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A Stock Return Decomposition Using Observables

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Abstract

We propose a new method for decomposing realized stock market capital gains into contributions from changes to the real yield curve, equity premia, and expected dividends. The method centers on changes to observable inputs of the present value formula and requires no regressions or log-linearization. In S&P500 data for 2005-2023, changes to expected dividends dominated the cumulative capital gain. Changes to the real yield curve and equity premia contributed more to capital gain fluctuations. A mix of higher equity premia and lower expected earnings drove the 2008 and 2020 market declines, while higher real yields drove the 2022 market drop.

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I. Introduction

A central theme in asset pricing is what types of news drive realized asset returns. A large literature combines the log-linearization of Campbell and Shiller (1988) with a VAR approach as in Campbell (1991) to decompose stock return variance into components coming from cash flow news, discount rate news, and the covariance of the two. In this paper we propose a decomposition not only of return variance but of the realized return for a given period. This allows for an interpretation of the movement of the stock market period by period. It can also be used to assess the effect of potential risks to the market ex-ante, similarly to the way investors use duration to assess risks ex-ante in the bond market.

Our approach relies on two main ideas. First, we observe that in recent decades, a lot of information about the inputs to the present value formula for the stock price is observable from financial market data and expectations data. The term structure of the real riskless rate can be measured out to 30 years using yields on Treasury inflation protected securities or nominal Treasury yields combined with inflation swaps. The term structure of the equity risk premium is not directly observable, but Martin (2017) provides a lower bound on the equity risk premium based on S&P500 index options. We extend Martin's empirical evidence that this lower bound is approximately tight and thus is close to the actual equity risk premium. The bound can be calculated out to around 2 years in recent years, based on available S&P500 options. Because fluctuations in near-term equity premia are substantial (especially in crisis periods), fluctuations in the first two years will account for an important part of equity risk premium news. Expectations data can also be used to obtain information about changes to expected dividends. Specifically, while current earnings have large transitory movements making them a poor guide to likely changes in expected future dividends, we argue that expected earnings a few years out from analyst forecasts filter out much of these transitory movements and therefore are informative about the likely updating to expected dividends down the road which account for most of the value of the market.

Second, to utilize the availability of rich discount rate data and earnings expectations data, we develop a new stock return decomposition for the overall stock market which is straightforward to map to available data using the S&P500 as the measure of the stock market. Because expectations data are available only for expected levels, not expected log levels, our method is developed to use levels as inputs, as opposed to logs in the Campbell-Shiller log-linearization. Our approach starts by expressing the stock price as the sum of the present values of the subsequent expected dividends. At each point in time, there are dividends one, two, three, ... years out. The realized capital gain on the stock market in a given period is therefore a weighted average of (1) how the value of "generic" dividend strips (i.e., dividend strips that pay off a certain number of periods out) evolve over time, and (2) the initial weights of each of the generic dividend strips in the overall market (the dividend strip weights). The effects of changes to the real yield curve, equity premia, or changes to expected dividends on the stock price follow from this expression. Specifically, the capital gain on the market is driven by changes to the inputs and what fraction of the stock price a given input change is relevant for.

Regarding expected dividends, an $x\%$ increase in the expected dividend at date $t+k$ leads to a capital gain of $x\%$ times the dividend strip weight for that dividend. As an example, suppose the expected dividend at time 10 accounts for 2% of today's stock price. Then, increasing this expected dividend by 10% increases today's stock price by 0.2% (a 10% increase in something accounting for 2% of value). In general, percentage changes to dividends that are larger and thus account for more of the stock market value will have a bigger effect on the stock price.

Regarding discount rates, the percentage capital loss from a y percentage point increase in the forward real yield or forward equity premium for a given future period $t+k$ is (approximately) y times the weight of dividends at date $t+k$ and beyond in today's stock price. For example, suppose expected dividends at time 10 and later account for 90% of today's stock price. Then, increasing the discount rate for year 10 by 1 percentage point lowers today's stock price by approximately 0.9% (a 1% shrinkage to 90% of stock value). Intuitively, only dividends from year 10 and later are affected in present value terms by a change to discounting in year 10. In general, changes in the forward real yield or the forward equity premium for a more distant forward period have a smaller stock price impact than changes to these forwards for earlier periods.

We highlight that our decomposition is based on very few assumptions. The effects of changes to expected dividends and to real yields require only the assumption that the stock price is determined by present value. Furthermore, regarding the effect of changing equity premia, our method is applicable even if the equity premium differs across dividend strips in ways that are not observable. By writing the stock price as a function of the terminal payoff at a given future date (the dividend plus the price), we observe that one period before that future date, the full value of the stock market is due solely to the terminal payoff. Therefore, for that period, the terminal payoff is discounted using the expected return on the market which can be expressed in terms of the forward real yield and the forward equity premium, and the effect of a change to the forward market equity premium follows. We show that this terminal value approach leads to exact effects of changes to the market equity premia if returns are independent over time and close to exact effects under realistic return processes.

Crucially for implementing our decomposition, dividend strip weights can be calculated from dividend futures prices.[1] We calculate dividend strip weights from dividend futures out to year 10 and show how dividend strip weights can be estimated past year 10 using market data, if expected returns and expected

[1]Before the availability of dividend futures, we follow van Binsbergen et al. (2013) and calculate dividend strip prices from options data and put-call-parity.

growth are approximately constant past year 10. Today's market price and today's prices of the near-term dividend futures imply today's value of the expected dividends after year 10. From that value, one can infer the market's perception today of the ratio G/R past year 10, where G denotes the gross expected growth rate and R the gross expected return, both past year 10. This ratio then is used to calculate dividend strip weights past year 10. We highlight that because our approach allows for time-varying dividend strip weights, it effectively allows for a time-varying duration of the stock market. By contrast, the Campbell-Shiller log-linearization is typically implemented with a constant log-linearization parameter ρ over time.

We consider two implementations of our decomposition. The first, which we refer to as Decomposition A, exploits only financial market data: Dividend futures data to obtain the dividend strip weights, real yield curve changes to year 30, and equity risk premium changes to year 2. This allows a decomposition the stock market capital gain for a given period into a factor due to the change in the real yield curve, a factor due to changes in near-term equity premia, and a factor which captures changes to expected cash flows (dividends) as well as changes to real yields or equity premia past the horizons of observable data. Because this decomposition only relies on financial market data, it can be implemented at frequencies as high as daily (even intra-day if researchers have access to intra-day financial markets data). Decomposition A provides insights about the role of real yield curve shifts and changes to near-term equity premium but bundles the effects of changes to expected cash flows with those of changes to long-term discount rates (forward real yields past year 30 or forward equity premia past year 2). Adding data for analyst earnings expectations, along with a set of assumptions mapping these to expected dividends, allows one to construct a measure of the effect of changes to expected cash flows and therefore a measure of the effect of changes to long-term discount rates. Our mapping from expected earnings to expected dividends is to assume that the growth rate in expected earnings for year 3 forward is a good proxy for the growth rate in expected dividends for all forward horizons. We then use data on inflation swaps to construct a measure of growth in expected real dividends. Decomposing the cash flow & long-term discounting component into its two parts, we show that the capital gain factor due to changes in long-term discount rates is strongly *negatively* correlated with the factor due to real yield curve changes, implying that it likely captures changes to forward equity premia past year 2 as opposed to changes to forward real yields past year 30. We verify this inference using data on asset manager equity premium expectations out to year $t + 10$, obtained from Dahlquist and Ibert (2021). The analyst forecast data therefore enable a second decomposition, Decomposition B, which separately provides capital gain factors due to real yield curve changes, changes to equity premia (at all horizons), and changes to expected dividends.

We apply our observables approach to monthly S&P500 data for 2005-2023.[2] We first document the relative roles of the capital gain and dividend yield. We then focus on the capital gain and decompose it using both Decomposition A and Decomposition B. We provide an (expanding window) decomposition of the cumulative capital gain based on monthly returns and also provide decompositions of each annual return over our sample. The contributions of the various factors driving the capital gain are multiplicative (for gross returns), making it simple to compound factor contributions over time. We report results of our decomposition along several dimensions: Which of the factors (real yield curve, equity premium, expected real dividends) mattered the most for the realized cumulative capital gain over the sample? What were the contributions of each of the factors to volatility? And how did the relative roles of the capital gain drivers differ across periods? The latter is a particular strength of our approach so we zoom in of three years with large market declines – 2008, 2020, and 2022 – to highlight how return drivers differed across these periods. Our findings can be summarized as follows based on Decomposition B.

First, changes to expected real earnings (and thus expected real dividends) played the dominant role for the realized cumulative capital gain on the market over the 2005-2023 period. We estimate a cumulative gross capital gain of 244% (i.e., a net capital gain of 144%) and a cumulative gross expected dividend factor of 217% while the cumulative gross return factors for each of the yield curve and equity premium components are close to one.

Second, the yield curve and the equity premium factors are more volatile than the expected dividend factor. In annual data, the standard deviations of the former two factors are between two and three times the standard deviation of the expected dividend factor. A lot of the variance of the equity premium factor comes from movements in equity premia past year 2, with fluctuations in the year 1-2 equity premia mattering mostly in crisis. In terms of correlation of factors, the yield curve factor is negatively correlated with both the equity premium factor and expected dividend factor, while the equity premium factor and expected dividend factor are positively correlated. In our variance decomposition of annual log returns, the variance of the yield curve factor and variance of the equity premium factor each account for over 100% of the capital gain variance, but the negative covariance between these two factors plays a large stabilizing role and account for around -200% of the log capital gain variance. In a variance decomposition which combines the yield curve and equity premium factors to study the relative roles of overall discount rate changes versus expected dividend changes, the variance of the combined discount rate (i.e., expected stock return) factor accounts for about half of the capital gain variance, while the variance of the expected dividend factor accounts for a fifth and the covariance of the combined discount rate factor and the expected dividend factor for the remainder.

[2] We explore Decomposition A for higher frequency returns around FOMC announcements in Knox and Vissing-Jorgensen (2024). Knox and Timmer (2023) also provide Decomposition A results for CPI announcement days.

Third, the mix of return drivers differs across periods. While the strong negative correlation between the yield curve factor and the equity premium factor (-0.80 for the log factors) means that these two components fairly consistently move in opposite directions, much lower correlations between these factors and the expected dividend factor are indicative of a heterogeneous mix of return drivers across periods. As an example of this, we highlight the contrast between year 2008 and year 2022, both of which saw a large negative capital gain on the market for the year. The market decline in 2008 was driven by a mix of higher equity premia and negative changes to expected earnings with the former playing the larger role, while the market drop in 2022 was driven by higher real yields. As for the COVID-related market crash in the first quarter of 2020, it looks much like 2008 in being driven by higher equity premia and negative changes to expected earnings with higher equity premia playing the larger role. In both 2008 and 2020Q1, higher year 1-2 equity premia play substantial (but not dominant) roles in the overall equity premium factor. For year 2020 as a whole, falling real yields explain why the market ended up with a large positive 15% real capital gain despite the recovery still being nascent and uncertain at the end of 2020.

Relating our approach to the literature

Relating our work to the large prior literature on return decomposition, we note that one could exploit our idea of using observable inputs to decompose returns using the Campbell and Shiller (1988) (CS) log-linearization for Decomposition A but not for Decomposition B (given the absence of data on expected log earnings or dividends). The inputs to the decomposition would be changes to expected log returns (log riskless forward yields and log forward equity premia, which can be constructed from options as in Gao and Martin (2021)). Expected log dividends would be backed out with the effects of changes to long-term discount rates as the residual factor and one would obtain a decomposition of log returns. Since our approach allows a decomposition of both returns (using multiplicative factors) and log returns (using additive log factors), we do not provide results based on the CS log-linearization.

In the literature on return decomposition, VAR models play a central role. These models are well suited for decomposing return variance over a long period of interest. We highlight several advantages of our observables approach relative to VARs. First, the R^2 of the predictive regressions in VARs is often modest, leading to large statistical uncertainty about whether expected excess stock returns are in fact time-varying or not. This issue does not arise when using our approach to decompose returns and perform variance decomposition. Second, a VAR decomposition would not allow for a decomposition of the cumulative capital gain over a full sample of interest, since it imposes that cash flow news and discount rate news each have mean zero. Third, a key strength of our observables approach is to allow for a decomposition of capital gains (and thus returns) period by period. The drawback of using a VAR for a period-by-period decomposition of returns is that VARs interpret all movements in the predictors similarly. For example, suppose the price-earnings (PE) ratio falls in a given period of interest and that, over the full VAR estimation sample, a lower PE ratio predicts higher stock returns. A VAR approach will then interpret the price move based on how the PE ratio moved, with a low return along with a lower PE ratio interpreted as discount rate news and a low return along with an unchanged PE ratio interpreted as cash flow news. In practice, the mix of discount rate changes and expected cash flow changes driving movements in the PE ratio could vary over time and our approach allows for this.[3] Effectively, because our decomposition is based on observable data and does not require regressions, it allows researchers to decompose realized stock returns in a way that is conceptually similar to that used in event studies of yield changes in bond markets (e.g., Krishnamurthy and Vissing-Jorgensen (2011) for quantitative easing announcements).

Our paper is also related to van Binsbergen (2024) who studies the performance of bond portfolios with durations roughly equal to that of the stock market, highlighting that over the past 50 years the realized return and volatility of the bond portfolios have been as high as their equity counterparts. The bond portfolio returns are conceptually similar to the yield curve factor of our stock return decomposition.[4] By using I/B/E/S analysts earnings forecasts, the implementation of the cashflow factor in Decomposition B relates our paper to a growing literature that also use these forecasts to highlight the important role changing cashflow expectations have for aggregate equity valuations.[5] Methodologically, we contribute to these papers by showing how to use cashflow expectations in a return decomposition framework with modest assumptions. Empirically, we contribute to these papers by first showing that in recent decades, which is our empirical sample, data quality has improved out to 3-5 year horizons, and second by utilizing these medium term horizons to measure how expected dividends further down the road update. Our paper also relates to Cieslak and Pang (2021) who use a stock-bond correlation sign restriction plus restrictions on the term-structure of interest rates to decompose stock returns into a growth news, a monetary news, and two risk premium news components. Finally, our paper relates to Gonçalves (2021), who studies the contribution of dividends of different maturities to the overall stock market return. His analysis is within a CS decomposition and VAR setting rather than the observables-based approach that we are focused on.

The outline of the paper is as follows. Section II derives our decomposition. Section III maps the

[3] Campbell and Vuolteenaho (2004) discuss different recession types — cashflow or discount rate driven — as estimated through the lens of a standard VAR implementation with constant coefficients. Bianchi (2020) uses a Markov-switching VAR to compare the Great Depression and the Great Recession, with the regime switching allowing time-varying coefficients.

[4] Greenwald et al. (2024) also study the impact of long-term yields on equity valuations, arguing that this has been an important driver of rising financial wealth inequality since the 1980s.

[5] For example, see Landier and Thesmar (2020); De La O and Myers (2021); McCarthy and Hillenbrand (2021); Bordalo et al. (2024); De la O and Myers (2024); Hillenbrand and McCarthy (2024); Bordalo et al. (2024).

decomposition to observable inputs. Section IV provides empirical results and section V concludes. The Appendix contains proofs along with a series of supplementary results.

II. A new stock return decomposition

We derive a new decomposition of the realized stock market capital gain into the contributions from changes in the real yield curve, changes in equity premia, and changes to expected dividends. Our approach relies on assessing the effect of changes to the inputs in the present value formula for the stock price. It formalizes two simple intuitions: (1) if the expected dividend at time 10 accounts for 2% of today's stock price, then increasing this expected dividend by 10% will increase today's stock price by 0.2% (a 10% increase in something accounting for 2% of value); and (2) if expected dividends at time 10 and later account for 90% of today's stock price, then increasing the discount rate for year 10 by 1 percentage point will lower today's stock price by approximately 0.9% (a 1% shrinkage to 90% of stock value). Capital gains are thus driven by how much the inputs change and what fraction of the stock price a given input change is relevant for.

A. Background definitions

Start from the present value formula of the stock market

$$P_t = \sum_{n=1}^{\infty} P_t^{(n)} = \sum_{n=1}^{\infty} \frac{E_t\left[D_{t+n}\right]}{E_t\left(R_{t+1}^{(n)} R_{t+2}^{(n-1)} ... R_{t+n}^{(1)}\right)} = \sum_{n=1}^{\infty} \frac{E_t\left[D_{t+n}\right]}{\left(1+y_t^{(n)}\right)^n \left[\frac{E_t\left(R_{t+1}^{(n)} R_{t+2}^{(n-1)} ... R_{t+n}^{(1)}\right)}{\left(1+y_t^{(n)}\right)^n}\right]} \tag{1}$$

where all variables are in real terms. $P_t^{(n)}$ is the value of the n^{th} dividend strip (i.e., the present value at time t of the expected dividend paid out at time $t+n$), $E_t\left(R_{t+1}^{(n)} R_{t+2}^{(n-1)} ... R_{t+n}^{(1)}\right)$ is the n-period cumulative gross discount rate at time t for discounting $E_t\left[D_{t+n}\right]$ back from $t+n$ to t, and $R_{t+1}^{(n)} = \frac{P_{t+1}^{(n-1)}}{P_t^{(n)}}$ is the one-period gross return of the n^{th} dividend strip where $P_{t+1}^{(0)} = D_{t+1}$.[6] $y_t^{(n)}$ denotes the yield on an n-year zero coupon bond. $\frac{E_t\left(R_{t+1}^{(n)} R_{t+2}^{(n-1)} ... R_{t+n}^{(1)}\right)}{\left(1+y_t^{(n)}\right)^n}$ is the ratio of the cumulative expected gross return on the n^{th} dividend strip relative to that on the zero coupon bond with the same maturity. It thus captures the risk premium on the dividend strip.

The one-period gross return on the market can be expressed as the value-weighted average of the

[6] The definition of the value of the n^{th} dividend strip, $P_t^{(n)}$, follows from the fact that the only payment is at maturity. The hold-to-maturity realized return from purchasing the strip today is thus $R_{t,n} = \frac{D_{t+n}}{P_t^{(n)}}$. Take time t expectations and rearrange to show $P_t^{(n)} = \frac{E_t\left[D_{t+n}\right]}{E_t\left(R_{t,n}\right)}$. $R_{t,n}$ can in turn be expressed as the product of one-period realized returns.

one-period gross returns on all dividend strips

$$R_{t+1} = \sum_{n=1}^{\infty} w_t^{(n)} R_{t+1}^{(n)} \tag{2}$$

where

$$w_t^{(n)} = \frac{P_t^{(n)}}{P_t} \tag{3}$$

is the weight of the n^{th} dividend strip (the present value of the expected dividend paid out at time $t+n$ relative to the overall stock market value) and $\sum_{n=1}^{\infty} w_t^{(n)} = 1$.

B. Decomposing capital gains and returns

Consider the capital gain over a period from t to $t+1$

$$\frac{P_{t+1}}{P_t} = \frac{P_{t+1}^{(1)}}{P_t} + \frac{P_{t+1}^{(2)}}{P_t} + ... = \frac{P_t^{(1)}}{P_t}\frac{P_{t+1}^{(1)}}{P_t^{(1)}} + \frac{P_t^{(2)}}{P_t}\frac{P_{t+1}^{(2)}}{P_t^{(2)}} + ... = w_t^{(1)}\frac{P_{t+1}^{(1)}}{P_t^{(1)}} + w_t^{(2)}\frac{P_{t+1}^{(2)}}{P_t^{(2)}} + ... \tag{4}$$

Equation (4) expresses the market's capital gain in terms of how the value of "generic" dividend strips (i.e., dividend strips that pay off a certain number of periods out, as opposed to on particular calendar dates) evolve over time. For example, the factor $\frac{P_{t+1}^{(1)}}{P_t^{(1)}}$ captures how the value of a dividend strip that pays off one year out differs from date t to $t+1$. The following result emerges.

Result 1 (**One-period capital gain decomposition**). *The one-period capital gain on the market is*

$$\frac{P_{t+1}}{P_t} = \sum_{n=1}^{\infty} w_t^{(n)} \frac{P_{t+1}^{(n)}}{P_t^{(n)}} = w_t^{(1)} \frac{G_{t+1}^{D,(1)}}{G_{t+1}^{YC,(1)} G_{t+1}^{EP,(1)}} + w_t^{(2)} \frac{G_{t+1}^{D,(2)}}{G_{t+1}^{YC,(2)} G_{t+1}^{EP,(2)}} + ... \tag{5}$$

where

$$G_{t+1}^{D,(n)} = \frac{E_{t+1}\left[D_{t+n+1}\right]}{E_t\left[D_{t+n}\right]} \quad G_{t+1}^{YC,(n)} = \frac{\left(1+y_{t+1}^{(n)}\right)^n}{\left(1+y_t^{(n)}\right)^n} \quad G_{t+1}^{EP,(n)} = \frac{\frac{E_{t+1}\left(R_{t+2}^{(n)} R_{t+3}^{(n-1)} ... R_{t+n+1}^{(1)}\right)}{\left(1+y_{t+1}^{(n)}\right)^n}}{\frac{E_t\left(R_{t+1}^{(n)} R_{t+2}^{(n-1)} ... R_{t+n}^{(1)}\right)}{\left(1+y_t^{(n)}\right)^n}} \tag{6}$$

For G-factors near one, approximately,

$$\begin{aligned}\frac{P_{t+1}}{P_t} \approx \quad & \left[w_t^{(1)} G_{t+1}^{D,(1)} + w_t^{(2)} G_{t+1}^{D,(2)} + ...\right] && \textit{Cash flow factor} \\ \times \quad & \left[w_t^{(1)} \frac{1}{G_{t+1}^{YC,(1)}} + w_t^{(2)} \frac{1}{G_{t+1}^{YC,(2)}} + ...\right] && \textit{Yield curve factor} \\ \times \quad & \left[w_t^{(1)} \frac{1}{G_{t+1}^{EP,(1)}} + w_t^{(2)} \frac{1}{G_{t+1}^{EP,(2)}} + ...\right] && \textit{Equity premium factor}\end{aligned} \tag{7}$$

Equations (5) and (6) follow directly from equation (4) and involve no assumptions or approximations. As for equation (7), each of the three factors are exact in that they state what the capital gain would be if only that factor was operative. The approximation in equation (7) is that the total capital gain can only approximately be expressed as the product of the three factors, with the approximation better the closer the G-factors are to one. The cash flow factor in equation (7) is the formal version of our first intuition regarding the capital gain resulting from changes to expected dividends.

The approximation in equation (7) exploits the fact that for arguments near one, geometric and arithmetic averages are equal up to a first-order approximation. This is a general result, not specific to an asset pricing context. For values $x_1, ..., x_n$ and weights $w_1, ..., w_n$, at $x_1 = ... = x_n = 1$:

$$w_1 x_1 + w_2 x_2 + ... w_n x_n = x_1^{w_1} x_2^{w_2} ... x_n^{w_n} = 1$$

$$\frac{\partial}{\partial x_i}\left[w_1 x_1 + w_2 x_2 + ... w_n x_n\right] = \frac{\partial}{\partial x_i}\left[x_1^{w_1} x_2^{w_2} ... x_n^{w_n}\right] = w_i.$$

We apply this result twice to obtain equation (7). First, the arithmetic average in equation (5) is approximately equal to the corresponding geometric average

$$w_t^{(1)} \frac{G_{t+1}^{D,(1)}}{G_{t+1}^{YC,(1)} G_{t+1}^{EP,(1)}} + w_t^{(2)} \frac{G_{t+1}^{D,(2)}}{G_{t+1}^{YC,(2)} G_{t+1}^{EP,(2)}} + ... \approx \left[\frac{G_{t+1}^{D,(1)}}{G_{t+1}^{YC,(1)} G_{t+1}^{EP,(1)}}\right]^{w_t^{(1)}} \times \left[\frac{G_{t+1}^{D,(2)}}{G_{t+1}^{YC,(2)} G_{t+1}^{EP,(2)}}\right]^{w_t^{(2)}} \times ... \tag{8}$$

Second, rewrite the geometric average of the growth factor ratios:

$$\begin{aligned}&\left[\frac{G_{t+1}^{D,(1)}}{G_{t+1}^{YC,(1)} G_{t+1}^{EP,(1)}}\right]^{w_t^{(1)}} \times \left[\frac{G_{t+1}^{D,(2)}}{G_{t+1}^{YC,(2)} G_{t+1}^{EP,(2)}}\right]^{w_t^{(2)}} \times ... = \left(\left[G_{t+1}^{D,(1)}\right]^{w_t^{(1)}} \times \left[G_{t+1}^{D,(2)}\right]^{w_t^{(2)}} \times ...\right) \\ &\times \left(\left[\frac{1}{G_{t+1}^{YC,(1)}}\right]^{w_t^{(1)}} \times \left[\frac{1}{G_{t+1}^{YC,(2)}}\right]^{w_t^{(2)}} \times ...\right) \times \left(\left[\frac{1}{G_{t+1}^{EP,(1)}}\right]^{w_t^{(1)}} \times \left[\frac{1}{G_{t+1}^{EP,(2)}}\right]^{w_t^{(2)}} \times ...\right)\end{aligned} \tag{9}$$

where each term on the right hand side approximately equals its corresponding arithmetic average.

The approximation in equation (7) is not the same as a Taylor approximation which would result in the three factors being added rather than multiplied.[7] The approximation in equation (7) is more accurate than a Taylor approximation for that reason. Intuitively, the growth rates from the three different types of changes (cash flow, yield curve, and equity premium) build on each other to generate the total capital gain, in a similar way to returns compounding over time. Equation (7) has the additional advantage that it can easily be used to decompose multi-period returns since each factor can be compounded over time. For readers interested in using our decomposition to understand a longer period of interest, we recommend applying the decomposition to shorter periods and then compounding the factors across periods up to the longer period, rather than applying the decomposition just once to the longer period of interest.[8]

B.1. The yield curve factor expressed in terms of forward rates

The yield curve return component in Result 1 is directly implementable. To gain intuition, and for comparison with a later result on the equity premium factor, we show how to express the yield curve return factor in terms of forward rates. Define the forward real yield for period n as:

$$1 + f_t^{YC,n} = \frac{\left(1 + y_t^{(n)}\right)^n}{\left(1 + y_t^{(n-1)}\right)^{n-1}} \tag{11}$$

and the yield curve growth factor for forward period n as:

$$G_{t+1}^{YC,fn} = \frac{\left(1 + f_{t+1}^{YC,n}\right)}{\left(1 + f_t^{YC,n}\right)}. \tag{12}$$

Spot and forward growth factors are then related as follows:

$$G_{t+1}^{YC,(1)} = G_{t+1}^{YC,f1}, \qquad G_{t+1}^{YC,(2)} = G_{t+1}^{YC,f1} G_{t+1}^{YC,f2}, \qquad G_{t+1}^{YC,(3)} = G_{t+1}^{YC,f1} G_{t+1}^{YC,f2} G_{t+1}^{YC,f3}, \quad \dots \tag{13}$$

The following result emerges straightforwardly from these definitions.

Result 2 (Yield curve return factor expressed using forward growth rates). *The yield curve*

[7] The first-order Taylor approximation of equation (5) around G-factors (and thus 1/G-factors) of one is

$$\frac{P_{t+1}}{P_t} \approx 1 + \left[w_t^{(1)} G_{t+1}^{D,(1)} + w_t^{(2)} G_{t+1}^{D,(2)} + \dots - 1\right] + \left[w_t^{(1)} \frac{1}{G_{t+1}^{YC,(1)}} + w_t^{(2)} \frac{1}{G_{t+1}^{YC,(2)}} + \dots - 1\right] + \left[w_t^{(1)} \frac{1}{G_{t+1}^{EP,(1)}} + w_t^{(2)} \frac{1}{G_{t+1}^{EP,(2)}} + \dots - 1\right] \tag{10}$$

[8] If only one of the three return factors changes, compounding that return factor over time will mechanically give the same total return as applying equation (7) once for the full period. This is not the case if two or three factors change and compounding will then be more accurate than applying equation (7) once for the full period.

return factor can be expressed using forward growth rates as:

$$\left[w_t^{(1)}\frac{1}{G_{t+1}^{YC,f1}}+w_t^{(2)}\frac{1}{G_{t+1}^{YC,f1}G_{t+1}^{YC,f2}}+w_t^{(3)}\frac{1}{G_{t+1}^{YC,f1}G_{t+1}^{YC,f2}G_{t+1}^{YC,f3}}+...\right] \tag{14}$$

Approximating around 1/G-factors of one and by multiplying the (gross) capital gains resulting from the change in each separate forward yield, gives

$$\left[1+\left(\frac{1}{G_{t+1}^{YC,f1}}-1\right)\right]\times\left[1+(1-w_t^{(1)})\left(\frac{1}{G_{t+1}^{YC,f2}}-1\right)\right]\times\left[1+(1-w_t^{(1)}-w_t^{(2)})\left(\frac{1}{G_{t+1}^{YC,f3}}-1\right)\right]\times ... \tag{15}$$

$$\approx\left[1-\left(\frac{\Delta f_{t+1}^{YC,1}}{1+f_t^{YC,1}}\right)\right]\times\left[1-(1-w_t^{(1)})\left(\frac{\Delta f_{t+1}^{YC,2}}{1+f_t^{YC,2}}\right)\right]\times\left[1-(1-w_t^{(1)}-w_t^{(2)})\left(\frac{\Delta f_{t+1}^{YC,3}}{1+f_t^{YC,3}}\right)\right]\times ... \tag{16}$$

where $\Delta f_{t+1}^{YC,n}=f_{t+1}^{YC,n}-f_t^{YC,n}$.

To see how equation (15) follows from equation (14), suppose only $f^{YC,n}$ changes. Then the gross capital gain in equation (14) is:

$$w_t^{(1)}+...+w_t^{(n-1)}+\left(w_t^{(n)}+w^{(n+1)}+...\right)\frac{1}{G_{t+1}^{YC,fn}}=1+\left(w_t^{(1)}+...+w^{(n-1)}\right)\left(\frac{1}{G_{t+1}^{YC,fn}}-1\right)$$

where $\left(w_t^{(n)}+w^{(n+1)}+...\right)=1-\left(w_t^{(1)}+...+w^{(n-1)}\right)$. We have verified that the quality of the approximation in equation (15) is very high.[9]

Equation (16) is the formal version of our second descriptive intuition (regarding the capital gain resulting from a change to the expected return for a forward period) that we set out at the top of Section II. For simplicity, we left out the $1/(1+f)$ factor (which is close to one) when giving the intuition. Equation (16) relies on the first-order approximation $\frac{1}{G_{t+1}^{YC,fn}}-1\approx-\frac{\Delta f_{t+1}^{YC,n}}{1+f_t^{YC,n}}$ and is thus only accurate for small changes to forward rates, similar to duration based analysis that ignores convexity. That being said, we use equation (15) in our empirical analysis.

B.2. An implementable equity premium return factor expressed using the market risk premium

The equity premium return factor in Result 1 is not directly implementable because equity premia on individual dividend strips are not observable. We therefore develop a method for deriving an equity

[9]In our sample of monthly data from 2005M1-2023M12, the exact yield curve return factor in has an average of 1.001034 and a standard deviation of 0.0456607, while the approximate yield curve return factor in equation (15) has an average 1.000823 and a standard deviation of 0.0454937. The correlation of the exact and approximate yield curve return factors is 0.99990.

premium return factor that is expressed in terms of the market equity premium which – using data from options markets or asset manager expectations – is (to some extent) observable. To proceed, we need a few additional equity premium definitions. Define the forward equity premium on the overall stock market for period n as

$$1 + f_t^{EP,n} = \frac{E_t\left(R_{t+1}R_{t+2}...R_{t+n}\right)/\left(1 + y_t^{(n)}\right)^n}{E_t\left(R_{t+1}R_{t+2}...R_{t+n-1}\right)/\left(1 + y_t^{(n-1)}\right)^{n-1}} \tag{17}$$

and the market equity premium growth factor for forward period n as

$$G_{t+1}^{EP,fn} = \frac{1 + f_{t+1}^{EP,n}}{1 + f_t^{EP,n}}. \tag{18}$$

Using these definitions, we state the following result.

Result 3 (**Equity premium return factor using market equity premium, in forwards**). *Approximating around 1/G-factors of one and by multiplying the (gross) capital gains resulting from the change in each separate forward equity premium, the equity premium return factor of the one-period capital gain is:*

$$\left[1 + \left(\frac{1}{G_{t+1}^{EP,f1}} - 1\right)\right] \times \left[1 + (1 - w_t^{(1)})\left(\frac{1}{G_{t+1}^{EP,f2}} - 1\right)\right] \times \left[1 + (1 - w_t^{(1)} - w_t^{(2)})\left(\frac{1}{G_{t+1}^{EP,f3}} - 1\right)\right] \times ... \tag{19}$$

In equation (19):

(a) The capital gain factor for $n = 1$, $1 + \left(\frac{1}{G_{t+1}^{EP,f1}} - 1\right)$, is exact.

(b) The capital gain factors for any $n > 1$, $1 + (1 - w_t^{(1)} - ... - w_t^{(n)})\left(\frac{1}{G_{t+1}^{EP,fn}} - 1\right)$ are exact if returns are independent over time and close to exact even if returns are not independent, for realistic return processes.

Proof: Please see Appendix A.

The intuition described following Result 2 for the effect of an increase in a forward yield carries over to understanding the effect of an increase in a forward equity premium in Result 3. The effect in both cases depends on the weight in the overall price of the dividends strips whose present value is affected by a change in discounting in period n and this weight is $1 - \left(w_t^{(1)} + ... + w^{(n-1)}\right)$.

We emphasize that Result 3 does not rely on any assumptions about how expected returns on dividend strips of various maturities relate. Intuitively, Result 3 is derived in terms of the forward equity premium on the entire market by writing the stock price as a function of the terminal payoff at a given future date. In the period before the future date, the terminal payoff accounts for the full value of the stock market and is therefore discounted over that period using the expected return on the market which can be expressed in terms of the forward real yield and the forward equity premium. The effect of a change to the forward market equity premium follows.

B.3. Summarizing the decomposition

Combining Result 1-3, we have the following decomposition result.

Result 4 (One-period capital gain decomposition, combining Result 1-3). *For G-factors near one, the one-period capital gain on the market is, approximately,*

$$
\begin{aligned}
\frac{P_{t+1}}{P_t} &\approx \left[w_t^{(1)} G_{t+1}^{D,(1)} + w_t^{(2)} G_{t+1}^{D,(2)} + ...\right] \qquad (20)\\
\times &\quad \frac{1}{G_{t+1}^{YC,f1}} \times \left[1 + (1 - w_t^{(1)}) \left(\frac{1}{G_{t+1}^{YC,f2}} - 1\right)\right] \times \left[1 + (1 - w_t^{(1)} - w_t^{(2)}) \left(\frac{1}{G_{t+1}^{YC,f3}} - 1\right)\right] \times ...\\
\times &\quad \frac{1}{G_{t+1}^{EP,f1}} \times \left[1 + (1 - w_t^{(1)}) \left(\frac{1}{G_{t+1}^{EP,f2}} - 1\right)\right] \times \left[1 + (1 - w_t^{(1)} - w_t^{(2)}) \left(\frac{1}{G_{t+1}^{EP,f3}} - 1\right)\right] \times ...
\end{aligned}
$$

In Result 4, $G_{t+1}^{D,(n)}$ captures how the expected n^{th} generic (i.e., constant maturity) dividend evolves from date t to $t+1$. Similarly, $G_{t+1}^{YC,fn}$ and $G_{t+1}^{EP,fn}$ capture how the n^{th} generic real forward yield and forward equity premium change from date t and $t+1$. The effect of a particular change depends on how much of the initial market value is affected by that change. The effect of an increase in the generic n^{th} expected dividend leads to a larger capital gain if this dividend initially was large and thus accounted for a larger fraction $w_t^{(n)}$ of the date t stock price. The effect of forward yields and forward equity premia depend on the initial weight of the dividend strips affected by such changes, $\left(w_t^{(n)} + w^{(n+1)} + ...\right) = 1 - \left(w_t^{(1)} + ... + w^{(n)}\right)$.

B.4. Drivers of G-factors: News versus roll

To clarify the economics underlying Result 4, it is informative to express the G-factors as follows.

$$
G_{t+1}^{D,(n)} = \frac{E_{t+1}[D_{t+n+1}]}{E_t[D_{t+n}]} = \frac{E_t[D_{t+n+1}]}{E_t[D_{t+n}]} \frac{E_{t+1}[D_{t+n+1}]}{E_t[D_{t+n+1}]} = G_t^{D,(n),roll} G_{t+1}^{D,(n),news} \qquad (21)
$$

$$
G_{t+1}^{YC,fn} = \frac{1 + f_{t+1}^{YC,n}}{1 + f_t^{YC,n}} = \left(\frac{1 + f_t^{YC,n+1}}{1 + f_t^{YC,n}}\right) \left(\frac{1 + f_{t+1}^{YC,n}}{1 + f_t^{YC,n+1}}\right) = G_t^{YC,fn,roll} G_{t+1}^{YC,fn,news} \qquad (22)
$$

$$
G_{t+1}^{EP,fn} = \frac{1 + f_{t+1}^{EP,n}}{1 + f_t^{EP,n}} = \left(\frac{1 + f_t^{EP,n+1}}{1 + f_t^{EP,n}}\right) \left(\frac{1 + f_{t+1}^{EP,n}}{1 + f_t^{EP,n+1}}\right) = G_t^{EP,fn,roll} G_{t+1}^{EP,fn,news} \qquad (23)
$$

where the "roll" and "news" components refer to the first and second fractions in the second to last term in each equation. The "roll" component is the effect of moving one calendar period forward, implying that each object in the PV formula now refers to a later period. This component is known as of t. The "news" component is due to changing expectations from t to $t+1$ about a particular object for a given future time period. In the absence of news, the realized capital gain would be driven by the roll components of the growth factors and can be calculated from the formula in Result 4 replacing the G_{t+1}-factors with the G_t-roll factors. The role of the news is then simply the actual change $\left(\frac{P_{t+1}}{P_t}\right)$ minus $\left(\frac{P_{t+1}}{P_t}\right)^{\text{no news}}$. This allows one to separate the importance of roll versus news in a given application and this further decomposition can be done for the cash flow, yield curve and equity premium factors separately.[10]

B.5. *A sub-period of a year*

Result 1 and 2 hold for any period length. However, in practice one typically starts from inputs that are in years (e.g., constant maturity yields for maturities that have one-year increments). Therefore, we provide a decomposition result where t denotes years but we consider a sub-period of a year that is expressed in terms of such inputs. In our empirical applications, we will use this result to decompose monthly returns, but we state the result more generally since others may want to analyze returns at other frequencies such as daily or weekly.

Consider a sub-period of a year going from a fraction s into the year to a fraction s' into the year, with $0 \leq s \leq 1$, $0 \leq s' \leq 1$, and $s' > s$. Denote these two points in time by $t+s$ and $t+s'$. Date t is thus the beginning of a calendar year, $t+s$ is a fraction s into the calendar year, and $t+s'$ is a later date in the same calendar year. We write the capital gain from $t+s$ to $t+s'$ as:

$$\frac{P_{t+s'}}{P_{t+s}} = \frac{P^{(1)}_{t+s'}}{P_{t+s}} + \frac{P^{(2)}_{t+s'}}{P_{t+s}} + ... = \frac{P^{(1)}_{t+s}}{P_{t+s}} \frac{P^{(1)}_{t+s'}}{P^{(1)}_{t+s}} + \frac{P^{(2)}_{t+s'}}{P_{t+s}} \frac{P^{(2)}_{t+s'}}{P^{(2)}_{t+s}} + ... = w^{(1)}_{t+s} \frac{P^{(1)}_{t+s'}}{P^{(1)}_{t+s}} + w^{(2)}_{t+s} \frac{P^{(2)}_{t+s'}}{P^{(2)}_{t+s}} + ... \tag{24}$$

where "(1)" refers to a dividend strip paying off one year from the date considered. This expression assumes that $P_{t+s'} = P^{(1)}_{t+s'} + P^{(2)}_{t+s'} + ...$ At any given point in time (not just at the end of each year, but also on a given day within the year), we thus implicitly assume that the next dividend is one year away. In practice, dividends are paid throughout a given year. The annual dividends in our formulas can be thought of as the future value of dividends to be paid over the next 1-year period, with the future value calculated as of one year out. Our formula with annual cash flows then holds not only at the start of each year but also on any day within the year.[11]

[10] The news components calculated this way are slightly different than what one will get by using only the news G-factors in Result 4, since the role of roll and news in the G-factors are multiplicative, implying that the roll and news components interact.

[11] We do not account for the fact that moving all dividends over a 1-year period out to the end of that period involves an

With then have the following version of Result 4, stating the decomposition for the sub-period.

Result 5 (Capital gain for a sub-period of a year). *For G-factors near one, the capital gain on the market for a sub-period of a year is, approximately,*

$$\begin{aligned}
&\frac{P_{t+s'}}{P_{t+s}} \approx \left[w_{t+s}^{(1)} G_{t+s'}^{D,(1)} + w_{t+s}^{(2)} G_{t+s'}^{D,(2)} + ...\right] \qquad (25)\\
\times \quad &\frac{1}{G_{t+s'}^{YC,f1}} \times \left[1 + (1 - w_{t+s}^{(1)}) \left(\frac{1}{G_{t+s'}^{YC,f2}} - 1\right)\right] \times \left[1 + (1 - w_{t+s}^{(1)} - w_{t+s}^{(2)}) \left(\frac{1}{G_{t+s'}^{YC,f3}} - 1\right)\right] \times ...\\
\times \quad &\frac{1}{G_{t+s'}^{EP,f1}} \times \left[1 + (1 - w_{t+s}^{(1)}) \left(\frac{1}{G_{t+s'}^{EP,f2}} - 1\right)\right] \times \left[1 + (1 - w_{t+s}^{(1)} - w_{t+s}^{(2)}) \left(\frac{1}{G_{t+s'}^{EP,f3}} - 1\right)\right] \times ...
\end{aligned}$$

where for $n = 1, 2, ...$

$$G_{t+s'}^{D,(n)} = \frac{E_{t+s'}\left[D_{t+s'+n}\right]}{E_{t+s}\left[D_{t+s+n}\right]}, \qquad G_{t+s'}^{YC,fn} = \frac{1 + f_{t+s'}^{YC,n}}{1 + f_{t+s}^{YC,n}}, \qquad G_{t+s'}^{EP,fn} = \frac{1 + f_{t+s'}^{EP,n}}{1 + f_{t+s}^{EP,n}}. \qquad (26)$$

B.6. Instantaneous price change

An interesting limit of Result 5 emerges as s' goes to s. Then Result 3 simply states the effect of instantaneous changes to expected cash flows, forward real yields or forward equity premia, similar to how duration analysis for bonds allows one to assess the capital gain on a bond resulting from an instantaneous shift in the yield curve. As s' goes to s, the expected capital gain is approximately zero and the capital gain in Result 3 is the unexpected capital gain from an instantaneous change to the inputs.

III. Implementing the stock return decomposition with observables

This section lays out how to implement our return decomposition for the S&P500 utilizing observable data. First, we describe how to use dividend futures prices and equity option prices to obtain dividend strip weights. Second, we describe available data on total returns, capital gains, and dividend yields as well as the data used to decompose capital gains: dividend strip weights, real yields, the equity premium and expected cash flows. Table I summarizes data sources. Third, given the available data, we provide two ways of implementing our decomposition. Decomposition A uses only financial market data while Decomposition B also uses data on the growth in analyst's expected earnings as a guide to the growth

interest rate to calculate the future value. This is an approximation that should have only a very small effect on our results. Specifically, at each point in time, this approach overstates the duration of the stock market by 1/2 year, which is very small relative to the very long duration of the stock market.

in expected dividends. We also address the issue that the main inputs (expected returns and expected dividends) are not available to infinite maturities.

A. Dividend strip weights: Methodology

Dividend strip weights $w_t^{(n)}$ drive the magnitude of the effect of changes to real yields, equity premia, and expected dividends on the stock market.

A.1. Obtaining dividend strip weights

It is well known that dividend strips (which are not traded) can be valued from dividend futures (e.g. van Binsbergen et al. (2013)) or equity option prices (e.g. van Binsbergen et al. (2012); Golez and Jackwerth (2023)). Since dividend futures pay off at maturity $(t+n)$, dividend strips and dividend futures prices are related by

$$P_t^{(n)} = F_{n,t} / \left(1 + y_{t,n}^{\text{nom}}\right)^n \tag{27}$$

where $F_{n,t}$ denotes the date t price of a dividend future paying the nominal dividend for period $t+n$ at $t+n$ and $y_{t,n}^{\text{nom}}$ is the riskless nominal yield at date t for an n-period investment. $F_{n,t}$ is nominal (since dividend futures contracts pay the nominal dividend) and therefore discounted using the nominal yield $y_{t,n}^{\text{nom}}$. We can then express the dividend strip weights as

$$w_t^{(n)} = \frac{P_t^{(n)}}{P_t} = \frac{F_{k,t} / \left(1 + y_{t,k}^{\text{nom}}\right)^k}{P_t}. \tag{28}$$

When dividend futures are not available, we use the van Binsbergen et al. (2012) approach to calculate dividend strip weights from equity options. In the absence of arbitrage opportunities, put-call parity for European options with maturity $t+n$ at time t implies:

$$P_t^{(1)} + P_t^{(2)} + ... + P_t^{(n)} = put_{t,n} - call_{t,n} + P_t - Xe^{-r_{t,n}^f} \tag{29}$$

where X denotes the strike price and $r_{t,n}^f$ is the (continuously compounded nominal) risk-free yield between t and $t+n$.

A.2. Computing dividend strip weights at all maturities

Dividend futures and equity options are observed to a maximum maturity that we will label N_t^D years, where the t subscript indicates that the maximum maturity varies over time depending on data availability (see Section III.B).

Using the available data on dividend strip prices, along with the market price, the total value of long-term dividends beyond the maximum maturity is observable as

$$L_t = P_t - \sum_{n=1}^{N_t^D} P_t^{(n)}. \tag{30}$$

The total weight of long-term dividends as a fraction of the stock market value $\frac{L_t}{P_t}$ is therefore observable. The individual dividend strip weights beyond year $t + N_t^D$ (that sum to $\frac{L_t}{P_t}$) are not observable and assumptions are needed to estimate these dividend strip weights. We assume a Gordon growth model for dividends beyond year $t + N_t^D$, with G_t^L denoting the expected annual gross dividend growth rate past year $t + N_t^D$ and R_t^L denoting the expected annual gross return past year $t + N_t^D$. Both rates are, as of time t, assumed to be constant in expectation across all periods past year $t+N_t^D$. Under this assumption, we have the following result.

Result 6 (**Long-maturity dividend strip weights estimates**).
Assume a Gordon growth model for dividends beyond year $t + N_t^D$. Then, the observable value of long-term dividends, $L_t = P_t - \sum_{n=1}^{N_t^D} P_t^{(n)}$, along with the last observed dividend strip price, $P_t^{(N_t^D)}$, reveal the market's expected ratio $\frac{G_t^L}{R_t^L}$:

$$L_t = P_t^{(N_t^D)} \left(\frac{G_t^L}{R_t^L - G_t^L} \right) \qquad \Longrightarrow \qquad \frac{G_t^L}{R_t^L} = \frac{1}{1 + \left(P_t^{(N_t^D)} / L_t \right)} \tag{31}$$

Dividend strip weights beyond N_t^D years can then be calculated as:

$$w_t^{(n)} = w_t^{(N_t^D)} \left(\frac{G_t^L}{R_t^L} \right)^{n - N_t^D} \qquad \text{for } n > N_t^D. \tag{32}$$

To verify that the weights across all horizons sum to one, observe that from equation (32), the weights beyond $N_t^{(D)}$ sum to $w_t^{N_t^{(D)}} \times \frac{G_t^L/R_t^L}{1-G_t^L/R_t^L}$ and the weights up to $N_t^{(D)}$ sum to $1 - \frac{L_t}{P_t} = 1 - \frac{P_t^{(N_t^{(D)})}}{P_t} \frac{L_t}{P_t^{(N_t^{(D)})}} = 1 - \left(w_t^{N_t^{(D)}} \times \frac{G_t^L/R_t^L}{1-G_t^L/R_t^L} \right)$.

A.3. Share repurchases and issuance

As we have shown, dividend strip weights determine the effect of changes in discount rates (real yields or equity premia) and expected dividends at different maturities. Is this correct, even in cases with share repurchases or share issuance? The answer is yes, with the following clarification.

As is well known, the stock price per share is the present value of dividends per share even in the presence of share repurchases/issuance. Furthermore, the S&P500 dividend futures from which we calculate the dividend strip weights are adjusted for share issues/repurchases so the contracts always reflect the dividends per share at the time the contract pays off.[12]

The subtlety is that if a company is expected to repurchase/issue shares (or repurchase/issue debt), then changes to expected returns may have not only a discount rate effect but also an effect on expected future dividends. In our decomposition, any such effects will enter the expected dividend factor, as they should, but it is nonetheless relevant for thinking about the underlying drivers of the expected dividend factor whether such effects are present.

In Appendix B, we show that there will be no discount rate effect on expected dividends if repurchases are funded by debt issuance while there will be such an effect if firms are expected to fund share repurchases/issuance by changing dividends. Asness et al. (2018) document that in the last few years leading up to their publication, net repurchases were substantial for firms in the Russell 3000 (as the are for the S&P500) but they were roughly equal to net debt issuance. Any effects of discount rates on expected dividends due to repurchases are thus likely to be modest.

B. Return data and data for decomposition inputs

B.1. Total return, capital gain and dividend yield

Since our decompositions pertain to capital gains, we first decompose the total real S&P500 return into its real capital gain and real dividend yield components. Our data inputs are the Bloomberg SPX Index, which is the price-level index of the S&P500 and excludes dividends, and the Bloomberg SPXT Index, which is the total-return index of the S&P500.[13] The total return index not only captures capital gains but also includes returns from reinvesting dividends paid by index constituents back into the index. For both the SPX Index and SPXT Index, we divide by the level of the CPI (from FRED, series CPIAUCSL) to obtain real variables. We then compute the dividend yield in each month as the difference between returns on the two real indexes.

Figure 1 shows the cumulative gross real return on the S&P500 index from 2005m1 to 2023m12. The sample period is based on the availability of other data series that we will discuss below. A dollar invested at the end of 2004 would have grown to $3.56 in real terms by the end of 2023, for a 256 percent real net return of which 144 percent was from real capital gains. In the figure, we show the monthly real dividend

[12] See https://www.spglobal.com/spdji/en/documents/additional-material/faq-sp-500-dividend-points-index.pdf

[13] The price-level index is the market capitalization of the index constituents after adjusting for the index divisor (which adjusts the index-level for changes in market capitalization that are due to corporate actions or index constituent changes).

yield summed over time, which amounts to 38 percent net (or 138 percent gross), in total. The remaining $256 - 144 - 38 = 74$ percent of the total real net return is from the return earned on the reinvested dividends (this return is dominated by the capital gain).

B.2. Dividend strip weights data

We obtain daily dividend futures prices from Bloomberg, available to year 10 from 2017. Proprietary dividend futures data from various banks back to the early 2000s have previously been used in the literature (starting with van Binsbergen et al. (2013)), but this data is not widely available. When dividend futures are not available, we obtain dividend strip prices from equity option prices to year 2 using equation (29) data from OptionMetrics, which is available from 1996.[14] For both types of data inputs, on each date we use linear interpolation across available maturities on the traded assets in order to calculate constant maturity dividend strip weights, which is a standard approach in the literature that studies dividend futures (i.e., van Binsbergen et al. (2013)).

The top left panel of Figure 2 shows the evolution of the 1-year dividend strip weight from 2005m1 to 2023m12 and how this dividend strip closely tracks the past year's dividend over the current stock price. On average, the 1-year dividend strip has contributed roughly 2 percent to the total stock market value in our sample period, although this declined to around 1.4 percent in the last few years of the sample. The top right panel of Figure 2 shows the evolution of the sum of dividend weights from year 1 to year 10 and from year 1 to year 30.

The bottom panels of Figure 2 show the average dividend strip weight (left hand side) and average cumulative dividend strip weight (right hand side) by maturity in the sample from 2017, which is the time from which we have dividend futures prices available out to 10-years (denoted by the gray shaded area in the figures). The average sum of dividend weights through to year 10 is 18 percent across our sample and the average sum of dividend weights through to year 30 is 42 percent. These numbers highlight the long duration of stock market (a point also made in van Binsbergen (2024)), which means that the stock market will be sensitive to changes in long-maturity discount rates.

Appendix D analyzes the robustness of our measured dividend strip weights to liquidity issues in dividend futures. Our method uses dividend future price levels, rather than changes in prices of dividend futures, which largely mitigates the impact of bid-ask spreads that is known to impact analysis on dividend futures returns (Bansal et al., 2021). We also show that results are not very sensitive to the maximum maturity of observed dividend futures used to implement Result 6.

[14] Results are similar when using options data from the CBOE.

B.3. *Real yield curve data*

We obtain forward real yields to year 30 from TIPS data when available and prior to that from nominal Treasury yields and inflation swaps.

Zero-coupon TIPS yields are available from Gürkaynak et al. (2010) which is updated by the Federal Reserve and available on the Federal Reserve website.[15] This data is available since 1999. However, Gürkaynak et al. (2010) note that liquidity in the TIPS market was initially poor, resulting in a liquidity premium in TIPS yields that unwound slowly over the first few years of the market's development. Given that this TIPS-specific declining liquidity premium of real yields is unlikely to be relevant for the stock market, we do not include the first few years of TIPS yields in our sample. Furthermore, 30-year TIPS were dropped from issuance in October 2001 and only reintroduced in January 2010. Until January 2010, we therefore measure real yields using nominal zero-coupon Treasury yields adjusted by inflation swap rates, with TIPS yields used subsequently. Nominal Treasury yields are also obtained from the Federal Reserve website and are based on Gürkaynak et al. (2007), while inflation swaps are from Bloomberg and are available from August 2004. To use full years, our sample starts in 2005.

Figure 3 shows the evolution of the real 30-year yield from 2005-2023 at a monthly frequency (our analysis uses all 30 yearly forward real yields, but for readability of the figure we show the 30-year spot real yield as a summary measure of how real yields evolved over our sample). Panel A shows the 30-year zero-coupon real yield as measured by TIPS and by the zero-coupon nominal Treasury adjusted for the inflation swap rate. In the overlapping period, the two real yield measures are tightly related. At the start of the sample, as measured by nominal Treasury yields and inflation swaps, the 30-year real yield was 1.67 percent. Real yields then generally trended down from 2005-2021, reaching a low of -0.54 percent, before rebounding dramatically at the end of the sample such that, on net, real yields were broadly unchanged over our sample period.

Figure 3 Panel B shows the components of the 30-year real yield, i.e., the nominal Treasury yield and expected inflation. Expected inflation is measured by either the inflation swap rate or by break-even inflation computed from the 30-year nominal Treasury yield and the 30-year TIPS yield. The nominal yield and expected inflation fluctuations are correlated over time, but the movements in expected inflation are smaller, thus resulting in the larges swings in the 30-year real yield illustrated in Panel A.

B.4. *Equity risk premium data: The Martin lower bound and asset manager expectations*

For the equity risk premium we use the methodology of Martin (2017) who calculates a lower bound on the equity premium using prices of stock market index options and argues that this lower bound is

[15] https://www.federalreserve.gov/data/tips-yield-curve-and-inflation-compensation.htm

approximately equal to the true risk premium. Martin's data covers the period 1996-2012. We replicate and extend the original series to December 2023 using data from OptionMetrics. The maximum maturity of equity options from 2005 are 2 to 3 years, which allows us to estimate equity premium out to 2-years throughout our 2005-2023 sample period. [16] Appendix C provides a recap of Martin's approach and details on our data construction.

Panel A of Figure 4, left chart, shows the time series of the estimated 1-year equity premium and the forward equity premium for year 2 (i.e., the 1-year equity premium in 1-year's time). The average 1-year equity premium is around 5 percent but with large increases around 2008 (the global financial crisis) and 2020 (the onset of the COVID pandemic). The spot 1-year equity premium increases more than the forward equity premium for year 2 in these crisis periods. This is also illustrated in the right chart in the same panel, which shows the cumulative equity premium by maturity on two example trade dates. The steep slope of the curve at short maturities on the crisis trade date, March 31, 2020, shows how near-term equity premia were particularly elevated.

We provide novel support for the use of the Martin lower bound as a measure of the equity risk premium by comparing it to equity premium estimates of asset managers.[17] Dahlquist and Ibert (2021) collect a dataset of equity risk premium estimates of asset managers (and some of the largest investment consultants). The data is based on asset managers' capital market assumptions, posted publicly or provided to clients. For the period 2005Q1-2021Q1, their data has 561 observations of equity risk premia from a total of 47 asset managers such as J.P. Morgan, BlackRock, Franklin Templeton and AQR. The most typical horizons in their dataset are 10 years (45% of the data), 7 years (13%), and 5 years (10%). Dahlquist and Ibert (2021) show that asset managers' expectations appear rational in that their perceived equity risk premium is high when the P/E ratio is low, consistent with statistical predictive relations.

Using their (unbalanced) panel data, we construct an asset manager equity premium time series for the 10-year horizon by taking out asset manager fixed effects.[18] We estimate this relation

$$EP^{10}_{m,t} = \alpha + \Sigma^{T}_{t=1}\beta_t D(\text{date} = t) + \Sigma^{M}_{m=1}\delta_m D(\text{manager} = m) + u_{m,t} \tag{33}$$

where m denotes a given asset manager. We calculate the predicted value, excluding manager fixed effects, for each date t, $\alpha + \Sigma^{T}_{t=1}\beta_t D(\text{date} = t)$. Figure 4, Panel B, graphs the resulting asset manager 10-year

[16] We note that, since 2022, the maximum maturity of options has extended to 5 years, which further strengthens our observables approach going forward (for consistency across years, we use Martin equity premium measures only to year 2).

[17] Appendix C provides an updated version of the regression evidence in Martin (2017) on the quality of Martin lower bound, as well as theoretical analysis of the how the change in the lower bound relates to the change in the true equity premium.

[18] The 10-year expected return sample, which begins in 2010, is by far the richest in data availability and covers 31 unique asset managers.

equity premium series along with the 1-year Martin measure. The correlation is high at 0.72.[19] This lends credence to the Martin measure and also suggests that asset manager equity premium perceptions are consistent with actual asset prices. We will exploit the fact that the asset manager equity premia are available for a longer maturity than the equity-options based series to assess the effect of equity premium past year 2 for stock prices in our decomposition implementations.

B.5. Expected earnings data

We use analyst forecast data to extract a measure of earnings expectations. Since 1976, Refinitiv's I/B/E/S Estimates Database provides analyst estimates of earnings per share (EPS) for U.S. publicly traded companies over the next 1 to 5 fiscal years at a monthly frequency. We use this database to generate constant-maturity EPS estimates for the aggregated S&P500 index, as has been done in prior work (De La O and Myers, 2021; Hillenbrand and McCarthy, 2024). The coverage of S&P500 firms in the I/B/E/S database is better for nearer term forecasts, and has improved in general over time.[20] Appendix Section E explains our EPS data construction in detail.

From nominal EPS forecasts we compute real earnings expectations by adjusting for expected inflation over the forecast horizon using inflation swaps (to get real values in date t dollars) and dividing through by the level of the CPI Index at date t to get real values in the CPI base-year dollars (remember that the stock price we are trying to understand is also in real terms, calculated using the same CPI index):

$$E_t\left(EPS^{real}_{t+n}\right) = \frac{E_t\left(EPS^{nominal}_{t+n}\right)}{CPI_t\ (1+\pi_{t,t+n-1})^{n-1}\,(1+\pi_{t+n-1,t+n})^{0.5}} \tag{34}$$

where π_{t_1,t_2} is the annualized inflation swap rate from year t_1 to year t_2. Note that the final year forward inflation swap rate is to the power of on half, which reflects that forward earnings occur on average halfway through the year.

Figure 5 illustrates the growth in real earnings and real earnings forecasts from 2005 through to 2023 at a monthly frequency. The actual real earnings is smoothed from a quarterly frequency and is taken from the Robert Shiller website.[21] Panel A shows cumulative growth and Panel B shows rolling 12-month growth rates. There are two major drawdowns in earnings and earnings forecasts in our sample, first during the global financial crisis in 2008 and 2009 and second during the COVID crisis in 2020. In our

[19]Regressing the 10-year asset manager series on the 1-year Martin measure results in a regression coefficient of 0.41 with a t-statistic of 9.6.

[20]At the start of the sample in December 2004, we observe 499, 499, 473, 267 and 205 S&P500 firms with an EPS forecast 1-year, 2-year, 3-year, 4-year and 5-years ahead respectively. By December 2023, this coverage is much more comprehensive, with these numbers rising to 500, 500, 500, 461 and 404 respectively.

[21]The Shiller earnings reflect GAAP earnings while the analysts in the I/B/E/S database forecast earnings that exclude various 'special' items (see Hillenbrand and McCarthy (2024)).

Decomposition B laid out in the next sub-section, we will make assumptions that allow us to map changes expected earnings to changes in expected dividends.

There are other potential sources of cash flow data that one could use to implement the expected dividend factor of our capital gain decomposition. First, dividend per share estimates are available since 2003 in I/B/E/S, but with lower coverage than for the EPS data in terms of both the number of firms within the S&P500 and the number of analysts updating forecasts each month.[22] Second, one could use the I/B/E/S long-term earnings growth variable, which captures earnings growth over the company's next full business cycle and (according to the I/B/E/S documentation) refers to a period of 3 to 5 years (McCarthy and Hillenbrand, 2021; Nagel and Xu, 2022; Bordalo et al., 2024). However, we find that this variable has appeared highly affected by the level of current earnings in recent data, and also that the number of firms with estimates has dropped, with S&P500 coverage falling below 450 firms by 2020 and below 400 firms by the end of the sample in 2023 (previously the coverage of S&P500 firms for this variable was close to complete). Finally, dividend futures, which we use for dividend strip weights, provide investors' risk-neutral expectations of dividends per share on the S&P500 (Gormsen and Koijen, 2020). Under the assumption of a flat equity risk premium structure, the Martin (2017) options-implied equity risk premium at the same maturity as a dividend futures could be used to adjust for equity premium and translate risk-neutral dividend expectations into dividend expectations (for an application of this in practice see Ibert, Knox, and Vazquez-Grande (2022)) though only out to the horizon of available options.

C. Two implementations of our stock return decomposition

Based on the available data, we propose two ways to implement our capital gain decomposition. The first implementation (Decomposition A) is based purely on financial market data and is thus implementable at a daily (or even intra-day) frequency. The second implementation (Decomposition B), incorporates analyst earnings forecasts, thus allowing for a more detailed decomposition but one that can be implemented only in monthly or lower frequency data.

C.1. Decomposition A: Financial Markets Data Only

From financial markets data, we observe the real yield curve growth factors to year 30 and the equity premium growth factors to year 2, $G_{t+1}^{YC,fn}, n = 1, ..., 30$ and $G_{t+1}^{EP,fn}, n = 1, 2$. We set the growth factors to one past the horizon with available data. Using Result 4, we can then back out the cash flow (i.e., expected dividend) factor from the observed capital gain and the yield curve and equity premium factors.

[22] Since 2010, the DPS coverage for the 1-year and 2-year maturities improved and since then nearly all S&P500 firms have updated forecasts each month at these maturities. For firms in the S&P500 with coverage, on average, since 2010, 18 (10) analysts update EPS (DPS) forecasts each month.

The cash flow factor will include the effects of changes to forward real yields past year 30 and forward equity premia past year 2 and we refer to it as the "Cash flow & Long-term discounting" factor. We thus have the following implementation of Result 4, which we refer to as Decomposition A:

$$\begin{aligned}\frac{P_{t+1}}{P_t} &\approx [\text{Cash flow \& Long-term discounting factor}] \\ &\times [\text{Yield curve factor, yr 1-30}] \times [\text{Equity premium factor, yr 1-2}]\end{aligned}$$

C.2. Decomposition B: Adding analyst EPS forecast data

To separate the cash flow and long-term discounting factor into its underlying drivers, our second decomposition incorporates cash flow expectations from analyst forecasts. The dividend growth factors in our methodology measures the growth expected dividends

$$G_{t+1}^{D,(i)} = \frac{E_{t+1}\left[D_{t+i+1}\right]}{E_t\left[D_{t+i}\right]} \qquad \text{for } i = 1, 2, ... \tag{35}$$

For our Decomposition B we assume:

$$G_{t+1}^{D,(i)} = G_{t+1}^{EPS,(3)} \qquad \text{for } i = 1, 2, ... \tag{36}$$

where $G_{t+1}^{EPS,(3)} = \frac{E_{t+1}[EPS_{t+4}]}{E_t[EPS_{t+3}]}$ is the growth rate in expectations of earnings per share on the S&P500 index three years ahead. With this assumption, the cash flow factor is simply

$$w_t^{(1)} G_{t+1}^{D,(1)} + w_t^{(2)} G_{t+1}^{D,(2)} + ... = G_{t+1}^{EPS,(3)} \tag{37}$$

since the sum of all weights $w_t^{(i)}$ equals one. We motivate this assumption with several observations.

First, in terms of earnings versus dividends, it is well documented that firms smooth dividends over time. Changes to near-term expected dividends are therefore likely to be a worse guide to changes to expected dividends further out than changes to near-term expected earnings, and those longer-term dividends account for most of the stock market value. Furthermore, as noted above, analyst coverage for dividends per share is worse than for earnings per share.

Second, in terms of the use of $G^{EPS,(3)}$ at all horizons, refer back to Figure 5 Panel B. Growth in EPS for the first year forward $G^{EPS,(1)}$ and, to a lesser extent, the second year forward $G^{EPS,(2)}$ moves more than growth in EPS for the subsequent years, which all move about the same as $G^{EPS,(3)}$. Using the 12-month growth rates from the figure, regressions of $G^{EPS,(n)}$ on annual $G^{EPS,(1)}$ for $n = 2, 3, 4, 5$ results in coefficients of 0.71 (t=14.90), 0.57 (t=9.80), 0.58 (t=11.55) and 0.55 (t=10.60), respectively (using

Newey-West standard errors with 12 lags). It thus appears a reasonable assumption to use $G^{EPS,(3)}$ for year 3 forward and subsequent years. We prefer $G^{EPS,(3)}$ due to higher analyst coverage in the I/B/E/S data but obtain similar results using longer maturities. In terms of the first two years' expected dividends, we assume they change with the same growth factor $G^{EPS,(3)}$ as later dividends, given dividend smoothing.

Given the assumption made in equation (36), we obtain our second implementation of Result 4, which we refer to as Decomposition B:

$$\begin{aligned} \frac{P_{t+1}}{P_t} &\approx [\text{Cash flow factor}] \times [\text{Yield curve factor, yr 1-30}] \\ &\times [\text{Equity premium factor, yr 1-2}] \times [\text{Long-term discounting factor}] \end{aligned} \tag{38}$$

where the Long-term discounting factor is backed out from the observed capital gain and the observed cash flow, yield curve and equity premium factors.

Our assumption in equation (36) is similar to that made by Landier and Thesmar (2020) in their study of the stock market during COVID in year 2020. They assume that the growth rate of earnings past year 2022 does not change over year 2020 and thus that expected earnings past year 2022 change percentage-wise the same over year 2020 as do expected earnings for year 2022.[23]

For Decomposition B, when calculating $G^{EPS,(3)}$ (the growth factor for the third year forward) in the data, we lead earnings forecasts by two months to capture sluggish updating. Results are similar when leading by only one month. By using leads of the EPS data, we implicitly assume that the earnings changes were expected by market participants at t (and thus drove returns from $t-1$ to t) but were only revealed to the econometrician via analyst forecast data available at $t+2$. This timing issue is less important in annual than in monthly data.

IV. Results: Decomposition of S&P500 returns, 2005-2023

This section provides results for the S&P500 over the period 2005 to 2023. For this period of almost two decades, we provide an expanding window decomposition of the cumulative capital gain based on monthly returns. We also provide variance decompositions as well as decompositions of returns year by year to show the heterogeneous mix of capital gain drivers across years.

[23] Landier and Thesmar (2020) assume that expected dividends in the first two years are proportional to expected earnings for those two years. Because the first one or two dividends each account for only about 2% of the stock market value, assumptions about these have little effect on decomposition results. Our assumption in this regard may be slightly more accurate given dividend smoothing.

A. Capital gain Decomposition A

Figure 6, Panel A (capital gain and capital gain factors) and Panel B (log capital gain and log capital gain factors) illustrate the evolution of the cumulative series over time. In Panel A, the factors *multiply* to the overall real gross capital gain. In Panel B, the log factors *sum* to the overall log real gross capital gain.

The cash flow & long-term discounting capital gain factor performs well in the second half of the sample. The yield curve factor provides a strong boost to the stock market in 2019 and 2020 as real yields fall sharply. Real yields increase in 2022 generating a strong reversal in the yield curve factor. The factor capturing changes to the equity premium for year 1-2 contributes negatively to the market capital gain at the onset of the financial crisis in fall 2008 and the COVID crisis in 2020, with less movement outside crisis periods.

The importance of each return factor for the overall capital gain varies across the sample. To illustrate this more clearly, Figure Panel C shows the decomposition of log returns for each year from 2005 to 2023. To obtain annual data, we compound returns and return factors across months of the year. The heterogeneous mix of return components is apparent. Notably, the large negative market return in 2008 was driven mainly by the cash flow & long-term discounting factor in contrast to the large negative market return in 2022 which was driven by a large negative yield curve factor (i.e., an upward shift in real yields).

Table II, Panel A, provides summary statistics for Decomposition A in annual data. The average annual net return is 8.4% with an average annual capital gain of 6.3%. The average capital gain is driven by the cash flow & long-term discounting factor which averages 7.9% per year. In terms of standard deviations, the yield curve and cash flow & long-term discounting factors are more important than the return factor for the equity premium in years 1 and 2. The panel also shows similar summary statistics for the log real gross capital gain and log capital gain factors. Table II, Panel B, documents the correlation of log return factors, with a -0.75 correlation between the log yield curve factor and the log cash flow & long-term discounting factor. Table II Panel C provides a variance decomposition of annual log returns. The variances of the log yield curve factor and the log cash flow & long-term discounting factor both contribute over 100% of the variance of the annual log capital gain, while their negative covariance contribute about -200%. The contribution of the log return factor for the equity premium in year 1-2 is more modest.

Given the important role of the cash flow & long-term discounting factor for average returns and return volatility, as well as its heterogeneous importance across years, separating this factor further is informative and will facility implementation of decomposition B.

B. *Dissecting the cash flow & long-term discounting return factor*

B.1. *Cash flows versus long-term discounting*

Figure 7, Panel A left, graphs the cumulative cash flow & long-term discounting return factor from Decomposition A along with the cumulative growth in real earnings (EPS) for the third year forward from analyst forecasts. The latter time series proxies for the cash flow (expected dividend) return factor under the assumption in equation (36).

The analyst forecast series indicates that growth in expected forward earnings was central for understanding the growth in the cash flow & long-term discounting return factor (and thus the market capital gain) over time. Rearranging equation (38) and using earning forecasts for the cash flow factor, an implied long-term discounting factor can be computed. The implied time series is graphed in Figure 7, Panel A right, along with the total cumulative cash flow & long-term discounting return factor from Decomposition A. The cumulative long-term discounting factor is much flatter that the cumulative earnings factor from the left chart but with substantial volatility.

To better assess the importance of the earnings factor and the long-term discounting factor for return volatility, Figure 7, Panel B graphs 12-month return factors as opposed to cumulative return factors. Both the earnings factor and the long-term discounting factor 12-month gross returns are strongly positively correlated with the overall cash flow & long-term discounting 12-month gross return factor, with correlations of 0.58 for the two series in the left chart and 0.91 for the two series in the right chart. The 12-month earnings factor has a standard deviation of 8%, lower than the 15% standard deviation of the 12-month long-term discounting factor.

B.2. *Long-term yield changes versus long-term equity premium changes*

The long-term discounting return factor in Figure 7, Panel A right, could be driven by movements in real forward rates past year 30 or by movements in forward equity premia past year 2, or both. We investigate this breakdown in Figure 8. Panel A left shows the cumulative long-term discounting return factor graphed against the cumulative yield curve (1-year to 30-year) return factor. The two should be strongly *positively* correlated if the long-term discounting return factor was dominated by movements in real forward rates past year 30. This is clearly not the case; the correlation is strongly negative at -0.43, with an even more negative correlation of -0.82 using 12-month return factors. This suggests an important role for movements in equity premia past year 2. Figure 8, Panel A right provides additional support for this claim using data on asset managers' equity premium expectations. Starting from 2010m9 (the first asset manager observation) it compares the cumulative log long-term discounting return factor to a cumulative log equity premium return factor calculated from changes in the asset managers' 10-year equity premium expectations. The latter is calculated using the assumption that equity premia of all maturities between 1 and 10 years change by the same amount as the observed 10-year equity premium change. While the asset manager data is sparse, especially toward the start of the sample graphed, the correlation between the two series is strongly positive at 0.70. This provides further support that the long-term discounting return factor is dominated by equity premium changes. We proceed under this interpretation and bundle the long-term discounting return factor with the return factor for the equity premium in years 1 and 2 to construct an overall equity premium return factor to use in Decomposition B.

Before turning to Decomposition B, it is worth thinking about the economics of Figure 8, Panel A left. With the long-term discounting return factor dominated by equity premium changes, the chart implies that real Treasury yields and the equity premium often move in opposite directions, thus partly insulating the expected real stock return from movements in long-term real yields. We illustrate this further in Figure 8, Panel B left. Adding the log yield curve factor and the log equity premium factor (the one that combines the contributions from the equity premium in years 1 and 2 and the equity premium in later years as measured by the long-term discounting return factor), we obtain a log expected equity return factor. The log expected equity return factor (the purple line) is less volatile than the log yield curve return factor (the blue line) due to movements in the log equity premium return factor (the green line) in the opposite direction of the log yield curve return factor. Based on a regression of the 12-month equity premium (all years) return factor on the 12-month yield curve (1-year to 30-year) return factor, the average offset is -0.89. However, the degree to which movements in equity premia insulate the expected stock return from movements in yields varies greatly over time. Importantly, the large yield curve decrease in 2019-2020 and the sharp yield curve increase in the first half of 2022 (visible as a sharp drop in the blue line in Figure 8, Panel B left) appear to be only partly counteracted by equity premium changes, suggesting that expected equity returns move with real yields in these episodes. By contrast there are several periods where movements in the yield component appear almost fully offset by movements in equity premia, thus implying little change in expected stock returns. Three such events are: 2008m12, 2011m7-2011m8 and 2013m5-2013m6. These are all periods with news about unconventional monetary policy.[24]

Data on asset manager expectations confirm the finding that real yield curve changes and equity

[24]December 2008 is a period with news about quantitative easing (QE) expansion to Treasury purchases. May-June 2013 is the period of the taper tantrum. July-August 2011 is the height of the European sovereign debt crisis, which led up to the ECB announcing purchases of Italian and Spanish government debt in early August 2011 and the Fed giving strong forward guidance about yields also in August 2011. We study the December 2008 event in detail below but (in the interest of space) do not delve into the other two episodes.

premium changes are negatively correlated, leading to the combined expected equity return being less volatile than real yields. Specifically, Figure 8, Panel B right illustrates asset managers' 10-year expected (nominal) equity return (per year), the 10-year (nominal) Treasury yield (from yield data), and the resulting asset manager 10-year equity premium series. Asset managers' 10-year expected stock market return trends down over the available sample but otherwise moves around less than the 10-year Treasury yield. As a result, movements in asset managers' 10-year equity premium is negatively correlated with the 10-year Treasury yield.

C. Capital gain Decomposition B

With the decomposition of the cash flow & long-term discounting return factor into a cash flow component and a long-term discounting component dominated by equity premium changes, we are ready for Decomposition B. Focusing on log returns and log return factors Figure 9, Panel A left shows the cumulative series for Decomposition A. The black and blue lines (the log real capital gain and the log yield curve return factor) are as for Decomposition A. The orange line shows the log cash flow (dividend) factor estimated using data on analyst earnings forecasts, while the green line shows the overall log equity premium return factor resulting from combining the contributions from the equity premium in years 1 and 2 and the equity premium in later years captured by the long-term discounting return factor. Figure 9, Panel A right combines the log yield curve return factor and the log equity premium return factor to assess the combined effect of expected equity return changes relative to cash flow changes. The log cash flow factor is important for understanding the log market capital gain over the sample and also contributes to the market drawdowns in the financial crisis and COVID (more on this shortly). However, there are large deviations between the log capital gain series and the log cash flow factor illustrating the importance of changing expected returns on the market.

Figure 9 Panel B provides the decomposition of annual returns using Decomposition B, with the left bar chart showing the log yield curve return factor and the log equity premium return factor separately and the right bar chart combining these two log return factors. Discount rate movements (for these years dominated by real yield curve movements) are central to understanding the market's strong performance in 2019 and 2020 and its poor performance in 2022 while changes to expected cash flows are central for understanding the market drop in 2008. We zoom in on the years 2008, 2020 and 2022 below.

Table III provides summary statistics on return factors based on Decomposition B as well as a variance decomposition for annual returns based on this decomposition. Table IV repeats Table III but combining the yield curve and equity premium return factors. Several key results emerge.

First, the expected earnings return factor contributes the vast majority of the overall average return

(Table III, Panel A). Second, the yield curve and equity premium factors are much more volatile than the cash flow factor but strongly negatively correlated. Specifically, the log yield curve factor and log equity premium factor have standard deviations of 0.195 and 0.212 respectively, over twice the standard deviation of the log cash flow factor based on analyst earnings forecasts. The equity premium (all years) is thus substantially more important than in Decomposition A. The log expected equity return factor has a lower standard deviation of either of its two inputs due to their strong negative correlation of -0.80 (Table III Panel B). In the variance decomposition in Table IV Panel C, the log expected equity return factor contributes 52% of the log capital variance, with the log cash flow factor contributing 20% while a positive covariance of these two factors contributes the remaining 28%.

D. Three eventful years in US stock market history

To illustrate the heterogeneous mix of capital gain drivers across years, we finish our analysis by zooming in on 2008, 2020 and 2022. Figure 10 shows the results of Decomposition A and Decomposition B for each of these years, plotting cumulative effects over each year based on monthly data. We present results in this section using gross returns, and the factor returns in each decomposition *multiply* together to equal the overall capital gain on the market.

D.1. 2008: The global financial crisis

Focus first on the period up to November 2008 and Decomposition B, shown in the right chart in Figure 10, Panel A top. By end of November, the cumulative gross real capital gain is 0.615 for a net loss of 39.5% (black line). Decomposition B reveals that the market decline was driven mainly by higher equity premia, contributing -23.0%, and lower expected dividends, contributing -16.6%.

Turning to December 2008, Figure 10, Panel A top right shows a dramatic upward move in the cumulative yield curve factor, driven by a sharp decline in real yields. As an example, the 20-year (zero coupon, spot) real yield based on nominal Treasuries and inflation swaps dropped 137 basis points over this month. The sharp drop in real yields occurred with little change in the stock market and only modest further decline in analyst earning forecasts, implying a sharp increase in equity premia and thus a sharp drop in the equity premium factor, visible in the figure. December 2008 thus emerges as an important example of a large yield curve move that is partially offset by an opposing equity premium move.

To gain insight into the likely driver of the disconnected (from the stock market) yield curve shift in December 2008, we exploit the fact that Decomposition A can be done in higher frequency data. Figure 10, Panel A bottom shows Decomposition A in daily data for 2008. In December 2008, the yield curve factor shifts up sharply around December 1 and December 16, indicated with the vertical dashed lines.

These dates are among the main days with news about quantitative easing (QE) studied in the QE literature (e.g., Gagnon et al. (2011) and Krishnamurthy and Vissing-Jorgensen (2011)). December 1, 2008 is the date of a speech by Chair Bernanke in which he mentions the possibility of the Fed expanding QE from MBS purchases to also include Treasuries and agency debt. December 16, 2008 is the date of an FOMC announcement which mentioned that the FOMC was evaluating the potential benefits of purchasing longer-term Treasuries. Since such Fed actions would be designed to stimulate the economy, it is unlikely that they led to *negative* changes to expected cash flows (though some role for the Fed information effect cannot be ruled out). Therefore, the downward moves in the cash flow & long-term discounting factor around December 1 and 16 are likely driven by increases in equity premia beyond year 2. The story that emerges is one where QE leads to effects on bond yields but not the expected return on stocks, thus explaining why the market moved sideways in December 2008 despite the large decline in real yields. In monetary policy terminology, the portfolio rebalancing effects of Treasury QE appear confined to the bond market in this episode.[25]

Figure 7, Panel C shows the importance of December 2008 for the decomposition of the cash-flow & long-term discounting return factor. This figure sets all return and return factors to zero in December 2008. The cash flow component now tracks the cash-flow & long-term discounting return factor even more closely than in Figure 7, Panel A (the two series diverge from mid-2022 and we study this below).

For the year 2008 as a whole, our assessment is that higher equity premia and lower expected cash flows both contributed substantially to the market decline. However, there was a large positive contribution from falling yields, driven to a large extent by QE announcements in December 2008.

D.2. 2022: Monetary tightening

By way of macroeconomic background, realized 12-month PCE inflation in the December 2021 release (i.e. from 2020m11 to 2021m11) was 5.7%, while the federal funds rate target range was 0 to 25 bps at the end of 2021. At that time, many still expected that inflation would be transitory and would revert toward the FOMC's target of 2% without much increase in the federal funds rate. During 2022, inflation turned out more persistent than expected and monetary policy tightened more than expected. Realized 12-month PCE inflation for 2022 was 5.44% and the target federal funds rate (mid-point) stood at 4.38% by the end of 2022, 363 bps higher than expected.

With this background, our decompositions of the market capital gain for 2022 are shown in Figure 10,

[25] Haddad et al. (2024) argue that the Fed's QE announcements in the fall of 2008 represented a fundamental change in Fed policy by revealing not just likely QE purchases in the near future but a regime change toward a dynamic state-contingent plan of QE interventions going forward. They document what appears to be a permanent downward shift in the term structure of bond yields post-2008 which they interpret as resulting from bonds becoming safer due to the Fed now being expected to buy bonds in bad economic states, with this increased safety lowering their ex-ante yields.

Panel B. In the first half of 2022, the market dropped dramatically in value, with a loss of 23.8% by the end of June. This is driven by sharply higher real yields leading to a large negative contribution from the yield curve factor. The dominant role for higher real yields for the 2022H1 market drawdown stands in sharp contrast to the 2008 market decline, thus illustrating how capital gain drivers differ across periods.

The market capital gain is roughly zero in 2022H2. Real yields kept increasing leading to a continued negative contribution from the yield curve factor. From the middle chart, the cash flow factor deteriorated modestly over this period. Decomposition B therefore implies that there must have been a boost to the market from lower equity premia leading to a positive equity premium factor (the dark green line in Decomposition B). The increase in real yields during this period is thus not (or not fully) present in expected stock returns.

In terms of the underlying reasons for real yield increases in 2022H2 that (unlike those in 2022H1) appear disconnected from the stock market, several factors could have contributed. First, as short rates rose during 2022H1, there may have been a reversal of reach for yield among fixed-income investors (for analysis of such effects in earlier data, see Hanson and Stein (2015)). This may disproportionately have affected the bond market, as opposed to stocks. Second, as real rates soared and bonds experienced losses not seen in decades (and even larger than the losses on stocks), some bond investors may have fundamentally reassessed the attractiveness of long-maturity bonds relative to stocks; long bonds may ex-ante have appealed to safety-minded investors but may have lost this appeal as losses mounted and bonds appeared to lose their hedging properties in an environment with simultaneous losses on both bonds and stocks (a reversal of the increase in appeal from December 2008). Both of these two effects could be non-linear. Third, several bond supply effects may have played a role in 2022H2. The UK government's fiscal plan introduced on September 23, 2022, led to a large yield increase that was only partially reversed after the Bank of England intervened and the package was later abandoned. Higher UK yields likely had spillovers to yields elsewhere. Also supply-related, the Federal Reserve initiated quantitative tightening (QT) in 2022Q2 and increased it in 2022Q3, thus reducing Fed Treasury holdings; the Bank of Japan sold Treasuries in September and October 2022 to counter dollar appreciation; and the Bank of England announced on September 22, 2022 that its QT would involve gilt sales (as opposed to only balance sheet reduction via securities maturing), thus adding to the global supply of bonds.

D.3. 2020: The COVID crash and rebound

There is a growing literature seeking to understand the drivers of the stock market crash and rebound in 2020. Landier and Thesmar (2020) (mentioned above) estimate a counterfactual path for the stock market which assumes unchanged discount rates and uses dividend expectations constructed from analyst earnings forecasts. They find that the cash flow component of the stock market return was modest, around -5% by March 23, 2020, and became more negative past March 23, 2020. This contrasts with the large crash and fast recovery of the actual stock market. Our approach accounts for the somewhat sluggish updating of analyst earnings forecasts (leading them by 2 months) and we will assign a bit more of the crash to changes to expected earnings. Cox, Greenwald, and Ludvigson (2020) use the estimated structural asset pricing model of Greenwald, Lettau, and Ludvigson (2019) in which the value of the stock market is expressed as GDP $\times$ [corporate profits/GDP] $\times$ [stock market value/corporate profits]. They also conclude that it is difficult to explain the V-shaped trajectory of the stock market over the COVID crisis with changes to expected cash flows alone. A central argument is that, based on data from the Survey of Professional Forecasters as of May 2020, GDP was expected to fall by about 10% in 2020Q2, but was expected to increase in 2020Q3. Using the method of Cieslak and Pang (2021), Cieslak estimates (in NBER presentation slides) that growth news account for a stock market drop of about 10% out to March 23. Gormsen and Koijen (2020) study dividend futures. They show that changes to the value of dividends out to year 7 can account for little of the stock market crash (given their modest weight in the market and the realized decline in dividend futures values) and none of the recovery up to July 20, 2020. They argue that longer-maturity dividends are likely to be only modestly affected by the COVID crisis, implying that changes to their present value and thus to the overall market may have been driven mostly by discount rate news. Overall, the literature suggests that changes to expected cash flows do not appear able to explain the majority of the stock market decline or recovery in 2020. Our decompositions allow us to assess whether information on real yields and equity premia is consistent with that conclusion and enables a decomposition of discount rate news into its two components.

Figure 10 Panel C shows our decompositions for year 2020. The market drops by 19.5% up to the end of March 2020.[26] In Decomposition A (left chart), the market drop is partly drive by higher near-term (year 1 and 2) equity premia which contribute -6.0%. Real yields fall to March and throughout the year.[27] Decomposition A therefore implies that a large negative cash flow & long-term discounting component was central for the market drop to March. Analyst expected real earnings (middle chart) for year 2, 3 and 4 forward all drop by less than 10% to March (as revealed by subsequent data given the use of 2-month leads of EPS forecasts), substantially less than the drop in the cash flow & long-term discounting component. Decomposition B (right chart) therefore assigns a substantial role to movements in equity premia (at all horizons), with it contributing 18.2% to the overall market drop of 19.5% to March.

The bottom row of charts in Figure 10 Panel C uses data on asset manager's 10-year equity premium

[26]In daily data, not shown, the market drop is even larger with a drop of 30.4% to March 23.

[27]The yield spike in mid-March studied in, e.g., Vissing-Jorgensen (2021) and He, Nagel, and Song (2022) was resolved fast and is not visible in monthly data (it led to Fed Treasury purchases of over $1T in 2020Q1 to stabilize markets).

expectations to validate this conclusion. We present these results at the quarterly frequency since two thirds of the asset manager data are for quarter ends.[28] The left chart illustrates the sharp increase in asset managers perceived 10-year equity premium in 2020Q1, from 2.8% to 5.0%. The middle chart shows the result of Decomposition A when we use equity premium data out to year 10.[29] The right chart shows Decompostion B. Decompositions A and B now lead to a similar message that the market drop in 2020Q1 was due to a combination of lower future expected cash flows and higher future equity premia with a larger role for the latter.

In the last three quarters of 2020, the market more than fully recovered and ended with a capital gain of 17% for the year. Expected cash flows fully recovered, equity premia eased somewhat (thus pushing up the equity premium factor), and real yields kept falling. As an example, the real 30-year zero-coupon yield TIPS graphed in Figure 3 fell 93 bps for 2020 as a whole. Falling real yields even far out the yield curve were central to understand why the market did so well in 2020 as a whole, despite the fact that the COVID crisis was far from resolved by the end of the year.

V. Conclusion

The paper contributes to answering a core question in asset pricing: what drives movements in the stock market? We assess the role of changes to real yields, to equity premia and to expected dividends. We argue that a lot of information about the three market drivers is observable from financial market data and expectations data and provide a novel decomposition of the market capital gain for a given period. Our decomposition inputs are in levels (as opposed to logs), thus facilitating the use of expectations data. Furthermore, dividend strip weights are allowed to be time-varying, therefore allowing for changing duration of the stock market over time. Additionally, the three capital gain factors due to real yields, equity premia and expected dividends are multiplicative, thus making it easy to decompose multi-period capital gains.

Implementing our approach for the S&P500 from 2005 to 2023, we reach three conclusions. First, changes to expected real earnings (and thus expected real dividends) played the dominant role for the realized cumulative capital gain over the sample. Second, the yield curve and equity premium factors are much more volatile than the expected dividend factor but are strongly negatively correlated. A combined expected stock return factor accounts for about half of the capital gain variance in annual data (with about 20% coming from the expected dividend factor and 30% from the covariance between the

[28] This is partly due to Dahlquist and Ibert (2021)'s (entirely reasonable) assumption that data are end of the prior month when the asset manager only states a year and month and not an exact date.

[29] We assume that equity premia changes are the same for each of the first 10 years. Results are similar if we use the equity premia from the Martin approach for year 1 and 2 and back out the forward equity premium for years 3 to 10 from the asset manager data.

expected stock return factor and the expected dividend factor). Third, the mix of capital gain drivers is heterogeneous across periods. Comparing the market drawdowns in 2008, 2020Q1 and 2022H1, the first two were driven by lower expected dividends and higher equity premia while the market decline in 2022H1 was due to higher real yields.

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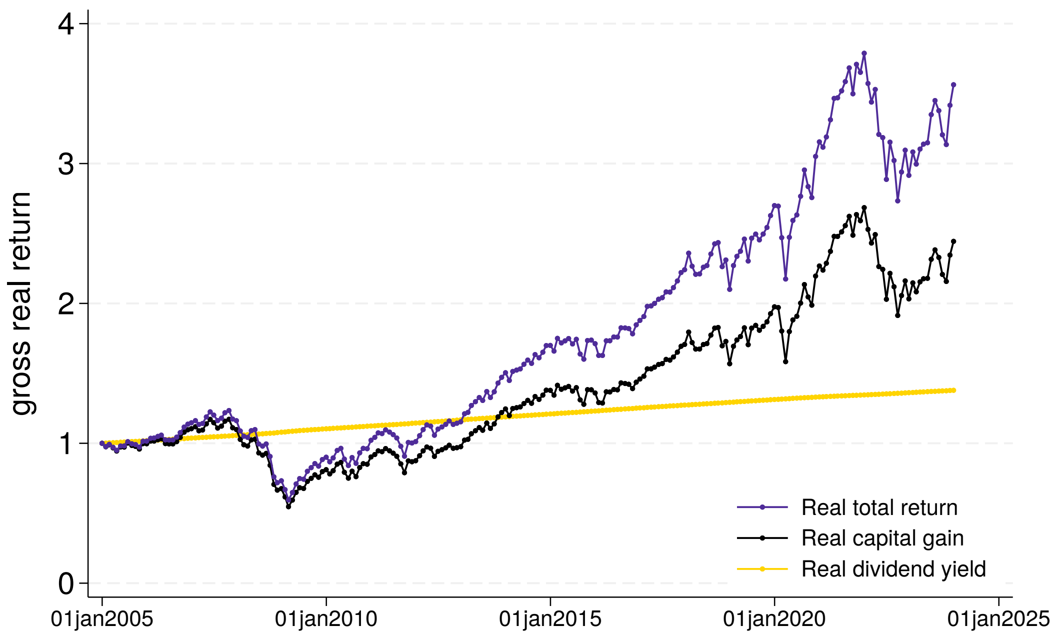
VI. Figures

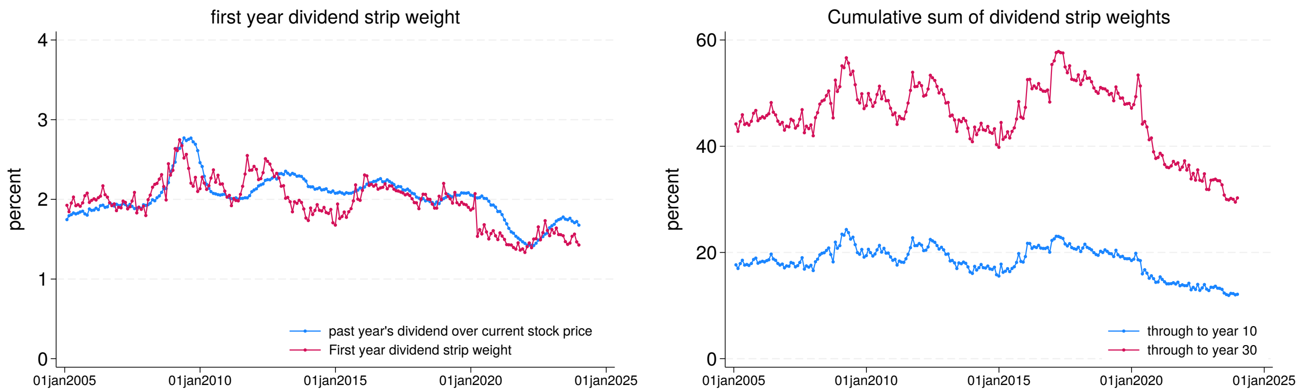
Figure 1. Cumulative Stock Return and Capital Gain, 2005 - 2023



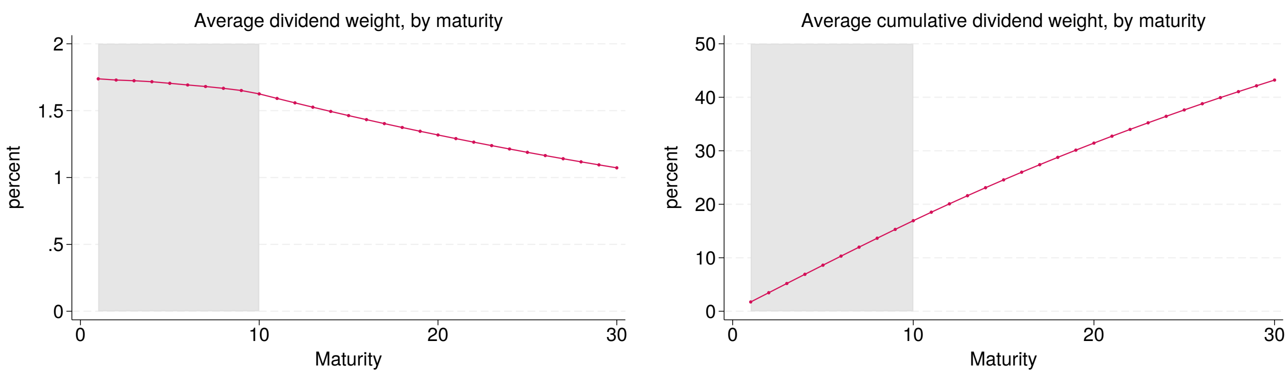
This figure shows the cumulative gross real return on the S&P500 index over the period 2005-2023. The graph plots the total real return, the real capital gain, and the realized dividend yield. All variables are plotted at a monthly frequency. Table I and Section III.B.1 provides further details on the data sources and the input construction.

Figure 2. Dividend Strip Weights Data

Panel A: Time series of dividend strip weights



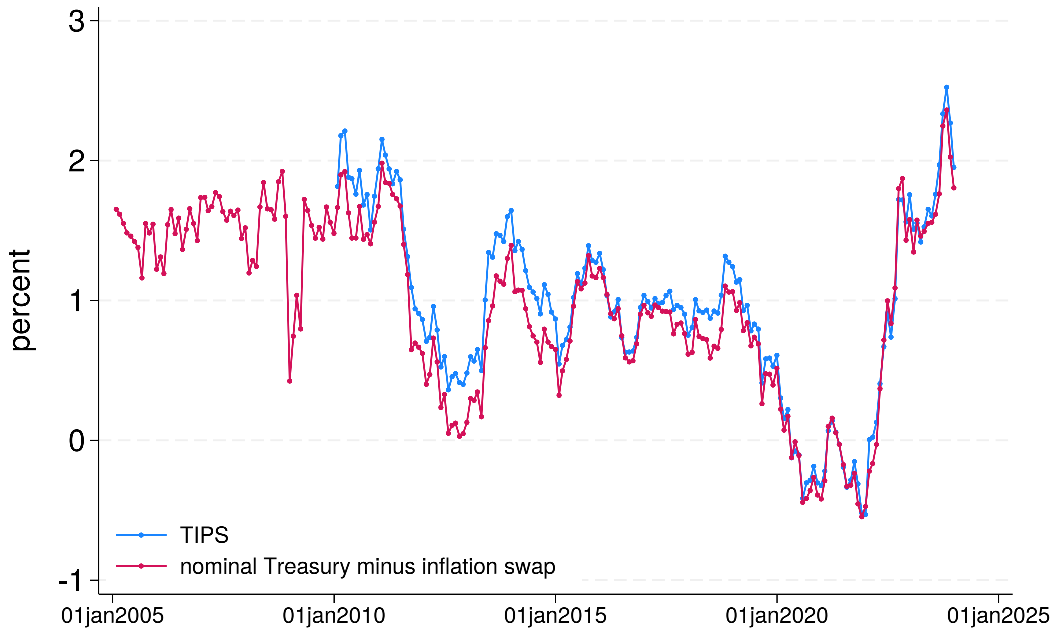
Panel B: Average dividend strip weights (dividend futures sample period)



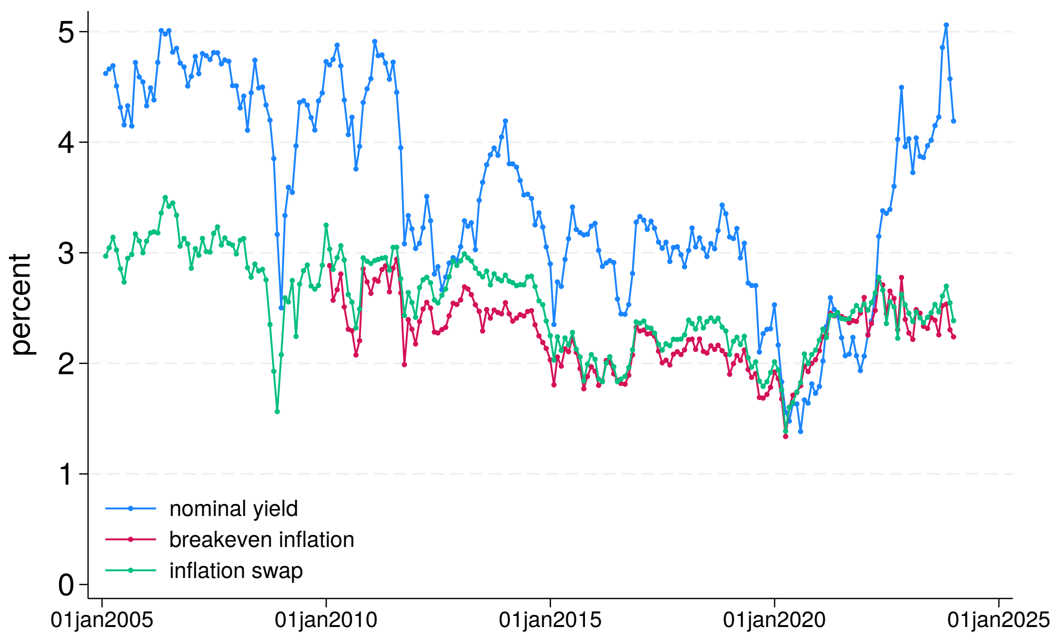
This figure shows the dividend strip weight data. Panel A plots the time series of the 1-year dividend strip weight (left hand side) and the sum of the first 10 and 30 years of dividend strip weights (right hand side). Panel B plots the average dividend strip weight (left hand side) and average cumulative dividend strip weight (right hand side) by maturity over the sample period where dividend futures are available (2017-2023). The shaded area on the figures denoted the first 10 years, which are maturities where weights are directly observable from traded dividend futures prices, while the unshaded area shows maturities where Result 6 is used to estimate dividend strip weights. Table I and Section III.B.2 provides further details on the data sources and the input construction.

Figure 3. Real Yield Data

Panel A: Measures of the 30-year real yield



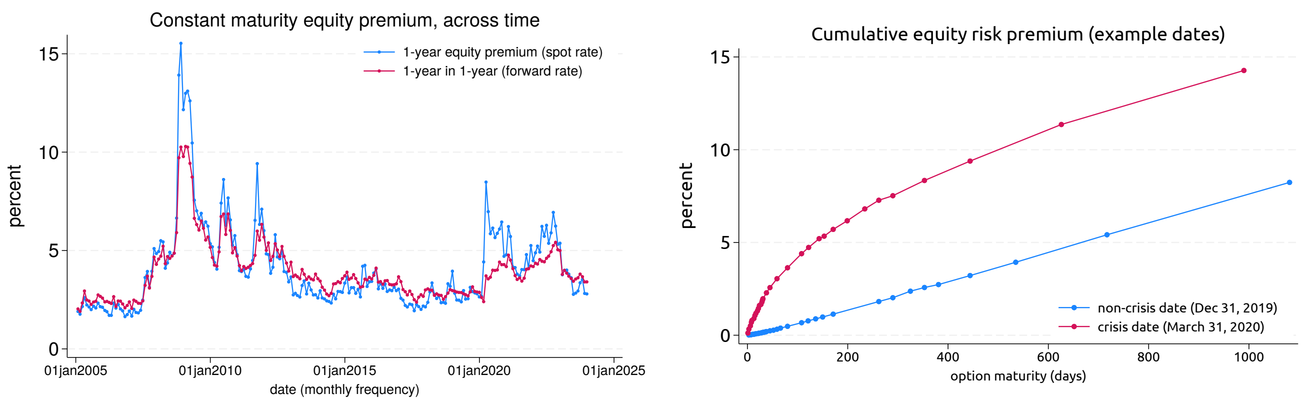
Panel B: Components of the 30-year real yield



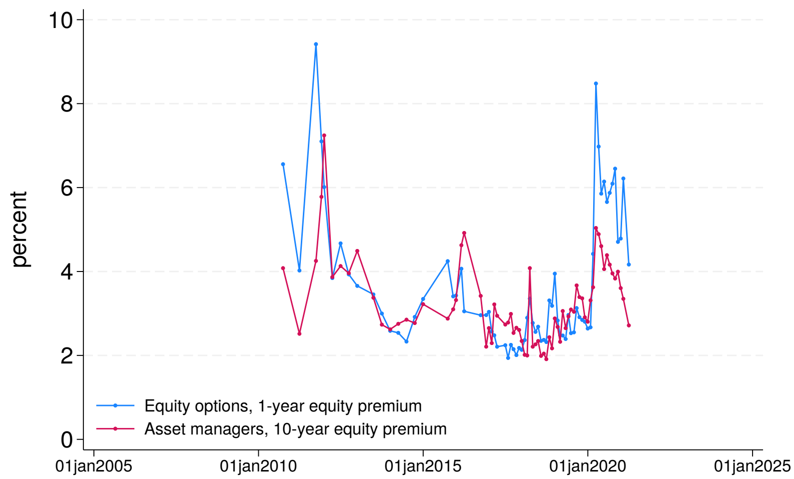
This figure shows the evolution of measures of the 30-year real yield (Panel A) and its component parts (Panel B) over the sample 2005-2023. The two measures in panel A are the real yield implied by the TIPS market and real yield implied by the nominal Treasury yields combined with inflation swap rates. In panel B, the evolution of the 30-year nominal yield, the breakeven inflation rate implied by the difference between nominal Treasury and TIPS yields, and the inflation swap rate are plotted. We omit yields related to TIPS in the pre-2010 period as there was no 30-year TIPS in issuance at this time. Table I and Section III.B.3 provides further details on the data sources and the input construction.

Figure 4. Equity Premium Data

Panel A: Equity options data



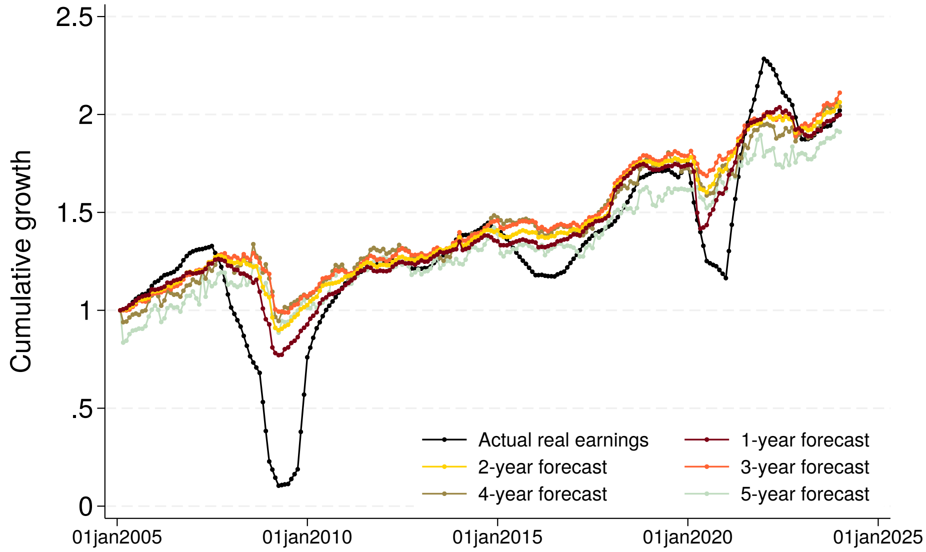
Panel B: Equity options with asset manager expectations data



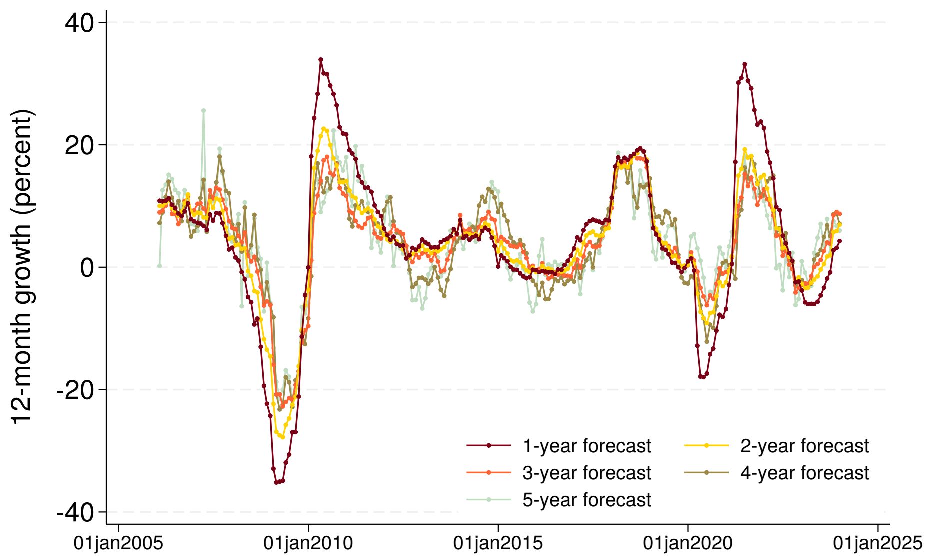
This figure shows equity premium data. Panel A focuses on equity option-implied equity premium based on the Martin (2017) method with the left hand side plotting the evolution of constant maturity equity premium through the sample 2005-2023 and the right hand side plotting the cumulative equity premium by maturity on two illustrative trade dates. Panel B compares the 1-year option implied equity premium to the 10-year equity premium estimates of asset managers in the Dahlquist and Ibert (2021) dataset. Table I and Section III.B.4 provides further details on the data sources and the input construction.

Figure 5. Earnings Forecast Data

Panel A: Cumulative growth of real earnings and real earnings forecasts



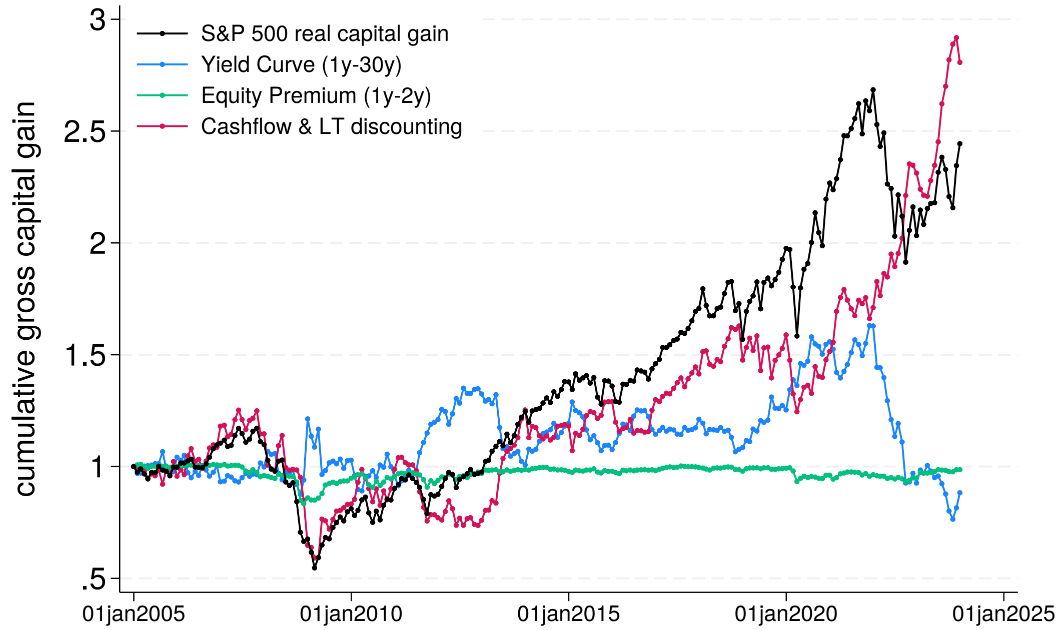
Panel B: 12-month growth of real earnings forecasts



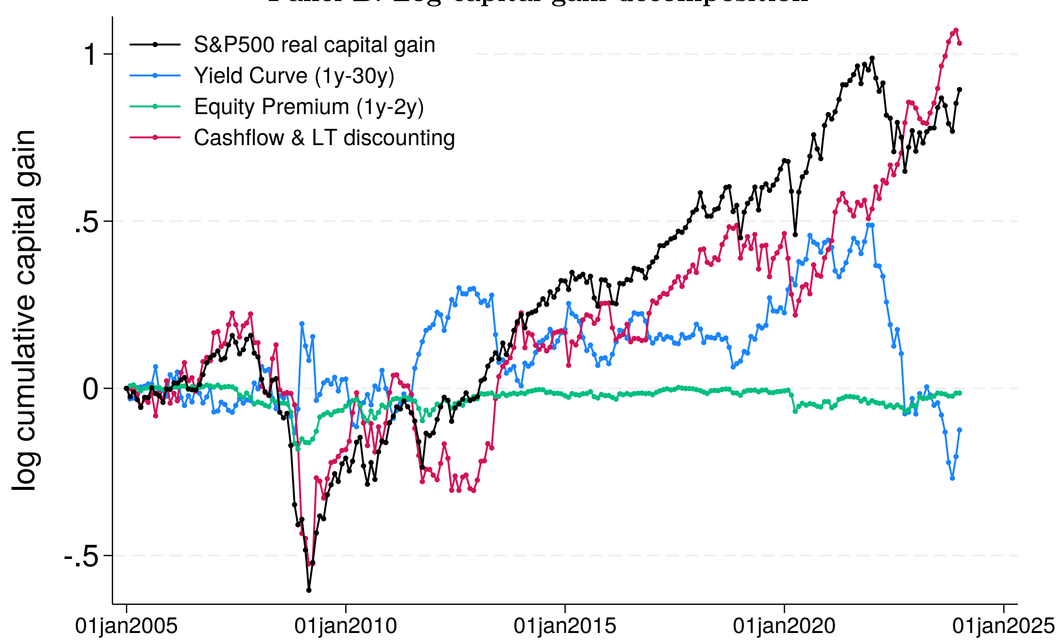
This figure shows near-term earnings per share forecast data for the S&P500. Panel A plots the cumulative growth in actual real earnings and constant maturity forecasts of real earnings 1-year to 5-years ahead. Panel B plots the 12-month growth rates on the earnings forecasts. Table I and Section III.B.5 provides further details on the data sources and the input construction.

Figure 6.
Capital Gain Decomposition Using Financial Market Data (Decomposition A)

Panel A: Gross capital gain decomposition



Panel B: Log capital gain decomposition



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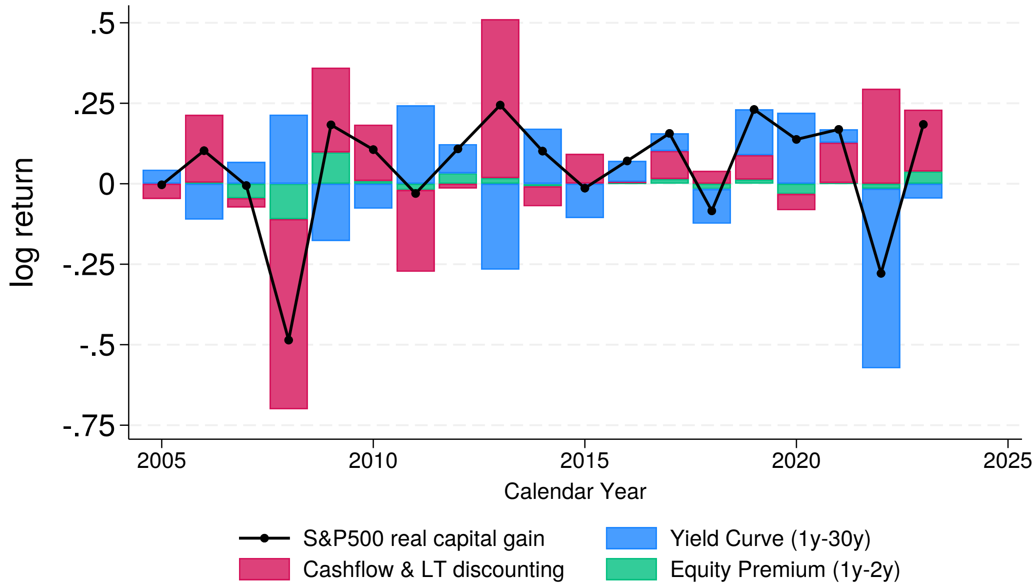
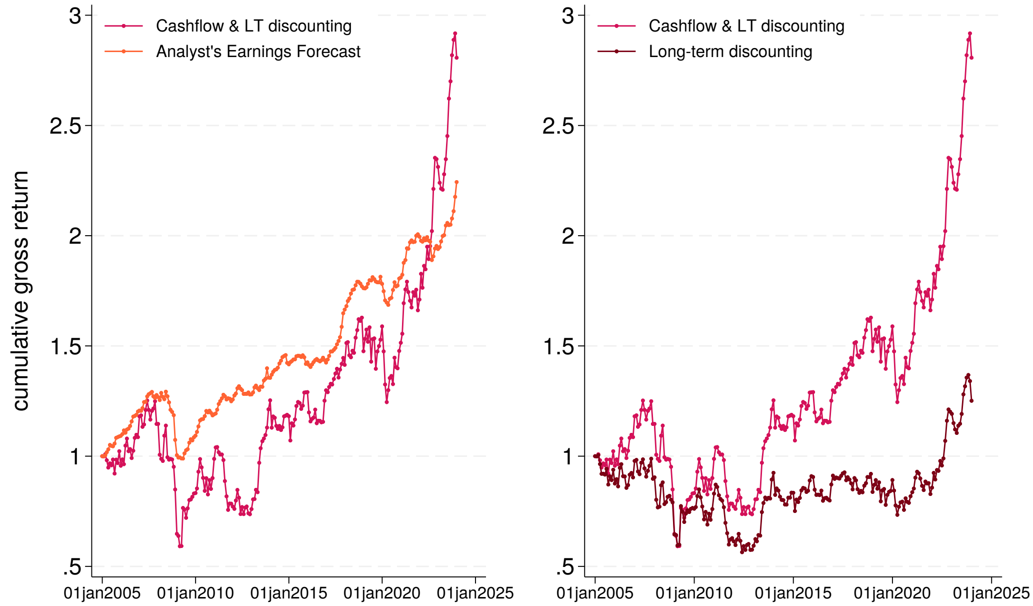
Panel C: Annual log return decomposition



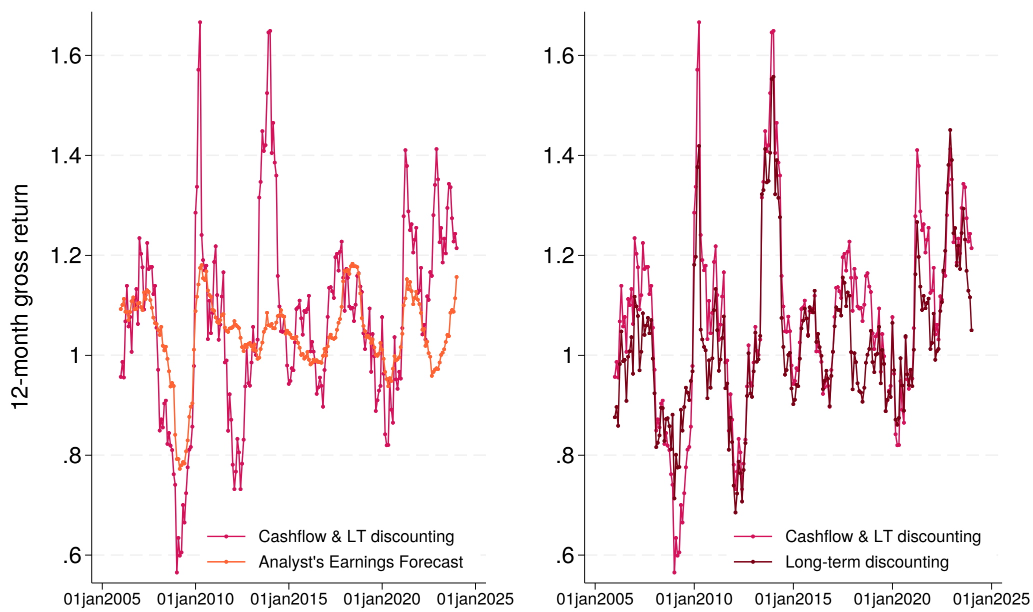
This figure presents results from the implementation of Decomposition A on the S&P500 over the period 2005-2023. Panel A plots the cumulative gross capital gain on the market along with the cumulative gross capital gain from individual return factors. Panel B plots the same decomposition but for cumulative log capital gains, and Panel C plots the decomposition of annual log returns by calendar year.

Figure 7. The Cash Flow and Long-Term Discounting Factor

Panel A: Cash flows versus long-term discounting



Panel B: 12-month return factors



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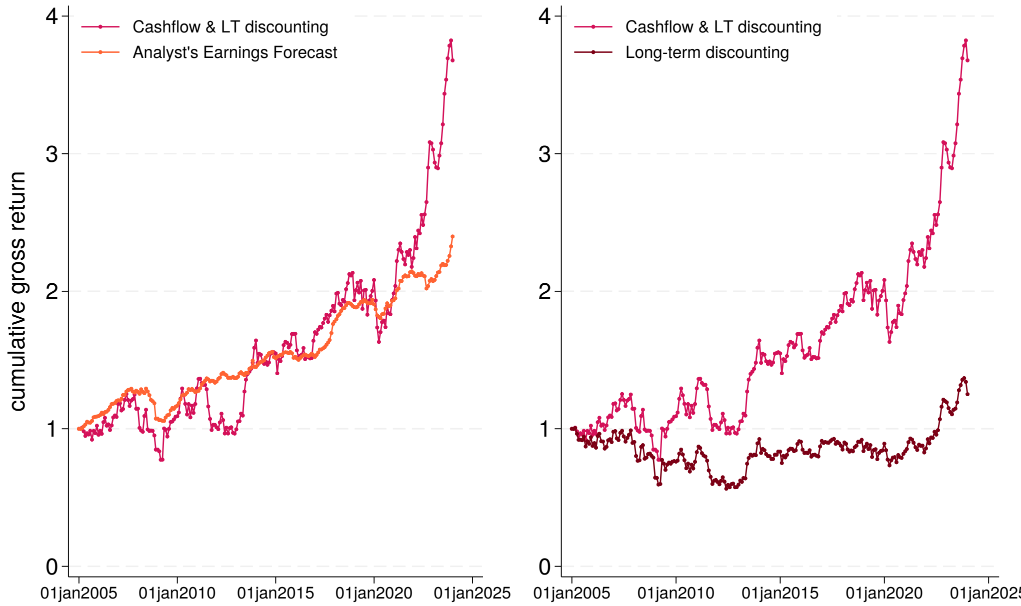
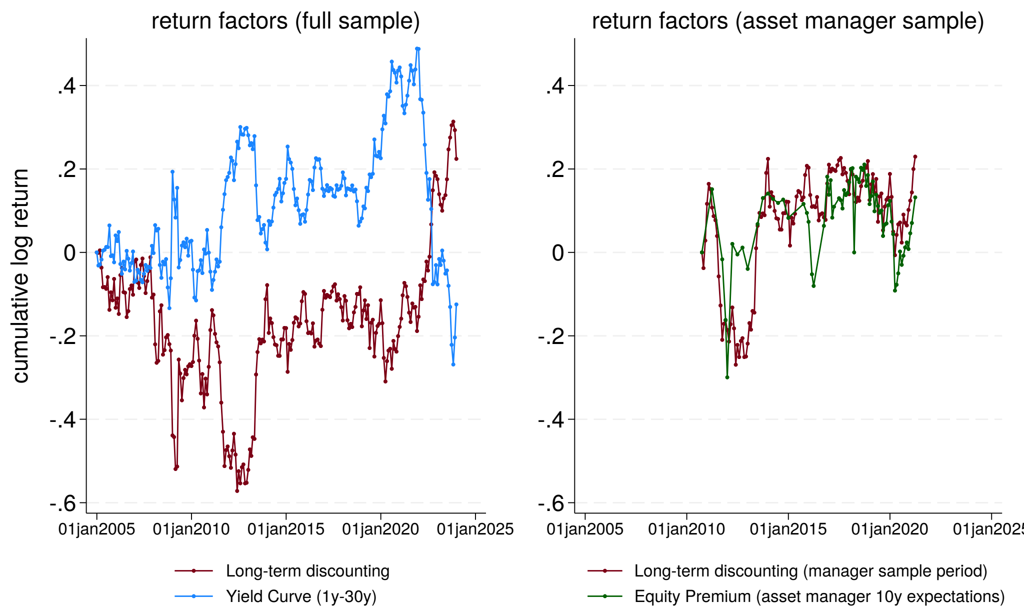
Panel C: Cumulative gross returns (excluding December 2008)



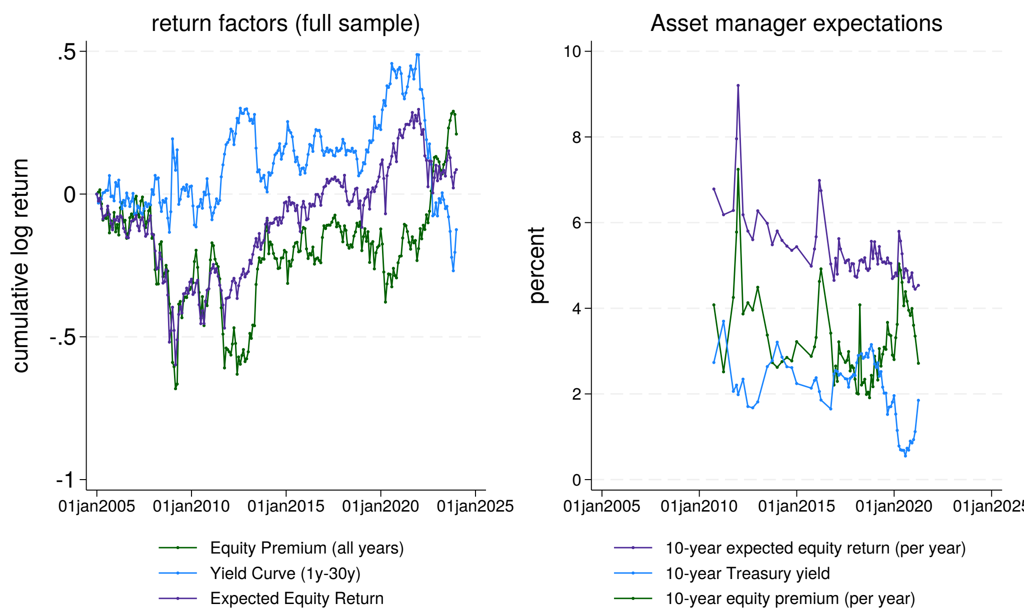
This figure decomposes the cash flow and long-term discounting factor from Decomposition A into two components. The left hand side of Panel A plots the cumulative gross return of the cash flow and long-term discounting factor against the cumulative return of a cashflow component that is estimated from analyst's forecasts of earnings per share for S&P500 firms. The right hand side of Panel A plots the cumulative gross return of the cash flow and long-term discounting factor against the remaining component not explained by analyst's earnings forecasts (labeled long-term discounting). Panel B plots the same decomposition as Panel A but shows 12-moth gross returns, and Panel C plots the same decomposition as Panel A but sets all component returns in December 2008 to zero.

Figure 8. What Drives the Long-Term Discounting Component?

Panel A: Long-term discounting mainly driven by equity premium movements



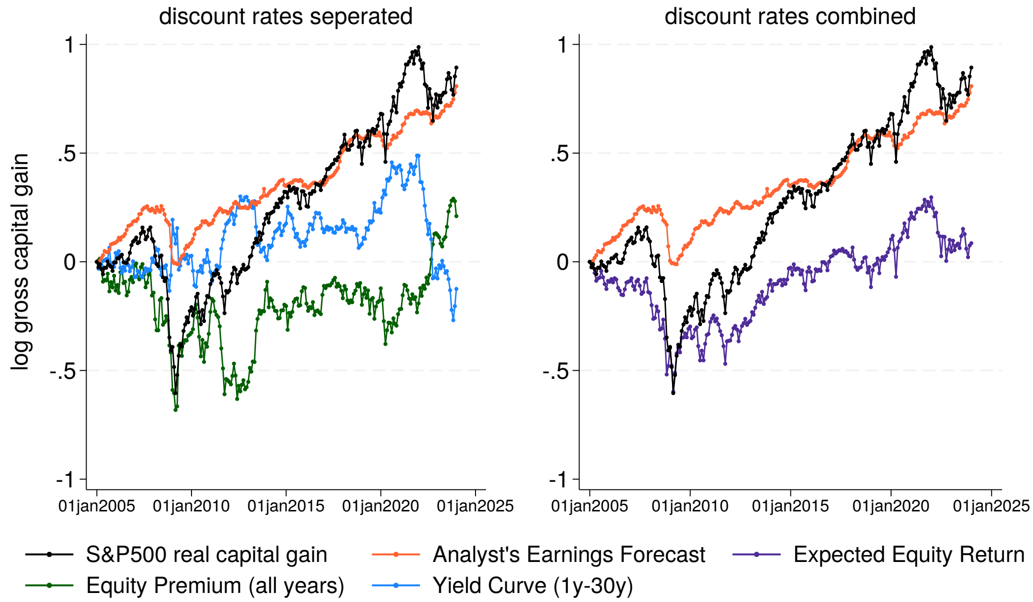
Panel B: Equity premium movements partially offset yield curve shifts



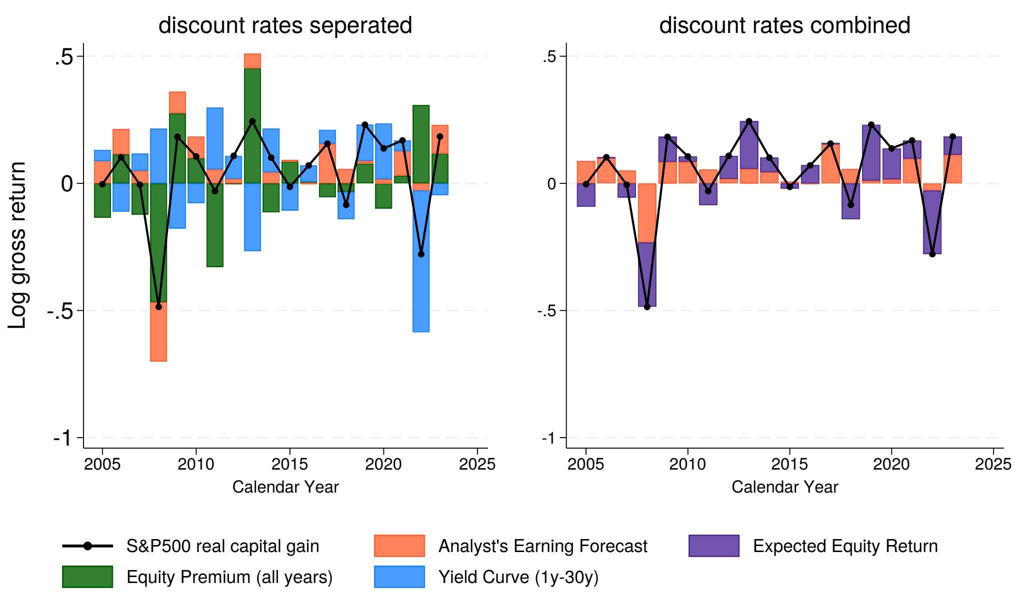
This figure explores the drivers of the long-term discounting return factor. Panel A plots the long-term discounting factor against the yield curve factor (left hand side) and against a long-term equity premium factor from 2010 (right hand side) where the equity premium factor is computed using asset manager equity premium estimates. The left hand side of Panel B shows plots the yield curve return factor, the equity premium (all maturities) factor and a combined equity return factor. The right hand side of Panel B shows asset manager 10-year expected equity returns, the 10-year Treasury yield, and the implied asset manager 10-year equity premium.

Figure 9. Decomposition B, 2005m1 - 2023m12

Panel A: Cumulative log returns



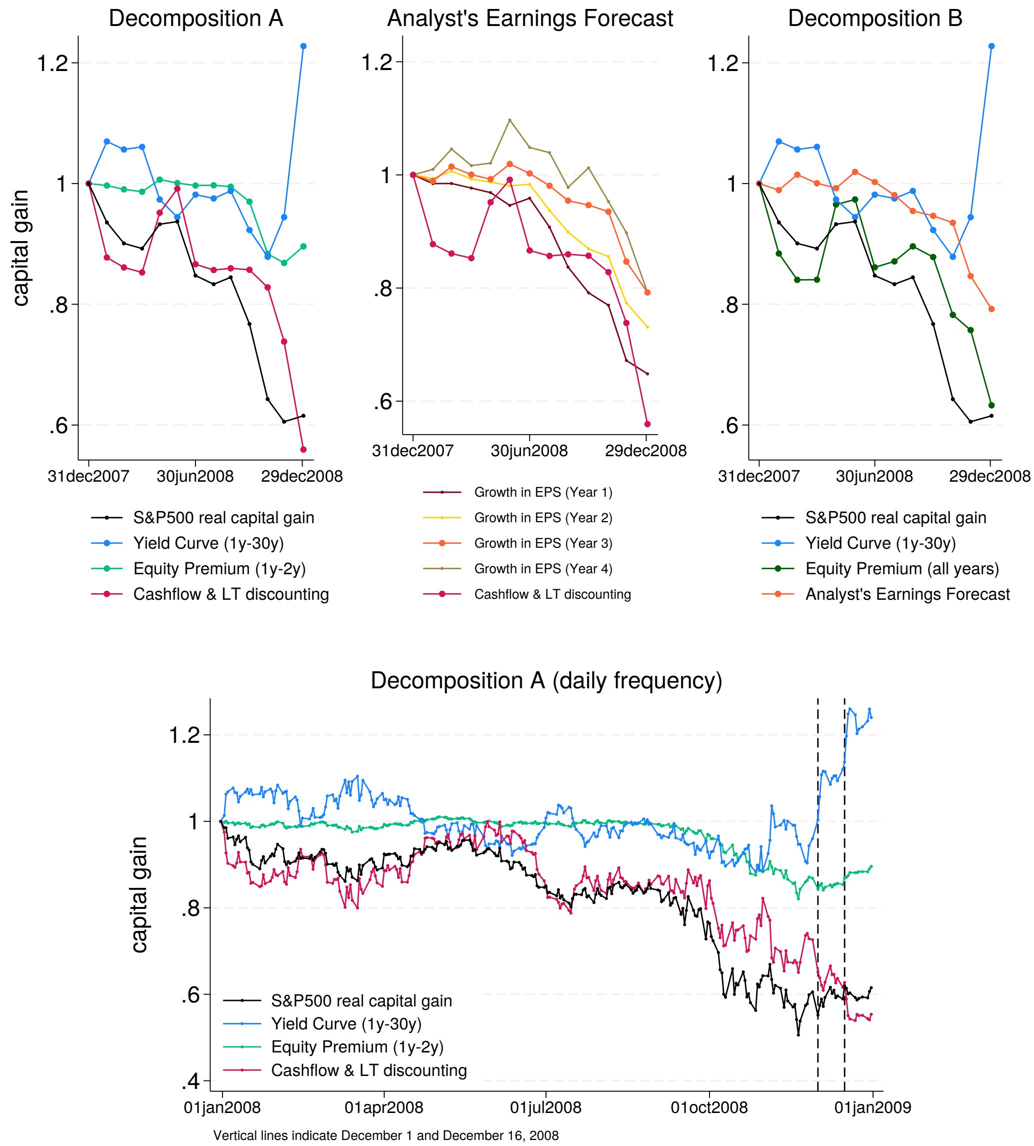
Panel B: Annual log returns



This figure presents results from the implementation of Decomposition B on the S&P500 over the period 2005-2023. Panel A plots the cumulative gross capital gain on the market along with the cumulative gross capital gain from individual return factors. Panel B plots annual log returns of Decomposition B by calendar year. The left hand side plot of each panel presents results with the equity premium and yield curve factors separated, and the right hand side plot of each panel shows the results with these factors combined for a total expected equity return factor.

Figure 10. Three Eventful Years in US Stock Market history

Panel A: Global financial crisis, 2008



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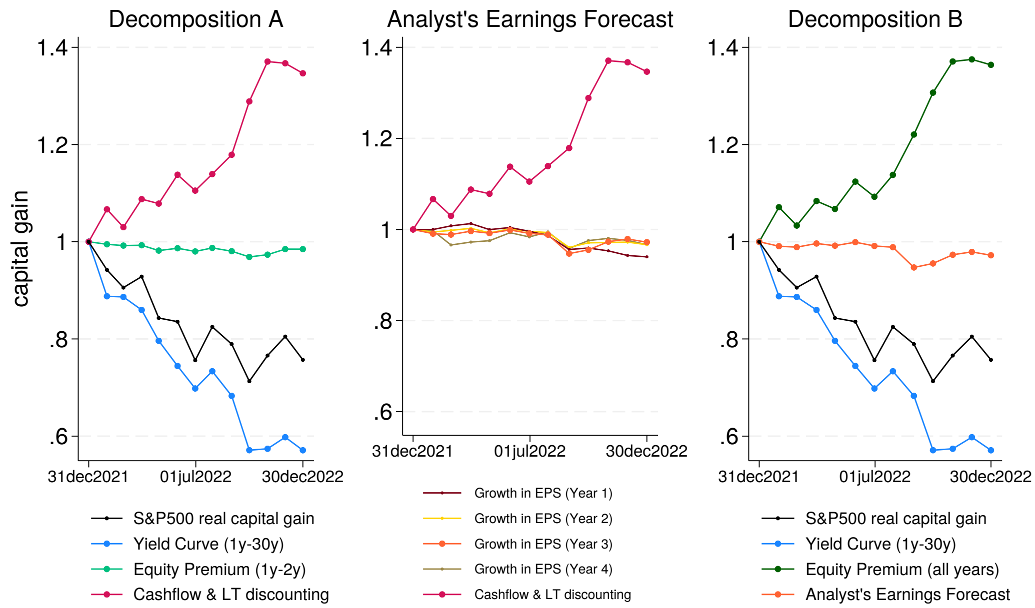
Panel B: Monetary tightening, 2022



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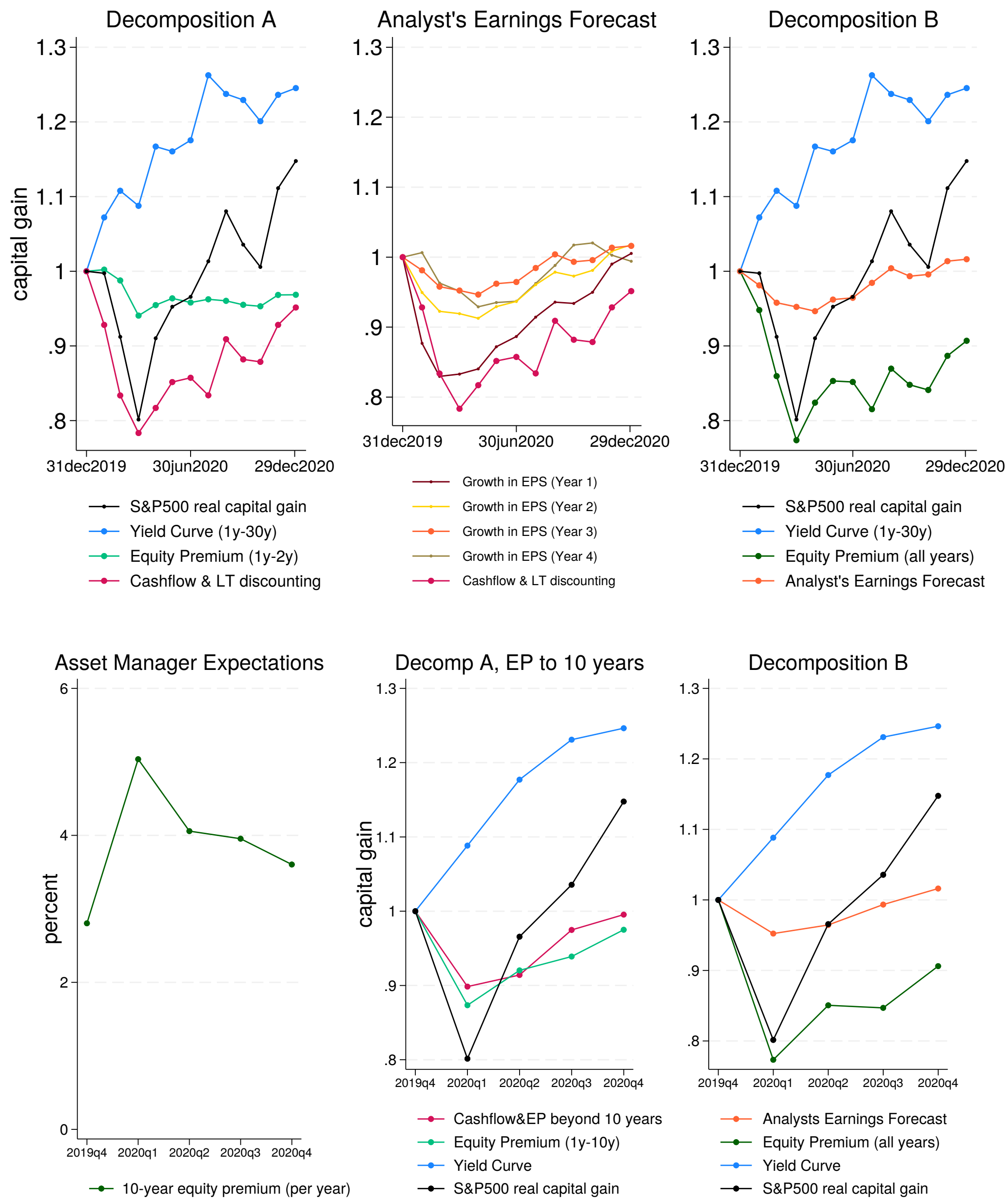
Panel C: COVID crash and rebound, 2020



This figure shows capital gains at the monthly frequency in three eventful years for the US stock market: the global financial crisis in 2008 (Panel A), the monetary tightening in 2022 (Panel B) and the COVID crash and rebound in 2020 (Panel C). The top row of each panel shows Decomposition A (left hand side), the cashflow and long-term discounting return factor and the growth rate in analyst's 1-year to 4-year ahead earnings expectations (middle) and Decomposition B (right hand side). Panel A is supplemented with a plot of Decomposition A at a daily frequency and Panel C is supplemented with decompositions that also incorporate asset manager 10-year expected returns.

VII. Tables

Table I. Overview of Observable Data.

This table reports the observable data on the S&P 500 index that we use for our implementations of Result 4. It includes information on the underlying financial instrument and survey measure, the data source, the start of sample availability and the maximum maturity of the traded instrument or survey. Section III provides further details on the data sources and the input construction.

Observable Input	**Financial Instrument or Survey**	**Source**	**Starts**	**Maximum maturity**
Realized total return	SPXT Index	Bloomberg	1988	-
Realized capital gain	SPX Index	Bloomberg	1927	-
Realized dividend yield	SPXT return - SPX return	Bloomberg	1988	-
Dividend strip weights	Dividend futures	Bloomberg	2016	5-year (2016), 10-year (2017)
	S&P500 equity options	OptionMetrics (or CBOE)	1996	2-year (1996), 3-year (2005) 5-year (2021)
Real yield curve	Zero-coupon TIPS yields	FRB	1999	20-year (1999), 30-year (2010)
	Zero-coupon nominal treasury yields and inflation swaps	FRB and Bloomberg	2004	30-year (2004)
Equity risk premium	S&P500 equity options	OptionMetrics (or CBOE)	1996	2-year (1996), 3-year (2005) 5-year (2021-)
Analyst's cashflow forecasts	Earnings per share	I/B/E/S	1976	2-year (1976) 4-year (2003) 5-year (2011)
Asset-Manager expected returns	Capital market projections	Dalquist&Ibert(2024) [proprietary data]	2005	7-year (2005), 10-year (2010) 30-year (2012)

Table II.
Decomposition A: Summary statistics and variance decomposition, 2005-2023

This table shows summary statistics, the correlation matrix and a variance decomposition from our implementation of Decomposition A on the S&P500 index over the sample 2005-2023. Returns, capital gains, the yield curve factor and the cashflow and long-term discounting factor are all in real terms.

Panel A: Annual gross returns, gross and log capital gains, and capital gain factors and log factors

	N	Avg.	SD	min	median	max	cumulative
Gross total return	19	1.084	0.170	0.630	1.130	1.304	3.563
Dividend yield	19	0.021	0.004	0.013	0.021	0.029	
Gross capital gain	19	1.063	0.167	0.615	1.108	1.277	2.443
Yield Curve (1y-30y) factor	19	1.012	0.179	0.573	1.044	1.275	0.908
Equity Premium (1y-2y) factor	19	1.000	0.040	0.896	1.003	1.103	0.986
Cashflow & LT discounting factor	19	1.079	0.228	0.554	1.079	1.637	2.728
Log capital gain	19	0.047	0.180	-0.486	0.103	0.244	0.893
ln(Yield Curve factor)	19	-0.005	0.195	-0.558	0.043	0.243	-0.096
ln(Equity Premium factor)	19	-0.001	0.040	-0.110	0.003	0.098	-0.014
ln(Cashflow & LT disc. factor)	19	0.053	0.226	-0.590	0.076	0.493	1.003

Panel B: Correlation matrix, annual log capital gains and log capital gain factors

	Gross Capital Gain	Yield Curve	Equity Premium	Cashflow & LT disc.
Gross Capital Gain	1.00			
Yield Curve (1y-30y)	0.07	1.00		
Equity Premium (1y-2y)	0.74	-0.35	1.00	
Cashflow & LT discounting	0.61	-0.75	0.71	1.00

Panel C: Variance decomposition, annual log capital gain and log capital gain factors

	value	contribution
Var(Gross capital gain)	0.032	100%
= Var(Yield Curve)	0.038	118%
+ Var(Equity Premium)	0.002	5%
+ Var(Cashflow & LT disc.)	0.051	158%
+ 2 Cov(Yield Curve, Equity Premium)	-0.0054	-17%
+ 2 Cov(Yield Curve, Cashflow & LT disc.)	-0.066	-204%
+ 2 Cov(Equity Premium, Cashflow & LT disc.)	0.013	40%

Table III.
Decomposition B: Summary statistics and variance decomposition, 2005-2023

This table shows summary statistics, the correlation matrix and a variance decomposition from our implementation of Decomposition B on the S&P500 index over the sample 2005-2023. Returns, capital gains, the yield curve factor and the analyst's earnings forecast factor are all in real terms. In this table we separate the two expected return factors, the yield curve factor and the equity premium factor, in the decomposition implementation.

Panel A: Annual capital gains factors and log capital gain factors

	N	Avg.	SD	min	median	max	cumulative
Gross capital gain	19	1.063	0.167	0.615	1.108	1.277	2.443
Analyst's Earnings Forecast factor	19	1.045	0.078	0.792	1.056	1.169	2.171
Yield Curve (1y-30y) factor	19	1.012	0.179	0.573	1.044	1.275	0.908
Equity Premium (all years) factor	19	1.033	0.220	0.627	1.007	1.574	1.239
Log capital gain	19	0.047	0.180	-0.486	0.103	0.244	0.893
ln(Analyst's Earnings factor)	19	0.041	0.081	-0.233	0.055	0.156	0.775
ln(Yield Curve factor)	19	-0.005	0.195	-0.558	0.043	0.243	-0.096
ln(Equity Premium factor)	19	0.011	0.212	-0.467	0.007	0.454	0.214

Panel B: Correlation matrix, annual log capital gains and log capital gain return factors

	Gross Capital Gain	Analyst's Earnings	Yield Curve	Equity Premium
Gross Capital Gain	1.00			
Analyst's Earnings	0.76	1.00		
Yield Curve (1y-30y)	0.07	-0.15	1.00	
Equity Premium (all years)	0.49	0.41	-0.80	1.00

Panel C: Variance decomposition, annual log capital gain

	value	contribution
Var(Gross capital gain)	0.032	100%
= Var(Yield Curve)	0.038	118%
+ Var(Equity Premium)	0.045	140 %
+ Var(Earnings)	0.006	20%
+ 2 Cov(Yield Curve, Equity Premium)	-0.066	-206%
+ 2 Cov(Yield Curve, Earnings)	-0.005	-15%
+ 2 Cov(Equity Premium, Earnings)	0.014	43%

Table IV. Decomposition B with expected equity return factors combined, 2005-2023

This table shows summary statistics, the correlation matrix and a variance decomposition from our implementation of Decomposition B on the S&P500 index over the sample 2005-2023. Returns, capital gains, the expected equity return factor and the analyst's earnings forecast factor are all in real terms. In this table we combine the two expected return factors, the yield curve factor and the equity premium factor from Table III, into one factor for the decomposition implementation.

Panel A: Annual capital gains factors and log capital gain factors

	N	Avg.	SD	min	median	max	cumulative
Gross capital gain	19	1.063	0.167	0.615	1.108	1.277	2.443
Analyst's Earnings Forecast factor	19	1.045	0.078	0.792	1.056	1.169	2.171
Expected Equity Return factor	19	1.014	0.127	0.777	1.021	1.246	1.125
Log capital gain	19	0.047	0.180	-0.486	0.103	0.244	0.893
ln(Analyst's Earnings factor)	19	0.041	0.081	-0.233	0.055	0.156	0.775
ln(Equity Return factor)	19	0.006	0.129	-0.253	0.021	0.220	0.118

Panel B: Correlation matrix, annual log capital gains and log capital gain return factors

	Gross Capital Gain	Analyst's Earnings	Equity Return
Gross Capital Gain	1.00		
Analyst's Earnings	0.76	1.00	
Equity Return	0.92	0.44	1.00

Panel C: Variance decomposition, annual log capital gain

	value	contribution
Var(Gross capital gain)	0.032	100%
= Var(Expected Equity Return)	0.017	52%
+ Var(Earnings Forecast)	0.006	20%
+ 2 Cov(Equity Return, Earnings)	0.009	28%

Appendix to "A Stock Return Decomposition Using Observables"

This Appendix provides theoretical proofs, additional descriptive and empirical evidence to supplement the analyses provided in the main text. Below, we list the content.

- Appendix A provides the proof of Result 3.
- Appendix B describes when expected repurchases/issuance lead to effects of discount rates on expected future dividends using simple illustrative examples.
- Appendix C provides a recap of the Martin (2017) lower bound of equity risk premium that is estimated from equity option prices, details our data construction, provides empirical support for the tightness of the lower bound, and also includes theoretical analysis of how the change in the lower bound relates to the change in the true equity risk premium.
- Appendix D documents the robustness of our estimated dividend strip weights to potential liquidity concerns in the dividend futures market.
- Appendix E details our data construction for earnings forecasts using the I/B/E/S dataset.

A. Proofs

Proof of Result 3:

(a) Define the date $t+1$ terminal payoff as $T_{t+1} = D_{t+1} + P_{t+1}$ and use it to express P_t as

$$P_t = \frac{E_t\left(T_{t+1}\right)}{E_t\left(R_{t+1}\right)} = \frac{E_t\left(T_{t+1}\right)}{(1+f_t^{YC,1})(1+f_t^{EP,1})}. \tag{A.1}$$

The return on the date $t+1$ terminal payoff (i.e., the right to the dividends at $t+1$ and later) is the return on the market since no dividends are paid before $t+1$. If only the market equity premium for year 1 changes then $\frac{P_{t+1}}{P_t} = \frac{1}{G_{t+1}^{EP,f1}}$, proving that Result 3(a) is exact for any return process.

(b) Write the stock price as a function of the date $t+n$ terminal payoff, $T_{t+n} = D_{t+n} + P_{t+n}$:

$$P_t = P_t^{(1)} + ... + P_t^{(n-1)} + \frac{E_t\left(T_{t+n}\right)}{E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}} R_{t+n}\right)}. \tag{A.2}$$

Notice that, in period $t+n$, the return on the terminal payoff (i.e., the right to the dividends at $t+n$ and later) is the return on the market (i.e., $R_{t+n}^{T_{t+n}} = R_{t+n}$) since the prior dividends have already been paid out.

If returns are independent over time, then

$$\begin{aligned} E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}} R_{t+n}\right) &= E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}}\right) E_t\left(R_{t+n}\right) \\ &= E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}}\right) (1+f_t^{YC,n})(1+f_t^{EP,n}). \end{aligned} \tag{A.3}$$

Since the terminal payoff term in equation (A.2) has weight $1 - w_t^{(1)} - ... - w_t^{(n-1)}$ in P_t, it follows that the effect on the stock price of a change in the forward equity premium for period n is:

$$\frac{P_{t+1}}{P_t} = 1 + \left(1 - w_t^{(1)} - ... - w_t^{(n-1)}\right)\left(\frac{1}{G_{t+1}^{EP,fn}} - 1\right) \tag{A.4}$$

If returns are not independent over time, then

$$\begin{aligned} E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}} R_{t+n}\right) &= E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}}\right) E_t\left(R_{t+n}\right) + cov_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}}, R_{t+n}\right) \\ &= E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}}\right) (1+f_t^{YC,n})(1+f_t^{EP,n}) + cov_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}}, R_{t+n}\right) \end{aligned} \tag{A.5}$$

Since the first term in equation (A.5) has weight $\frac{E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}}\right) E_t(R_{t+n})}{E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}} R_{t+n}\right)}$ in $E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}} R_{t+n}\right)$, it follows that the effect on the stock price of a change in the forward equity premium for period n is:

$$\frac{P_{t+1}}{P_t} = 1 + \left(1 - w_t^{(1)} - ... - w_t^{(n-1)}\right) \left(\frac{1}{1 + \frac{E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}}\right) E_t(R_{t+n})}{E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}} R_{t+n}\right)} \left(G_{t+1}^{EP,fn} - 1\right)} - 1 \right) \tag{A.6}$$

If returns on terminal values follow a CAPM structure then regardless of the values of alphas and betas, $\frac{E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}}\right) E_t(R_{t+n})}{E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}} R_{t+n}\right)}$ will be near one if the market return has little autocorrelation so $\frac{E_t(R_{t+1} ... R_{t+n-1}) E_t(R_{t+n})}{E_t(R_{t+1} ... R_{t+n-1} R_{t+n})}$ is close to one. To see this, start from a CAPM structure for multi-period returns on terminal values:

$$R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}} - R_{t+1}^f ... R_{t+n-1}^f = \alpha_t^{(n)} + \beta_t^{(n)} \left(R_{t+1}^T ... R_{t+n-1}^T - R_{t+1}^f ... R_{t+n-1}^f\right) + \epsilon_{t+1 \text{ to } t+n-1}^{T_{t+n}}$$

$$\Longrightarrow R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}} = \left[\alpha_t^{(n)} + \left(1 - \beta_t^{(n)}\right) R_{t+1}^f ... R_{t+n-1}^f\right] + \beta_t^{(n)} \left(R_{t+1}^T ... R_{t+n-1}^T\right) + \epsilon_{t+1 \text{ to } t+n-1}^{T_{t+n}}$$

Define $a_t = \alpha_t^{(n)} + \left(1 - \beta_t^{(n)}\right) R_{t+1}^f ... R_{t+n-1}^f$. Then

$$\begin{aligned}
& \frac{E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}}\right) E_t\left(R_{t+n}\right)}{E_t\left(R_{t+1}^{T_{t+n}} ... R_{t+n-1}^{T_{t+n}} R_{t+n}\right)} \\
= \; & \frac{a_t E_t\left(R_{t+n}\right) + \beta_t^{(n)} E_t\left(R_{t+1} ... R_{t+n-1}\right) E_t\left(R_{t+n}\right)}{a_t E_t\left(R_{t+n}\right) + \beta_t^{(n)} E_t\left(R_{t+1} ... R_{t+n-1} R_{t+n}\right)} \\
= \; & 1 + \beta_t^{(n)} \frac{E_t\left(R_{t+1} ... R_{t+n-1}\right) E_t\left(R_{t+n}\right) - E_t\left(R_{t+1} ... R_{t+n-1} R_{t+n}\right)}{a_t E_t\left(R_{t+n}\right) + \beta_t^{(n)} E_t\left(R_{t+1} ... R_{t+n-1} R_{t+n}\right)} \\
= \; & 1 + \left[\frac{E_t\left(R_{t+1} ... R_{t+n-1}\right) E_t\left(R_{t+n}\right)}{E_t\left(R_{t+1} ... R_{t+n-1} R_{t+n}\right)} - 1\right] \frac{\beta_t^{(n)} E_t\left(R_{t+1} ... R_{t+n-1} R_{t+n}\right)}{a_t E_t\left(R_{t+n}\right) + \beta_t^{(n)} E_t\left(R_{t+1} ... R_{t+n-1} R_{t+n}\right)}
\end{aligned}$$

We estimate the ratio $\frac{E_t(R_{t+1}...R_{t+n-1})E_t(R_{t+n})}{E_t(R_{t+1}...R_{t+n-1}R_{t+n})}$ using returns on the overall US stock market back to 1926 for value of n from 1 to 30. Across these values of n, the estimated ratio averages 1.01 with a range from 1.00 to 1.02. This does not change materially if we using conditional expectations focusing on observations with P/E ratios in the top half of the sample, or on observations with P/E ratios in the bottom half of the sample. Therefore, $\frac{E_t(R_{t+1}...R_{t+n-1})E_t(R_{t+n})}{E_t(R_{t+1}...R_{t+n-1}R_{t+n})} - 1$ is close to zero and $\frac{E_t\left(R_{t+1}^{T_{t+n}}...R_{t+n-1}^{T_{t+n}}\right)E_t(R_{t+n})}{E_t\left(R_{t+1}^{T_{t+n}}...R_{t+n-1}^{T_{t+n}}R_{t+n}\right)}$ therefore is close to one, implying that the approximation resulting from omitting this ratio in Result 3 is very small.

B. When do expected repurchases/issuance lead to effects of discount rates on expected future dividends?

Consider a firm that generates a perpetual stream of free cash flows of C at times t = 0, 1, 2,.... The firm has a cost of capital of r and for simplicity assume there is no uncertainty. The firm has N shares outstanding at $t = 0$ and no debt outstanding. Compare the following cases.

Case 1 (base case, no repurchases): The firm pays all free cash flows as dividends, period by period. Dividends per share are $D_t = C/N$ for all t. By the formula for the present value of a perpetuity, the stock price per share at $t = 0$ and at all later dates is

$$P_0 = \frac{D}{r} = \frac{C/N}{r} \tag{A.7}$$

The duration of dividend payments (i.e., the present-value weighted time-to-maturity of payments) is

$$\begin{aligned}\mathbb{D} &= \sum_{i=1}^{\infty} i\frac{P_0^{(i)}}{P_0} \\ &= r\sum_{i=1}^{\infty} i\,(1+r)^{-i} \\ &= \frac{1+r}{r}\end{aligned} \tag{A.8}$$

where the last line uses the following property of geometric sums: $\sum_{i=1}^{\infty} i\, x^{i-1} = (1-x)^{-2}$ for $0 < x < 1$.

At the same time, the price elasticity with respect to the cost of capital (in all periods, as opposed to just one period in our earlier derivations) is

$$\Psi^R = \frac{\partial P_0/P_0}{\partial r/(1+r)} = -\frac{1+r}{r}, \tag{A.9}$$

With fixed dividend payments, the base case therefore produces the classic fixed income result that

$\Psi^R = -\mathbb{D}$.

Case 2 (repurchase at $t = 1$, funded with debt issuance): At $t = 1$, the firm issues debt with market value of C and uses the proceeds to buy back X shares at the market price P_1. X and P_1 solve:

$$\begin{aligned} P_1 X &= C && \text{(A.10)} \\ P_1(N - X) &= \frac{C}{r} - C && \text{(A.11)} \end{aligned}$$

In the second expression, C/r is the present value of free cash flows as of $t = 1$, of which a value of C in present value terms will go to repaying debt. Solving for X and P_1,

$$X = Nr,\ P_1 = \frac{C/N}{r}. \quad \text{(A.12)}$$

The price at $t = 1$ is thus unaffected by the repurchase as is the price at $t = 0$ which remains $P_0 = \frac{C/N}{r}$ (because the dividend at $t = 1$ and the price at $t = 1$ are both unaffected by the repurchase). Assuming that the debt issued is perpetual or rolled over perpetually, interest payments are rC at $t = 2, 3, ...$ and dividends per share are C/N at $t = 1$ and $(1 - r)C/(N - X) = C/N$ at $t = 2, 3, ...$ Dividends per share are thus the same period by period as in Case 1 and therefore unaffected by the share repurchases. In this case, there is no effect of r on dividends even with repurchases.

Case 3 (repurchases at $t = 1$, funded by reduced dividends): At $t = 1$, the firm pays no dividend and instead spends all free cash flows C on buying back X shares at the market price P_1. X and P_1 solve:

$$\begin{aligned} P_1 X &= C && \text{(A.13)} \\ P_1(N - X) &= \frac{C}{r} && \text{(A.14)} \end{aligned}$$

which imply

$$\begin{aligned} X &= Nr\frac{1}{1+r} = N\frac{1}{1+\frac{1}{r}} && \text{(A.15)} \\ P_1 &= \frac{C/N}{r}(1+r) = (C/N)\left(1+\frac{1}{r}\right) && \text{(A.16)} \end{aligned}$$

The price per share at $t = 0$ is unaffected since $P_0 = \frac{1}{1+r}\frac{C/(N-X)}{r} = \frac{C/N}{r}$. The duration of dividends is one year longer than in case 1, since shareholders get a perpetuity but starting only at $t = 2$. Since P_0 is unchanged relative to Case 1, the price elasticity with respect to r (accounting for effects of r via both discounting and dividends) is unchanged relative to Case 1. It is thus no longer the case that $\Psi^R = -\mathbb{D}$. The dividend duration overstates the overall interest rate risk because a higher interest rate improves cash flows from $t = 2$ onward: At a higher r, P_1 is lower, allowing the firm to buy back more shares with C at $t = 1$. This increases dividends per share from $t = 2$ onward.

These cases illustrate how discount rate effects on expected dividends emerge if a firm is expected to buy back shares and is expected to fund repurchases by lowering dividends (Case 3). By contrast, no discount rate effects on expected dividends emerge from repurchases if the firm is expected to fund repurchases with debt issuance (and the debt is rolled over perpetually) (Case 2). A third way to fund repurchases would be to use resources available inside the firm that would otherwise have been kept invested in the firm. This would work out much like Case 2, with no discount effects of repurchases on expected dividends. Expected share issuance will work with opposite effects of share repurchases, leading to discount rate effects on expected dividends if issuance proceeds are expected to be used to pay dividends, but no such effects if issuance proceeds are expected to be used to reduce debt.

C. The Martin lower bound of the equity premium

A. *Theoretical motivation*

Martin (2017) starts from the fact that the time t price of a claim to a cash flow X_T at time T can either be expressed using the stochastic discount factor M_T or using risk-neutral notation

$$\text{Price}_t = E_t\left(M_T X_T\right) = \frac{1}{R_{f,t}} E_t^*\left(X_T\right)$$

where the expectation E_t^* is defined by

$$E_t^*\left(X_T\right) = E_t\left(R_{f,t} M_T X_T\right).$$

The return on an investment can similarly be written in terms of the SDF or using risk-neutral notation

$$1 \quad = \quad E_t\left(M_T R_T\right) = \frac{1}{R_{f,t}} E_t\left(R_{f,t} M_T R_T\right) = \frac{1}{R_{f,t}} E_t^*\left(R_T\right).$$

The conditional risk-neutral variance can be expressed as

$$\text{var}_t^* R_T = E_t^* R_T^2 - \left(E_t^* R_T\right)^2 = R_{f,t} E_t\left(M_T R_T^2\right) - R_{f,t}^2$$

The risk premium expressed as a function of the risk-neutral variance is then

$$\begin{aligned} E_t R_T - R_{f,t} &= \left[E_t\left(M_T R_T^2\right) - R_{f,t}\right] - \left[E_t\left(M_T R_T^2\right) - E_t R_T\right] \\ &= \frac{1}{R_{f,t}} \text{var}_t^* R_T - cov_t\left(M_T R_T, R_T\right) \\ &\geq \frac{1}{R_{f,t}} \text{var}_t^* R_T \text{ if } cov_t\left(M_T R_T, R_T\right) \leq 0 \end{aligned}$$

Thus $\frac{1}{R_{f,t}}\text{var}_t^* R_T$ provides a lower bound on $E_t R_T - R_{f,t}$ if $cov_t\left(M_T R_T, R_T\right) \leq 0$, denoted the "negative correlation condition" (NCC).

The Martin (2017) lower bound is the discounted risk-neutral variance and can thus be calculated from put and call option prices as follows

$$\frac{1}{R_{f,t}} \text{var}_t^* R_T = \frac{2}{S_t^2}\left[\int_0^{F_{t,T}} \text{put}_{t,T}(K)\, dK + \int_{F_{t,T}}^{\infty} \text{call}_{t,T}(K)\, dK\right] \tag{A.17}$$

where $\text{put}_{t,T}(K)$ and $\text{call}_{t,T}(K)$ are time t put and call option prices for strike price K and maturity T. The forward price $F_{t,T}$ is the unique solution K where $\text{put}_{t,T}(K) = \text{call}_{t,T}(K)$. One can then estimate the equity risk premium by discretizing the right-hand side of equation (A.17) using the range of date t option prices that expire on date $t + T$.

B. *Data cleaning and construction*

For our baseline results we use option price data from OptionsMetrics. For the application to 2020, we have replicated the equity premium results using use option price data from CBOE intra-day traded price data. The results mirror those reported in the main results using OptionMetrics end of day quotes.

To clean the OptionMetrics data and generate the equity premium estimates we take the following steps. First we drop observations if the bid price or ask price is missing and if the best bid price is zero. We then calculate the mid price as the average of the best bid and best ask price and, for date-maturity-strike-type combinations where there are multiple mid-prices, we use the option with the highest open interest.[30] We next keep date-maturity-strike observations where there is both a call and put mid-price, and then select the option with the lowest mid-price. This step automatically deletes put options greater than $F_{t,T}$ and deletes call option prices less than $F_{t,T}$, as required for equation (A.17). Before implementing the discretizion of the integral, we then take two extra steps to ensure the accuracy of the

[30] Type refers to call or put option. The existence of multiple maturity-strike-type observations is caused by the increase in the number of options issued. For example, if a newly issued weekly option has the same expiry as an existing annual option that is expiring in a weeks time, then we observe two mid-prices. Typically, shorter horizon options are the most liquid and have highest open interest (i.e. weekly options are more liquid than annual options). We drop all quarterly options (expiring end of quarter) from the sample as these are particularly illiquid throughout their issuance period.

discretizion approximation. First, we drop date-maturity observations where the number of unique strikes is less than 10. Second, we drop date-maturity observations where the difference between the maximum put strike and the minimum call strike is greater than 50 (100) for maturities less (greater) than 1-year. This step makes sure discretization is not too coarse in the most important range of the integral (where prices are at the highest levels). We allow a larger gap between strike prices for long-maturity options as these are typically issued with a lower range of strikes.

Equation (A.17) is then estimated, providing date-maturity equity risk premium estimates at the maturities that correspond to the expires of the options in issue. To generate constant maturity risk premium estimates across dates, we linearly interpolate risk premium estimates across maturities within dates. We also extrapolate to extend maturity. However, to avoid over extrapolation, we limit this extrapolation to a maximum of half a year greater than the longest maturity option available at that date.

C. Is the Martin lower bound a good measure of the equity risk premium?

We proxy the equity risk premium with the Martin lower bound, thus assuming the bound is tight. This section provides additional empirical evidence to support this assumption as well as theoretical results on how the *change* in the bound relates to the *change* in the true equity premium.

C.1. The tightness of the Martin lower bound

Martin (2017) documents an average lower bound over the 1996-2012 period of about 5%, close to the equity premium estimates obtained by Fama and French (2002) using average realized dividend (or earnings) growth rates as an estimate of ex-ante expected capital gains. Martin also tests whether the lower bound is a good predictor of the realized excess return, with small intercepts. He estimates the relation

$$\frac{1}{T-t}\left(R_T - R_{f,t}\right) = a + b \times \frac{1}{T-t}\frac{\text{var}_t^* R_T}{R_{f,t}} + \epsilon_{i,t} \tag{A.18}$$

We extend the Martin (2017) empirical results by first re-estimating equation (A.18) over the 1996-June 2022 for the S&P500 index.[31] The estimated parameters are shown in Table A.1, Panel A. We cannot reject the null of $b = 1$, $a = 0$ for horizons $T - t = 1$, 2, 3, 6 and 12 months.

We re-estimate equation A.18 over the 1996-2022 as shown in Table A.1. Over this longer sample, we find that β is higher than one for most horizons, though not significantly so for most horizons. The intercept is close to zero and insignificant across all horizons.

[31] Martin's defines a variable $SVIX^2_{t\to T} = \frac{1}{T-t}\text{var}_t^*\left(\frac{R_T}{R_{f,t}}\right)$ and his regressor is thus expressed as $R_{f,t}SVIX^2_{t\to T}$.

Table A.1. The Martin lower bound as a predictor variable.
This table reports the parameter estimate from the following time series regression: $\frac{1}{T-t}\left(R_T - R_{f,t}\right) = a + b \times \frac{1}{T-t}\frac{1}{R_{f,t}}\mathrm{var}_t^* R_T$ together with Newey-West standard errors with lag selection based on the number of overlapping observations. Columns refer to separate estimations with $T-t = 1$, 2, 3, 6 and 12 months respectively. The sample period is January 1996 - June 2022.

	Realized Return				
	1 month	2 month	3 month	6 month	1 year
Martin lower bound	1.43	1.41	1.36	2.04**	1.70**
	(1.00)	(1.03)	(1.26)	(0.86)	(0.82)
Constant	0.00	0.00	0.00	-0.01	-0.00
	(0.00)	(0.01)	(0.01)	(0.02)	(0.04)
R^2 (perc.)	1.14	1.76	2.04	5.45	4.09
Observations	6,618	6,618	6,618	6,595	6,470

We find that b is greater than one in all estimations, though not significantly. Our decomposition relies on *changes* in equity risk premia. The b estimates above one imply that the true risk premium change exceeds that of the change in the lower bound. It is possible, however, that realized excess returns exceeded expected returns over this particular time period, more so in times of stress (high values of the risk-neutral variance). Fama and French (2002) argue that realized returns exceeded expected returns even over a sample as long as 1951-2000. Cieslak, Morse, and Vissing-Jorgensen (2019) argue that over the post-1994 period, unexpectedly accommodating monetary policy has contributed to much of the realized excess return on the stock market. If the unexpected positive component of realized returns is sufficiently correlated with risk-neutral variance, then an estimated b above one may not imply that changes in the lower bound are smaller than the true changes in the equity risk premium for a given horizon.

Given the lack of conclusive empirical evidence on whether $b = 1$ or $b > 1$ it is relevant to ask what theory says about how the *change* in the bound relates to the *change* in the true equity risk premium.

C.2. Theoretical results for the Martin lower bound in changes

We supplement the above empirical evidence with theoretical analysis for the log-normal case, the CRRA log-normal case and more generally for a unconstrained investor who is fully invested in the market. In each case, we show that the same parameters and conditions that ensure that the lower bound is in fact a lower bound (Martin's negative correlation condition) also ensure that the change in the lower bound is smaller than the change in the true risk premium. To the extent the lower bound is not right, our return decomposition will thus tend to understate the role of risk premium changes.

Suppose an underlying state variable s_t changes and that s_t is signed such that $\frac{\partial\left[\frac{1}{R_{f,t}}\mathrm{var}_t^* R_T\right]}{\partial s_t} > 0$.

Then

$$
\begin{aligned}
\frac{\partial\left[E_t R_T - R_{f,t}\right]}{\partial s_t} &= \frac{\partial\left[\frac{1}{R_{f,t}}\text{var}_t^* R_T\right]}{\partial s_t} - \frac{\partial cov_t\left(M_T R_T, R_T\right)}{\partial s_t} \\
&\geq \frac{\partial\left[\frac{1}{R_{f,t}}\text{var}_t^* R_T\right]}{\partial s_t} \text{ iff } \frac{\partial cov_t\left(M_T R_T, R_T\right)}{\partial s_t} \leq 0
\end{aligned}
$$

It follows that the change in the lower bound is, on average, equal to the true change in the risk premium if the regression coefficient b in (A.18) equals one. If instead $b > 1$ that would suggest that the regressor is positively correlated with the omitted variable $-cov_t\left(M_T R_T, R_T\right)$ implying that $\frac{\partial cov_t(M_T R_T, R_T)}{\partial s_t} < 0$ and thus that the true change in the risk premium is larger than the change in the lower bound.

To assess theoretically whether $b > 1$ is likely, assume conditional log-normality as follows:

$$
\begin{aligned}
M_T &= e^{-r_{f,t}+\sigma_{M,t} Z_{M,T} - \frac{1}{2}\sigma_{M,t}^2} \\
R_T &= e^{\mu_{R,t}+\sigma_{R,t} Z_{R,T} - \frac{1}{2}\sigma_{R,t}^2}
\end{aligned}
$$

where $Z_{M,t}$ and $Z_{R,t}$ are (potentially correlated) standard normal random variables. Martin (2017) shows that in the log-normal case, the NCC holds iff the conditional Sharpe ratio exceeds the conditional standard deviation:

$$
cov_t\left(M_T R_T, R_T\right) \leq 0 \text{ iff } e^{r_{f,t}+\sigma_{R,t}^2} \leq e^{\mu_{R,t}} \iff \sigma_{R,t} \leq \frac{\mu_{R,t} - r_{f,t}}{\sigma_{R,t}}
$$

The following result states conditions that allow us to relate the true change in the risk premium to the change in the lower bound.

Result 7 (**True change vs. lower bound change in equity risk premium**).
Suppose an underlying state variable s_t changes such that $\frac{\partial\left[\frac{1}{R_{f,t}} var_t^* R_T\right]}{\partial s_t} > 0$ and $\frac{\partial \sigma_{R,t}}{\partial s_t} \geq 0$. The true change in the equity risk premium is at least as large as the change in the lower bound iff $\frac{\partial cov_t(M_T R_T, R_T)}{\partial s_t} \leq 0$. Under log-normality, it is sufficient for $\frac{\partial cov_t(M_T R_T, R_T)}{\partial s_t} \leq 0$ that
(1) The NCC holds: $cov_t\left(M_T R_T, R_T\right) \leq 0 \iff \frac{\mu_{R,t} - r_{f,t}}{\sigma_{R,t}} \geq \sigma_{R,t}$, and
(2) $\frac{\partial}{\partial s_t}\left[\frac{\mu_{R,t} - r_{f,t}}{\sigma_{R,t}}\right] \geq \frac{\partial \sigma_{R,t}}{\partial s_t}$.

In addition to log-normality, assume CRRA utility,

$$
M_T = \beta\left(\frac{C_T}{C_t}\right)^{-\gamma} = e^{\ln\beta - \gamma\ln(C_T/C_t)}
$$

with $\ln(C_T/C_t) \sim N(\mu_{c,t}, \sigma^2_{c,t})$ conditional on information known at t. Define the consumption beta relative to the market as $\beta^C_t = \frac{cov_t(\ln R_T, \ln(C_T/C_t))}{\sigma^2_{R,t}}$. The following result emerges.

Result 8 (**True change vs. lower bound change in equity risk premium**).
In the log-normal CRRA case,

$$\frac{\mu_{R,t} - r_{f,t}}{\sigma_{R,t}} = \gamma \beta^C_t \sigma_{R,t}. \tag{A.19}$$

so the NCC holds if $\gamma\beta^C_t \geq 1$. *Furthermore,*

$$\frac{\partial}{\partial s_t}\left[\frac{\mu_{R,t} - r_{f,t}}{\sigma_{R,t}}\right] = \gamma\beta^C_t \frac{\partial \sigma_{R,t}}{\partial s_t} + \gamma \frac{\partial \beta^C_t}{\partial s_t}\sigma_{R,t}$$

so it is sufficient for

$$\frac{\partial}{\partial s_t}\left[\frac{\mu_{R,t} - r_{f,t}}{\sigma_{R,t}}\right] \geq \frac{\partial \sigma_{R,t}}{\partial s_t}$$

that $\gamma\beta^C_t \geq 1$ *and* $\frac{\partial \beta^C_t}{\partial s_t} \geq 0$.

Therefore, the same condition that ensures the NCC holds, $\gamma\beta^C_t \geq 1$, also helps to ensure that the true change in the risk premium is larger than the change in the lower bound. Martin (2017) argues that the NCC is very likely to hold in the log-normal case since the Sharpe ratio based on realized returns has substantially exceeded the realized standard deviation. The additional condition, $\frac{\partial \beta^C_t}{\partial s_t} \geq 0$ holds if β^C_t is constant. This will be the case for an investor who is fully invested in the market, since then $\beta^C_t = 1$. It will also (approximately) be the case for an investor who is not fully invested in the market as long as the the investor has a roughly constant portfolio weight in the market and the covariance between the market and non-market risky assets is roughly constant over time.

Overall, theoretical considerations suggest that to the extent that the Martin lower bound is not exact, the most likely direction of any bias is that the true changes in the equity risk premium are larger than the changes in the Martin lower bounds.

Proof of Result 7: $E_t(M_T R_T) = 1$ implies that

$$\begin{aligned}
\ln(E_t(M_T R_T)) &= E_t(\ln M_T + \ln R_T) + \frac{1}{2}V_t(\ln M_T + \ln R_T) \\
&= \left(\mu_{R,t} - r_{f,t} - \frac{1}{2}\sigma^2_{M,t} - \frac{1}{2}\sigma^2_{R,t}\right) + \frac{1}{2}\left(\sigma^2_{M,t} + \sigma^2_{R,t} + 2cov_t(\ln R_T, \ln M_T)\right) \\
&= \mu_{R,t} - r_{f,t} + cov_t(\ln R_T, \ln M_T) = 0
\end{aligned}$$

and thus

$$\mu_{R,t} - r_{f,t} = -cov_t(\ln R_T, \ln M_T). \tag{A.20}$$

$E_t\left(M_T R_T\right) = 1$ furthermore implies that

$$cov_t\left(M_T R_T, R_T\right) = E_t\left(M_T R_T^2\right) - E\left(R_T\right)$$

Consider each term on the right hand side separately.

$$\begin{aligned}
\ln E_t\left(M_T R_T^2\right) &= E_t\left(\ln M_T + 2\ln R_T\right) + \frac{1}{2}V_t\left(\ln M_T + 2\ln R_T\right) \\
&= -r_{f,t} - \frac{1}{2}\sigma_{M,t}^2 + 2\left(\mu_{R,t} - \frac{1}{2}\sigma_{R,t}^2\right) + \frac{1}{2}\left(\sigma_{M,t}^2 + 4\sigma_{R,t}^2 - 4\left(\mu_{R,t} - r_{f,t}\right)\right) \\
&= r_{f,t} + \sigma_{R,t}^2
\end{aligned}$$

$$\begin{aligned}
\ln E_t\left(R_T\right) &= E_t\left(\ln R_T\right) + \frac{1}{2}V_t\left(\ln R_T\right) \\
&= \mu_{R,t}
\end{aligned}$$

Combining these two expressions

$$cov_t\left(M_T R_T, R_T\right) = e^{r_{f,t}+\sigma_{R,t}^2} - e^{\mu_{R,t}} \tag{A.21}$$

The derivative with respect to a state variable s_t is

$$\frac{\partial cov_t\left(M_T R_T, R_T\right)}{\partial s_t} = e^{r_{f,t}+\sigma_{R,t}^2}\left[\frac{\partial r_{f,t}}{\partial s_t} + 2\sigma_{R,T}\frac{\partial \sigma_{R,t}}{\partial s_t}\right] - e^{\mu_{R,t}}\left[\frac{\partial \mu_{R,t}}{\partial s_t}\right]$$

If the NCC holds, $cov_t\left(M_T R_T, R_T\right) \leq 0$ and thus $e^{r_{f,t}+\sigma_{R,t}^2} \leq e^{\mu_{R,t}}$. Therefore, it is sufficient for $\frac{\partial cov_t(M_T R_T, R_T)}{\partial s_t} \leq 0$ that $\frac{\partial r_{f,t}}{\partial s_t} + 2\sigma_{R,t}\frac{\partial \sigma_{R,t}}{\partial s_t} \leq \frac{\partial \mu_{R,t}}{\partial s_t}$. Rewrite this sufficient condition as follows

$$\left(\frac{\partial \mu_{R,t}}{\partial s_t} - \frac{\partial r_{f,t}}{\partial s_t}\right)\frac{1}{\sigma_{R,t}} - \frac{\partial \sigma_{R,t}}{\partial s_t} \geq \frac{\partial \sigma_{R,t}}{\partial s_t}$$

Consider now the change in the conditional Sharpe ratio (for log returns):

$$\begin{aligned}
\frac{\partial}{\partial s_t}\left[\frac{\mu_{R,t} - r_{f,t}}{\sigma_{R,t}}\right] &= \frac{1}{\sigma_{R,t}^2}\left[\left(\frac{\partial \mu_{R,t}}{\partial s_t} - \frac{\partial r_{f,t}}{\partial s_t}\right)\sigma_{R,t} - \left(\mu_{R,t} - r_{f,t}\right)\frac{\partial \sigma_{R,t}}{\partial s_t}\right] \\
&= \left(\frac{\partial \mu_{R,t}}{\partial s_t} - \frac{\partial r_{f,t}}{\partial s_t}\right)\frac{1}{\sigma_{R,t}} - \frac{\left(\mu_{R,t} - r_{f,t}\right)}{\sigma_{R,t}^2}\frac{\partial \sigma_{R,t}}{\partial s_t} \\
&\geq \left(\frac{\partial \mu_{R,t}}{\partial s_t} - \frac{\partial r_{f,t}}{\partial s_t}\right)\frac{1}{\sigma_{R,t}} - \frac{\partial \sigma_{R,t}}{\partial s_t}
\end{aligned}$$

where the last line follows from (1) the fact that $\frac{(\mu_{R,t}-r_{f,t})}{\sigma^2_{R,t}} \geq 1$ under the NCC and (2) the assumption that $\frac{\partial \sigma_{R,t}}{\partial s_t} \geq 0$. Thus, it is sufficient for $\frac{\partial cov_t(M_T R_T, R_T)}{\partial s_t} \leq 0$ that the change in the conditional Sharpe ratio is at least as large as the change in the conditional standard deviation

$$\frac{\partial}{\partial s_t}\left[\frac{\mu_{R,t}-r_{f,t}}{\sigma_{R,t}}\right] \geq \frac{\partial \sigma_{R,t}}{\partial s_t}.$$

Proof of Result 8: We can exploit equation (A.20) to get

$$\begin{aligned}
\mu_{R,t} - r_{f,t} &= -cov_t\left(\ln R_T, \ln M_T\right) \\
&= \gamma cov_t\left(\ln R_T, \ln\left(C_T/C_t\right)\right).
\end{aligned}$$

This implies (A.19),

$$\begin{aligned}
\frac{\mu_{R,t} - r_{f,t}}{\sigma_{R,t}} &= \gamma \frac{cov_t\left(\ln R_T, \ln\left(C_T/C_t\right)\right)}{\sigma^2_{R,t}}\sigma_{R,t} \\
&= \gamma \beta_t^C \sigma_{R,t}
\end{aligned}$$

where β_t^C is the (potentially time-varying) beta of $\ln\left(C_T/C_t\right)$ with respect to $\ln R_T$. The rest of Result 6 follows directly from equation (A.19).

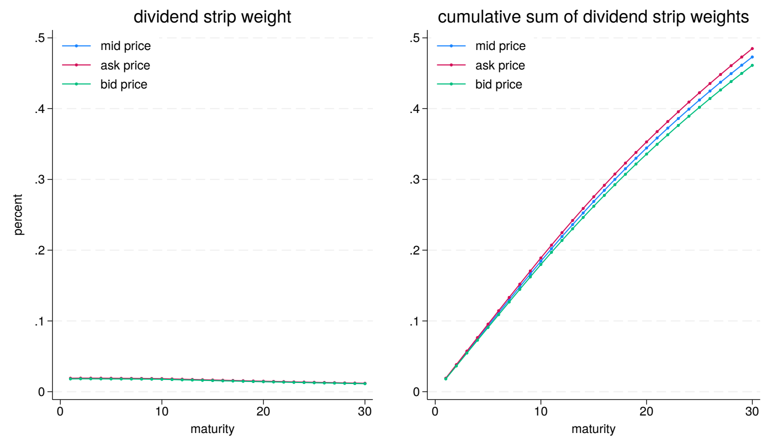
D. Dividend strip weights: Liquidity and robustness

Our dividend strip weights are based on dividend futures prices. These are a relatively new product and liquidity may be an issue. Our dividend futures prices are trade prices from Bloomberg. Bloomberg does not provide bid-ask spreads for dividend futures. However, using a proprietary data source, Bansal et al. (2021) document that over their sample period from January 2010 to February 2017, bid-ask spreads on S&P500 dividend futures averaged around 2% for each maturity (out to 5 years in their data), with a time series standard deviation around 1% for a given maturity. This is large enough to have an economically large effect on the monthly returns generated by these contracts. Because dividend strip weights are based on the *level* of dividend futures prices and not on dividend futures price changes (to calculate dividend strip returns), the economic impact of bid-ask spreads on weights is far lower than the impact on returns. To take an example, consider the first year's dividend strip weight, which is 1.80% of the total market on January 2nd, 2020. Even if we consider a bid-ask spread of 4% (the sample mean plus two sample standard deviations), in the extreme the dividend strip weight would be 1.764% using bid prices and 1.836% using ask prices. To illustrate the point, the top panel of Figure A.1 shows how the dividend strip weights and cumulative dividend strip weights vary with bid-ask spreads of 4%. The impact on dividend strip weights is very small across all maturities.[32]

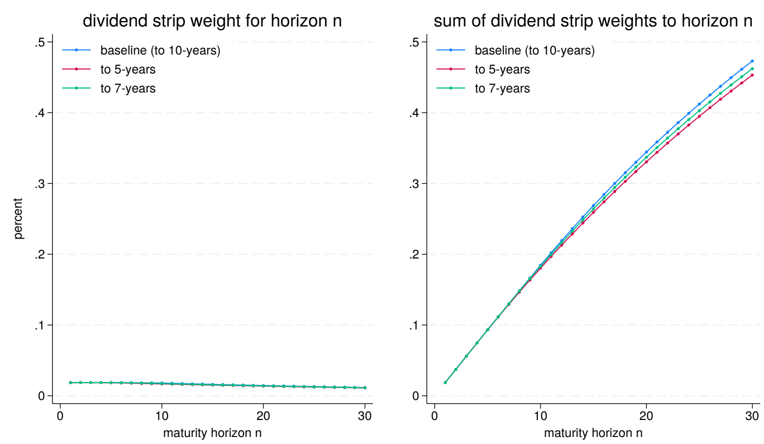
Figure A.1. Dividend strip weights and dividend futures liquidity.

This figure shows how dividend strip weights are impacted by bid-ask spreads and the choice of the maximum maturity of dividend futures used in Result 6. For illustration purposes, the dividend strips are measured using the first day of 2020.

Panel A: Robust to bid-ask spreads



Panel B: Robust to maximum maturity of dividend futures



Beyond bid-ask spreads, another important issue in our context is that limited open interest in dividend futures may lead to a risk that these are priced by particular investors, rather than a broad set of investors relevant for the overall stock market. Across contracts from year 1 to year 10, open interest has increased over time, with the average daily open interest across 2020 was 60% higher than the average daily open interest across 2017. However, across maturities, open interest in 2020 (annual

[32]Gormsen and Koijen (2020) provide updated liquidity analysis on the dividend futures market in 2020, with a focus on the euro-area. The bid-ask spreads observed in this period are slightly lower than those measured in the Bansal et al. (2021) sample.

average) declines from \$802M at maturity 1, to \$351M at maturity 3, \$77M at maturity 5, \$17M at maturity 8, and less than \$10M at maturity 9 and 10.

Dividend weights beyond the maximum maturity of observed dividend futures are estimated using Result 6 in our methodology, with our baseline implementation using the maximum observed dividend maturity $N_D = 10$ years. We therefore assess the robustness of our results to shortening the maximum dividend futures maturity used. The bottom panels of Figure A.1 show how the dividend strip weights and cumulative divividend strip weights change when Result 6 is implemented with either the 8-year or 5-year dividend future selected as the maximum maturity. Dividend strip weights are broadly consistent across specifications. As with the impact of bid-ask spreads, we therefore find that the sensitivity of results to adjustments in the maximum maturity of dividends futures is limited.

E. Cashflow expectations: Data construction

This section details of our data construction for near-term earning forecasts, which largely follows the approaches taken in De La O and Myers (2021) and Hillenbrand and McCarthy (2024).

To begin, we download the monthly CRSP data and the "DSP500LIST" file obtained from WRDS that allows us to generate a panel of the S&P constituents along with each firm's price per share, total shares outstanding and thus market capitalisation. We merge this panel with Refinitiv's I/B/E/S Unadjusted Summary Statistics database using the "iclink" file, also obtained from WRDS, which allows us to generate a panel of S&P500 firms with earnings forecasts.

We then interpolate firm-level fiscal year EPS estimates to generate constant maturity forecasts 1-year to 5- years ahead. Because fiscal years don't end at the same time, it is important to interpolate forecasts at a firm-level before aggregating. Around 75 percent of S&P500 firms have fiscal year ending in December, but the other firms have fiscal years closing across a variety of other months in the year. In the interpolation procedure, we allow for extrapolation of up to 11 months. For example, for firm-month observation, if we observe forecasts for fiscal year ends that are 1, 13 and 25 months away, we will use the interpolated 12-month, 24-month and 36-month estimates. However, if the forecasts are for fiscal year ends that are 11 and 23 months away, we will only use the interpolated 12-month and 24-month estimates.

Once we have constant maturity EPS estimates that are for consistent horizons across all firms, we then multiply EPS forecasts by the number of shares outstanding for each firm to get the dollar earnings and aggregate across all firms to get a measure of expected earnings for the S&P500 index constituents where we have EPS forecasts to each horizon. Finally, divide through by an adjusted S&P500 index divisor to generate a EPS measure for the index.[33]

Note that the summary data of the monthly I/B/E/S forecasts is a snapshot of all forecasts made over the previous 30-days, and is taken on the third Thursday of the month (so a bit after the middle of the month). If forecasts occur uniformly between snapshots, the average forecast is thus taken approximately at the end of the month prior to the summary release date. We make this assumption when merging I/B/E/S forecasts with our stock return components.

[33]The index-level is the total market capitalisation of all firms in the index divided by the index divisor. We compute an adjusted divisor that is representative of the sample of firms in our merged CRSP and I/B/E/S dataset by dividing the market capitalisation of the S&P500 firms in our sample over the index price-level.