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

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Abstract

I develop a state-space model to extract information about future dividend growth from dividend futures. Combining the longest available proprietary over-the-counter (OTC) dividend futures data with synthetic data from Giglio et al. (2024), I find that the model outperforms all existing approaches in forecasting dividend growth for the S&P 500 and demonstrates strong predictive performance for the Euro Stoxx 50, Nikkei 225, and FTSE 100—particularly during market downturns. This superior performance reflects the model's ability to capture dynamic predictive relationships, enabled by the long time series used to estimate its parameters. The results underscore the value of short-maturity futures in isolating information about near-term cash flow expectations and represent a significant improvement over traditional dividend yield-based forecasts.

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

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Introduction

This paper investigates the out-of-sample predictability of dividend growth. I present evidence that dividend growth is more predictable than previously recognized, which may help explain a larger portion of the variation in valuation ratios. Prior research has relied on stock prices to forecast dividend growth. However, stock prices, which aggregate all future cash flows, provide only a noisy proxy for near-term expectations. I instead use dividend strips, which isolate cash flow expectations at specific horizons. Moreover, rather than relying on traditional regression approaches, I employ a state-space model, which allows recursive updating, explicitly represents latent states, and captures time-varying relationships. The combination of dividend strips and a state-space framework substantially improves forecasts of dividend growth.

My key innovation lies in integrating short-maturity dividend strip pricing into a state-space framework. The short end of the term structure is particularly informative about near-term dividend-growth expectations, where economic conditions are more observable and revisions in those expectations map more directly into cash-flow news. This framework reduces measurement noise by separating latent state dynamics from observed data, improving the extraction of dividend-growth signals.

However, this approach requires a sufficiently long history of dividend strip data to identify the parameters of a state-space model. Dividend derivatives are relatively new, and the available time series are therefore limited in length, which may explain why this approach has been largely absent in prior work. My dataset, obtained from a leading financial institution active in the dividend strips market, provides the longest known continuous series of dividend futures prices, beginning with the inception of the over-the-counter swap market in 2003[1] and, subsequently, the transition to listed futures, extending through 2023[2]. With just over 20 annual observations, this dataset provides, to my knowledge, the first sufficiently long history enabling state-space modeling of dividend growth.

Moreover, I further extend the U.S. dataset by incorporating synthetic dividend strip data constructed by Giglio et al. (2024)[3], which provide a longer historical sample for initial parameter

[1]The data begin in 2003 for the U.S., 2002 for Europe, and 2004 for Japan and the U.K.

[2]The availability of dividend futures has expanded over time, with the earliest swap contracts emerging in 2002 in the OTC market for the Euro Stoxx 50 index before being listed on an exchange in 2008, while S&P 500 dividend futures began trading on exchanges in late 2015.

[3]They estimate an affine model using equity return data to construct synthetic U.S. equity yields back to 1974, which align reasonably well with traded strip yields during the overlapping period.

estimation. This construction improves identification by allowing parameters to be pre-estimated before traded strip data become available, thereby avoiding reliance solely on the relatively short span of traded data. It also ensures a sufficiently long sample period to conduct out-of-sample forecasting tests. Specifically, by combining equity yields[4] derived from market-traded dividend derivatives with synthetic equity yields from Giglio et al. (2024) for the pre-2003 period, I construct a comprehensive 50-year equity yield series for the U.S. market, spanning 1974–2023. This augmented dataset thus enables robust calibration of the state-space model and subsequent out-of-sample tests of dividend growth.

For the traded data, dividend strip prices in practice are not directly observable in spot markets, as they are typically traded through futures or swaps. Accordingly, I construct equity yields using dividend futures prices[5]. These contracts provide direct claims on the total dividends paid within a given calendar year by the underlying index, with settlement occurring at maturity when the long pays the futures price and the short delivers the actual dividends distributed by the underlying asset.

Initially introduced in the early 2000s, dividend swap contracts were exclusively traded in the over-the-counter (OTC) market, before transitioning to listed futures beginning in Europe in 2008 and shortly thereafter in the UK and Japan[6] (Mixon & Onur, 2017). Notably, the U.S. market did not introduce listed dividend futures until late 2015.

In this paper, I utilize proprietary dividend derivative data consisting of OTC quotes of dividend swaps for periods prior to the official listing of each index's dividend futures, together with post-listing prices, and extend through December 2023. The dataset covers the S&P 500, Euro Stoxx 50, Nikkei 225, and FTSE 100, offering the most comprehensive historical record of dividend strip derivatives across these four major equity markets, spanning each market's history of dividend derivatives since inception.

Leveraging this dataset, I first investigate the relationship between the one-year equity yields and NBER-defined recession periods. I find a strong association between one-year equity yields and all U.S. recessions identified by the NBER, as illustrated in Figure 2. Specifically, one-year

[4]Equity yields are defined as $e_{t,n} = \frac{1}{n} log(\frac{D_t}{P_{t,n}})$, where D_t is the current dividend level and $P_{t,n}$ is the price of an n-year dividend strip. See Binsbergen et al. (2013).

[5]Assuming no-arbitrage, spot and futures prices are linked through the nominal government bond yields.

[6]Euro Stoxx 50 dividend futures launched on Eurex in June 2008, FTSE 100 Dividend Index Futures in May 2009, and Nikkei 225 Dividend Futures on the Singapore Exchange in June 2010.

equity yields tend to rise before and during recessions, peaking as economic conditions deteriorate, and subsequently declining after the recession ends. This pattern is particularly pronounced during the two most recent downturns—the Great Recession of 2008 and the COVID-19 recession of 2020. Similar dynamics appear across the Euro Stoxx 50, Nikkei 225, and FTSE 100, with equity yield movements largely synchronized across the four major markets. These findings offer initial empirical evidence of the predictive potential of one-year equity yields.

To build on this initial evidence, I incorporate one-year equity yields into the state-space model and document the in-sample fit. My model achieves in-sample R^2 value of 29.41% for cash-reinvested dividend growth over full study period of 1974–2023. By contrast, Binsbergen and Koijen (2010), using the price-dividend (pd) ratio, report in-sample R^2 of 13.9% for cash-reinvested dividend growth over their study period, 1946–2007. My model, which incorporates one-year equity yields as a predictor, delivers a markedly higher in-sample fit for U.S. dividend growth.

Applying the same approach to Europe, Japan, and the U.K., I rely exclusively on equity yields constructed from traded dividend derivatives, as synthetic equity yields are unavailable for these markets. The analysis is therefore limited to shorter sample periods—2002–2023 for Europe and 2004–2023 for both Japan and the U.K. Over these samples, the state-space model yields in-sample R^2 values of 51.89% for Europe, 61.54% for Japan, and 30.94% for the U.K.

More importantly, I evaluate the model's real-time forecasting performance through out-of-sample testing. For the 50-year U.S. equity yield series, I use the first 22 years (1974–1995) to estimate the initial parameters and then implement an expanding-window approach to generate forecasts through 2023. In these out-of-sample tests, the model's one-year-ahead dividend growth forecasts significantly outperform the historical mean benchmark, achieving an out-of-sample R^2 of 15.70% over the subsequent 28 years. This provides strong evidence of the model's out-of-sample forecasting power.

Beyond the historical mean benchmark, I evaluate the model against alternative approaches. In out-of-sample tests over the same sample periods, my equity-yield-based approach significantly outperforms benchmark models, including a standard OLS predictive regression and the present-value approach of Binsbergen and Koijen (2010). I further compare my forecasts with the survey-based dividend expectations of De La O and Myers (2021), which aggregate analyst forecasts for S&P

500 firms. Over the 2004–2022 study period, corresponding to their sample[7], my model produces forecasts that are more accurate than survey expectations. This outperformance, measured using the MSPE-adjusted statistic of Clark and West (2007), provides additional evidence of the model's forecasting ability.

I also extend the analysis beyond the U.S. market. Using parameters estimated from U.S. data in a pseudo out-of-sample evaluation[8], the model delivers an out-of-sample R^2 of about 26% for Europe and 28% for Japan, while forecasts for the U.K. fail to beat the historical mean benchmark.

Having established the model's overall forecasting ability, I next examine horizon-specific predictability. Predictability is strong at the one-year horizon, weakens and becomes statistically insignificant in the second year, and then exhibits a sign reversal with marginal significance in the third year. This horizon-specific pattern suggests that dividend growth predictability might be horizon dependent, with predictive content confined to the immediate one-year horizon, while predictability beyond that is weak or unreliable.

These findings motivate three main contributions to the literature. First, by incorporating dividend futures prices, the analysis suggests that aggregate U.S. dividends are more predictable than is commonly assumed in prior research. Whereas most prior research limits predictive information to the price–dividend ratio, I extend the framework with a state-space model that leverages traded dividend futures to forecast dividend growth, delivering both improved in-sample fit and superior out-of-sample performance.

Second, I show that the appraoch can be applied across markets. Using parameters estimated from the U.S. together with dividend futures data from Europe, Japan, and the U.K., the model delivers consistent evidence of predictability in these markets as well.

Third, I provide the initial evidence on horizon-specific predictability using dividend futures, documenting the limits of dividend growth forecasting beyond the immediate one-year horizon.

The rest of the paper is organized as follows. Section 1 details the data and sources. Section 2 introduces equity yields and outlines the state-space model and methodology. Section 3 covers

[7]The I/B/E/S database has collected dividend forecasts since 2003.

[8]As synthetic equity yields are unavailable for Europe, Japan, and the U.K., the limited sample length leaves too few periods for a meaningful out-of-sample evaluation once market-specific parameters are estimated. A pseudo out-of-sample exercise is implemented instead, using parameters estimated from U.S. data to generate forecasts. When predicting dividend growth at $t+1$ in these three markets, the procedure relies only on parameters estimated from information available up to time t in the U.S. data, together with futures data up to time t in the respective markets.

parameter estimation. Section 4 presents empirical results, evaluating in-sample and out-of-sample performance and comparing forecasts to benchmark models. Section 5 conducts robustness tests, and Section 6 concludes.

Related Literature

This paper relates to two strands of literature. First, this paper contributes to the literature on dividend growth predictability and its link to return predictability. Seminal work by Campbell and Shiller (1988) introduced a log-linearized present-value model that ties variation in the dividend–price ratio to either expected returns or expected dividend growth. This framework established the standard practice of using dividend yields to test for dividend growth predictability and by construction, its inseparability from return predictability. When applied to U.S. postwar data, however, empirical research has found little evidence that dividend yields forecast dividend growth. Fama and French (1988), Cochrane (1992), and Campbell and Ammer (1993) concluded that most of the variation in the dividend–price ratio reflects discount-rate news, reinforcing the influential view that dividend growth is difficult to predict in this setting.

Subsequent studies provide important nuance to this view. Using prewar U.S. data, Chen (2009) shows that dividend–price ratios predict dividend growth, whereas in the postwar era they forecast returns instead, indicating that the evidence is sample-dependent. Chen, Da, and Priestley (2012) identify a mechanism for this shift: stronger postwar dividend smoothing attenuates the informational content of dividend yields for cash flows, helping to explain the weak dividend-growth predictability in that period. Building on this smoothing insight, Garrett and Priestley (2012) apply a dividend-smoothing model to historical data to derive a new expectation measure. Using this measure, they show that dividend growth is strongly predictable once smoothing is accounted for. By contrast, international evidence shows that the postwar U.S. experience is not universal. Engsted and Pedersen (2010) and Rangvid, Schmeling, and Schrimpf (2014) document dividend-growth predictability in many other countries, suggesting that the postwar U.S. findings are more the exception than the rule.

Methodological advances have also reshaped the literature. Goyal and Welch (2008) demonstrate that conventional univariate predictive regressions generally fail out of sample, raising doubts about the robustness of earlier findings. In contrast, Binsbergen and Koijen (2010) propose a

latent-variable present-value model in which expected returns and expected dividend growth are modeled as latent processes. Their approach shows that both returns and dividend growth appear predictable in-sample, but dividend growth fails to exhibit out-of-sample predictive power. Against this backdrop, my paper integrates equity yields derived from dividend futures prices into a state-space model to estimate expected dividend growth. The fixed-maturity structure of dividend futures provides a cleaner separation of cash-flow expectations across horizons than conventional dividend yields. This approach revisits the question of dividend growth predictability by combining improved measurement with an established state-space framework, revealing stronger evidence of cash-flow predictability than previously recognized.

Second, this paper connects to the emerging literature on traded dividend claims. This strand of research builds on Binsbergen et al. (2013), who introduced dividend futures as a traded asset class and showed how they can be used to extract forward-looking information about both discount rates and expected dividends. Subsequent studies—including Binsbergen and Koijen (2017), Bansal et al. (2021), and Gormsen (2021)—have debated the term structure of risk premia embedded in dividend claims, focusing in particular on whether short-maturity dividend strips carry unusually high risk premia and Sharpe ratios. In contrast, this paper does not take a stance on the risk premia debate, but instead leverages short-maturity dividend claims as a direct input for forecasting near-term dividend growth.

One of the main challenges in this emerging literature is the short span of available data. Several recent studies—such as Cejnek and Randl (2020), Gonçalves (2021a), and Gormsen (2021)—rely on proprietary over-the-counter dividend swap datasets that cover only limited periods, typically spanning a single recession and recovery. For example, Gonçalves (2021a) uses data from 2005–2017, while Bansal et al. (2021) use data from 2004–2017, and Gormsen (2021) extends the sample with listed futures through mid-2019, but this still excludes the COVID-19 recession. As a result, empirical analyses are constrained by both short sample lengths and limited variation across macroeconomic regimes.

In contrast to prior studies, this paper uses the longest U.S. dividend futures dataset to date, spanning 2003–2023 and covering both OTC and listed markets. The expanded horizon includes the COVID-19 recession and recovery, providing multiple economic cycles and supporting a more comprehensive and robust analysis of dividend growth predictability.

1 Data

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

For the U.S. aggregate market, I obtain monthly returns for both the value-weighted index with dividends and without dividends from the Center for Research in Security Prices (CRSP) for the period 1974–2023. The difference between these two return series is used to compute the monthly dividend on the value-weighted portfolio. To construct annual dividend growth, I assume that dividends paid each month are reinvested at the 30-day Treasury bill rate within the same year. The 30-day T-bill rates are also obtained from CRSP. This method yields a measure of annual aggregate dividends that mitigates the seasonality in dividend payments, following prior studies such as Lettau and Ludvigson (2005), Binsbergen and Koijen (2010), and Zhu (2015).

For international markets, I obtain monthly total return and price return indices for the Euro Stoxx 50 (Europe), Nikkei 225 (Japan), and FTSE 100 (UK) from Bloomberg. The difference between total and price returns is used to compute monthly dividend returns for each index.

To construct equity yields, I follow Binsbergen et al. (2013) in combining dividend futures prices with maturity-matched nominal government bond yields. For the U.S., I use zero-coupon Treasury yields from the Gurkaynak, Sack, and Wright (2006) dataset, as in both Binsbergen et al. (2013) and Giglio et al. (2024).

For dividend futures data, although S&P 500 dividend futures are currently exchange-traded, most historical prices originate from over-the-counter (OTC) transactions and are not publicly available[9]. In this paper, I use proprietary dividend derivative data provided by a leading 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[10]. For the U.S., this dataset offers the most extensive pricing history available for dividend futures, spanning from the inception of the OTC swap market through 2023. In contrast to earlier studies, which only cover the Great Recession, this dataset also captures the

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

[10] After the launch of listed dividend futures, daily closing prices and trading volumes became publicly available. The proprietary dataset I received matches exactly with the publicly available data for each trading day after the listing of the respective index dividend futures across the four markets.

additional recession and recovery associated with the COVID-19 pandemic.

The dataset contains daily prices, open interest, and trading volumes for dividend derivatives linked to four major equity indices: the S&P 500, Euro Stoxx 50, Nikkei 225, and FTSE 100[11]. The coverage periods are:

- S&P 500: January 2003 to December 2023
- Euro Stoxx 50: January 2002 to December 2023
- Nikkei 225: January 2004 to December 2023
- FTSE 100: December 2004 to December 2023

However, due to relatively late emergence of this type of derivative, even the earliest dividend swap 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 data reconstructed by Giglio et al.(2024). This ensures that the annual time series dataset is sufficiently long to enable reliable parameter estimation and robust out-of-sample evaluation of my methodology.

Giglio et al.(2024) 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 track well with those calculated from actual traded dividend futures prices, as shown by a comparison with Bansal et al. (2017) over the overlapping period[12]. The synthetic equity 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.

This combination is necessary because neither dataset alone is sufficient. Using only the actual traded dividend derivative data results in a relatively short annual time series. While the post-2003 market data provides reliable parameter estimates, the limited sample leaves virtually no remaining

[11]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.

[12]See Giglio et al.(2024)

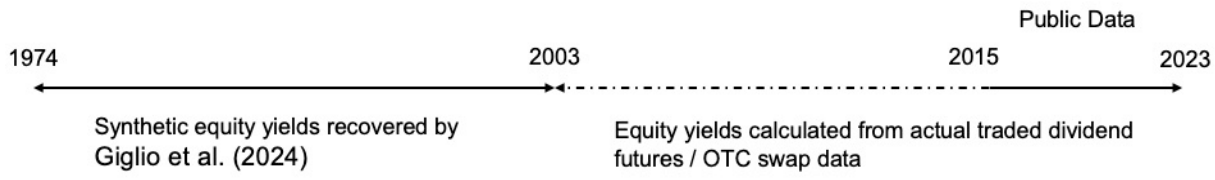


Figure 1: Data Sources for US Equity Yields

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

observations for a meaningful out-of-sample (OOS) evaluation[13]. Conversely, the synthetic dataset (1974–2020) spans a long enough period to accommodate both parameter estimation and OOS testing. However, it is considerably noisy and delivers poor forecasting performance[14]. This is not surprising, given that the estimates are derived solely from the cross-section of equity returns, without incorporating any dividend strip data. As a result, their informational content is akin to that of a standard price-dividend ratio, since they do not leverage the additional signals embedded in short-maturity dividend strips.

Table 1 presents summary statistics of the dataset. Panel A reports realized annual dividend growth rates for the U.S. aggregate market over the full study period from 1974 to 2023, calculated by reinvesting the monthly dividends of the CRSP value-weighted portfolio at the 30-day Treasury bill rate. Panel B provides summary statistics for monthly forward equity yields[15] across four equity indexes and five maturities[16], as in Binsbergen et al. (2013). For the U.S., I report the monthly forward equity yields derived from actual traded prices of dividend swaps and futures. For further

[13]The state-space model used in this paper typically requires at least 20 annual observations to ensure reliable estimation accuracy.

[14]Giglio et al.(2024) acknowledge that their model-implied dividend strip yields are not exact point-by-point matches to observed data and are subject to estimation uncertainty. Nevertheless, by extending the time series of dividend strips, their model enables more precise estimation of moments than relying solely on the shorter observable time series.

[15]I follow Binsbergen et al. (2013) in calculating forward equity yields. Reinvestment is not incorporated in these monthly time series.

[16]While the summary statistics report monthly data across multiple maturities, the subsequent analysis relies exclusively on the annual time series of one-year equity yields, which are, arguably, the most responsive and most informative predictor to incorporate into the model.

Δd_t	
	1974-2023
Mean	0.0639
Median	0.0722
St.dev.	0.0744
Maximum	0.2677
Minimum	-0.2238

(a) Summary Statistics of Annual Dividend Growth Rates for the 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	0.0373	0.0331
Eurostoxx 50 January 2002 – December 2023					
Mean	0.0091	0.0219	0.0214	0.0206	0.0191
St.dev.	0.1301	0.1017	0.0720	0.0549	0.0444
Nikkei 225: January 2004 – December 2023					
Mean	-0.0179	-0.0177	-0.0189	-0.0177	-0.0157
St.dev.	0.0975	0.0927	0.0721	0.0589	0.0502
FTSE 100: December 2004 – December 2023					
Mean	-0.0081	0.0045	0.0081	0.0108	0.0182
St.dev.	0.1085	0.0859	0.0599	0.0476	0.0595

(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 index 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 $y_{t,n}$: $e^f_{t,n} = e_{t,n} - y_{t,n}$.

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

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

details on the synthetic equity yield dataset used for earlier periods, see Giglio et al. (2024)[17]. In line with Binsbergen et al. (2013), I find the volatilities of the yields decline monotonically with maturity for across four indexes.

2 Equity Yields and the Model

2.1 Equity Yields

This section introduces the concept of equity yields and their integration into the model used to derive expected dividend growth.

Following Binsbergen et al. (2013), equity yields can be constructed from dividend futures prices in a manner analogous to how bond yields are derived from bond prices. Specifically, the forward equity yield at time t for maturity n, denoted by $e^f_{t,n}$, is given by:

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

where:

- D_t is the trailing sum of 12-month dividends at time t,
- $F_{t,n}$ is the price of an n-year constant-maturity dividend futures contract, obtained through interpolation across available maturities,
- $\theta_{t,n}$ is the dividend risk premium for maturity n,
- $g_{t,n}$ is the expected average annual dividend growth over the next n years, defined as:

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

This decomposition separates the forward equity yield into two components: (1) a risk compensation term, $\theta_{t,n}$ and (2) the expected dividend growth, $g_{t,n}$.

For the special case of a one-year horizon ($n = 1$), the forward equity yield simplifies to:

[17] See https://serhiykozak.com/#/data-code

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

where:

- $\mu_{t,1} = E_t\left[log(\frac{D_{t+1}}{F_{t,1}})\right]$ denotes the expected return from holding a one-year dividend futures contract to maturity, i.e., the one-year hold-to-maturity expected return
- $y_{t,1}$ denotes the one-year nominal yield on government bonds

For notational simplicity, I hereafter denote the one-period expected return as $\mu_t \equiv \mu_{t,1}$, and the one-period-ahead expected dividend growth as $g_t \equiv g_{t,1}$.

In addition to forward equity yields, equity yields at time t for maturity n can also be defined using dividend strip prices:

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

where $P_{t,n}$ is the price of an n-year dividend strip.

Under a no-arbitrage condition, the spot and futures prices of dividend strips are related through nominal government bond yields[18] $y_{t,n}$ as:

$$F_{t,n} = P_{t,n} exp(n y_{t,n})$$

Substituting this relationship into the equity yield formula yields:

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

Hence, the equity yield $e_{t,n}$ exceeds the forward equity yield $e^f_{t,n}$ by the nominal bond yield:

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

For the one-year case ($n = 1$), the equity yield is directly linked to both the hold-to-maturity expected return and the expected dividend growth (see Equation (1)):

[18] To compute equity yields, I use maturity-matched U.S. Treasury yields from Gurkaynak, Sack, and Wright (2006), as in Binsbergen et al. (2013) and Giglio et al. (2024).

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

Equation (3) is the key relationship for deriving one-period-ahead expected dividend growth, which will be introduced in the next section. Before proceeding, I first show how the forward-looking measure—equity yields—can predict economic variables, such as dividend growth. Specifically, I examine the comovement between equity yields and U.S. business cycles, as shown 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[19]. Extending the analysis beyond U.S. markets, similar dynamics appear across the Euro Stoxx 50, Nikkei 225, and FTSE 100, with equity yield movements largely synchronized across the four major markets; additional plots are presented in the Appendix A2.

Building on this evidence, I next examine whether investors' expectations, as embedded in equity yields derived from futures prices, can be extracted to forecast economic variables such as dividend growth.

[19]Equity yields across different maturities generally move in the same direction, though with varying magnitudes (see Binsbergen et al. (2013) and Giglio et al. (2024)). In this analysis, I focus on the one-year equity yield to illustrate this pattern, as it is the most sensitive yield measure and serves as the predictor in my model for forecasting dividend growth.

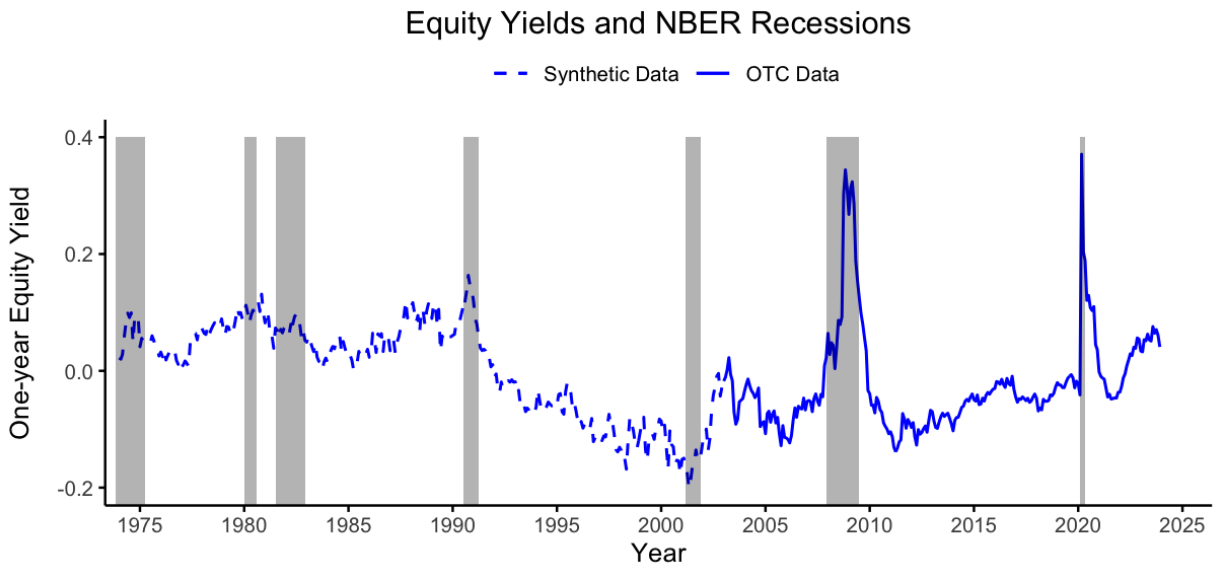


Figure 2: Equity Yields and NBER Recessions

This figure illustrates the relationship between the one-year equity yield and NBER-defined recessions from January 1974 through December 2023. Since the start of OTC trading in January 2003, equity yields have been computed using dividend futures prices (solid line). For the pre-2003 period, monthly equity yields are taken from the synthetic dataset of Giglio et al. (2024), shown as a dashed line. The one-year equity yield is calculated from futures prices as $e_{t,1} = ln(\frac{D_t}{F_{t,1}}) + y_{t,1}$.

2.2 The State-Space Model

Let $F_{t,1}$ denote the price of one-year constant-maturity dividend futures contract, and let r_{t+1} represent the realized log return from holding the contract to 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)[20].

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

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

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:

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

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

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

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

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

This system models expected dividend growth by below three equations. It consists of one transition equation (Eq. 6), which models expected dividend growth as an AR(1) process, and two measurement equations (Eq. 7 and Eq. 8)

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

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

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

21

[21]Note that the final system includes only one transition equation, despite the initial specification modeling 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 (Eq. 8).

3 Parameter Estimation

I estimate parameters in Equations (6) through (8) using conditional maximum likelihood estimation (MLE). To maximize the likelihood[22], I employ simulated annealing, an algorithm designed to search for the global maximum[23], 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[24]. 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 A3. My estimates, averaged across multiple estimation periods, indicate that the average expected dividend growth persistence (γ_1) in the U.S. is 0.295, while the average expected return persistence (δ_1) is 0.754 [25]. The unconditional expected dividend growth (γ_0) across estimation periods is 6.0%, whereas the unconditional expected log return for holding one-period dividend strips (δ_0) are 4.6%.

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

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

[24]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.

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

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	0.295	0.120
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}	0.508	0.208
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 and 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 A3.

4 Empirical Results

4.1 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 computed using block bootstrapping (N=500, block length=2).

My estimates indicate that the unconditional expected dividend growth rate in the U.S. over the 1974–2023 period is $\gamma_0 = 6.2\%$, while the unconditional one-year hold-to-maturity expected return is $\delta_0 = 7.1\%$. Consistent with prior research, I find that expected returns are more persistent than expected dividend growth. Specifically, the annual persistence of expected returns is estimated at δ_1=0.710, whereas the persistence of expected dividend growth is γ_1=0.168.

Panel A: Maximum Likelihood Estimates		
	Estimate	Standard Errors
δ_1	0.710	0.167
γ_1	0.168	0.223
δ_0	0.071	0.011
γ_0	0.062	0.018
σ_μ	0.067	0.018
σ_g	0.072	0.024
σ_d	0.000	0.022
ρ_{gu}	0.564	0.449
ρ_{du}	0.373	0.253
ρ_{dg}	–	–
Panel B: R^2 values		
R^2_{IS}	29.41%	

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. Standard errors are computed using block bootstrapping.

Follow Harvey (1989) and Binsbergen and Koijen (2010), the in-sample R^2 value is calculated 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.

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 29.41% for cash-reinvested dividend growth. Binsbergen and Koijen (2010), using the price-dividend (pd) ratio and a state-space model, report an in-sample R^2 values of 13.9% for cash-reinvested dividend growth over their study period of 1946–2007[26]. Although our study periods do not fully overlap, the difference

[26]They also report an in-sample R^2 values of 31.6% for market-reinvested dividend growth. However, market-reinvested dividend growth is not directly comparable to my methodology due to differences in assumptions and

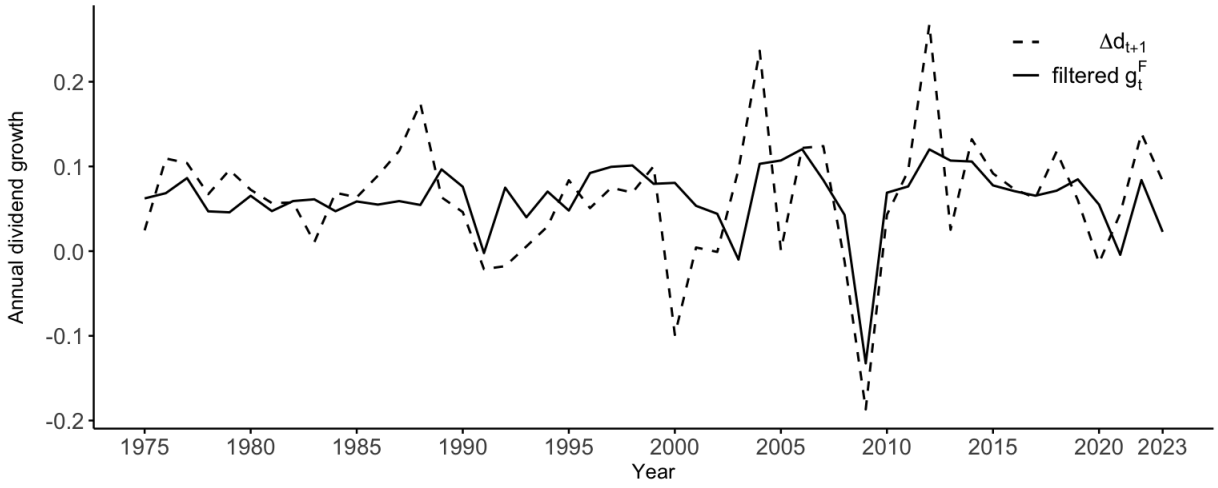


Figure 3: In-Sample: Filtered Series for Expected Dividend Growth in the US

The graph presents the filtered series of expected dividend growth (g_t^F) generated by my forecasting model, plotted alongside the time series of realized dividend growth (Δd_{t+1}). The expected dividend growth (g_t^F) is presented as lagged values, enabling a direct comparison with realized outcomes. This comparison serves as an evaluation of the model's in-sample performance in the US over time.

in sample length is not substantial. The higher in-sample R^2 obtained in my analysis suggests that the proposed approach provides a strong fit to the data, effectively capturing variations in dividend growth over time. 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.

approach.

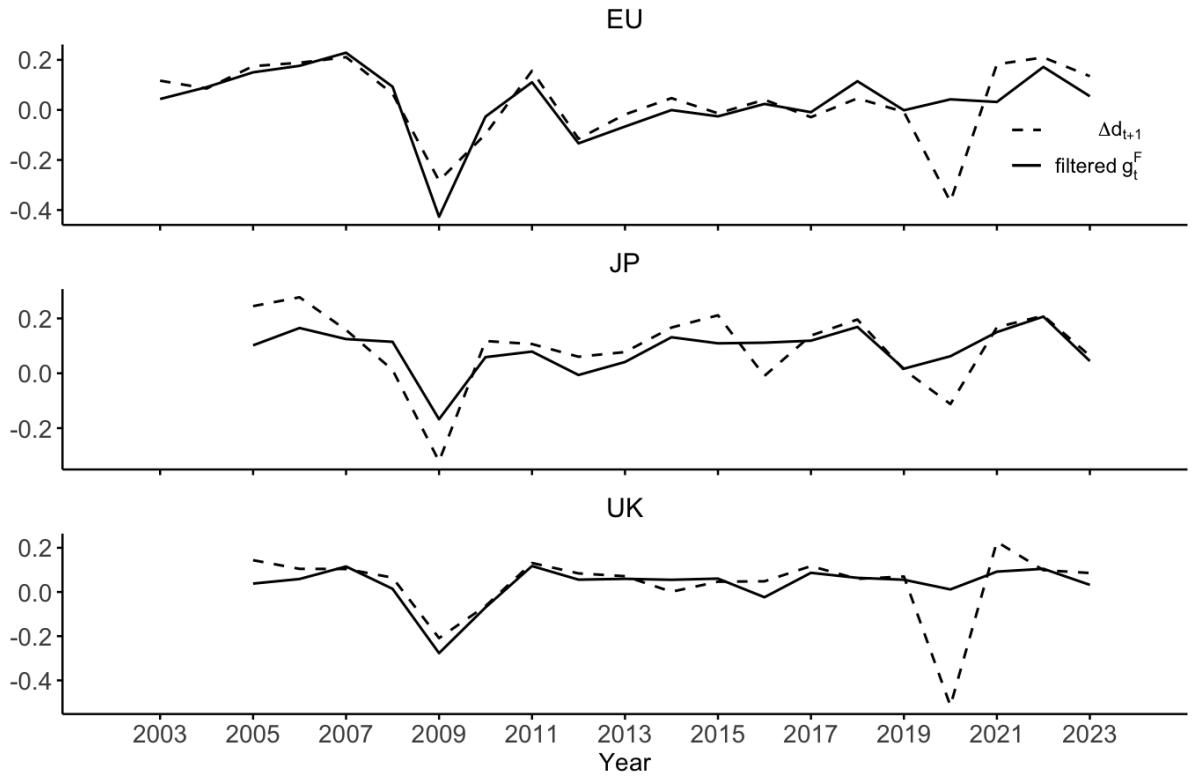


Figure 4: In-Sample: Filtered Series for Expected Dividend Growth in Europe, Japan, and the UK

The figure presents the filtered series of expected dividend growth (g_t^F) produced by my forecasting model, plotted alongside the realized dividend growth series (Δd_{t+1}). The expected values (g_t^F) are shown in their lagged form to allow a direct comparison with realized outcomes. This side-by-side comparison provides an in-sample evaluation of the model's performance across Europe, Japan, and the UK over time.

I reproduce the in-sample analysis for other markets over the periods during which one-year equity yield data are available. The sample period spans 2002–2023 for Europe, and 2004–2023 for both Japan and the UK. Across these three markets, the in-sample R^2 values are notably high: 51.89% for Europe, 61.54% for Japan, and 30.94% for the UK. The corresponding filtered series of expected dividend growth, along with their realized values, are presented in the three panels of Figure 4.

	Europe	Japan	UK
Period	2002-2023	2004-2023	2004-2023
R^2_{IS}	51.89%	61.54%	30.94%

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

Follow Harvey (1989) and Binsbergen and Koijen (2010), the in-sample R^2 value is calculate 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.

The elevated in-sample R^2 values can be partly attributed to the relatively short sample periods available for these markets. In addition, the in-sample analysis benefits from incorporating all data within the sample window, enhancing the model's ability to explain extreme events such as the 2009 macroeconomic trough.The negative relationship between the sharp spike in equity yields and the subsequent decline in dividend growth is evident in hindsight. While the model successfully captures the Great Recession across all three markets, it fails to anticipate the COVID-19 recession. This result, however, reinforces the model's reliance on investor expectations as a predictive mechanism.

Specifically, one-year equity yields spiked across all three markets at the end of 2008, reflecting investors' heightened concerns during the global financial crisis. In contrast, by the end of 2019, one-year equity yields remained stable, as the sudden and unpredictable nature of the COVID-19 outbreak left investors unaware of the impending recession. Thus, the model's inability to capture the COVID-19 episode further supports the interpretation that it functions through forward-looking expectations.

Overall, this analysis highlights the model's strength in forecasting recessions when investor expectations are aligned with future macroeconomic conditions, while also revealing its limitations in the face of unanticipated, exogenous shocks such as the COVID-19 pandemic.

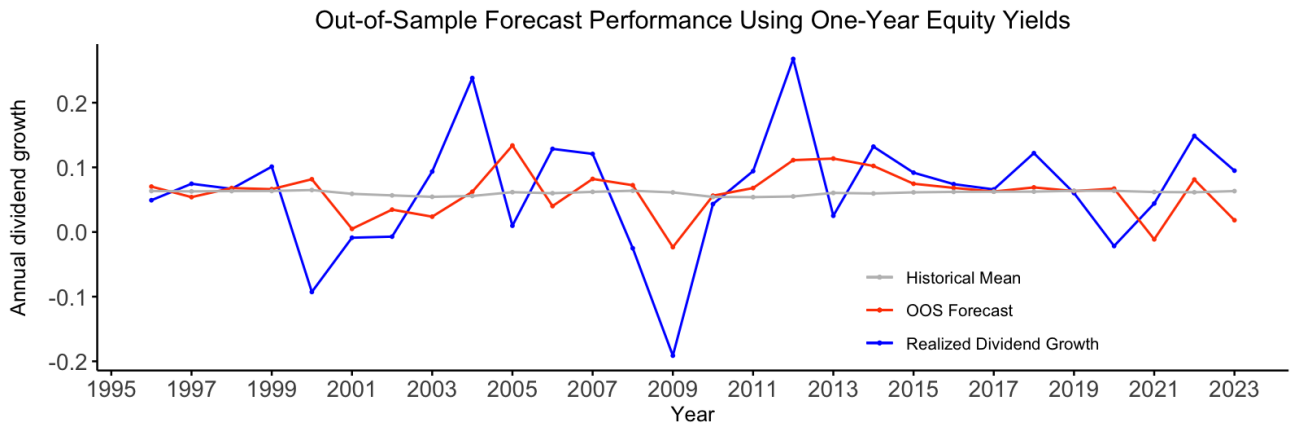


Figure 5: Out-of-Sample Forecasting Results in the US

The graph presents the filtered series of expected dividend growth (g_t^F) generated by my forecasting model using information available up to time t, plotted alongside the time series of realized dividend growth (Δd_{t+1}), and the benchmark series representing the historical mean of dividend growth (calculated up to time t), denoted as $\overline{\Delta d_t}$. Both the expected dividend growth (g_t^F) and the historical mean of dividend growth ($\overline{\Delta d_t}$) are presented as lagged values, enabling a direct comparison with realized outcomes. This comparison provides an evaluation of the model's out-of-sample performance in the U.S. over time.

4.2 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 such as future dividends. 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 4.1 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 approach[27]. 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.

[27]See Goyal and Welch (2008)

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.

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

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 forecast 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 A3.

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 approach 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 determine 1974–1995 as the shortest initial estimation period necessary to obtain reliable parameter estimates.[28]; 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 indicated by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

[28]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.

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 method using the present-value approach and price-dividend (pd) ratio, as in Binsbergen and Koijen (2010). [29] 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 15.70% for the evaluation period of 1996–2023 and 20.71% for 2001–2023[30](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 regressions, as opposed to my state-space model. As shown in Column 4, the out-of-sample R^2 is only 2.82% for 1996–2023 and 3.77% for 2001–2023, indicating marginal improvement over the benchmark. When conducting predictive regressions with expanding windows for out-of-sample testing, 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 shows that the estimated slope relating EY_1 to realized dividend growth $\triangle d_{t+1}$ varies substantially depending on whether the sample includes recession years[31], with a much stronger relationship during downturns than in normal times. This state-dependent variation highlights the limitations of a standard linear OLS framework, since a constant-parameter specification cannot account for such shifts. In contrast, my state-space model employs Kalman filter techniques to estimate latent states in real time, allowing it to adapt more effectively to changing market conditions. The Kalman gains provide the necessary responsiveness to shifts in market sentiment,

[29]The parameter estimates across expanding estimation periods for Binsbergen and Koijen (2010)'s model are provided in Appendix A4.

[30]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.

[31]The OLS estimates referenced here are reported in Appendix A5.

Evaluation Period	State-Space Model using EY_1	Present-Value Approach using pd Ratio	Predictive Regression using EY_1
1996-2023	15.70%*	-6.55%	2.82%
2001-2023	20.71%*	-2.93%	3.77%

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

Campbell and Thompson (2008)'s out-of-sample R^2 statistic is calculated as follows:

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

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 indicated by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

making the state-space model—combined with Kalman filter–based estimation and forecasting—a more robust and suitable approach for this setting.

Overall, the state-space model using one-year equity yields (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.

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 in Figure 6, 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.

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. To further illustrate this point, I present Figure 7, which depicts the monthly time series of the two predictors.

As shown, the two time series are closely synchronized, despite moving 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

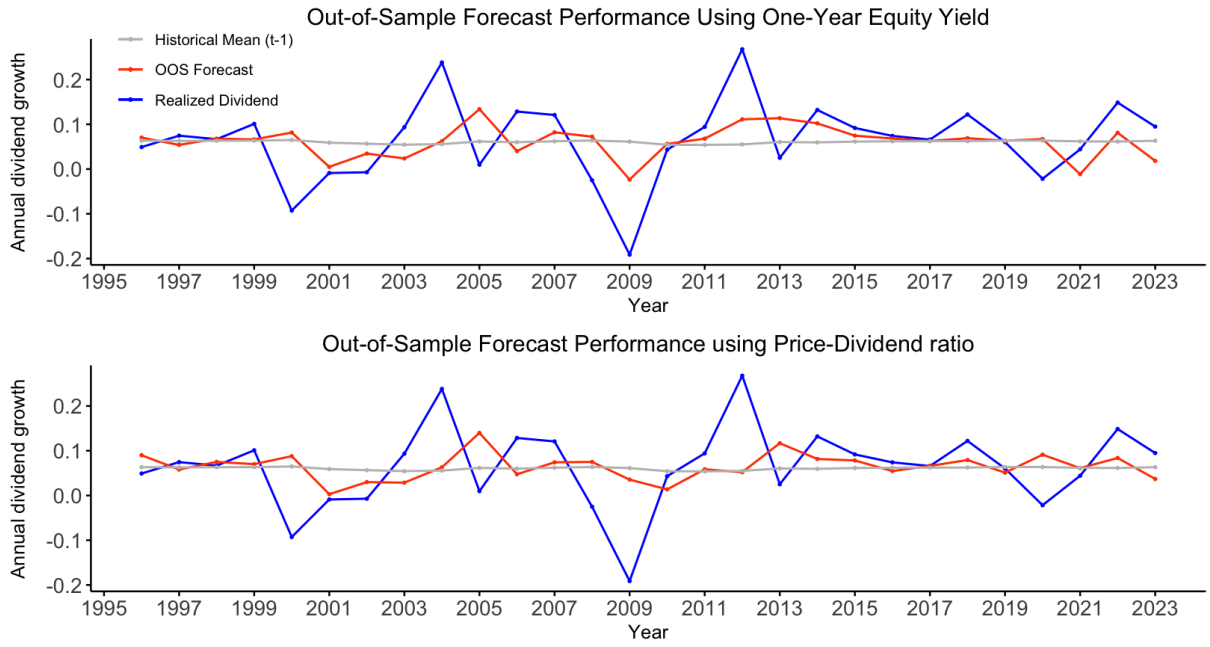


Figure 6: Forecasting Performance: One-Year Equity Yields vs. Price-to-Dividend Ratios

This figure compares the out-of-sample forecasting performance (1996–2023) of two models: the state-space model that incorporates one-year equity yields (top panel), and the present-value model based on the price-dividend (*pd*) ratio (bottom panel), following Binsbergen and Koijen (2010). Forecasts are made on an annual basis using expanding estimation windows starting from 1974, with both models re-estimated each year to update their parameters. For the state-space model, estimation begins with data from 1974 to 1995, and parameters are derived via maximum likelihood to forecast dividend growth for 1996. In each subsequent year, the estimation window expands by one year (e.g., 1974–1996 to forecast 1997), and the model is re-estimated accordingly. The same iterative approach is applied to the present-value model based on the *pd* ratio, ensuring a consistent forecasting framework. This process continues through 2023 to produce forecasts for the entire 1996–2023 period. Parameter estimates for the state-space model across the expanding windows are provided in Appendix A3, and those for the present-value model are reported in Appendix A4.

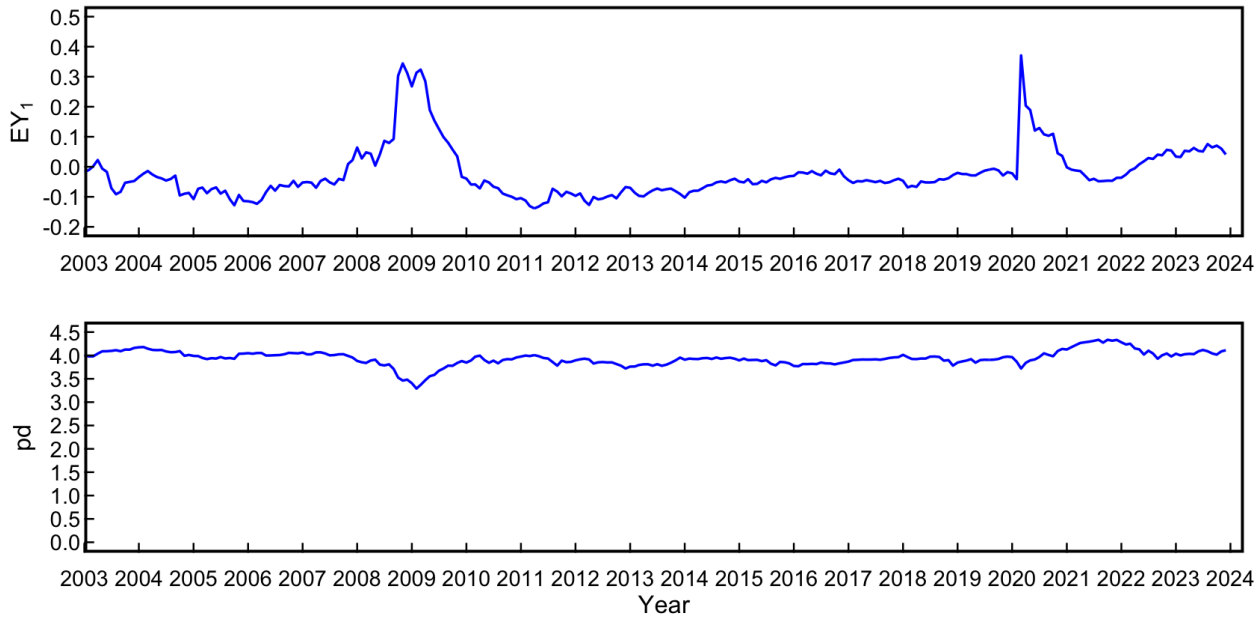


Figure 7: Monthly Time Series of One-Year Equity Yields and Price-Dividend Ratio

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, from January 2003 to December 2023. 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 price of the S&P 500.

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.

4.3 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 8. 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[32] , 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. [33]In such scenarios, my approach demonstrates strong predictive performance, effectively capturing these dynamics.

In comparison, the present-value approach 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 price (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.

[32]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.

[33]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.

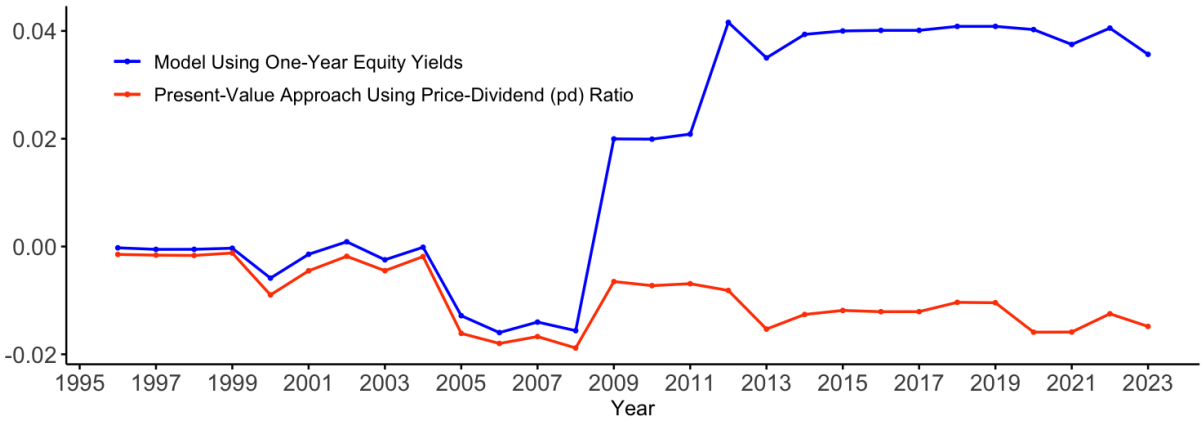


Figure 8: Cumulative Squared Prediction Error Difference: Benchmark Model minus Predictive Models

This figure plots the time series of the cumulative squared prediction error differences for both out-of-sample forecasts generated by my model and those produced by the models outlined in Binsbergen and Koijen (2010). Specifically, it displays the cumulative squared prediction errors of the benchmark model (the historical mean of dividend growth) minus those of the test models. To illustrate, using my model forecasts as an example, the cumulative squared prediction error difference is calculated as follows:

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

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 $t+1$. The historical mean of dividend growth (calculated up to time t), denoted as $\overline{\Delta d_t}$ is used as the benchmark model. An increases in a line indicates that the test model outperforms the benchmark, with higher values signifying superior out-of-sample performance.

This fundamental difference in maturity horizons likely affects their respective abilities to capture short-term drastic market fluctuations.

4.4 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 approach, by using the Clark and West(2007) out-of-sample MSPE-adjusted statistic

H_0 : Forecasts from the 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 approach using *pd* ratio

H_A: Forecasts from the 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 approach 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, 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 approach 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.

Evaluation Period	Clark and West (2007) MSPE-Adjusted Statistic	p-value
1996-2023	1.8487**	0.0376
2001-2023	1.7561**	0.0462

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 indicated by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

4.5 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. [34] Therefore, I conduct a pseudo out-of-sample evaluation instead. Given that business cycles are largely synchronized across markets[35], 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.

[34] 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.

[35] See Appendix A2 for the one-year equity yield series across four markets, which exhibit notable synchronization over time.

	Europe	Japan	UK
Period	2003-2023	2005-2023	2005-2023
$R^2_{Pseudo_{OS}}$	26.49%**	28.37%	-10.10%

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

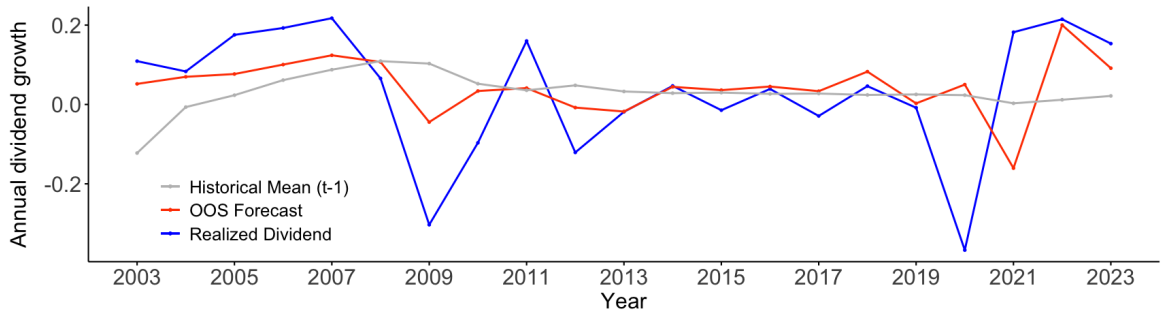
Campbell and Thompson (2008)'s out-of-sample R^2 statistic is calculated as follows:

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

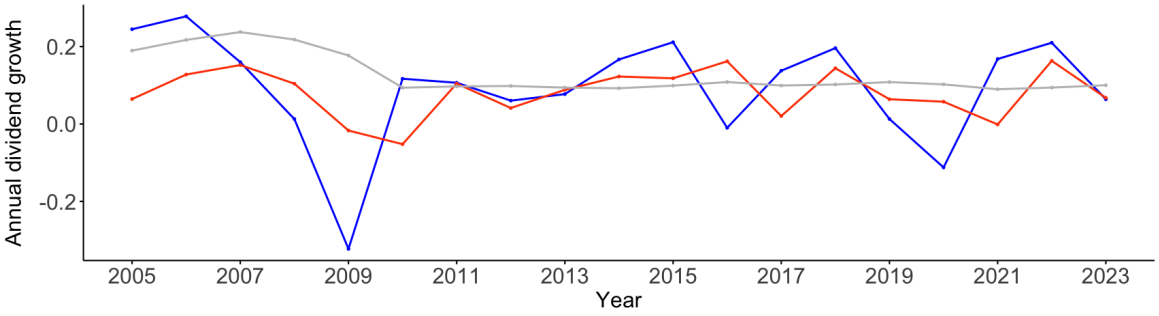
where g_t^F represents the filtered value generated using the US parameter estimates and equity yield data of Europe, Japan, and the UK available up to time t, as shown in the top, middle, and bottom panels. This value serves as the expected value for time $t+1$. Δd_{t+1} denotes the realized value at time $t+1$. The historical mean of dividend growth, calculated up to time t and denoted by $\overline{\Delta d_t}$, is used as the benchmark model. 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 indicated 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 26.49% for Europe, which is significant at 5% level. For Japan, the out-of-sample R^2 is 28.37%. 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.

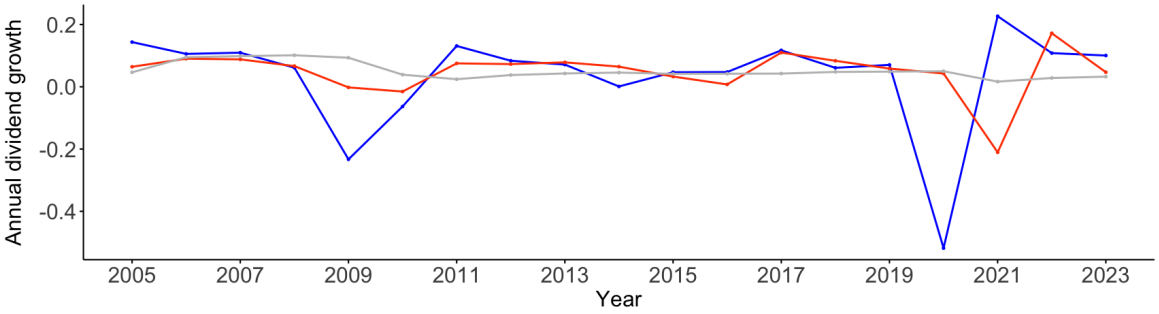
Additionally, due to differences in market characteristics, the parameters estimated from the U.S. market may inherently lead to suboptimal out-of-sample (OOS) forecast results for these non-U.S. markets. In the future, if dividend futures data series become sufficiently long to allow us to estimate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



(a) Europe



(b) Japan



(c) UK

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

The graph presents the filtered series of expected dividend growth (g_t^F) generated by my forecasting model, plotted alongside the time series of realized dividend growth (Δd_{t+1}). The expected dividend growth (g_t^F) is presented as lagged values, enabling a direct comparison between forecast and realized values. To generate these forecasts, model parameters estimated from the US market up to time t are applied, combined with equity yields from each respective market to produce forecasts for $t+1$. The parameter estimates derived from the US market across the expanding estimation windows are detailed in Appendix A3.

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.

4.6 Comparison to Survey-Based Dividend Expectations

De La O and Myers (2021) aggregate survey-based expectations for S&P 500 constituent firms to construct a one-year subjective dividend expectation. Using available analyst forecasts from I/B/E/S, they generate 12-month dividend expectations on a quarterly basis[36]. Since I/B/E/S estimates are not available for all S&P 500 companies, they aggregate dividend expectations only for firms with available forecasts and provide evidence that these forecast companies form a representative sample of the S&P 500.

Additionally, in the I/B/E/S database, dividend forecasts are provided on a fiscal-year basis rather than a calendar-year basis. Because firms have different fiscal year-end dates, De La O and Myers (2021) derive their 12-month-ahead expectations through horizon interpolation. For instance, if a forecast is made in Quarter 4 and the firm's fiscal year ends three months after the survey date, they interpolate using another forecast for the end of the next fiscal year—representing a 15-month dividend expectation—to estimate a 12-month-ahead dividend expectation.

To assess the forecasting performance of De La O and Myers (2021)'s method—which aggregates analyst forecasts—and my method, which is based on a state-space model and dividend futures pricing data, I compare the forecasts from both methods against the realized dividend values for the following year. This comparison is presented in Figure 10.

I use De La O and Myers (2021)'s 12-month dividend expectation, made in Quarter 4 of each year, as the benchmark, replacing the historical mean benchmark used throughout this paper, as it is the closest counterpart to the annual dividend expectation derived from my state-space model and year-end dividend futures pricing. The I/B/E/S database has collected dividend forecasts since 2003, and De La O and Myers (2021) provide expected one-year log dividend growth for the period from 2003 to 2021. Consequently, I evaluate these two forecasting methods by comparing their predictions with realized dividends for the period from 2004 to 2022.

[36]De La O and Myers (2021) made their data available on their website. See "https://www.sean-myers.net/data".

Evaluation Period	State-Space Model using EY_1 Benchmarked Against Subjective Expectations	p-value
2004-2022	3.97%*	0.0545

Table 8: Out-of-Sample Forecasting Performance Relative to Subjective Expectations

The out-of-sample R^2 statistic is calculated as follows:

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

where g_t^F represents the filtered value generated by my model using data available up to time t, serving as the expected value for time $t+1$. Similarly, g_t^S represents De La O and Myers (2021)'s 12-month subjective dividend expectation, which aggregates available analyst forecasts for S&P 500 constituent firms, made in Quarter 4, and serves as the benchmark model. Finally, Δd_{t+1} denotes the realized value at time $t+1$.

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 $f_{t+1} = (\Delta d_{t+1} - g_t^S)^2 - [(\Delta d_{t+1} - g_t^F)^2 - (g_t^S - g_t^F)^2]$. 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 De La O and Myers (2021) aggregate survey-based expectations, against the alternative hypothesis that the forecasting model has greater predictive accuracy. Statistical significance is indicated by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

The equity-yield-based forecasting model outperforms survey-based expectations, achieving an out-of-sample R^2 of 3.97% [37]for the period from 2004 to 2022 when benchmarked against subjective expectations. This outperformance is statistically significant at the 10% level, based on the Clark and West (2007) out-of-sample MSPE-adjusted statistic. The results are reported in Table 8.

[37]Rather than calculating realized dividend by the difference between index returns with and without dividend distributions, De La O and Myers (2021) construct their aggregate realized dividends using the same methodology applied to subjective expected dividends. Their approach relies on I/B/E/S data and focuses on dividends paid by S&P 500 companies for which one-year subjective dividend expectations exist in the I/B/E/S database. De La O and Myers (2021) also provide aggregate realized next-year dividend growth in their published dataset. When using their realized next-year dividend growth, I find a similar outperformance of my forecasting model, achieving an out-of-sample R^2 of 5.34%.

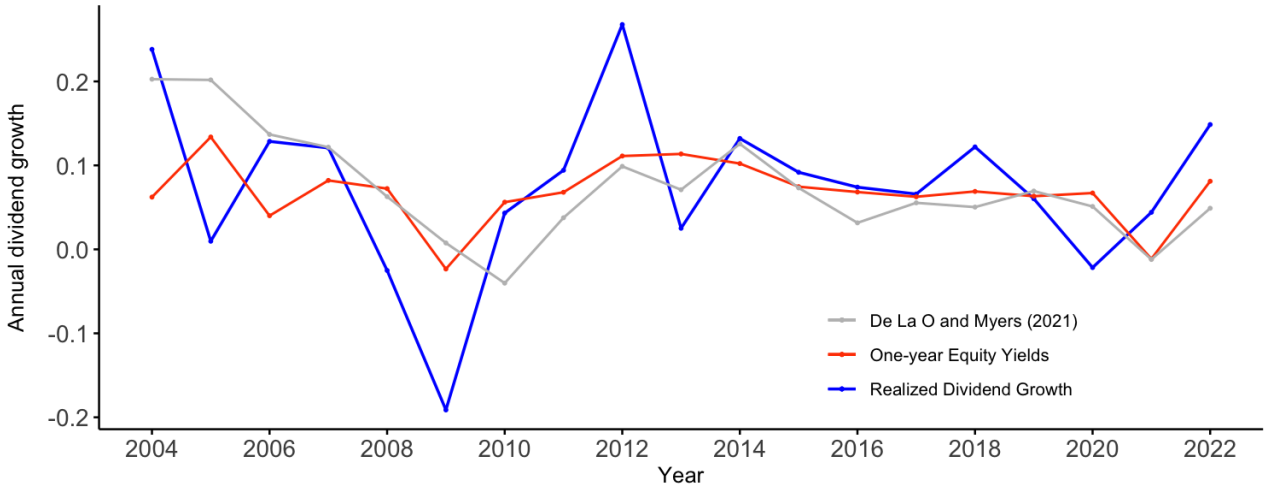


Figure 10: Out-of-Sample Forecasting Results: Benchmarking Against Subjective Expectations

The graph displays the filtered series of expected dividend growth (g_t^F) generated by my forecasting model using information available up to time t, alongside De La O and Myers (2021)'s 12-month subjective dividend expectation (g_t^S), which aggregates available analyst forecasts for S&P 500 constituent firms, made in Quarter 4. These are plotted against the time series of realized dividend growth (Δd_{t+1}). Both the g_t^F and g_t^S are presented as lagged values, enabling a direct comparison with realized outcomes. This comparison evaluates the out-of-sample performance of the two competing models in the U.S. over time.

4.7 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 baseline estimation, 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 ensures flexibility, the range may be excessively broad, particularly when the simulated annealing algorithm searches for the global maximum of the likelihood function. A search space that is too wide could lead the algorithm to explore unrealistic regions, reducing the precision of parameter estimates.

To address this concern, I impose more plausible upper bounds to restrict the algorithm's search to economically meaningful regions. This adjustment is intended to concentrate more iterations within the relevant parts of the parameter space, thereby improving estimation accuracy. In this subsection, I conduct an experiment by tightening the upper bounds and evaluating whether these adjustments improve out-of-sample forecasting performance.

Specifically, to determine a more plausible upper bound for σ_μ, I calculate the standard deviation of realized returns on a one-year constant-maturity dividend futures contract. These are constructed using dividend futures prices recovered by Giglio et al. (2024), over the period from 1974 to 1995. This sample period precedes the out-of-sample evaluation window beginning in 1996, ensuring that the bound is not informed by future information and thus avoiding look-ahead bias. The resulting value, 6.58%, is adopted as the new upper bound for σ_μ, replacing the previous 100%[38]. I then re-estimate model parameters using MLE under these revised constraints and reassess the model's out-of-sample forecasting performance.

Under this new restriction, the U.S. out-of-sample R^2 values (R^2_{OS}) for the evaluation period from 1996 to 2023 is 23.70% compared to 15.70% (reported in Table 5) when estimated under the previously unrestrictive upper bound. For Europe, Japan, and the UK, where equity yield data are more limited, I report pseudo out-of-sample R^2 values ($R^2_{Pseudo_{OS}}$) using model parameters estimated from the U.S. market. The corresponding values are 29.19% for Europe, 31.70% for

[38]The lower and upper bounds for σ_g and σ_d remain within the range of (0, 1).

Japan, and -8.23% for the UK, showing notable improvements relative to their earlier counterparts of 26.49%, 28.37%, and -10.10%, respectively (Table 7). These forecasts are generated using an expanding window approach, applying U.S.-estimated parameters up to time t and combining them with equity yields from each respective market to forecast dividend growth at $t+1$.

Overall, these results demonstrate that imposing more realistic parameter constraints improves out-of-sample performance across all four markets. The findings, summarized in Table 9, underscore the value of economically motivated parameter restrictions in enhancing forecast accuracy.

	US	Europe	Japan	UK
Period	1996-2023	2003-2023	2005-2023	2005-2023
R^2_{OS} or $R^2_{Pseudo_{OS}}$	23.70%*	29.19%**	31.70%	-8.23%

Table 9: Out-of-Sample Forecasting Performance Under Imposed Restrictions

This table reports the out-of-sample R^2 values (R^2_{OS}) for the U.S. and pseudo out-of-sample R^2 values ($R^2_{Pseudo_{OS}}$) for Europe, Japan, and the UK, based on parameters estimated from the U.S. market under the upper bound constraint of $\sigma_\mu = 0.0658$. Forecasts are generated using an expanding window approach. The corresponding values under the unrestrictive upper bound ($\sigma_\mu \in [0,1]$) are reported in Tables 5 and 7 for comparison.

4.8 Return Predictability

This section evaluates the return predictability of the proposed methodology. The returns under consideration are defined as the log returns from holding a one-year constant-maturity dividend futures contract to maturity, calculated as

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

where $F_{t,1}$ denotes the one-year maturity dividend futures price observed at time t, and D_{t+1} is the realized dividend level at time $t+1$.

From Equation 3, we have $e_{t,1} = \mu_t - g_t$, where $\mu_t = E_t\left[log(\frac{D_{t+1}}{F_{t,1}})\right]$ denotes the expected return and g_t is the expected dividend growth. Since $e_{t,1}$ is observed at time t, obtaining the filtered estimate of g_t^F from the state-space model allows us to simultaneously recover μ_t^F, the filtered expected return.

To evaluate the model's forecasting performance for returns, I compute the out-of-sample mean squared error by comparing μ_t^F with the realized returns r_{t+1}, using the historical mean $\overline{r_t}$ as a benchmark. The out-of-sample R^2 statistic is given by:

$$R^2_{OS-Ret} = 1 - \frac{\sum_{t=1}^{T-1}(r_{t+1} - \mu_t^F)^2}{\sum_{t=1}^{T-1}(r_{t+1} - \overline{r_t})^2}$$

where μ_t^F is the model-generated expected return based on information available at time t, and $\overline{r_t}$ is the historical average of realized returns up to t. The evaluation period spans 2005–2023, reflecting data availability for the one-year maturity futures contract $F_{t,1}$, which became tradable in 2003. This setup yields the first observed return in 2004 and enables the initial benchmark forecast—based on information up to 2004—to be made for 2005. The out-of-sample performance is reported in Table 10.

Benchmark	Evaluation Period	R^2_{OS} (State-Space Model using EY_1)
Historical Mean	2005–2023	-21.94%
Constant Zero Benchmark	2004–2023	6.26%

Table 10: Out-of-Sample Return Forecast Performance

Over the evaluation window, the out-of-sample R^2 statistic is -21.94%, suggesting underperformance relative to the historical mean benchmark. However, this benchmark is constructed under nonstandard conditions, especially in early years. For example, the 2005 benchmark forecast relies solely on the 2004 return, while the 2006 forecast averages just the 2004 and 2005 values. With only two or three observations in the early years, the rolling historical mean is highly volatile and may not provide a meaningful standard for comparison. To address this limitation, I also evaluate the model against a constant benchmark of zero return over the full sample period for which traded futures prices and realized returns are available. Under this alternative benchmark, the model achieves an out-of-sample R^2 of 6.26% and demonstrating improved forecasting performance relative to the zero-return benchmark.

Figure 11 presents a visual summary of the model's performance. The top panel plots the filtered expected returns alongside realized returns and the historical mean benchmark, while the bottom panel revisits the filtered dividend growth forecasts—originally shown in Figure 5—which are estimated jointly with expected returns within the same state-space framework. This estimation yields the two jointly recovered time series, and Figure 11 allows them to be placed side by side for a unified comparison.

This comparison helps clarify key sources of forecast error. A substantial portion of the model's out-of-sample forecast error is driven by the year 2009, a pivotal moment during the global financial crisis. Although the model correctly captured the direction of change in both expected returns and dividend growth, the magnitude of the dividend contraction was underestimated ex ante. As implied by Equation (3), this underestimation of dividend growth mechanically inflated return expectations, thereby affecting out-of-sample return forecast performance.

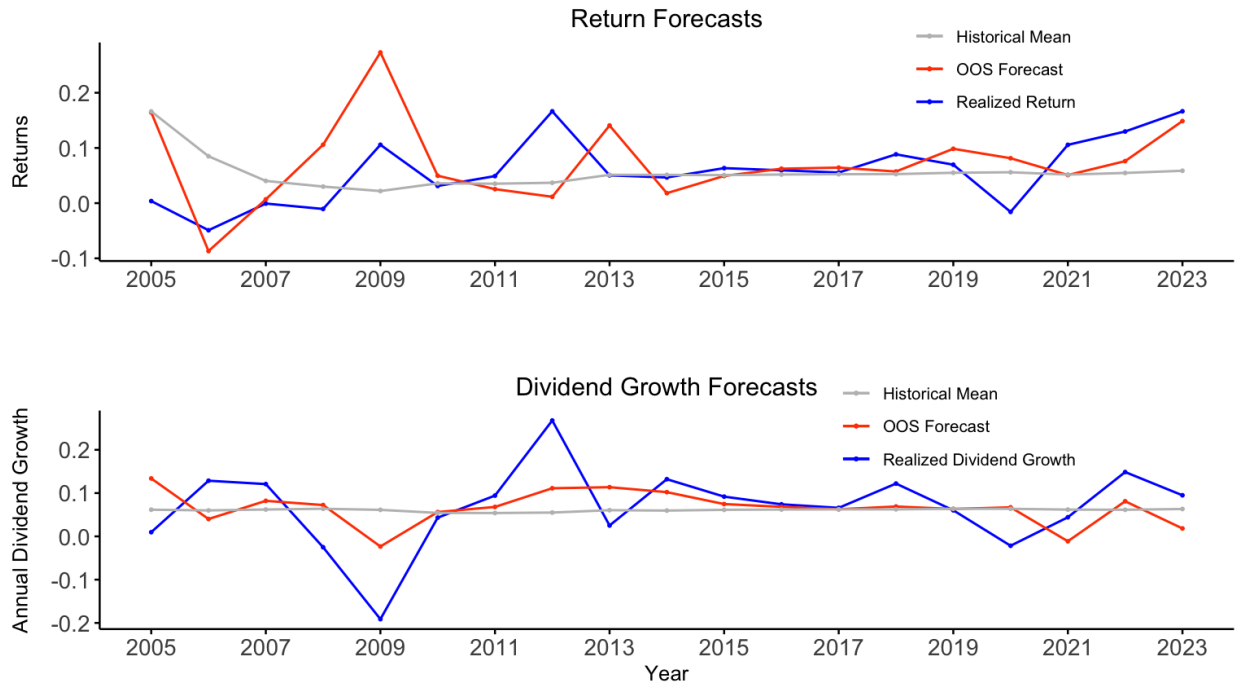


Figure 11: Out-of-Sample Forecasting Performance in the US

The top portion of the graph displays the filtered series of expected returns (μ_t^F) generated by my forecasting model using information available up to time t, plotted alongside the realized returns (r_{t+1}) and the benchmark series representing the historical mean return up to time t, denoted as $\overline{r_t}$. Both μ_t^F and $\overline{r_t}$ are shown as lagged values to allow a direct comparison with realized returns, serving as an evaluation of the model's out-of-sample return forecasting performance in the U.S. over time. The bottom portion of the graph presents the corresponding forecasts for dividend growth in the same years, which are obtained jointly with the expected returns.

4.9 Predictability of dividend growth beyond one-period horizon

In this section, I investigate whether equity yields forecast dividend growth beyond the one-year horizon. Earlier analysis in the paper demonstrated the one-year-ahead predictability of dividend growth using the state-space model proposed in this study. Here, I extend the analysis by employing regression analysis to test the in-sample one-year-ahead predictability and, more importantly, to explore the potential for forecasting dividend growth for periods beyond one year, specifically for the $t+1 \rightarrow t+2$ year period and $t+2 \rightarrow t+3$. These tests assess whether the short-term expectations embedded in dividend futures prices remain informative for periods further ahead.

The analysis estimates a series of univariate predictive regressions of annual dividend growth, $\triangle d_{t+h-1 \rightarrow t+h}$, on the n-year equity yield $e_{t,n}$, where $n = 1, 2, 3$ and $h = 1$ for $t \rightarrow t+1$, $h = 2$ for $t+1 \rightarrow t+2$, and $h = 3$ for $t+2 \rightarrow t+3$:

$$\triangle d_{t+h-1 \rightarrow t+h} = \alpha_{h,n} + \beta_{h,n} e_{t,n} + \epsilon_{t+h}$$

where $\triangle d_{t+h-1 \rightarrow t+h} = log(\frac{D_{t+h}}{D_{t+h-1}})$, and D_{t+h} denotes cash-reinvested annual dividend for year $t+h$ in each market.

For overlapping samples, all months are pooled to estimate $\beta_{h,n}$, and t-statistics are computed using Newey–West corrections with 12 lags; results are robust to alternative lag lengths of 24 or 36. For non-overlapping samples, twelve separate regressions are estimated on annual observations beginning in each calendar month (January through December). The reported statistic is the average t-statistic across these regressions, with Newey–West corrections applied using three lags.

Table 11 reports $\beta_{h,n}$, its t-statistic, and R^2 for each horizon and market. These results indicate that while the predictability of dividend growth is confirmed across markets for the immediate one-year horizon ($t \rightarrow t+1$), with significance at the 1% level, the predictability for longer horizons ($t+1 \rightarrow t+2$) and ($t+2 \rightarrow t+3$) exhibits notable variation. The U.S., EU, and U.K. show a similar pattern, with predictability diminishing in the $t+1 \rightarrow t+2$ period and then recovering in the $t+2 \rightarrow t+3$ period. The reversal in the sign of the estimated parameters for the $t+2 \rightarrow t+3$ period, coupled with marginal significance at the 5% level, suggests that the relationship between equity yields and future dividend growth may extend beyond the immediate one-year horizon. Market sentiment captured by equity yields appears to have predictive value not only for the immediate

year($t \to t+1$) but also for subsequent periods, where dividend movements are likely influenced by broader economic conditions and the periodic nature of dividends.

Index		S&P500: Jan 2003 – Dec 2023		
		t → t+1		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	-0.79	-6.73	-6.27	0.59
2	-1.08	-6.67	-5.64	0.52
3	-1.43	-5.50	-4.61	0.46
		t+1 → t+2		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	0.00	0.01	-0.02	0
2	-0.05	-0.27	-0.40	0
3	-0.07	-0.24	-0.30	0
		t+2 → t+3		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	0.34	2.19	2.04	0.13
2	0.46	2.30	1.96	0.11
3	0.74	2.24	1.86	0.14

(a) US

Index		Euro Stoxx 50: Jan 2002 – Dec 2023		
		t → t+1		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	-0.88	-8.97	-8.25	0.50
2	-1.06	-7.34	-7.03	0.44
3	-1.50	-8.56	-7.39	0.45
		t+1 → t+2		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	-0.02	-0.16	0	0
2	-0.11	-0.71	-0.36	0
3	-0.22	-0.94	-0.63	0.01
		t+2 → t+3		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	0.37	2.05	2.02	0.09
2	0.49	2.13	2.31	0.10
3	0.71	2.25	2.30	0.11

(b) EU

Index		Nikkei 225:Jan 2004 – Dec 2023		
		t → t+1		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	-0.93	-9.61	-8.63	0.48
2	-1.00	-9.07	-8.38	0.50
3	-1.27	-10.12	-7.63	0.48
		t+1 → t+2		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	0.25	2.22	2.16	0.03
2	0.22	1.88	1.79	0.02
3	0.26	1.52	1.59	0.02
		t+2 → t+3		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	0.30	1.34	1.47	0.05
2	0.32	1.23	1.51	0.06
3	0.53	1.43	1.74	0.09

(c) Japan

Index		FTSE 100: Dec 2004 – Dec 2023		
		t → t+1		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	-0.78	-11.73	-7.30	0.36
2	-0.94	-4.68	-4.72	0.33
3	-1.32	-4.13	-3.47	0.31
		t+1 → t+2		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	0.14	0.73	0.26	0.01
2	0.02	0.09	-0.60	0
3	-0.07	-0.22	-0.29	0
		t+2 → t+3		
Maturity	β	t-stat (Overlap)	t-stat (Nonoverlap)	R^2
1	0.31	1.95	2.27	0.05
2	0.45	2.95	2.68	0.07
3	0.68	3.24	2.74	0.08

(d) UK

Table 11: Dividend Growth Predictability Across Horizons and Subsequent Periods

The table reports the predictive coefficient β_n, the t-statistic, and the R^2 value of a predictive regression of annual dividend growth $\triangle d_{t+h-1 \to t+h}$ on forward equity yields with maturities of 1, 2, and 3 years, where $h = 1$ for $t \to t+1$, $h = 2$ for $t+1 \to t+2$, and $h = 3$ for $t+2 \to t+3$. The analysis is conducted separately for the U.S., Europe, Japan, and the U.K., with sample periods based on traded futures data availability: U.S. (Jan 2003–Dec 2023), Europe (Jan 2002–Dec 2023), Japan (Jan 2004–Dec 2023), and the U.K. (Dec 2004–Dec 2023), using monthly data. For overlapping samples, t-statistics are computed using Newey–West corrections with 12 lags, robust to alternative lag lengths of 24 or 36. For non-overlapping samples, twelve separate regressions are estimated on annual observations starting in each calendar month (Jan–Dec), with the reported statistic being the average t-statistic across these regressions and Newey–West corrections applied with three lags.

In contrast, Japan remains an outlier. The sign reversal begins in the $t+1 \to t+2$ period, and no marginal recovery is observed in the $t+2 \to t+3$ period. Additionally, the state-space model

proposed in this study also attempts to predict the $t+1 \rightarrow t+2$ period, but out-of-sample testing showed it could not effectively predict this period. This finding aligns with the regression analysis results.

5 Robustness

In this section, following Binsbergen and Koijen (2010), I reproduce my out-of-sample analysis for the U.S. aggregate market by calculating annual dividend growth in the same manner as they did. Rather than using the CRSP Value-Weighted Portfolio to compute monthly dividends, as in the main body of the paper, I obtain monthly returns—with and without dividends—for all NYSE, Amex, and NASDAQ stocks from CRSP over the period 1974 to 2023. I then use the return difference of this portfolio to compute monthly dividends and construct the annual time series of dividends D_t, which I use to repeat my out-of-sample tests.

Evaluation Period	State-Space Model using EY_1	Present-Value Approach using pd Ratio	Predictive Regression using pd Ratio	Predictive Regression using EY_1
1996-2023	17.93%*	5.91%	-2.90%	0.79%
2001-2023	19.73%**	8.60%*	-2.31%	1.77%

Table 12: Out-of-Sample Performance – US (Robustness)

Campbell and Thompson (2008)'s out-of-sample R^2 statistic is calculated as follows:

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

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 indicated by *, **, and ***, representing significance levels of 10%, 5%, and 1% level, respectively.

The results, presented in Table 12, show that when the value-weighted portfolio used to calculate monthly dividends is restricted to all NYSE, Amex, and NASDAQ stocks, my findings align more closely with those reported by Binsbergen and Koijen (2010). Specifically, using the present-value approach 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.

6 Conclusion

This paper develops a state-space model that forecasts one-year-ahead dividend growth using equity yields derived from short-maturity dividend futures. By integrating proprietary over-the-counter dividend derivative data with synthetic yields from Giglio et al. (2024), the model exploits forward-looking information embedded in traded dividend claims. It consistently outperforms traditional approaches, including Binsbergen and Koijen (2010), in both in-sample and out-of-sample settings, with especially strong predictive power during periods of economic stress.

The model captures the sharp rise in equity yields during the Great Recession—reflecting heightened investor concern—but fails to anticipate the COVID-19 downturn, highlighting its limitation in forecasting sudden, exogenous shocks. These results suggest that the model effectively tracks shifts in investor sentiment when expectations evolve gradually.

In out-of-sample evaluations, the model also outperforms subjective expectations constructed by De La O and Myers (2021), underscoring the value of market-based signals in capturing timely information about near-term macroeconomic conditions. Overall, the study shows that incorporating traded dividend claims meaningfully enhances the predictability of dividend growth and provides forward-looking signals that are useful for both investors and policymakers.

Appendix A1

This section outlines the Kalman filtering procedure applied in my model. I first express the model in the standard state-space form and define the state vector as:

$$X_t = \begin{bmatrix} \hat{g}_{t-1} \\ \epsilon_t^d \\ \epsilon_t^g \\ \epsilon_t^\mu \end{bmatrix}$$

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 $\epsilon_t = \begin{bmatrix} \epsilon_t^d \\ \epsilon_t^g \\ \epsilon_t^\mu \end{bmatrix}$ is assumed to be jointly normally distributed. $\epsilon_t \sim \underbrace{\begin{bmatrix} \sigma_d^2 & 0 & \sigma_{d\mu} \\ 0 & \sigma_g^2 & \sigma_{g\mu} \\ \sigma_{d\mu} & \sigma_{g\mu} & \sigma_\mu^2 \end{bmatrix}}_{Q}$[39].

Namely,

$$\underbrace{\begin{bmatrix} \hat{g}_t \\ \epsilon_{t+1}^d \\ \epsilon_{t+1}^g \\ \epsilon_{t+1}^\mu \end{bmatrix}}_{X_{t+1}} = \underbrace{\begin{bmatrix} \gamma_1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}}_{F_t} \underbrace{\begin{bmatrix} \hat{g}_{t-1} \\ \epsilon_t^d \\ \epsilon_t^g \\ \epsilon_t^\mu \end{bmatrix}}_{X_t} + \underbrace{\begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{\Gamma} \underbrace{\begin{bmatrix} \epsilon_{t+1}^d \\ \epsilon_{t+1}^g \\ \epsilon_{t+1}^\mu \end{bmatrix}}_{\epsilon_{t+1}}$$ [40]

[39] Folllow Binsbergen and Koijen (2010) , I normalize the correlation between realized dividend growth shocks (ϵ_{t+1}^d) and expected dividend growth shocks (ϵ_{t+1}^g) to zero.

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

$$\text{Let } Y_t = \begin{bmatrix} \Delta d_t \\ e_{t,1} \end{bmatrix}$$

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

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

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

The Kalman filtering procedure is then specified as follows:

Step 0: Initialization [41]

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 Residual (Innovation): $\eta_t = Y_t - \overbrace{M_0 - M_1 Y_{t-1} - M_2 X_{t|t-1}}^{\hat{Y}_t}$

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

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

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

The likelihood is constructed from the prediction error (η_t) and the innovation covariance (S_t), which captures the uncertainty associated with the discrepancy between the observed and predicted values of 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

In Figure 12, I plot the one-year equity yields for the US, EU, JP, and UK markets from their respective initial OTC trading dates through December 2023. The panels show that these yields are broadly synchronized over time, with common peaks during crises and generally similar trends, highlighting strong cross-market co-movement. This suggests that it is feasible to conduct a pseudo out-of-sample forecasting exercise for the EU, JP, and UK markets by applying state-space parameters estimated from the US, given the lack of synthetic yield data required to estimate these parameters directly in the EU, JP, and UK.

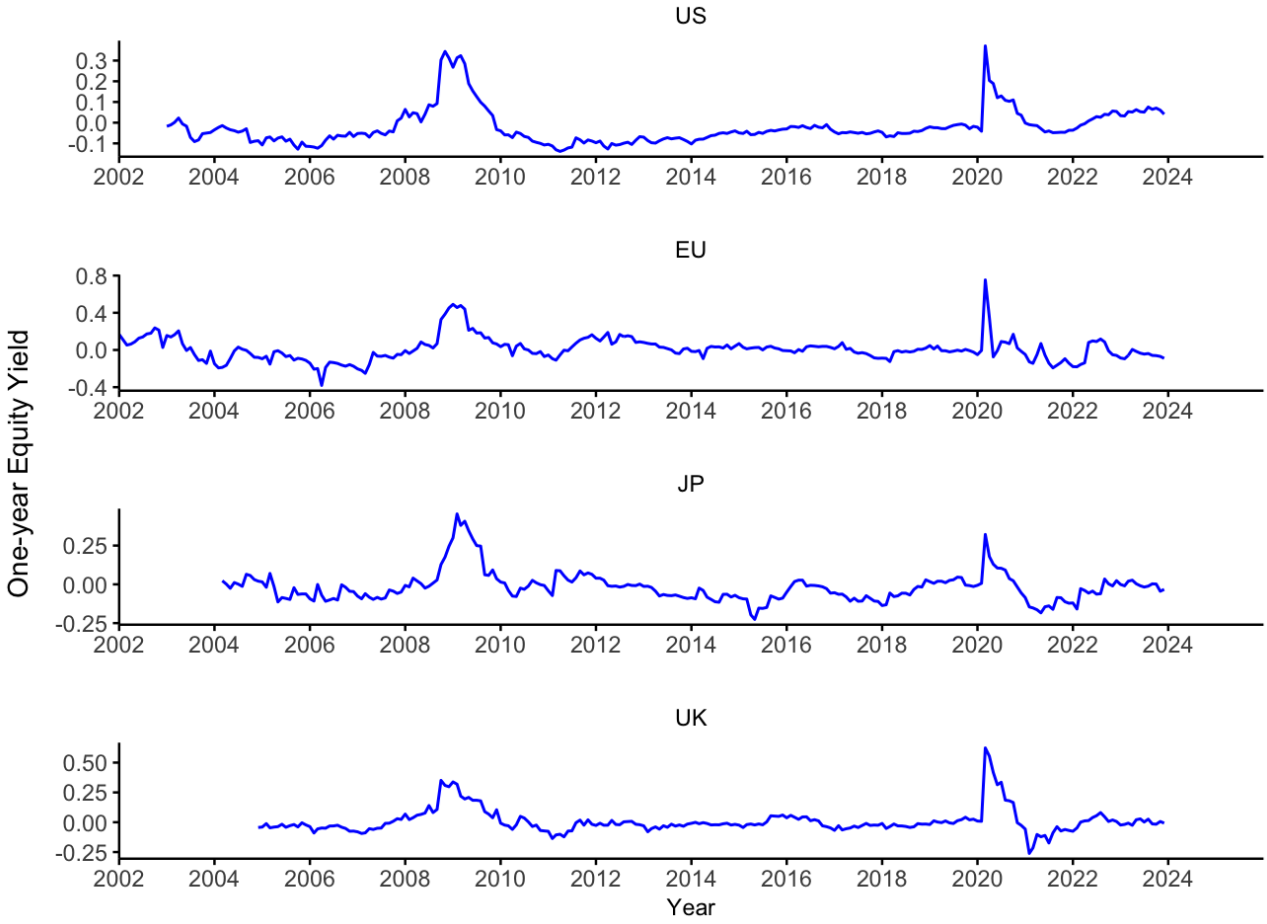


Figure 12: One-Year Equity Yields Across Four Markets

The one-year equity yield is calculated as $e_{t,1} = ln(\frac{D_t}{F_{t,1}}) + y_{t,1}$. The figure is plotted for the U.S., Europe, Japan, and the U.K., with sample periods based on the availability of traded futures data: U.S. (Jan 2003–Dec 2023), Europe (Jan 2002–Dec 2023), Japan (Jan 2004–Dec 2023), and the U.K. (Dec 2004–Dec 2023), using monthly data.

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	0.774	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	0.178	0.060	0.062	0.067	0.074	0.004	0.566	0.442	-
1974-2019	0.696	0.178	0.059	0.063	0.066	0.073	0.004	0.566	0.406	-
1974-2020	0.693	0.193	0.056	0.059	0.066	0.074	0.001	0.570	0.359	-
1974-2021	0.686	0.180	0.059	0.061	0.067	0.072	0.000	0.569	0.227	-
1974-2022	0.696	0.157	0.065	0.061	0.066	0.073	0.000	0.562	0.194	-
1974-2023	0.710	0.168	0.071	0.062	0.067	0.072	0.000	0.564	0.373	-

Table 13: Parameter Estimation Results for the Equity Yield Model: Expanding Windows from 1974–1995 to 1974–2023

* Please note that the parameter estimates related to expected returns (μ_t) in this table refer to returns from holding a one-year constant-maturity dividend futures contract to maturity, rather than expected stock returns. These include the persistence of expected returns (δ_1), the unconditional mean of expected returns (δ_0) and their standard deviation (σ_μ).

Appendix A4

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 14: Parameter Estimation Results for Binsbergen and Koijen (2010)'s Present-Value Approach: Expanding Windows from 1974–1995 to 1974–2023

* Please note that the parameter estimates related to expected returns(μ_t) refer to expected stock returns, consistent with the specification in Binsbergen and Koijen (2010).

Appendix A5

Est. Period	constant	slope
1974-1995	0.058	0.074
1974-1996	0.058	0.078
1974-1997	0.061	0.036
1974-1998	0.062	0.018
1974-1999	0.064	-0.022
1974-2000	0.056	0.085
1974-2001	0.054	0.120
1974-2002	0.053	0.146
1974-2003	0.054	0.139
1974-2004	0.061	0.086
1974-2005	0.059	0.079
1974-2006	0.061	0.040
1974-2007	0.063	0.021
1974-2008	0.061	0.010
1974-2009	0.055	-0.207
1974-2010	0.055	-0.206
1974-2011	0.056	-0.211
1974-2012	0.061	-0.267
1974-2013	0.060	-0.269
1974-2014	0.062	-0.281
1974-2015	0.062	-0.283
1974-2016	0.062	-0.283
1974-2017	0.062	-0.283
1974-2018	0.064	-0.285
1974-2019	0.064	-0.284
1974-2020	0.062	-0.287
1974-2021	0.062	-0.286
1974-2022	0.064	-0.288
1974-2023	0.065	-0.269

Table 15: OLS Parameter Estimation

Appendix A5 reports the coefficient estimates from linear OLS regressions of realized dividend growth $\triangle d_{t+1}$ on the one-year equity yields $e_{t,1}$ for the U.S. market, using expanding windows from 1974–1995 to 1974–2023.

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