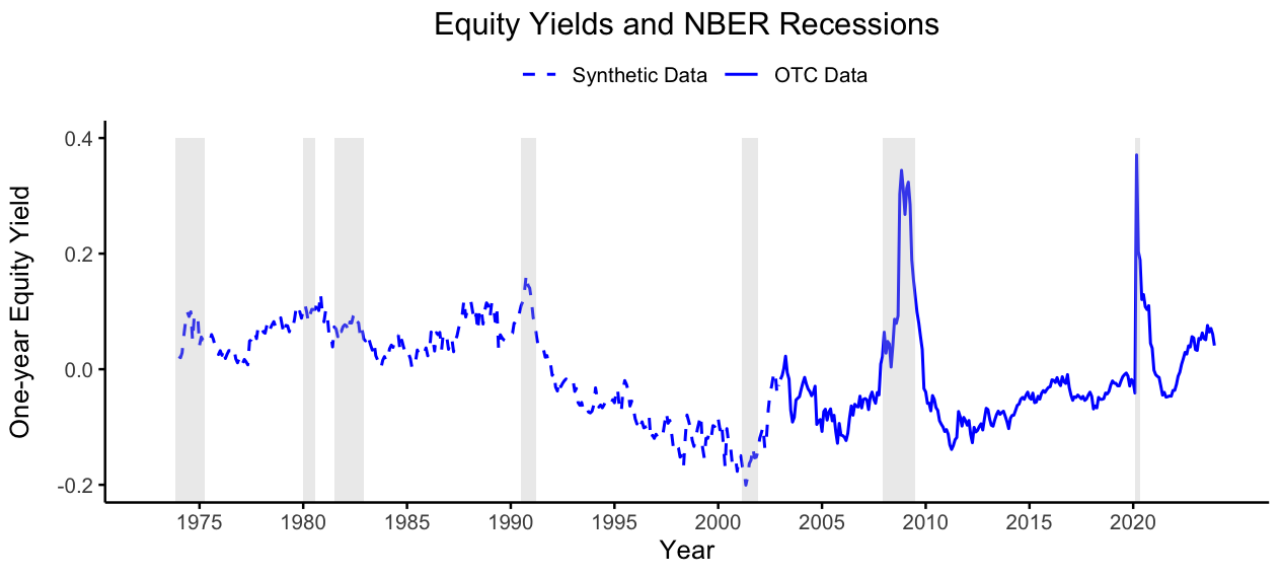


Figure 2: Equity Yields and NBER Recessions

In this figure, I illustrate the relationship between the one-year equity yield and NBER recessions. One-year equity yields typically rise before and during recession periods, then decline to a low point after recessions end. This trend is especially evident during the two most recent recessions—the Great Recession of 2008 and the COVID-19 recession of 2020.

Since January 2003, equity yields have been calculated using dividend futures prices, depicted by the solid line. Prior to that, monthly equity yields were derived from the dataset provided by Giglio et al.(2024), depicted by the dashed line. Equity yields across various maturities generally move synchronously(see Binsbergen et al.(2013) and Giglio et al.(2024)). For my analysis, I focus on one-year equity yields to illustrate the pattern, as this is the most sensitive yield measure and the predictor used in my model to forecast dividend growth. The one-year equity yield is calculated as $e_{t,1} = ln(\frac{D_t}{F_{t,1}}) + y_{t,1}$.

3.2 The State-Space Model

Let $F_{t,1}$ denote the price of one-year constant-maturity dividend futures, and r_{t+1} represent the realized log return from holding this contract until maturity,

$$r_{t+1} \equiv log(\frac{D_{t+1}}{F_{t,1}})$$

let Δd_{t+1} denote the realized log dividend growth rate,

$$\Delta d_{t+1} \equiv log(\frac{D_{t+1}}{D_t})$$

Following Binsbergen and Koijen (2010) , I assume an AR(1) process for expected dividend growth rates (g_t) and expected returns (μ_t)[15].

$$\mu_{t+1} = \delta_0 + \delta_1 \hat{\mu_t} + \epsilon^{\mu}_{t+1} \tag{4}$$

$$g_{t+1} = \gamma_0 + \gamma_1 \hat{g_t} + \epsilon^{g}_{t+1} \tag{5}$$

where

$$\mu_t \equiv E_t[r_{t+1}]$$

$$g_t \equiv E_t[\Delta d_{t+1}]$$

$\hat{\mu_t}$ and $\hat{g_t}$ are de-meaned variables:

$$\hat{\mu_t} = \mu_t - \delta_0$$

$$\hat{g_t} = g_t - \gamma_0$$

[15]Please note that the expected returns discussed here refer to holding a one-year constant-maturity dividend futures contract until maturity. In contrast, the expected returns discussed in Binsbergen and Koijen (2010) pertain to stock returns.

I substitute Equations (4) and (5) into Equation (3), I subsequently have

$$\begin{aligned}
e_{t+1,1} &= \mu_{t+1} - g_{t+1} \\
&= \delta_0 + \delta_1\hat{\mu}_t + \epsilon^{\mu}_{t+1} - (\gamma_0 + \gamma_1\hat{g}_t + \epsilon^{g}_{t+1}) \\
&= \delta_0 - \gamma_0 + \delta_1\hat{\mu}_t - \gamma_1\hat{g}_t + \epsilon^{\mu}_{t+1} - \epsilon^{g}_{t+1} \\
&= \delta_0 - \gamma_0 + \delta_1(\hat{\mu}_t - \hat{g}_t) + (\delta_1 - \gamma_1)\hat{g}_t + \epsilon^{\mu}_{t+1} - \epsilon^{g}_{t+1} \\
&= \delta_0 - \gamma_0 + \delta_1(\mu_t - \delta_0 - g_t + \gamma_0) + (\delta_1 - \gamma_1)\hat{g}_t + \epsilon^{\mu}_{t+1} - \epsilon^{g}_{t+1} \\
&= \delta_0 - \gamma_0 + \delta_1(e_{t,1} - \delta_0 + \gamma_0) + (\delta_1 - \gamma_1)\hat{g}_t + \epsilon^{\mu}_{t+1} - \epsilon^{g}_{t+1} \\
&= \delta_1 e_{t,1} + (1 - \delta_1)(\delta_0 - \gamma_0) + (\delta_1 - \gamma_1)\hat{g}_t + \epsilon^{\mu}_{t+1} - \epsilon^{g}_{t+1}
\end{aligned}$$

The system proposed by us models expected dividend growth by below three equations. It consists of one transition equation, which models expected dividend growth as an AR(1) process, and two measurement equations

$$\hat{g}_{t+1} = \gamma_1\hat{g}_t + \epsilon^{g}_{t+1} \tag{6}$$

$$\Delta d_{t+1} = \gamma_0 + \hat{g}_t + \epsilon^{d}_{t+1} \tag{7}$$

$$e_{t+1,1} = \delta_1 e_{t,1} + (\delta_1 - \gamma_1)\hat{g}_t + (1 - \delta_1)(\delta_0 - \gamma_0) + \epsilon^{\mu}_{t+1} - \epsilon^{g}_{t+1} \tag{8}$$

16

[16]Note that the final system contains only one transition equation, even though I initially model both expected dividend growth and expected returns. Similar to Binsbergen and Koijen (2010), the AR(1) process for expected returns is embedded in the second measurement equation (Equation (8)).

4 Parameter Estimation

I estimate parameters in Equations (6) through (8) using conditional maximum likelihood estimation (MLE). To maximize the likelihood[17], I employ simulated annealing, an algorithm designed to search for the global maximum[18], over the parameter set $\Theta(\delta_0, \gamma_0, \delta_1, \gamma_1, \sigma_\mu, \sigma_g, \sigma_d, \rho_{gu}, \rho_{du}, \rho_{dg})$. To facilitate estimation, I express the final system, which consists of one transition equation (Equation (6)) and two measurement equations (Equations (7) and (8)), in state-space form. A detailed description of the state-space equations and the Kalman filtering procedure used in my model is provided in Appendix A1. Further details on the estimation procedure can also be found in Appendix A1.

In this paper, my core analysis involves performing out-of-sample tests to assess the predictive accuracy of my approach. To this end, I utilize an expanding window methodology. Specifically, for the US, I estimate the parameters using data from the beginning of 1974 up to time t. The estimated parameters are then applied to the model to generate a forecast for $t+1$. This process is repeated by extending the dataset to include data from 1974 up to $t+1$, re-estimating the parameters, and generating a forecast for $t+2$. The iterative procedure continues, incorporating additional data points sequentially, until the final forecast for 2023 is produced.

Using maximum likelihood estimation, I empirically determined that the shortest period required to obtain reliable parameter estimates for the US is from 1974 to 1995[19]. Table 2 displays the average values of these estimates across the expanding estimation windows, ranging from 1974–1995 to 1974–2022. The detailed results for each individual estimation period can be found in Appendix A2. My estimates, averaged across multiple estimation periods, indicate that the average expected dividend growth persistence (γ_1) in the U.S. is 0.294, while the average expected return persistence (δ_1) is 0.754 [20].The average unconditional expected dividend growth (γ_0) across estimation periods is 6.0%, whereasthe average unconditional expected log return for holding one-period dividend strips (δ_0) are 4.6%.

[17]The likelihood is based on the prediction errors and the innovation covariance matrix. See Appendix A1.

[18]See Goffee, Ferrier, and Rogers (1994) and Binsbergen and Koijen (2010).

[19]The minimum period of data required to run a Kalman filter for parameter estimation depends on several factors. However, for a simple AR(1) state-space model, at least 20 or more observations are typically needed to achieve reasonable estimation accuracy.

[20]Please note that the expected returns referred to here are those from holding a one-period dividend strips, whereas the expected returns discussed in Binsbergen and Koijen (2010) pertain to stock returns.

Average Parameter Estimates Across Expanding Time Periods: 1974–1995 to 1974–2022 (U.S.)		
	Mean	Standard deviation
δ_1	0.754	0.073
γ_1	0.296	0.119
γ_0	0.060	0.004
δ_0	0.046	0.021
σ_μ	0.067	0.007
σ_g	0.061	0.015
σ_d	0.008	0.008
ρ_{gu}	0.645	0.108
ρ_{du}	0.505	0.223
ρ_{dg}	–	–

Table 2: Average Estimation Results Across Expanding Time Periods

This table summarizes the average and standard deviation of the estimation results for Equations (6) through (8) across expanding time periods from 1974–1995 to 1974–2022. These estimates are subsequently applied to model to generate forecasts for the years 1996, 1997...2023. The parameters are derived using conditional maximum likelihood estimation (MLE), based on annual time series data of equity yields and realized dividend growth data. To mitigate concerns about seasonality affecting dividend growth predictability, annual time series data is used.

Following Binsbergen & Koijen (2010), the correlation parameter (ρ_{dg}) between realized dividend growth shocks (ϵ^d_{t+1}) and expected dividend growth shocks (ϵ^g_{t+1}) is normalized to zero. Further details on the estimation procedure are provided in Appendix A1, while the detailed results for each estimation period can be found in Appendix A2.

5 Empirical Results

5.1 In-Sample Forecasting Results

I first validate the methodology based on equity yields by examining the model's in-sample fit to the data. Table 3 presents the maximum likelihood estimation results for Equations (6) through (8) over the full sample period, utilizing data from 1974 to 2023 on the US equity yields and dividend growth rates. Standard errors are calculated through bootstrapping.

My estimates indicate that the unconditional expected dividend growth in the U.S. during the 1974–2023 period is $\gamma_0 = 6.2\%$, while the unconditional expected log returns for holding one-period dividend strips are $\delta_0 = 7\%$. Consistent with prior research, I find that expected returns exhibit greater persistence compared to expected dividend growth. Specifically, the annual persistence of expected returns for dividend strips is estimated at δ_1=0.711, whereas the persistence of dividend

growth is γ_1=0.174.

Follow Harvey (1989) and Binsbergen and Koijen (2010), I next calculate the in-sample R^2 value for dividend growth rates as

$$R^2_{IS} = 1 - \frac{\hat{var}(\Delta d_{t+1} - g^F_t)}{\hat{var}(\Delta d_{t+1})}$$

where g^F_t represents the filtered series of expected dividend growth, $\hat{var}$ denotes the sample variance. For my study period spanning 1974–2023, I find an in-sample R^2 value of 30.08% for cash-reinvested dividend growth. Binsbergen and Koijen (2010), using the price-dividend (pd) ratio and a state-space model, report in-sample R^2 values of 13.9% for cash-reinvested dividend growth and 31.6% for market-reinvested dividend growth over their study period of 1946–2007. Additionally, I plot the filtered series of expected dividend growth rates against the realized values in Figure 3, providing a visual comparison of the model's performance over time. This allows for a clearer assessment of how well the model captures the dynamics of dividend growth expectations and their realizations.

Panel A: Maximum Likelihood Estimates		
	Estimate	Standard Errors
δ_1	0.711	0.167
γ_1	0.174	0.223
δ_0	0.070	0.011
γ_0	0.062	0.018
σ_μ	0.067	0.018
σ_g	0.072	0.024
σ_d	0.001	0.022
ρ_{gu}	0.560	0.449
ρ_{du}	0.532	0.253
ρ_{dg}	–	–
Panel B: R^2 values		
R^2_{IS}	30.08%	

Table 3: Parameter Estimates Based on the Full Sample Period in the US: 1974–2023

This table presents the estimated parameters and the standard error of the estimation results of the equation (6) to (8) using data between 1974 and 2023 on the US equity yields and dividend growth rates.

Follow Harvey (1989) and Binsbergen and Koijen (2010), I calculated the in sample R^2 value as

$$R^2_{IS} = 1 - \frac{\hat{var}(\Delta d_{t+1} - g^F_t)}{\hat{var}(\Delta d_{t+1})}$$

where g^F_t represents the filtered series of expected dividend growth, $\hat{var}$ denotes the sample variance.

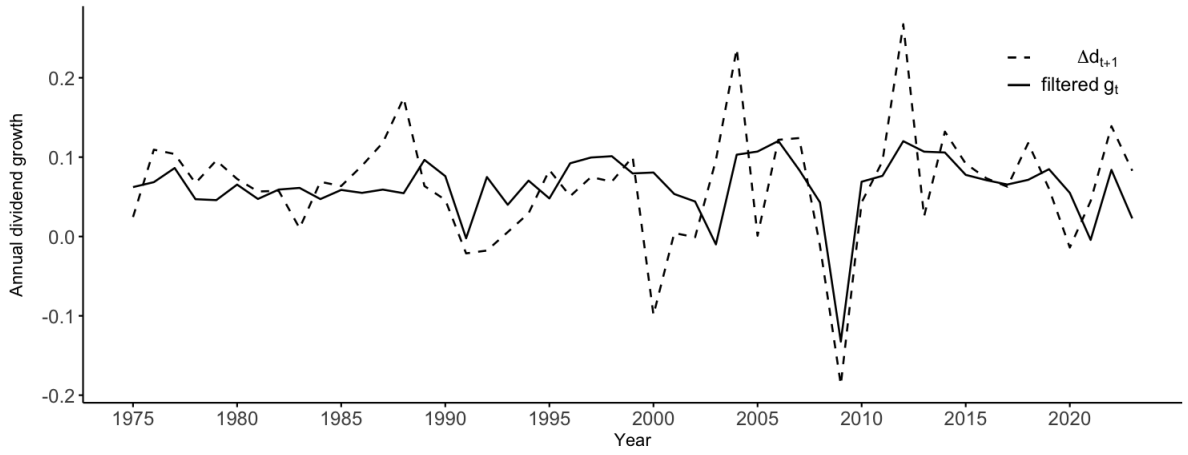


Figure 3: In-Sample: Filtered Series for Expected Dividend Growth in the US

The graph presents the filtered series of expected dividend growth (g_t) generated by my model, plotted alongside the time series of realized dividend growth (Δd_{t+1}). This comparison serves as an evaluation of the model's in-sample performance in the US over time.

I reproduce the in-sample analysis for other markets during the periods when one-year equity yield data is available. The sample period spans 2002–2023 for Europe, and 2004–2023 for both Japan and the UK. Across these three markets, I observe high in-sample R^2 values: 48.86% for Europe, 61.55% for Japan, and 28.40% for the UK. The corresponding filtered series of expected dividend growth and their realized values for each market are displayed in the three panels of Figure 4.

I acknowledge that the high in-sample R^2 values are partly attributable to the relatively short sample periods in these markets. Additionally, the in-sample analysis allows the model to leverage all available data during the period, which makes events like the Great Recession of 2008 easier to predict[21]. Notably, the model successfully captures the Great Recession across all three markets but fails to predict the COVID-19 recession. This outcome, however, underscores the model's effectiveness in utilizing investors' expectations to predict recessions. Specifically, one-year equity yields spiked across all three markets at the end of 2008, reflecting heightened investor concerns during the Great Recession. In contrast, at the end of 2019, one-year equity yields remained stable,

[21]The negative correlation between the unusual surge in equity yields and the sharp decline followed in dividend growth is fairly evident in hindsight.

	Europe	Japan	UK
Period	2002-2023	2004-2023	2004-2023
R^2_{IS}	48.86%	61.55%	28.40%

Table 4: In-Sample Forecasting Results – Europe, Japan, and the UK

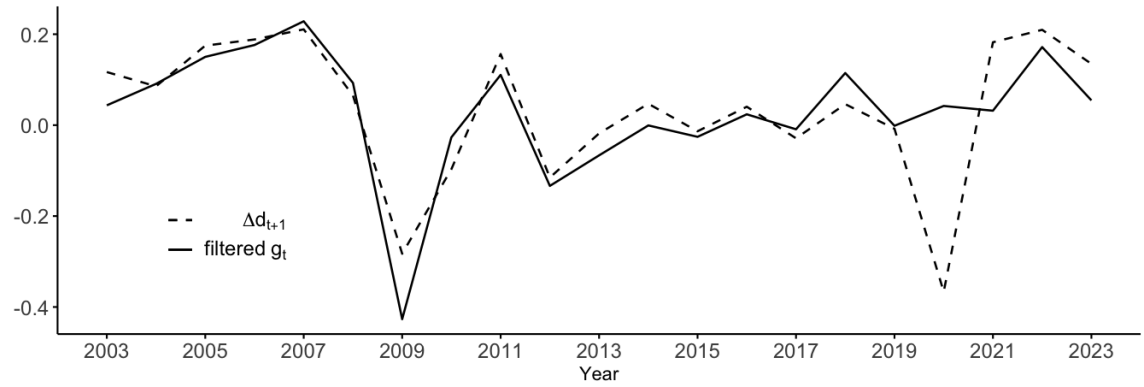
Follow Harvey (1989) and Binsbergen and Koijen (2010), I calculated the in sample R^2 value as

$$R^2_{IS} = 1 - \frac{\hat{var}(\Delta d_{t+1} - g^F_t)}{\hat{var}(\Delta d_{t+1})}$$

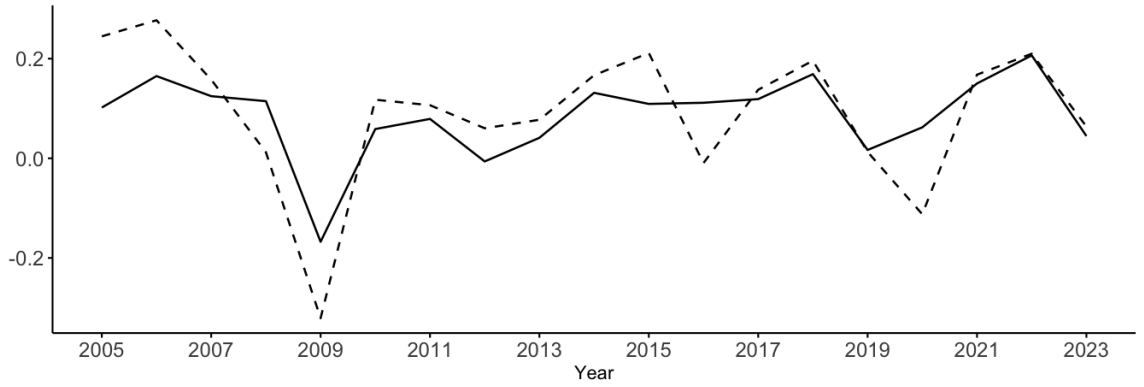
where g^F_t represents the filtered series of expected dividend growth. $\hat{var}$ denotes the sample variance.

as the unpredictable nature of the COVID-19 pandemic meant that investors did not anticipate the ensuing recession. Consequently, the model's inability to capture the COVID-19 recession further validates its reliance on investor expectations.

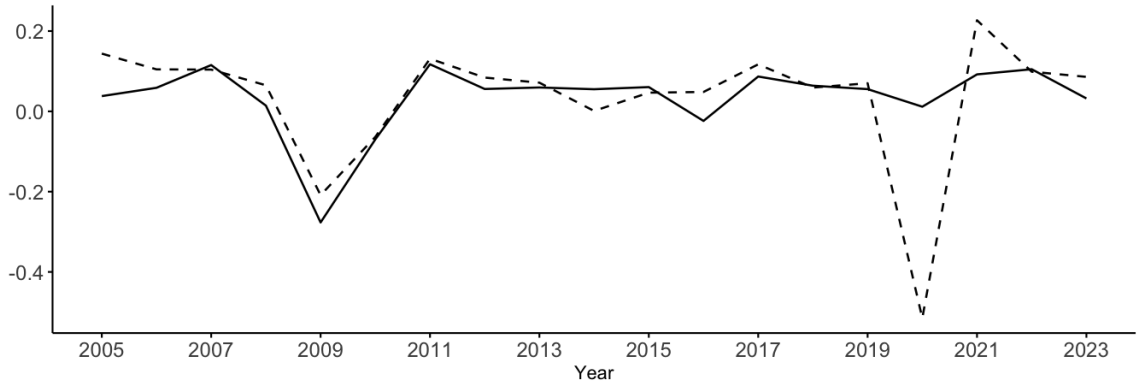
This analysis highlights the model's strength in predicting recessions when investor expectations are well-aligned with economic conditions, while also revealing its limitations in the face of unprecedented and unforeseen events like the COVID-19 pandemic.



(a) Europe



(b) Japan



(c) UK

Figure 4: In-Sample: Filtered Series for Expected Dividend Growth in Europe, Japan, and the UK

The graph presents the filtered series of expected dividend growth (g_t) generated by my model, plotted alongside the time series of realized dividend growth (Δd_{t+1}). This comparison serves as an evaluation of the model's in-sample performance in the Europe, Japan and the UK over time.

5.2 Out-of-Sample Forecasting Results: The U.S.

The central question I aim to address in this paper is whether investor expectations can be used to forecast economic variables. Figure 2 demonstrates that my chosen predictor, the one-year equity yield, is closely associated to economic conditions and may serve as a leading indicator. The R^2_{IS} values reported in Section 5.1 provide in-sample measure of fit between the expected dividend growth series estimated by my model and the realized values.

However, while in-sample analysis, which leverages all available data, yields more accurate parameter estimates and consequently more precise predictions, out-of-sample tests are more relevant for assessing the true real-time predictive power of my method[22]. Building on this insight, I evaluate the model's predictive capability by investigating whether my state-space model—calibrated using dividend growth and equity yield data up to time t can produce a filtered series that quantitatively forecasts dividend growth beyond time t. To this end, I conduct out-of-sample tests to rigorously assess the predictive power of my approach.

I begin by presenting a plot in Figure 5 that compares my filtered series of expected dividend growth rates with the realized values. This visual representation allows us to assess the model's out-of-sample forecasting performance over time. The expected values, calculated as $g_t = E_t[\Delta d_{t+1}]$ using information available up to time t, are aligned with the realized values Δd_{t+1} for the same year, enabling a direct comparison to evaluate the model's out-of-sample accuracy. Additionally, I include a benchmark—the historical mean of dividend growth—in the same figure. This benchmark serves as the basis for computing the out-of-sample R^2 metrics of my forecasts, providing a clear reference point for assessing the model's forecasting ability.

Following Goyal and Welch (2008), Binsbergen and Koijen (2010), Rapach, Strauss, and Zhou (2010), Ferreira and Santa-Clara (2011), Neely et al. (2014), among others, I compute the out-of-sample R^2 statistics, developed by Campbell and Thompson (2008), to evaluate the predictive performance of competing models for forecasting dividend growth.

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T-1} (\Delta d_{t+1} - g_t^F)^2}{\sum_{t=1}^{T-1} (\Delta d_{t+1} - \overline{\Delta d_t})^2}$$

[22]Goyal and Welch (2008)

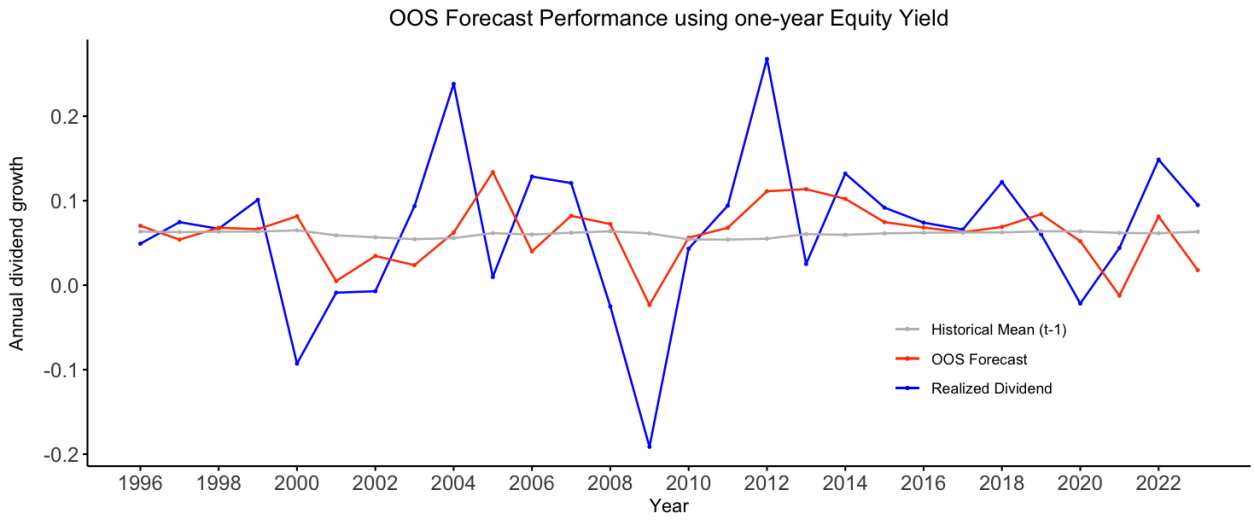


Figure 5: Out-of-Sample Forecasting Results in the US

The graph presents the filtered series of expected dividend growth (g_t) generated by my model using information available up to time t, plotted alongside the time series of realized dividend growth (Δd_{t+1}), and the benchmark series of the historical mean of dividend growth (calculated up to time t), denoted as $\overline{\Delta d_t}$. This comparison serves as an evaluation of the model's out-of-sample performance in the US over time.

where g_t^F represents the filtered value generated by my model using data available up to time t, which serves as the expected value for time $t+1$. Δd_{t+1} denotes the realized value at time $t+1$. I use the historical mean of dividend growth (calculated up to time t), denoted as $\overline{\Delta d_t}$ as the benchmark for computing the out-of-sample R^2 values. The R^2_{OS} statistic measures the proportional reduction in the mean squared prediction errors (MSPE) of the predictive model's forecasts and those of the benchmark model's forecasts. A positive value indicates that the predictive model outperforms the historical average forecast, with higher values representing greater outperformance relative to the benchmark model.

Out-of-sample forecasts of dividend growth are generated using an expanding estimation window. For instance, as illustrated in the parameter estimation section, data from 1974 to 1995 are used to fit the state-space model, and the resulting parameters—estimated via maximum likelihood—are applied to forecast dividend growth for 1996. The process is then repeated iteratively: data from 1974 to 1996 are used to refit the model, with the updated parameters forecasting dividend growth for 1997. This iterative procedure continues until 2023. The forecasted values from the model are then compared with the realized values to calculate R^2_{OS}, serving as the measure of out-of-sample performance. The average parameter estimates across expanding estimation periods for my model are reported in Table 2, while detailed results of estimation periods are provided in Appendix A2.

I evaluate the out-of-sample performance of my model alongside two alternative models. The first alternative is the model proposed in the seminal work of Binsbergen and Koijen (2010). Their study demonstrates how their present-value model can extract aggregate information embedded in the price-dividend (pd) ratio, uncovering unobserved expected dividend growth and expected returns in-sample. However, their model exhibits only modest predictive power when applied out-of-sample. My state-space model follows a similar structure, modeling expected returns and dividend growth as AR(1) processes in the transition equations. However, it incorporates a more sensitive predictor—one-year equity yields—to achieve stronger predictability. The second alternative model I test together is a standard predictive regression using one-year equity yields. This comparison allows us to evaluate whether my model's strong predictability is driven exclusively by the use of equity yields as a predictor and whether the inclusion of a state-space model remains necessary.

Table 5 reports the out-of-sample R^2 values based on two evaluation periods. The first row

presents results from the longest out-of-sample evaluation period. It is worth noting that my state-space model requires a minimal sample size to produce stable and reliable parameter estimates. Using maximum likelihood estimation (MLE), I identify 1974–1995 as the shortest initial estimation period necessary to obtain reliable parameter estimates.[23]; In the second row, following the out-of-sample implementation in Binsbergen and Koijen (2010), I use an initial estimation period of 27 years and also employ an expanding window approach through 2023. The statistical significance of the R^2_{OS} statistic is determined using the p-value of the out-of-sample MSPE-adjusted statistic, as proposed by Clark and West (2007); The statistic corresponds to the one-side test of the null hypothesis that the forecasting model's predictive accuracy is equal to or lower than that of the historical average benchmark model, against the alternative hypothesis that the forecasting model has greater predictive accuracy. Statistical significance is denoted by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

I compare out-of-sample predictability across three methodologies. Column 2 of Table 5 reports the results for my state-space model using one-year equity yields. Column 3 presents results for approach using the present-value model and price-dividend (pd) ratio, as in Binsbergen and Koijen (2010). [24] For their study period (1946–2007), Binsbergen and Koijen (2010) find that their approach perform well in-sample but showed only moderate out-of-sample improvement over standard predictive regressions for dividend growth rates.

During my evaluation period, the pd ratio exhibits weaker predictability, with negative R^2 values out of sample, indicating that the pd ratio predicts dividend growth less effectively than simply using the benchmark - historical mean. In contrast, my model, which utilizes one-year equity yields, achieves an out-of-sample R^2 of 16.47% for the evaluation period of 1996–2023 and 21.59% for 2001–2023[25](using a comparable 27-year initial estimation period (1974–2000)). This demonstrates that my model, leveraging one-year equity yields, remarkably outperforms both the benchmark model and the price-dividend (pd) ratio model in out-of-sample forecasting.

Finally, I examine the performance of one-year equity yields when used in standard predictive

[23]I provide 10 sets of initial points for the simulated annealing algorithm. Convergence of all parameters across these initializations is required to ensure that the global maximum is likely achieved.

[24]The parameter estimates across expanding estimation periods for Binsbergen and Koijen (2010)'s model are provided in Appendix A3.

[25]Binsbergen and Koijen (2010) uses data between 1946 and 1972 to compute the parameters of their mode, then compute expexted dividend growth for 1973. They proceed with an expanding windows to make forecasts up until 2007.

regressions, as opposed to my state-space model. As shown in Column 4, the out-of-sample R^2 is only 2.83% for 1996–2023 and 3.78% for 2001–2023, indicating marginal improvement over the benchmark. When conducting predictive regressions with expanding windows for out-of-sample testing, I I find that standard OLS accurately estimates the intercept (historical mean) of realized dividend growth. However, it fails to appropriately adjust the slope across different periods.

An ex post analysis suggests the "ideal" slope for the relationship between the predictor EY_1 and the realized dividend growth in the following year ($\triangle d_{t+1}$) should be close to -1 during recession years and near zero during normal years. This non-linear relationship highlights the limitations of a linear OLS approach, which is unable to capture such dynamic variations effectively. In contrast, my state-space model, which employs Kalman filter techniques to estimate time-varying parameters, adapts seamlessly to changing market conditions. The Kalman gains provide the necessary sensitivity to capture shifts in market sentiment, making the state-space model—combined with Kalman filter-based parameter estimation and forecasting—a more robust and suitable method for this purpose.

Overall, my model (Column 2) is the only approach among three demonstrates considerably better out-of-sample predictability for dividend growth. These results suggest that the information embedded in one-year equity yields can help forecast one-period-ahead dividend growth. However, extracting this information requires an appropriate modeling approach, rather than just relying on standard predictive regressions.

Evaluation periods	State-space model using EY_1	Present-value model using pd ratio	Predictive regression using EY_1
1996-2023	16.47%*	-6.54%[26]	2.83%
2001-2023	21.59%*	-2.92%	3.78%

Table 5: Out-of-Sample Forecasting Results – US

I compute Campbell and Thompson (2008)'s out-of-sample R^2 statistic

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T-1} (\Delta d_{t+1} - g_t^F)^2}{\sum_{t=1}^{T-1} (\Delta d_{t+1} - \overline{\Delta d_t})^2}$$

where g_t^F represents the filtered value generated by my model using data available up to time t, which serves as the expected value for time $t+1$. Δd_{t+1} denotes the realized value at time $t+1$. As a benchmark model for forecasting $t+1$, I use the historical mean of dividend growth, calculated up to time t and denoted by $\overline{\Delta d_t}$. The statistical significance of the R^2_{OS} statistic is determined using the p-value of the out-of-sample MSPE-adjusted statistic, as proposed by Clark and West (2007); MSPE-adjusted statistic can be calculated as $f_{t+1} = (\Delta d_{t+1} - \overline{\Delta d_t})^2 - [(\Delta d_{t+1} - g_t^F)^2 - (\overline{\Delta d_t} - g_t^F)^2]$. The statistic corresponds to the one-side test of the null hypothesis that the forecasting model's predictive accuracy is equal to or lower than that of the historical average benchmark model, against the alternative hypothesis that the forecasting model has greater predictive accuracy. Statistical significance is denoted by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

I next present the out-of-sample test results of my state-space model using one-year equity yields in direct comparison with the price-dividend (pd) ratio model for the evaluation period from 1996 to 2023. This side-by-side presentation enables a clear assessment of the specific mechanisms and time periods in which my model outperforms. The upper panel displays the out-of-sample forecasting results for my state-space model, while the lower panel shows the corresponding results for the pd ratio model. As illustrated in the plots, the two models produce similar forecasts for many periods. However, during critical economic turning points—such as the Great Recession in 2009 and the strong recovery in 2012—my model, which utilizes one-year equity yields, generates significantly more accurate out-of-sample forecasts.

[26]When calculating the U.S. aggregate market annual dividend growth using a value-weighted portfolio of NYSE, AMEX, and NASDAQ stocks (as in Binsbergen and Koijen (2010)), rather than the CRSP Value-Weighted Portfolio used here, I find an out-of-sample R^2 of 5.97% for the evaluation period from 1996 to 2023. This result aligns more closely with the out-of-sample performance reported in Binsbergen and Koijen (2010), where the present-value model marginally outperforms the benchmark. For detailed results, see Section 6: Robustness.

This outperformance can be attributed to the design of my predictor, one-year equity yields. Unlike the *pd* ratio, which captures the discounted expectation of future cash flows with an infinite maturity horizon and is thus a long-term metric, one-year equity yields are calculated from one-year constant-maturity dividend futures prices. This reflects the discounted values of expected dividends within a specific one-year horizon, making it a short-term metric. The short-term expectations embedded in this metric enable my model to be more sensitive to near-term changes in economic conditions and market sentiments, compared to the *pd* ratio model, which relies on a longer-term perspective. To further illustrate this point, I present Figure 8, which depicts the monthly time series of the two predictors.

As shown, the two time series are closely synchronized, although they move in opposite directions. During periods of heightened market stress, such as the approach of a recession, investor sentiment deteriorates: equity yields rise while the *pd* ratio declines. This pattern suggests that the two predictors play a similar role or operate under a similar mechanism in terms of how they store and reflect expectations. However, the magnitude of the fluctuations in their time series confirms my reasoning that one-year equity yields, calculated from short-maturity asset pricing, are a more sensitive predictor compared to the price-dividend (*pd*) ratio. Additionally, the figures highlight the differing responses of the two metrics to short-term changes in economic conditions and market sentiments. This is particularly evident when comparing the patterns of the time series around the COVID-19 recession period: one-year equity yields increased drastically, while the *pd* ratio reacted relatively mildly. This difference arises because the *pd* ratio captures the pricing of future cash flows over an infinite horizon. If the market expects the pandemic to be a short-term or mid-term event, the valuation will not be affected as significantly as it is for one-year equity yields, which focus solely on the expected market aggregate dividend one year ahead.

This figure underscores the dynamic responsiveness of my one-year equity yields to abrupt shifts in market conditions, highlighting their advantage over the *pd* ratio in capturing real-time economic fluctuations. When forecasting short-term dividend growth, it is no surprise that one-year equity yields serve as a more informative predictor.

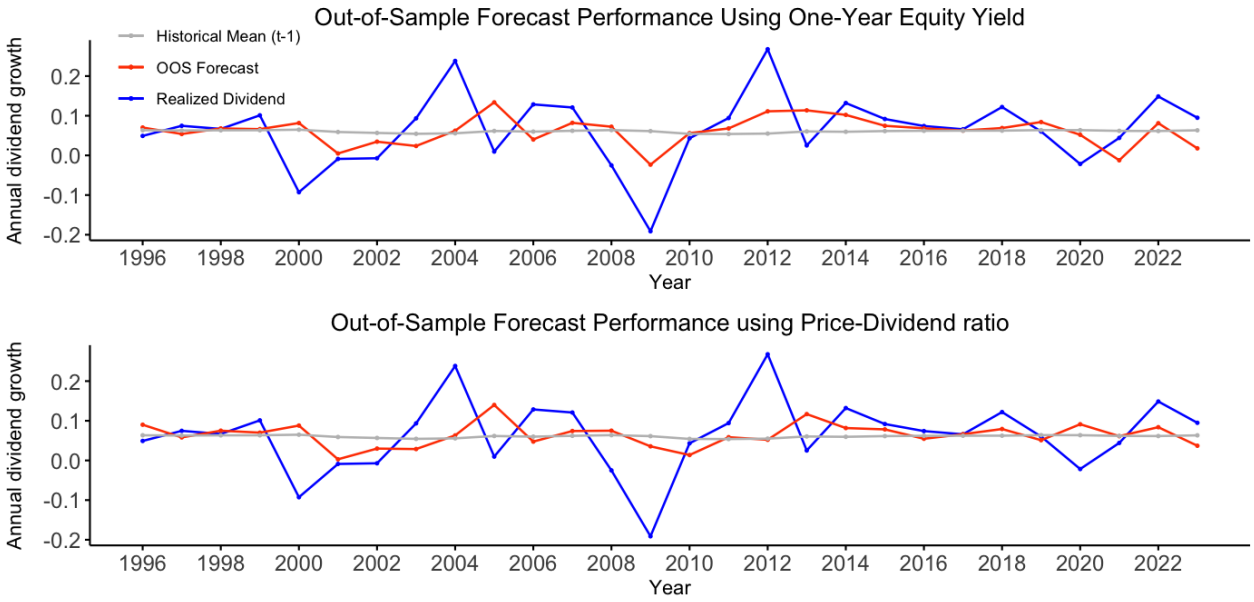


Figure 6: Forecasting Performance: One-Year Equity Yields vs. Price-to-Dividend Ratios

This figure compares the out-of-sample forecasting performance of two models: my state-space model, which incorporates one-year equity yields, and the present-value model based on the price-dividend (pd) ratio, as introduced by Binsbergen and Koijen (2010). The evaluation period covers 1996 to 2023. The upper panel presents the out-of-sample forecasting results for my state-space model, while the lower panel shows the corresponding results for the pd ratio model.

Both models generate out-of-sample forecasts of dividend growth using an expanding estimation window. The state-space model is first estimated using data from 1974 to 1995, with parameters derived via maximum likelihood. These parameters are then used to forecast dividend growth for 1996. The process is repeated iteratively: for each subsequent year, the estimation window expands by one year (e.g., 1974 to 1996 for forecasting 1997), and the model is re-estimated to update the parameters. This iterative approach continues through 2023.The parameter estimates for my state-space model across the expanding estimation windows are detailed in Appendix A2, while the parameter estimates for the present-value model are provided in Appendix A3.

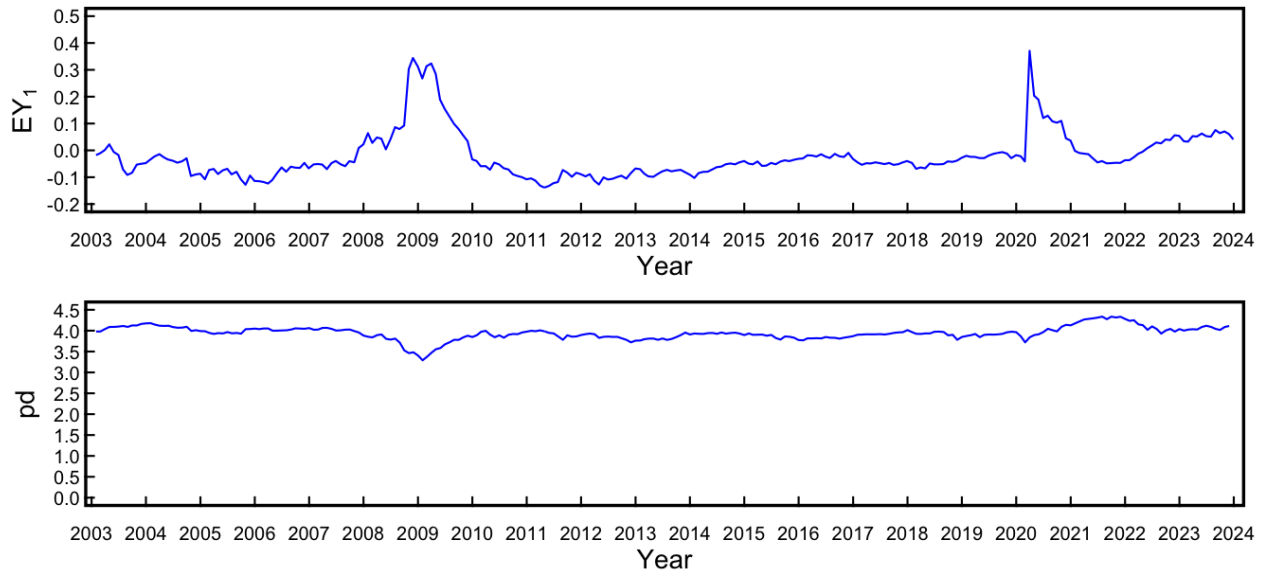


Figure 7: Monthly Time Series of One-Year Equity Yields and Price-Dividend Ratio

This figure presents the monthly time series of one-year equity yields alongside the monthly time series of the price-dividend (pd) ratio in the U.S. market. One-year equity yields are calculated as the logarithmic ratio of the current level of dividends to the one-year constant-maturity dividend futures price, expressed as $e_{t,1} = log(\frac{D_t}{F_{t,1}}) + y_{t,1}$, where $y_{t,1}$ denotes the one-year government nominal bond yield. I present the time series of one-year equity yields since the launch of the dividend derivatives market, ensuring that the calculation is based solely on real trading price data. The pd ratio is calculated as $pd = log(\frac{P_t}{D_t})$, where$D_t$ represents the trailing sum of 12-month dividends at time t, and P_t represents the index level of the S&P 500.

5.3 Cumulative Squared Prediction Errors

As pointed out in Goyal and Welch (2008), a common "perplexity" in out-of-sample (OOS) analysis is the lack of certainty on how to select the time periods over which parameters are estimated and what is left for evaluation. A general principle to follow is to ensure that there is sufficient initial data to obtain a set of reliable parameter estimates at the start of the evaluation period and to also have an evaluation period long enough to be representative. However, some level of arbitrariness is inevitable in these decisions. In Table 5, I present two sets of results. In the first set, I use the shortest length of data required to produce reliable parameter estimates for my model, thereby maximizing the length of the out-of-sample evaluation period given my dataset. In the second set, I follow the choice made in Binsbergen and Koijen (2010) and use 27 years as the initial estimation period before applying the expanding windows to enable a better comparison with their predictor.

To further assess the out-of-sample predictive performance of my approach and confirm its advantage in forecasting one-period-ahead dividend growth, I follow Goyal and Welch (2008) and compute the cumulative squared prediction errors of competing models over out-of-sample evaluation periods and present the results in Figure 6. In the figure, I plot the cumulative squared prediction errors of the benchmark model minus those of the test models. A positive value indicates that the test model outperforms the benchmark, with higher values signifying superior out-of-sample performance. As is common in out-of-sample tests, I use the historical mean as the benchmark. As pointed out in Rapach, Strauss, and Zhou (2010), the plot can conveniently illustrate whether a predictive model has lower MSPE (mean squared prediction error) than the benchmark for any particular out-of sample period. This mitigates the concern on the arbitrariness of the choice of the out-of-sample evaluation period.

I plot the time series of the cumulative squared prediction error differences based on out-of-sample forecasts generated by my model and those produced by the models outlined in Binsbergen and Koijen (2010). The initial evaluation period for both models spans 1974 to 1995. This figure allows us to observe the evolution of out-of-sample forecast performance over time. When a curve in the figure increases, it indicates that the predictive model outperforms the benchmark. An ideal predictive model should consistently outperform the benchmark, resulting in a curve that increases monotonically, with a consistently positive slope.

The out-of-sample forecast line generated by my model predominantly exhibits a positive slope over the period 1996–2023[27] , indicating effective out-of-sample dividend growth prediction. However, this trend is not consistently positive throughout the entire period. Notably, in the early 2000s—particularly before 2008—there are substantial declines, reflecting periods where my model's forecasts underperformed relative to the historical average.

Interestingly, the outperformance of my model over historical mean tends to be concentrated during periods of significant economic fluctuations, such as 2009 and 2012. These years are characterized by pronounced growth or declines, and the market appears to have incorporated this information one year in advance. [28]In such scenarios, my approach demonstrates strong predictive performance, effectively capturing these dynamics.

In comparison, the present-value model using the price-dividend (pd) ratio from Binsbergen and Koijen (2010) fails to outperform the benchmark throughout the entire evaluation period. This aligns with their negative R^2_{OS} statistics reported in Table 5. My model consistently delivers superior out-of-sample forecasts compared to the (pd) model across the evaluation period, with my curve positioned above theirs at all times, indicating a lower cumulative squared prediction error. I hypothesize that this performance gap arises because, as a predictor for one-year-ahead variables (e.g., next year's dividend growth), the pd ratio is less responsive to short-term drastic market fluctuations compared to the one-year equity yield. The pd ratio ($pd = log(\frac{P_t}{D_t})$) and the one-year equity yield ($EY_{t,1} = log(\frac{D_t}{F_{t,1}})$) share a common component—the current dividend level D_t. However, the index level (P_t) in the pd ratio reflects an infinite maturity horizon, whereas the one-year dividend futures price ($F_{t,1}$) in the equity yields has a maturity of only one-year. This fundamental difference in maturity horizons likely affects their respective abilities to capture short-term drastic market fluctuations.

[27]In Rapach, Strauss, and Zhou (2010), no model consistently maintains a positive slope throughout the entire period. Most regression-based models struggle to achieve a predominantly positive slope even when considering the broader trend.

[28]The one-year equity yields exhibit pronounced values at the end of both 2008 and 2011, enabling my model to successfully predict the significant decline and growth in the following year. This results in outperformance relative to the historical average.

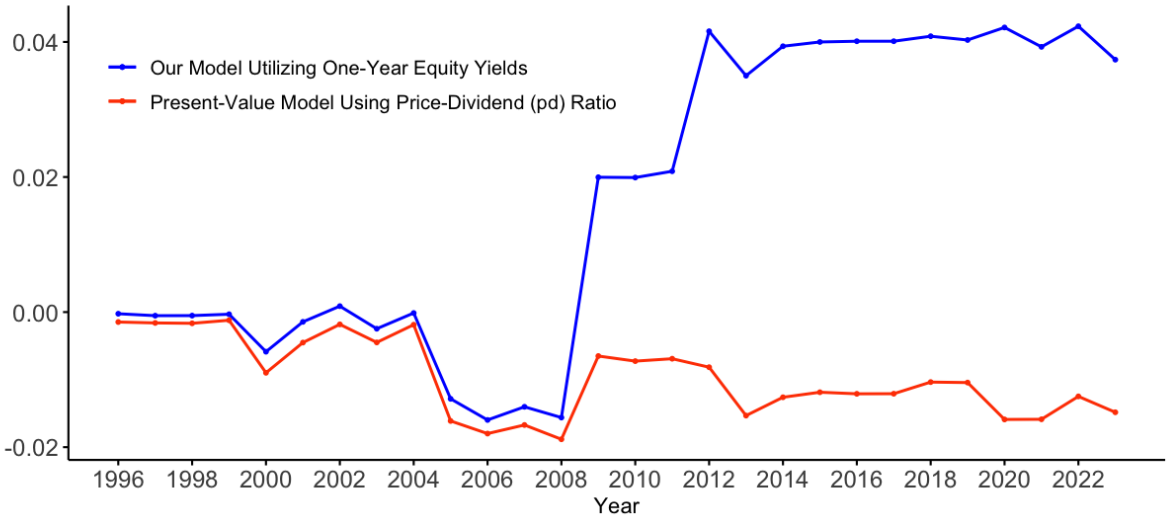


Figure 8: Cumulative Squared Prediction Error Difference: Benchmark Model minus Predictive Models

Use my model as an example, the cumulative squared prediction error difference can be calculated as below:

$$\sum_{t=1}^{T-1}(\Delta d_{t+1} - \overline{\Delta d_t})^2 - \sum_{t=1}^{T-1}(\Delta d_{t+1} - g_t^F)^2$$

where g_t^F represents the filtered value generated by my model using data available up to time t, which serves as the expected value for time $t+1$. Δd_{t+1} denotes the realized value at time $t+1$. I use the historical mean of dividend growth (calculated up to time t), denoted as $\overline{\Delta d_t}$ as the benchmark.

5.4 Hypothesis Testing

In this section, I formally test my model's out-of-sample forecast relative to that from Binsbergen and Koijen (2010)'s present-value model, by using the Clark and West(2007) out-of-sample MSPE-adjusted statistic

H_0 : Forecasts from my state-space model using one-year equity yields have higher or equal mean squared prediction errors (MSPE) that compared to Binsbergen and Koijen (2010)'s present-value model using pd ratio

H_A: Forecasts from my state-space model using one-year equity yields have lower mean squared prediction errors (MSPE) that compared to Binsbergen and Koijen (2010)'s present-value model using pd ratio

Although the Diebold and Mariano (1995) statistic is widely used to test competing forecast models, it is severely undersized when comparing forecasts from nested models[29], resulting in tests with very low power. In contrast, Clark and West (2007) demonstrate that the MSPE-adjusted statistic performs well in terms of both size and power when evaluating forecasts from nested linear models (see Rapach, Strauss, and Zhou, 2010). The Clark and West (2007) MSPE-adjusted statistic for my competing predictive models is calculated as:

$$f_{t+1} = (\Delta d_{t+1} - g_t^{F,pd})^2 - [(\Delta d_{t+1} - g_t^{F,EY_1})^2 - (g_t^{F,pd} - g_t^{F,EY_1})^2]$$

where Δd_{t+1} denotes the realized dividend growth value at time $t+1$. g_t^{F,EY_1} represents filtered values generated by my model using one-year equity yield data available up to time t, serving as the forecast for $t+1$. Similarly, $g_t^{F,pd}$ represents filtered values generated by the present-value model from Binsbergen and Koijen (2010) using price-dividend ratio available up to time t, which serves as their forecast values for time $t+1$. The statistics and p-values correspond to a one-sided (upper-tail) test.

For both evaluation periods used throughout the paper, I reject the null hypothesis at the 5% significance level, concluding that my model's forecasts exhibit lower mean squared prediction errors (MSPE) compared to Binsbergen and Koijen (2010)'s state-space model. This indicates that my model achieves higher out-of-sample predictive accuracy.

[29] my two competing models are nested.

EY_1 forecasts vs pd forecasts	Clark and West (2007) MSPE-adjusted statistic	p-value
1996-2023	1.9321	0.0319
2001-2023	1.8434	0.0394

Table 6: Hypothesis Test Results for Competing Models

MSPE-adjusted statistic can be calculated as

$$f_{t+1} = (\Delta d_{t+1} - g_t^{F,pd})^2 - [(\Delta d_{t+1} - g_t^{F,EY_1})^2 - (g_t^{F,pd} - g_t^{F,EY_1})^2]$$

where Δd_{t+1} denotes the realized dividend growth value at time $t+1$. g_t^{F,EY_1} represents filtered values generated by my model using one-year equity yield data available up to time t, serving as the forecast for $t+1$. Similarly, $g_t^{F,pd}$ represents filtered values generated by the state-space model from Binsbergen and Koijen (2010) using price-dividend ratio available up to time t, which serves as their forecast values for time $t+1$. The statistic corresponds to the one-side test of the null hypothesis that the forecasting model's predictive accuracy is equal to or lower than that of the historical average benchmark model, against the alternative hypothesis that the forecasting model has greater predictive accuracy. Statistical significance is denoted by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

5.5 Pseudo Out-of-Sample Forecasting Results: Europe, Japan, and the UK

Due to the limited availability of equity yield data for Europe, Japan, and the UK, I do not have sufficient data to first estimate parameters for each individual market and subsequently conduct an out-of-sample performance evaluation, as I did for the US market. [30] Therefore, I conduct a pseudo out-of-sample evaluation instead. Given that business cycles are largely synchronized across markets, I apply the model parameters estimated from the US market up to time t, combining them with equity yields from each market to generate forecasts for $t+1$. I then assess whether these forecasts are sufficient to predict the realized dividend growth at $t+1$ for each market. I again compute out-of-sample R^2 to evaluate the accuracy of the out-of-sample forecasts.

[30] Reliable parameter estimation for my state-space model generally requires 20 to 25 periods. For Europe, Japan, and the UK, the full available equity yield data spans 22 years, 20 years, and 20 years, respectively.

	Europe	Japan	UK
Period	2003-2023	2005-2023	2005-2023
$R^2_{Pseudo_{OS}}$	26.21%**	28.32%	-10.66%

Table 7: Pseudo Out-of-Sample Forecasting Results – Europe, Japan, and the UK

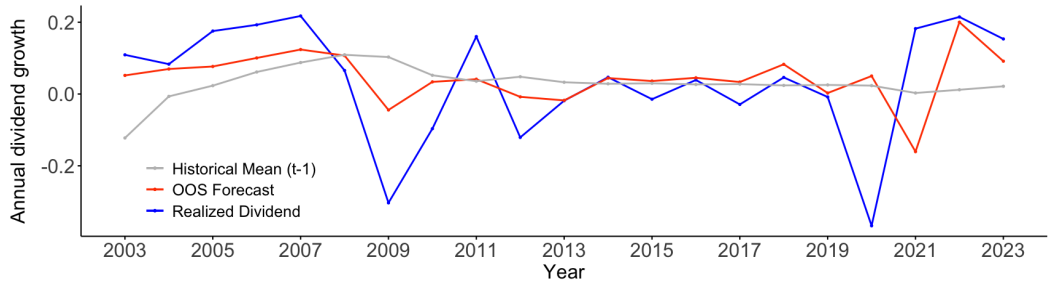
I compute Campbell and Thompson (2008)'s out-of-sample R^2 statistic

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T-1}(\Delta d_{t+1} - g_t^F)^2}{\sum_{t=1}^{T-1}(\Delta d_{t+1} - \overline{\Delta d_t})^2}$$

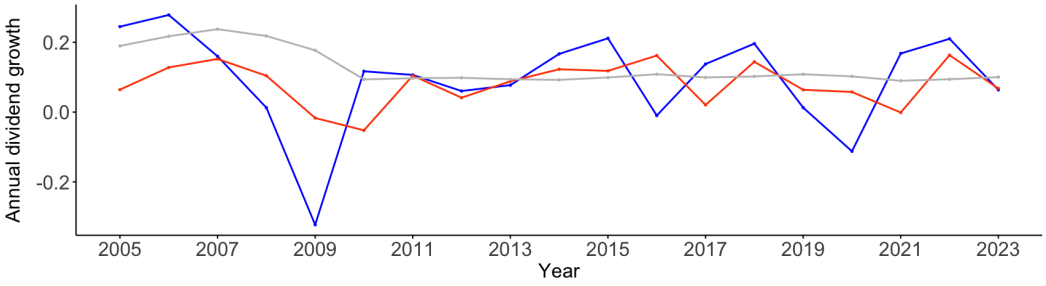
where g_t^F represents the filtered value generated by my model using the US parameter estimates and equity yield data of Europe, Japan, and the UK available up to time t, which serves as the expected value for time $t+1$. Δd_{t+1} denotes the realized value at time $t+1$. As a benchmark model for forecasting $t+1$, I use the historical mean of dividend growth, calculated up to time t and denoted by $\overline{\Delta d_t}$. The statistical significance of the R^2_{OS} statistic is determined using the p-value of the out-of-sample MSPE-adjusted statistic, as proposed by Clark and West (2007); The statistic corresponds to the one-side test of the null hypothesis that the forecasting model's predictive accuracy is equal to or lower than that of the historical average benchmark model, against the alternative hypothesis that the forecasting model has greater predictive accuracy. Statistical significance is denoted by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

Using model parameters estimated from the U.S. market, I achieve an out-of-sample R^2 of 26.21% for Europe, which is significant at 5% level. For Japan, the out-of-sample R^2 is 28.32%. However, when evaluating the MSPE-adjusted statistic, I find that it is not significant at conventional levels. In the case of the UK, the forecasts yield a negative out-of-sample R^2. I attribute this to the fact that the UK market experienced the most severe decline in log dividend growth in 2020 due to the impact of COVID-19 among the markets I studied. This sharp decline hindered the effectiveness of my forecasting approach, as the economic implications of the pandemic were not reflected in dividend futures markets as of the end of 2019, when the forecasts were generated.

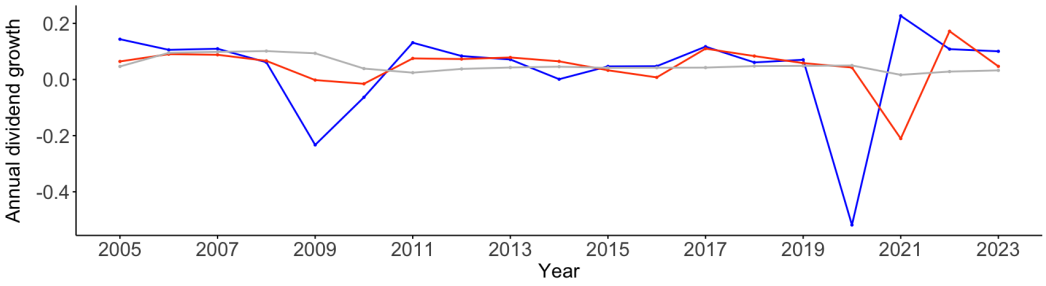
Additionally, due to differences in market characteristics, the parameters estimated from the U.S. market may inherently lead to suboptimal out-of-sample (OOS) forecast results for these non-U.S. markets. In the future, if dividend futures data series become sufficiently long to allow us to estimate parameters using each market's own data for OOS forecasting, the results are likely



(a) Europe



(b) Japan



(c) UK

Figure 9: Pseudo Out-of-sample Forecasting results - Europe, Japan and UK

to improve further. This is because market-specific parameter estimates would better capture the unique dynamics of each market, enhancing the accuracy of the forecasts. The pseudo out-of-sample forecasting curves across these markets are displayed in Figure 9.

5.6 Out-of-Sample Forecasting Results Using Parameter Estimates with Imposed Restrictions

In this subsection, I present the out-of-sample results obtained using parameter estimates derived under imposed restrictions. In the main body of the paper, I employ the most flexible parameter configuration during estimation to avoid introducing any unjustified constraints that might bias the results. Specifically, I set lower and upper bounds for σ_μ, σ_g and σ_d within the range of (0, 1). While this wide range ensures flexibility, I recognize that it may be excessively broad, particularly when the simulated annealing algorithm is used to search for the global maximum of the likelihood function. Such a broad range could lead to less precise parameter estimates, as the algorithm may explore unrealistic regions of the parameter space. [31]To address this, I conduct an experiment in this subsection by imposing more reasonable restrictions on the upper bounds and evaluate whether these adjustments lead to improved out-of-sample performance.

To establish a more plausible upper bound for σ_μ, I calculate the standard deviation of the realized returns on a one-year constant-maturity dividend futures contract for the period from 1974 to 1995, which precedes the evaluation period beginning in 1996. This value, calculated as 6.58%, is deemed a reasonable constraint and is used as the new upper bound for σ_μ, replacing the previously assumed 100% upper bound. [32]This adjustment ensures that the parameter space is restricted to a more realistic range, reflecting the observed volatility in the data. I then re-estimate the parameters using maximum likelihood estimation (MLE) under this revised constraint and evaluate the out-of-sample performance.

The results indicate that the newly estimated parameters, derived under the more restrictive upper bound, lead to improved out-of-sample performance across all four markets examined. These findings are summarized in Table 8, which can be compared to the unrestricted result reported in Table 5 (for the R^2_{OS} of the US) and Table 7 (for the $R^2_{Pseudo_{OS}}$ of Europe, Japan and the UK). This exercise demonstrates that imposing reasonable constraints on parameter bounds can enhance the accuracy of parameter estimates and, consequently, improve out-of-sample forecasting performance.

[31]By limiting the search space to more plausible ranges, I increase the likelihood of exploring only meaningful regions, thereby improving the algorithm's ability to locate the global maximum. This is achieved by allowing more iterations to refine the search within the correct region, enhancing the precision of the estimates.

[32]I still set lower and upper bounds for σ_g and σ_d within the range of (0, 1).

	US	Europe	Japan	UK
Period	1996-2023	2003-2023	2005-2023	2005-2023
R^2_{OS} or $R^2_{Pseudo_{OS}}$	22.52%*	28.87%**	31.61%	-8.91%

Table 8: Pseudo Out-of-Sample Forecasting Results – Europe, Japan, and the UK

For the US: the out-of-sample $R^2(R^2_{OS})$ for the evaluation period from 1996 to 2023 is 22.52%. This result is based on parameters estimated under the more restrictive upper bound for σ_μ, compared to the 16.47% (reported in Table 5) based on parameters estimated under the unrestrictive upperbound.

For Europe, Japan, and the UK: Due to limited availability of equity yield data, the pseudo out-of-sample R^2 ($R^2_{Pseudo_{OS}}$), is reported instead. The values are 28.87% for Europe, 31.61% for Japan, and -8.91% for the UK. These results are derived using an expanding window approach, where model parameters estimated from the US market up to time t, combined with equity yields from each respective market to generate forecasts for $t+1$. In comparison, the pseudo out-of-sample R^2 values based on parameters estimated under the unrestrictive upper bound (0, 1) are 26.21% for Europe, 28.32% for Japan, and -10.66% for the UK.

I compute Campbell and Thompson (2008)'s out-of-sample R^2 statistic

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T-1}(\Delta d_{t+1} - g_t^F)^2}{\sum_{t=1}^{T-1}(\Delta d_{t+1} - \overline{\Delta d_t})^2}$$

where g_t^F represents the filtered value generated by my model using the US parameter estimates and equity yield data of Europe, Japan, and the UK available up to time t, which serves as the expected value for time $t+1$. Δd_{t+1} denotes the realized value at time $t+1$. As a benchmark model for forecasting $t+1$, I use the historical mean of dividend growth, calculated up to time t and denoted by $\overline{\Delta d_t}$. The statistical significance of the R^2_{OS} statistic is determined using the p-value of the out-of-sample MSPE-adjusted statistic, as proposed by Clark and West (2007); The statistic corresponds to the one-side test of the null hypothesis that the forecasting model's predictive accuracy is equal to or lower than that of the historical average benchmark model, against the alternative hypothesis that the forecasting model has greater predictive accuracy. Statistical significance is denoted by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

6 Robustness

In this section, following Binsbergen and Koijen (2010), I reproduce my out-of-sample analysis on the U.S. aggregate market by calculating annual dividend growth in the same manner as they did. Instead of using the CRSP Value-Weighted Portfolio to compute monthly dividends, as in the main body of the paper, I obtain monthly returns—both with and without dividends—for all NYSE, Amex, and NASDAQ stocks from CRSP for the study period from 1974 to 2023. Using the return difference of this portfolio, I calculated monthly dividends to construct the annual time series of dividends D_t and repeated my out-of-sample tests. The results are presented in Table 9. This time, my findings align more closely with those reported by Binsbergen and Koijen (2010). Specifically, using the present-value model and the price-dividend (pd) ratio, I achieve modest out-of-sample performance, which is somewhat better than that of standard regression models using the pd ratio. However, the state-space model, when combined with one-year equity yields as the predictor, continues to demonstrate superior forecast performance compared to the approach of Binsbergen and Koijen (2010). It also yields a significantly smaller mean squared prediction error (MSPE) relative to the historical average benchmark, with statistical significance at the 5% level.

Evaluation periods	state-space model using EY_1	present-value model using pd ratio	predictive regression using pd ratio	predictive regression using EY_1
1996-2023	18.53%**	5.97%*	-2.92%	-0.62%
2001-2023	20.46% **	8.68%*	-2.35%	0.24%

I compute Campbell and Thompson (2008)'s out-of-sample R^2 statistic

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T-1}(\Delta d_{t+1} - g_t^F)^2}{\sum_{t=1}^{T-1}(\Delta d_{t+1} - \overline{\Delta d_t})^2}$$

where g_t^F represents the filtered value generated by my model using data available up to time t, which serves as the expected value for time $t+1$. Δd_{t+1} denotes the realized value at time $t+1$. As a benchmark model for forecasting $t+1$, I use the historical mean of dividend growth, calculated up to time t and denoted by $\overline{\Delta d_t}$. The statistical significance of the R^2_{OS} statistic is determined using the p-value of the out-of-sample MSPE-adjusted statistic, as proposed by Clark and West (2007); MSPE-adjusted statistic can be calculated as $f_{t+1} = (\Delta d_{t+1} - \overline{\Delta d_t})^2 - [(\Delta d_{t+1} - g_t^F)^2 - (\overline{\Delta d_t} - g_t^F)^2]$. The statistic corresponds to the one-side test of the null hypothesis that the forecasting model's predictive accuracy is equal to or lower than that of the historical average benchmark model, against the alternative hypothesis that the forecasting model has greater predictive accuracy. Statistical significance is denoted by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

Table 9: Out-of-Sample Performance – US (Robustness)

7 Conclusion

In this paper, I develop a state-space model utilizes equity yield data to predict one-year-ahead dividend growth across four major markets: the U.S., Europe, Japan, and the UK. I demonstrate that the one-year equity yield—my chosen predictor—exhibits a strong relationship with NBER recessions, suggesting its potential as a leading indicator for forecasting economic variables.

Through in-sample analysis, I demonstrate the model's robust fit for dividend growth across all four markets. In the U.S. (1974–2023), the model achieves an in-sample R^2 of 30.08%, representing a significant improvement over the model of Binsbergen and Koijen (2010), which relies on the price-dividend *pd* ratio and achieves an R^2 of only 13.9% for their cash-reinvested dividend growth (1946–2007). This enhanced performance stems from the one-year equity yield's closer alignment with near-term economic conditions, making it a more effective predictor of dividend growth compared to the *pd* ratio, which reflects infinite-horizon expectations through the index level. Notably, the model accurately captures the Great Recession but fails to predict the COVID-19 recession across all markets, reflecting its reliance on investor expectations. Specifically, one-year equity yields surged sharply in 2008, mirroring heightened investor concerns during the Great Recession, but remained stable in 2019, as the unprecedented nature of the COVID-19 pandemic caught investors off guard. These results validate the model's ability to leverage investor expectations for recession prediction while highlighting its limitations during extraordinary, unforeseen events like COVID-19. This underscores my broader contribution: the robustness of my forecasting framework and its dependence on investor sentiment, particularly during periods of economic stress.

Turning to out-of-sample performance, my model demonstrates superior predictive accuracy in the U.S. during the evaluation period (1996–2023). For annual cash-reinvested dividend growth, the model achieves an out-of-sample R^2 of 16.47%, a statistically significant improvement over the historical average benchmark. Furthermore, when comparing cumulative squared prediction errors, my model consistently outperforms the the *pd* ratio-based approach of Binsbergen and Koijen (2010). This outperformance is further confirmed by the Clark and West (2007) MSPE-adjusted statistic. A key finding is that the out-of-sample predictive advantage of my model is particularly pronounced during periods of economic turmoil, underscoring its robustness in capturing extreme economic fluctuations. However, this also reveals a limitation: its predictive power weakens when

market expectations are less pronounced. These findings highlight my broader contribution—the robustness of my forecasting framework and its reliance on investor sentiment, especially during periods of economic stress.

Building on the foundational work of Binsbergen and Koijen (2010), who employed state-space methods to model expected returns and dividend growth, and Binsbergen et al. (2013), who constructed equity yields and analyzed their predictive capacity for dividend growth, my study, to the best of my knowledge, is the first to integrate equity yield data into a state-space framework. This innovative model successfully extracts investor expectations and leverages them to predict dividend growth, underscoring the predictability of dividend growth and the critical role of investor expectations in forecasting.

Overall, my findings underscore the effectiveness of the one-year equity yield as a reliable predictor of dividend growth, particularly during periods of economic stress. The proposed model offers a robust alternative to existing approaches, demonstrating superior in-sample accuracy and out-of-sample forecasting ability across markets. These results not only provide empirical evidence for dividend growth predictability but also offer meaningful insights for investors and policymakers seeking to anticipate economic trends in times of uncertainty.

Appendix A1

In this section, I provide details on the Kalman filter procedure employed in my model. Following the approach of Binsbergen and Koijen (2010), I define the state vector as follows:

$$X_t = \begin{bmatrix} \hat{g}_t \\ \epsilon^d_{t+1} \\ \epsilon^g_{t+1} \\ \epsilon^\mu_{t+1} \end{bmatrix}$$

The transition equation (Eq (6)) can be written as

$$X_{t+1} = FX_t + \Gamma\epsilon_{t+1}$$

where $F_t = \begin{bmatrix} \gamma_1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$, $\Gamma = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, the residual $\epsilon_t = \begin{bmatrix} \epsilon^d_{t+1} \\ \epsilon^g_{t+1} \\ \epsilon^\mu_{t+1} \end{bmatrix}$ is assumed to be jointly normally distributed. $\epsilon_t \sim \underbrace{\begin{bmatrix} \sigma_d^2 & 0 & \sigma_{d\mu} \\ 0 & \sigma_g^2 & \sigma_{g\mu} \\ \sigma_{d\mu} & \sigma_{g\mu} & \sigma_\mu^2 \end{bmatrix}}_{Q}$[33].

Namely,

$$\underbrace{\begin{bmatrix} \hat{g}_{t+1} \\ \epsilon^d_{t+2} \\ \epsilon^g_{t+2} \\ \epsilon^\mu_{t+2} \end{bmatrix}}_{X_{t+1}} = \underbrace{\begin{bmatrix} \gamma_1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}}_{F_t} \underbrace{\begin{bmatrix} \hat{g}_t \\ \epsilon^d_{t+1} \\ \epsilon^g_{t+1} \\ \epsilon^\mu_{t+1} \end{bmatrix}}_{X_t} + \underbrace{\begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{\Gamma} \underbrace{\begin{bmatrix} \epsilon^d_{t+2} \\ \epsilon^g_{t+2} \\ \epsilon^\mu_{t+2} \end{bmatrix}}_{\epsilon_{t+1}}$$ [34].

[33] Folllow Binsbergen and Koijen (2010) , I normalize the correlation between realized dividend growth shocks (ϵ^d_{t+1}) and expected dividend growth shocks (ϵ^g_{t+1}) to zero.

[34] Please note that the expected returns discussed here refer to holding a one-year constant-maturity dividend futures contract until maturity. In contrast, the expected returns examined in Binsbergen and Koijen (2010) pertain to stock returns.

Let

$$Y_t = \begin{bmatrix} \triangle d_{t+1} \\ e_{t+1,1} \end{bmatrix}$$

The measurement equations (Eq (7) and Eq (8)) are then given by

$$Y_t = M_0 + M_1 Y_{t-1} + M_2 X_t$$

$$\underbrace{\begin{bmatrix} \triangle d_{t+1} \\ e_{t+1,1} \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} \gamma_0 \\ (1-\delta_1)(\delta_0 - \gamma_0) \end{bmatrix}}_{M_0} + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & \delta_1 \end{bmatrix}}_{M_1} \underbrace{\begin{bmatrix} \triangle d_t \\ e_{t,1} \end{bmatrix}}_{Y_{t-1}} + \underbrace{\begin{bmatrix} 1 & 1 & 0 & 0 \\ (\delta_1 - \gamma_1) & 0 & -1 & 1 \end{bmatrix}}_{M_2} \underbrace{\begin{bmatrix} \hat{g}_t \\ \epsilon^d_{t+1} \\ \epsilon^g_{t+1} \\ \epsilon^\mu_{t+1} \end{bmatrix}}_{X_t}$$

Step 0: Initialization [35]

Initial System State:$X_{0|0} = E[X_0] = 0_{4x1}$

Initial State Covariance:$P_{0|0} = E[X_t X_t^T]$

Step1: Prediction

State Predict:$X_{t|t-1} = F X_{t-1|t-1}$

Covariance Predict: $P_{t|t-1} = F P_{t-1|t-1} F^T + \Gamma Q \Gamma^T$

Step 2: Measurement

Measurement: $\eta_t = Y_t - M_0 - M_1 Y_{t-1} - M_2 X_{t|t-1}$

$S_t = M_2 P_{t|t-1} M_2^T$

Calculate the Kalman Gain: $K_t = P_{t|t-1} M_2^T S_t^{-1}$

Step 3: Update

State Update: $X_{t|t} = X_{t|t-1} + K_t \eta_t$

Covariance Update: $P_{t|t} = (I - K_t M_2) P_{t|t-1}$

[35] See Binsbergen and Koijen (2010) and Becker (2020): Kalman Filter from the Ground Up

The likelihood is based on the prediction errors (η_t) and the innovation covariance matrix (S_t), which quantifies the uncertainty of the discrepancy between the observed Y_t and the predicted Y_t.

$$L = -\sum_{t=1}^{T} log(det(S_t)) - \sum_{t=1}^{T} \eta_t^{'} S_t^{-1} \eta_t$$

I estimate the parameters by maximizing the sum of likelihood across periods using simulated annealing over the set of parameters $\Theta(\delta_0, \gamma_0, \delta_1, \gamma_1, \sigma_\mu, \sigma_g, \sigma_d, \rho_{gu}, \rho_{du}, \rho_{dg})$.

Appendix A2

Est. Period	δ_1	γ_1	δ_0	γ_0	σ_μ	σ_g	σ_d	ρ_{gu}	ρ_{du}	ρ_{dg}
1974-1995	0.774	0.379	0.081	0.063	0.056	0.040	0.006	0.753	0.641	-
1974-1996	0.863	0.447	0.035	0.062	0.058	0.039	0.007	0.747	0.641	-
1974-1997	0.910	0.467	0.000	0.064	0.056	0.038	0.006	0.732	0.627	-
1974-1998	0.901	0.461	0.008	0.064	0.055	0.037	0.005	0.730	0.685	-
1974-1999	0.895	0.459	0.031	0.066	0.054	0.037	0.006	0.736	0.651	-
1974-2000	0.871	0.340	0.000	0.057	0.062	0.050	0.006	0.816	0.464	-
1974-2001	0.836	0.405	0.011	0.054	0.065	0.048	0.012	0.795	0.609	-
1974-2002	0.766	0.448	0.038	0.052	0.067	0.046	0.017	0.730	0.566	-
1974-2003	0.763	0.366	0.039	0.055	0.070	0.049	0.009	0.790	0.461	-
1974-2004	0.776	0.411	0.064	0.064	0.072	0.057	0.009	0.798	0.596	-
1974-2005	0.748	0.432	0.032	0.058	0.083	0.056	0.024	0.765	0.634	-
1974-2006	0.745	0.449	0.043	0.062	0.074	0.050	0.034	0.697	0.553	-
1974-2007	0.722	0.351	0.055	0.063	0.075	0.055	0.025	0.710	0.568	-
1974-2008	0.762	0.229	0.076	0.057	0.075	0.060	0.015	0.547	-0.262	-
1974-2009	0.707	0.190	0.052	0.053	0.071	0.072	0.003	0.509	0.655	-
1974-2010	0.707	0.198	0.050	0.053	0.070	0.071	0.005	0.505	0.546	-
1974-2011	0.715	0.210	0.048	0.056	0.069	0.071	0.003	0.493	0.524	-
1974-2012	0.706	0.232	0.062	0.061	0.071	0.077	0.006	0.550	0.525	-
1974-2013	0.693	0.183	0.052	0.059	0.072	0.077	0.003	0.558	0.707	-
1974-2014	0.698	0.176	0.054	0.060	0.070	0.077	0.003	0.565	0.436	-
1974-2015	0.695	0.181	0.055	0.061	0.069	0.076	0.002	0.564	0.870	-
1974-2016	0.697	0.180	0.056	0.061	0.068	0.075	0.003	0.563	0.420	-
1974-2017	0.696	0.180	0.055	0.061	0.068	0.074	0.003	0.563	0.471	-
1974-2018	0.696	0.183	0.059	0.063	0.067	0.074	0.003	0.568	0.453	-
1974-2019	0.698	0.178	0.057	0.062	0.066	0.073	0.002	0.570	0.517	-
1974-2020	0.694	0.199	0.055	0.059	0.066	0.074	0.001	0.567	0.373	-
1974-2021	0.687	0.184	0.058	0.061	0.066	0.072	0.000	0.568	0.246	-
1974-2022	0.698	0.162	0.065	0.061	0.066	0.073	0.001	0.559	-0.037	-
1974-2023	0.711	0.174	0.070	0.062	0.067	0.072	0.001	0.560	0.532	-

Table 10: Parameter Estimation Results for the Equity Yield Model: Expanding Windows from 1974–1995 to 1974–2022, and the Full Sample 1974–2023

Appendix A3

Est. Period	δ_1	γ_1	δ_0	γ_0	σ_μ	σ_g	σ_d	ρ_{gu}	ρ_{du}	ρ_{dg}
1974-1995	0.926	0.535	0.083	0.065	0.015	0.041	0.008	0.483	0.378	-
1974-1996	0.965	0.534	0.052	0.061	0.010	0.040	0.010	0.536	0.423	-
1974-1997	0.983	0.511	0.000	0.064	0.007	0.040	0.008	0.483	0.518	-
1974-1998	0.983	0.513	0.000	0.065	0.007	0.039	0.008	0.480	0.525	-
1974-1999	0.984	0.513	0.000	0.068	0.007	0.039	0.007	0.457	0.520	-
1974-2000	0.980	0.384	0.000	0.055	0.007	0.049	0.015	0.515	-0.056	-
1974-2001	0.952	0.390	0.053	0.053	0.011	0.051	0.004	0.530	-0.610	-
1974-2002	0.911	0.421	0.068	0.051	0.018	0.050	0.005	0.524	-0.491	-
1974-2003	0.925	0.371	0.068	0.055	0.016	0.050	0.009	0.532	-0.636	-
1974-2004	0.923	0.449	0.080	0.063	0.017	0.057	0.009	0.575	-0.328	-
1974-2005	0.930	0.251	0.072	0.058	0.014	0.058	0.018	0.458	-0.322	-
1974-2006	0.933	0.221	0.075	0.061	0.013	0.057	0.023	0.439	-0.277	-
1974-2007	0.930	0.242	0.079	0.063	0.013	0.059	0.015	0.470	-0.479	-
1974-2008	0.912	0.238	0.081	0.059	0.018	0.058	0.024	0.382	-0.576	-
1974-2009	0.923	0.274	0.068	0.050	0.015	0.072	0.012	0.272	-0.495	-
1974-2010	0.927	0.244	0.069	0.052	0.014	0.071	0.012	0.247	-0.578	-
1974-2011	0.923	0.236	0.071	0.053	0.014	0.071	0.011	0.240	-0.567	-
1974-2012	0.911	0.284	0.081	0.059	0.017	0.076	0.015	0.382	-0.350	-
1974-2013	0.916	0.196	0.076	0.058	0.016	0.077	0.012	0.321	-0.452	-
1974-2014	0.917	0.185	0.078	0.060	0.015	0.076	0.019	0.284	-0.193	-
1974-2015	0.915	0.191	0.079	0.060	0.016	0.075	0.019	0.288	-0.178	-
1974-2016	0.916	0.193	0.080	0.060	0.015	0.075	0.011	0.308	-0.572	-
1974-2017	0.919	0.193	0.079	0.061	0.015	0.075	0.010	0.304	-0.621	-
1974-2018	0.914	0.190	0.082	0.061	0.015	0.074	0.010	0.292	-0.475	-
1974-2019	0.917	0.189	0.081	0.062	0.015	0.074	0.008	0.282	-0.750	-
1974-2020	0.920	0.186	0.077	0.060	0.015	0.074	0.008	0.318	-0.552	-
1974-2021	0.930	0.192	0.075	0.060	0.014	0.073	0.008	0.309	-0.495	-
1974-2022	0.911	0.176	0.080	0.061	0.017	0.074	0.004	0.274	-0.250	-
1974-2023	0.913	0.198	0.081	0.063	0.016	0.073	0.004	0.301	-0.513	-

Table 11: Parameter Estimation Results for Binsbergen and Koijen (2010)'s *pd* Model: Expanding Windows from 1974–1995 to 1974–2022, and the Full Sample 1974–2023

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