A Model-Free Term Structure of U.S. Dividend Premiums*

Maxim Ulrich† Stephan Florig‡ Christian Wuchte§

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Abstract

We construct a model-free term structure of dividend risk premiums from option prices and aggregate analyst forecasts. Applying the method to 2004 - 2017 U.S. data, we find it is hump-shaped. Its level increases in business cycle contractions and decreases during expansions. The on average negative dividend term premium steepens in contractions and flattens in expansions, driven by strong variations in short-horizon dividend premiums. Buying the next year of S&P 500 dividends whenever the one-year dividend risk premium is positive has earned twice the Sharpe ratio of the index.

Keywords: Dividend Risk Premium, Dividend Term Structure, Dividend Growth

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†Professor for Financial Economics and Risk Management, Karlsruhe Institute of Technology (KIT), E008, Blücherstr. 17, 76185 Karlsruhe, Germany, Phone: +49 721 608-44270, Email address: maxim.ulrich@kit.edu

‡Stephan Florig, Karlsruhe Institute of Technology (KIT), stephan.florig@kit.edu

§Christian Wuchte, Karlsruhe Institute of Technology (KIT), christian.wuchte@student.kit.edu

1 Introduction

Finding the proper risk-adjusted discount rate for dividends paid at different points in the future is a classical, yet still unresolved, challenge in financial economics.[1] The seminal work of Binsbergen et al. [2012] has shown how to use European index options to construct options-implied expected dividend growth rates of the S&P 500 in a model-free way. The authors show that such growth rates coincide with the spread between expected dividend growth rates and the respective dividend risk premium. In order to compute the expected dividend risk premium in a model-free way, we propose in this paper to approximate expected dividend growth rates with a value-weighted aggregation of company specific dividend forecasts. The dividend forecasts are from the Thomson Reuters I/B/E/S database and cluster at low maturities that do not necessarily match the maturities of the options-implied dividend growth rates. We therefore choose to apply a smooth Nelson and Siegel [1987] interpolation to both growth rates to uncover their respective complete term structures. Such a model-free identification of the dividend risk premium term structure is new to the literature and an alternative to existing approaches that rely either on probabilistic model assumptions or on a short sample of realized returns; see Binsbergen et al. [2012] and Binsbergen et al. [2013], among others.

The survey-implied dividend growth expectations are strong predictors of future dividend growth and superior to popular measures in the dividend growth literature. Their accuracy contributes to the superior predictive power of our expected dividend risk premiums, which are strong predictors of future excess returns on dividend assets. The term structure of the dividend risk premium between January 2004 and October 2017 has been hump-shaped on average. Its level increases during business cycle contractions and decreases in expansions. Yet, the on average negative dividend term premium steepens during contractions and flattens in expansions, driven by strong variations in short-horizon dividend premiums. Our new approach allows us to quantify the term structure of dividend growth and the dividend risk premium without parametric assumptions, in real-time and for arbitrary maturities; three features new to the literature.

Our findings relate to different strands of the literature and can be summarized as follows. First, annual dividend growth rate expectations implied by I/B/E/S dividend estimates are unbiased predictors and explain roughly half of the variation in future annual

[1] Classical contributions of highest importance are Lucas [1978], who shows that the discounted value of future consumption coincides with total wealth; and Gordon [1962], who shows that the discounted value of future dividends coincides with the value of a equity.

dividend growth. Compared to popular models in recent literature of dividend growth, survey-implied growth estimates produce the lowest forecast errors and are free of statistical biases. Options-implied S&P 500 dividend growth rates are, on the other hand, biased predictors, caused by a strongly time-varying, and economically sizable, dividend risk premium. Second, a variance decomposition across maturities unveils that at least 77% of unconditional variations in options-implied dividend growth rates are due to risk premium shocks, whereas a maximum of 23% are due to cash flow shocks.

Third, we shed new light on the conditional time-variation of the hump-shaped, model-free dividend risk premium term structure. We find that investors demand a similar premium for dividends across all maturities during expansionary periods and a higher premium for exposure to near-future dividends during contractionary periods. Yet, the level of the dividend risk premium term structure moves counter-cyclically. Fourth, we find that the implied dividend risk premium is a noteworthy predictor for future returns on dividend assets. It adds predictive information on top of the corrected dividend yield measure of Golez [2014], the SVIX measure derived by Martin [2017] and the price-dividend ratio of dividend strips derived in Binsbergen et al. [2012].

Fifth, we analyze the monthly return profile of a trading strategy that buys the next twelve months of S&P 500 dividends whenever the respective twelve month dividend risk premium is positive. In our sample, this investment strategy earns on average an annualized excess return of 14.95% with a Sharpe ratio of 1.28. We could not find evidence that this sizable average excess return is explained by any of the five Fama and French [2015] risk factors; which contributes to the finding in Binsbergen et al. [2012] that short-term dividend assets are potentially a new asset for cross-sectional asset pricing tests. Once we incorporate transaction costs and once we trade all options at the quoted CBOE bid and ask prices, the Sharpe ratio falls to 0.72, still significantly larger than the 0.36 Sharpe ratio of an S&P 500 investment. Sixth, we also compare the respective excess return of strategies that invest every month into the next 6, 18, 24, 30 and 36 month S&P 500 dividends and find sizable Sharpe ratios and a downward sloping term structure of average excess returns.

In section 2, we derive the dividend risk premium estimate. We discuss our data in section 3 and present our findings in section 4. In section 5, we compare our methodology to alternative approaches in recent literature. Section 6 concludes.

1.1 Related Literature

Our paper complements the new literature on estimating the term structure of expected dividend risk premiums, pioneered by Binsbergen et al. [2012] and Binsbergen et al. [2013]. Binsbergen et al. [2013] identify the term structure of conditional expected dividend risk premiums based on parametric model assumptions.[2] Binsbergen et al. [2012] approximate the unconditional term structure of the dividend risk premium by computing the sample average excess return of a short-term dividend and a dividend steepener trading strategy. Our new approach has the advantage that it provides in real-time a model-free, forward-looking estimate of the full term structure of the conditional expected dividend risk premium.

We also contribute to the literature on equity return predictability (e.g. Fama and French [1992], Lettau and van Nieuwerburgh [2008], Binsbergen and Koijen [2010], Golez [2014], Bilson et al. [2015] and Martin [2017]). Martin [2017] derives an options-implied lower bound on the term structure of the conditional expected equity risk premium and shows it has superior predictive abilities for future realized equity returns. He also argues that the options-implied expected equity risk premium is more volatile than previously thought. Our model-free term structure of expected dividend risk premiums allows a more nuanced view on how the equity risk premium is distributed across the duration spectrum. We confirm that option prices contain valuable information about future returns: our options- and survey-implied dividend risk premium estimate is a superior predictor of future realized dividend returns. In addition, the conditional expected dividend risk premium is volatile, especially for exposure to short-duration dividend risk.

Golez [2014] and Bilson et al. [2015] present important evidence for the usefulness of options-implied dividend yields for predicting equity returns in- and out-of-sample. Our work relates to these important contributions by showing that the embedded expected dividend risk premium is a superior predictor of realized dividend returns and by showing that correcting options-implied dividend yields by expected dividend growth from analyst forecasts predicts future dividend returns better than the options-implied dividend yield alone.

Our paper also contributes to the recent literature that studies time-series variations of dividend risk premiums across the business cycle. Classical asset pricing theories, such

[2]The first assumption is that the unobserved expected dividend growth rate is a linear function of two observed options-implied dividend growth rates. The second assumption is that these options-implied dividend growth rates follow a Gaussian distribution, modeled by means of a VAR(1) model.

as Campbell and Cochrane [1999] and Bansal and Yaron [2004], imply an upward sloping term structure of dividend risk premiums. More recently, theories have been developed that rationalize a downward sloping term structure of dividend risk premiums (e.g. Lettau and Wachter [2007], Croce et al. [2014], Belo et al. [2015]).[3] Empirical evidence on the business cycle variations of the term structure of dividend risk premiums is scarce and inconclusive. Gormsen [2018] presents evidence that the term structure of holding-period equity returns is downward sloping in good times and upward sloping in bad times. Bansal et al. [2017] extract the conditional term structure of the dividend risk premium from dividend futures and a parametric model for dividend growth, to find that the term structure of dividend risk premiums is upward sloping in normal times and downward sloping in recessions. We add to this important literature by showing how to use analyst dividend forecasts from the Thomson Reuters I/B/E/S database to construct a model-free estimate for the term structure of expected dividend growth, allowing a model-free extraction of the dividend risk premium term structure. Looking at its business cycle variations, we document three important features: First, the level of the term structure is counter-cyclical, as both the long-end and short-end decrease (increase) during business cycle expansions (contractions). Second, we find an unconditionally negative dividend term premium, or downward slope, which steepens further during contractions and flattens during expansions. Third, we document that expected risk premiums for short-duration dividends react stronger to business cycle shocks than risk premiums for long-duration dividends.

Our methodology of constructing the term structure of conditional expected dividend risk premiums adds to the implied-cost of capital literature that is actively used by finance and accounting researchers. Early work has used realized returns or dividend yields to estimate a firm's cost of capital (e.g. Foerster and Karolyi [1999], Foerster and Karolyi [2000], Errunza and Miller [2000]). More recently, that literature has used the dividend discount model and a firm's stock price and expected future dividends from analysts to uncover the implied-cost of capital by means of the internal rate of return (e.g. Hail and Leuz [2009]).[4] Pastor et al. [2008] and Li et al. [2013] show that such internal rate of returns are indeed useful in capturing conditional variations in expected equity returns. It is worth noticing that the internal rate of return in the dividend discount model aggregates the complete term structure of expected dividend risk premiums into one number. Our contribution to that literature is to show how to derive in each point in time the model-free

[3] See also Eisenbach and Schmalz [2013], Nakamura et al. [2013], Hasler and Marfe [2016], and Andries et al. [2018], among others.

[4] Other influential studies are Claus and Thomas [2001], Gebhardt et al. [2001], Easton [2004], and Ohlson and Juettner-Nauroth [2005].

complete term structure of expected dividend risk premiums. Such data allows for a more nuanced view on how corporate decisions affect the expected evolution of the firms' cost of capital.

Our paper also contributes to the literature on biases in analyst forecasts. That literature has focused on documenting and sub-sequentially rationalizing why average analyst earnings forecasts are upward biased. Early work has documented that analyst earnings forecasts are on average optimistically biased (e.g. Brown et al. [1985], Stickel [1990], Abarbanell [1991], Berry and Dreman [1995], and Chopra [1998]]). There are three lines of explanation. First, analysts suffer from cognitive failures that lead to over- and under-reaction to good and bad earnings news (e.g. Easterwood and Nutt [1999]).[5] Second, analysts have pay and career related incentives to publish overly optimistic earnings forecasts (e.g. Hong and Kubik [2003]).[6] Third, analysts trade-off a positive forecast bias to improve access to management and forecast precision to produce forecasts with the minimum expected squared prediction error. Abarbanell and Lehavy [2003] shows that while the average earnings forecast is upward biased, the median earnings forecast is right on target. Our work relates to this strand of the literature as we focus on analysts dividend forecasts, as opposed to earnings forecasts. Point estimates for our regression results confirm that the average I/B/E/S dividend forecast for the S&P 500 is overly optimistic, yet statistically speaking, we cannot reject a zero bias. The point estimate for the median forecast error is very close to zero. To the best of our knowledge we are the first to document that the upward bias in mean analyst dividend forecasts for the S&P 500 disappears as the analyst coverage ratio of the total S&P 500 market capitalization approaches 100%.[7]

[5] De Bondt and Thaler [1990] argue that analysts have a behavioral tendency to overreact. Mendenhall [1991], Abarbanell and Bernard [1992] and Klein [1990] provide evidence that analysts underreact to past earnings and return information. Easterwood and Nutt [1999] present evidence that analysts have a behavioral tendency to underreact to negative earnings news and overreact to positive earnings news.

[6] There has also been empirical evidence that analysts are rewarded by their brokerage houses for overly optimistic forecasts (e.g. Dugar and Nathan [1995], Dechow et al. [2000], Lin and McNichols [1998], Michaely and Womack [1999]). Hong and Kubik [2003] analyze earnings forecasts of 12,336 analysts who covered in total 8,441 firms during the period 1983 and 2000. The authors conclude that while forecasting accuracy appears to be the main driver of an analyst's career, optimistic forecasts relative to the consensus are also rewarded; especially during the stock market boom of the late 1990s.

[7] Since July 2009, we find I/B/E/S fiscal year one dividend forecasts for companies which together contribute on average 98.4% to the market capitalization of the S&P 500.

2 Model-Free Dividend Premium Estimates

We follow the exposition in Binsbergen et al. [2013] to show that the dividend risk premium coincides with the spread between the expected dividend growth rate under $\mathcal{P}$ and $\mathcal{Q}$, where $\mathcal{P}$ denotes the physical probability measure and $\mathcal{Q}$ denotes the risk-neutral one.

Let $n > 0$ be the maturity of a dividend payment, denoted as D_n. We denote the $\mathcal{P}$ expectation at time t about an uncertain dividend payout in $t+n$, D_{t+n}, as $D^P_{t,n}$. Likewise, the $\mathcal{Q}$ expectation at time t about D_{t+n} is denoted as $D^Q_{t,n}$. Formally, the definition reads

$$D^P_{t,n} \equiv E^P_t\left[D_{t+n}\right] \qquad \text{and} \qquad D^Q_{t,n} \equiv E^Q_t\left[D_{t+n}\right]. \tag{1}$$

We denote the continuously compounded expected dividend growth rate from t to $t+n$ as $g^P_{t,n}$ and $g^Q_{t,n}$, depending on whether the expectation is taken with regard to $\mathcal{P}$ or $\mathcal{Q}$:

$$g^P_{t,n} \equiv \frac{1}{n}\ln\left(\frac{D^P_{t,n}}{D_t}\right) \qquad \text{and} \qquad g^Q_{t,n} \equiv \frac{1}{n}\ln\left(\frac{D^Q_{t,n}}{D_t}\right). \tag{2}$$

Let $S_{t,n}$ be the time t net present value of D_{t+n}. Based on risk-neutral pricing, $S_{t,n}$ coincides with

$$S_{t,n} \equiv D^Q_{t,n}e^{-ny_{t,n}} = D_t e^{n(g^Q_{t,n}-y_{t,n})}, \tag{3}$$

where $y_{t,n}$ is the time t value of the continuously compounded risk-free bond yield with time to maturity n. On the other hand, $S_{t,n}$ also coincides with the expected discounted present value of D_{t+n}, where the risk-free rate and the dividend risk premium make up the discount rate, i.e.

$$S_{t,n} \equiv D^P_{t,n}e^{-n(y_{t,n}+z_{t,n})} = D_t e^{n(g^P_{t,n}-y_{t,n}-z_{t,n})}, \tag{4}$$

where $z_{t,n}$ is the time t premium for dividend risk between t and $t+n$. Matching the last two equations and solving for $z_{t,n}$ reveals

$$z_{t,n} = g^P_{t,n} - g^Q_{t,n}, \tag{5}$$

which says that the spread between the $\mathcal{P}$ and $\mathcal{Q}$ expectation of expected dividend growth coincides with the respective dividend risk premium. A model-free estimate for $z_{t,n}$ requires a model-free estimate for $g^P_{t,n}$ and $g^Q_{t,n}$. We now show that one can use survey forecasts to estimate $g^P_{t,n}$ and index options to estimate $g^Q_{t,n}$. Applying a Nelson and Siegel [1987] interpolation allows us to infer the full maturity spectrum of both quantities. Such a model-free identification of $z_{t,n}$ is straight-forward, yet, new to the literature and an alternative to existing approaches which rely on probabilistic model assumptions, such as Binsbergen et al. [2012] and Binsbergen et al. [2013].

2.1 Dividend Growth Implied by Survey Estimates

The literature relies mainly on time-series models for estimating $g^P_{t,n}$, see Ang and Bekaert [2007] and Da et al. [2015], among others. In recent work, De la O and Myers [2017] construct one-year and two-year survey-implied expectations of S&P 500 dividends from the Thomson Reuters I/B/E/S Estimates Database by aggregating analyst dividend estimates for individual firms in the S&P 500 on a quarterly basis. This approach has been used before with earnings estimates in several studies on the implied cost of capital. Among them are Pastor et al. [2008] and Li et al. [2013], who aggregate single company estimates to a market-wide measure. We report key statistics of our data in table 1. To illustrate the accuracy, we show in figure 1 that one year trailing S&P 500 dividends from return differences between the total return and normal return index match accurately with our aggregate value of realized dividends from I/B/E/S reports. We follow the methodology in De la O and Myers [2017] and construct empirical expectations $D^P_{t,n}$ for dividends paid over the next 12 and 24 months, i.e.

$$D^P_{t,12} \equiv E^{IBES}_t \left[D_{t+12}\right] \qquad \text{and} \qquad D^P_{t,24} \equiv E^{IBES}_t \left[D_{t+24}\right]. \tag{6}$$

We complement these near-future estimates with the I/B/E/S long term (LT) earnings growth median estimates as a proxy for the long term dividend growth estimate, assuming that the aggregate expected payout ratio remains constant over the future. According to Thomson Reuters, the long-term earnings growth estimate is assumed to be realized over a period corresponding in length to the company's next full business cycle, in general a period between three to five years (see Reuters [2010]). We set the corresponding n to 60 months:

$$g^P_{t,60} \equiv E^{IBES}_t \left[g_{t,LT}\right].$$

Next, we apply equation (2) to back out the survey-implied expected dividend growth rates for horizons 12 and 24 months. In contrast to De la O and Myers [2017], we recover the full maturity spectrum of $g^P_{t,n}$ by means of a smooth Nelson and Siegel [1987] interpolation, which is a popular interpolation scheme in the fixed-income literature. For each point in time t, we use four data points to estimate the four parameters of the Nelson and Siegel [1987] interpolation defined in the equation below. The first data point is current dividend growth. We define current dividend growth, as it is common in the literature, to coincide with annual growth in 12-month trailing dividends. We treat current growth as a proxy for the one day ahead growth expectation $g^P_{t,\frac{1}{30}}$ to calibrate the very short end. The other points used in the interpolation are growth forecasts implied by the I/B/E/S estimates, $g^P_{t,12}$, $g^P_{t,24}$ and $g^P_{t,60}$:

$$g^P_{t,n} = \delta_{0,t} + \delta_{1,t}\frac{1-e^{-n\lambda_t}}{n\lambda_t} + \delta_{2,t}\left(\frac{1-e^{-n\lambda_t}}{n\lambda_t} - e^{-n\lambda_t}\right). \tag{7}$$

The free parameters $\delta_{0,t}$, $\delta_{1,t}$, $\delta_{2,t}$ and λ_t are estimated for each time period t using data on $g^P_{t,\frac{1}{30}}$, $g^P_{t,12}$, $g^P_{t,24}$ and $g^P_{t,60}$. The estimation approach is considered standard in the fixed-income literature, and summarized in appendix A of our paper.

The advantages of using survey-implied I/B/E/S dividend forecasts instead of traditional time-series methods are fourfold. First, I/B/E/S forecasts do not rely on probabilistic model assumptions and are not prone to model risk. Second, these forecasts get updated monthly and incorporate all quantitative and qualitative information that a forecaster finds useful for assessing future dividend payments of a firm. Third, I/B/E/S forecasts are forward-looking. Lastly, aggregate I/B/E/S dividend median estimates are superior to other popular approaches to predict S&P 500 dividends, as we show in section 4.1.

2.2 Dividend Growth Implied by Option Prices

Several noteworthy contributions have been made recently to the measurement of expected dividends under the risk-neutral probability measure $\mathcal{Q}$, we refer to Binsbergen et al. [2012], Golez [2014] and Bilson et al. [2015], among others. We follow Bilson et al. [2015] and exploit put call parity to infer the options-implied dividend yield $y^d_{t,n}$. Put call parity in 'dividend yield' representation reads

$$C_{t,n} - P_{t,n} = S_t e^{-ny^d_{t,n}} - Ke^{-ny_{t,n}}, \tag{8}$$

where $C_{t,n}$ and $P_{t,n}$ is the price at time t of a n maturity call and put option on S_t, respectively. S_t is the value of the stock index of interest and K is the strike of both option contracts. Solving for $y^d_{t,n}$ reveals

$$y^d_{t,n} = \frac{1}{n}\left(\ln(S_t) - \ln(C_{t,n} - P_{t,n} + Ke^{-ny_{t,n}})\right), \tag{9}$$

where maturities n, for which we obtain dividend yields $y^d_{t,n}$, coincide with the available option maturities at time t. In addition to Bilson et al. [2015], we apply a Nelson and Siegel [1987] interpolation to all observed $y^d_{t,n}$ to recover the full maturity spectrum of options-implied dividend yields. Hence, instead of assuming a constant slope between two observed values of $y^d_{t,n}$, we fit for each time point t the following smooth Nelson and Siegel [1987] interpolation

$$y^d_{t,n} = \tilde{\delta}_{0,t} + \tilde{\delta}_{1,t} \frac{1 - e^{-n\tilde{\lambda}_t}}{n\tilde{\lambda}_t} + \tilde{\delta}_{2,t} \left(\frac{1 - e^{-n\tilde{\lambda}_t}}{n\tilde{\lambda}_t} - e^{-n\tilde{\lambda}_t} \right). \tag{10}$$

The parameters $\tilde{\delta}_{0,t}$, $\tilde{\delta}_{1,t}$, $\tilde{\lambda}_t$ and $\tilde{\delta}_{2,t}$ are estimated by least-square methods, based on all observed dividend yields. Further details on the estimation are summarized in appendix A of our paper. We show in section 5.1 that our short-horizon estimates are almost the same if we apply a linear interpolation.

Based on the full maturity spectrum of $y^d_{t,n}$, we determine the respective values for $g^Q_{t,n}$ as follows. As in Binsbergen et al. [2012], we let $V_{t,n}$ be the price of a dividend asset that pays all future dividends up to $t + n$, i.e.

$$V_{t,n} := \sum_{i=1}^{n} S_{t,i}. \tag{11}$$

Put call parity in ‘present value’ representation reads

$$C_{t,n} - P_{t,n} = S_t - V_{t,n} - Ke^{-ny_{t,n}}. \tag{12}$$

We now subtract equation (8) from equation (12) and solve for $V_{t,n}$ to arrive at

$$V_{t,n} = S_t \left(1 - e^{-ny^d_{t,n}}\right). \tag{13}$$

Finally, the term structure of $D^Q_{t,n}$ coincides with

$$D^Q_{t,n} = (V_{t,n} - V_{t,n-1})\, e^{ny_{t,n}}, \tag{14}$$

which provides us directly with the full maturity spectrum of the options-implied expected dividend growth rate $g^Q_{t,n}$.

3 Data and Dividend Trading Strategy

We estimate the term structure of the dividend risk premium with data from the most common sources found in the empirical literature on dividends. Here we describe in detail all the ingredients to replicate our results. Furthermore, we show how to set-up a trading strategy that costs $V_{t,n}$ and that pays S&P 500 dividends from t to $t + n$.

3.1 Data Source and Data Selection

We follow the advice in Hull and White [2013] and proxy the term structure of the risk-free rate, $y_{t,n}$, with the U.S. Dollar Overnight Index Swap (OIS) rate. We take the OIS term structure with maturities of 1 day to 10 years from Bloomberg. Hull and White [2013] advocate the use of overnight rates for derivatives discounting and note that since the Great Recession, more and more banks use OIS rates to price collateralized positions. We discuss alternative rate choices and show estimates obtained with LIBOR rates in section 5.2.

We construct expected S&P 500 dividend growth rates, $g^P_{t,n}$, from single company dividend estimates as reported in the Thomson Reuters I/B/E/S database. We find the CUSIP identifier of all index constituents for the S&P 500 index on the last day of each month in Bloomberg. For each CUSIP in our sample, we then use Thomson Reuters Datastream to download the following quantities: (i) number of shares outstanding (IBNOSH), (ii) dividends per share (DPS), (iii) price (P), (iv) end dates of quarter one, two, three and four as well as fiscal year one, two and three (DPSI1YR, DPSI2YR, DPSI3YR, DPSI4YR, DPS1D, DPS2D, DPS3D), (v) the corresponding dividend per share median estimates (DPSI1MD, DPSI2MD, DPSI3MD, DPSI4MD, DPS1MD, DPS2MD, DPS3MD) and (vi) the long term operating earnings growth median estimate (LTMD). As can be seen from figure 2, the fiscal year one single company I/B/E/S dividend forecasts cover at least 95% of the market capitalization of the S&P 500 since July 2009. Prior to that, the coverage ratio has increased from 74% in January 2004 to 95% in June 2009. In order to overcome noise in dividend forecasts that arise from a low coverage ratio at the beginning of our sample, we are going to report selected statistics not only for the full sample, but also for the time after June 2009.

We construct model-free estimates of options-implied S&P 500 dividend growth forecasts, $g^Q_{t,n}$, as follows. We use CBOE intra-day trade quotes on S&P 500 index options with standard monthly expiration to extract the present values of expected dividends over different horizons for the period between January 2004 and October 2017. The price of the underlying S&P 500 index level corresponding to each option trade is also provided by the CBOE. We match options and underlying as follows. We use intra-day data from the last ten trading days of a month, see Golez [2014] and Bilson et al. [2015] for published work applying similar filters. Alternative choices such as the last trading day of a month (Binsbergen et al. [2012]) or end of day quotes have only a minor impact on the resulting dividend yields and dividend risk premiums. We consider all option trades between 10 am and 2 pm, a moneyness between 0.9 and 1.1, a remaining maturity of at least five days and a non-negative dividend yield. Then we match call and put prices with the same strike and maturity if they are traded within the same minute and share the same underlying price.

3.2 Earning the Dividend Risk Premium

To earn the dividend risk premium associated with all dividends paid between t and $t+n$, one can go long the dividend asset $V_{t,n}$. Equation (12) shows how to invest into this asset, whose only future cash flows are the realized dividends between t and $t+n$:

$$-V_{t,n} = P_{t,n} - C_{t,n} + S_t - Ke^{-ny_{t,n}}. \quad (15)$$

Going long the dividend asset $V_{t,n}$ is equivalent to buying a put and shorting a call on the S&P 500, both with strike K and maturity n, as well as buying the index at price S_t and taking a short position in the money market with a notional of K. As the pay-off of the right hand side will be exactly zero upon maturity, the only risk associated with this trade is linked to the uncertain dividends paid between t and $t+n$, which the holder of $V_{t,n}$ receives.

We test two monthly trading strategies which involve investing into the upcoming 12-month ahead dividends. *Strategy A* buys $V_{t,12}$ at the end of each month t. *Strategy B* invests into $V_{t,12}$ at the end of a month if the condition

$$z_{t,12} > 0$$

holds, which is equivalent to a trade execution if $g^P_{t,12} > g^Q_{t,12}$. Intuitively, investment strategy B buys the next 12 months' dividends if (I/B/E/S) dividend estimates are higher than the options-implied dividends. We also add transaction costs to both strategies. These costs take into account bid and ask quotes. For trading the underlying, we assume a total expense ratio of 0.07% per year and an average bid ask spread of 0.01%, as it is common for large ETFs on the S&P 500. For options, we include transaction costs by working with the actual bid and ask prices from the CBOE option database.

4 Findings

Our findings shed new light on aggregate analyst dividend forecasts and the term structure of dividend risk premiums. We document that aggregate analyst dividend forecasts are unbiased and of higher accuracy than other popular measures of the literature. The on average negative slope of the dividend risk premium steepens further during contractionary periods and flattens during business cycle expansions. These business cycle variations stem largely from the short end of the term structure.

4.1 Survey- and Options-Implied Dividend Growth Estimates

Table 2 summarizes the sample mean and standard deviation for one-year, two-year and long-term estimates of $g^P_{t,n}$ and $g^Q_{t,n}$. The average $g^P_{t,n}$ has been close to 10% across all maturities. During the Great Recession, we find a strong decrease in the short end of the term structure of $g^P_{t,n}$. The one-year expectation decreased by almost two thirds to 3.60%, while the long-term estimate increased slightly to 10.74%. Options-implied growth rates are on average negative and of decreasing magnitude with increasing maturity. The average one-year and long-term estimate of $g^Q_{t,n}$ have been -8.91% and -2.67%, respectively. During the Great Recession, these numbers fell to -39.59% and -5.86%. Looking at the standard deviations of $g^Q_{t,n}$ and $g^P_{t,n}$ reveals that options-implied growth is on average twice as volatile as survey-implied growth.

We separately assess whether $g^P_{t,12}$ and $g^Q_{t,12}$ are accurate expectations of future annual dividend growth, denoted as $g_{t,t+12}$, by the following regressions:

$$g_{t,t+12} = a^g + b^g X_t + \epsilon^g_{t+12}, \qquad \epsilon^g_{t+12} \sim i.i.d.(0, \sigma^2_g), \qquad X_t \in \{g^P_{t,12}, g^Q_{t,12}\}. \tag{16}$$

The results of these regressions are summarized in table 3. Notice, X_t is an unbiased predictor for $g_{t,t+12}$ if the respective a^g and b^g estimates are zero and one, respectively. While $g^Q_{t,12}$ explains 53.2% of variations in $g_{t,t+12}$, it is a biased predictor, with a significant estimate of $a^g = 10.72$ and an estimate of $b^g = 0.39$ that is significantly smaller than one. For $g^P_{t,12}$, we find a R^2 of 43.5%, an insignificant estimate of $a^g = -2.34$ and an estimate of $b^g = 0.97$ that is statistically not different from one. Consistent with asset pricing theory, $g^P_{t,12}$ captures the conditional and unconditional level of $g_{t,t+12}$, whereas $g^Q_{t,12}$ is biased because it contains the dividend risk premium $z_{t,12}$.[8] All in one, we find that $g^P_{t,12}$ is an unbiased predictor for $g_{t,t+12}$, while $g^Q_{t,12}$ is not. The slightly higher R^2 for $g^Q_{t,12}$ implies that $z_{t,12}$ has predictive information for $g^P_{t,12}$.

We perform a more extensive analysis on forecast biases in section 5.3 and compare $g^P_{t,12}$ to other popular measures of dividend growth in section 5.4.

[8]The documented bias is consistent with a different, yet important, literature on the rejection of the expectation hypothesis for Treasury yields (e.g. Fama and Bliss [1987], Stambaugh [1988], Campbell and Shiller [1991], Cochrane and Piazzesi [2005], and Piazzesi and Swanson [2008]).

4.2 Implied Dividend Risk Premium Estimates

Figure 3 displays our estimate of the average term structure of the dividend risk premium, which we find to be hump-shaped. The shape is consistent with arguments in Binsbergen et al. [2012] and Golez [2014]. The hump-shape mirrors the term structure of $g_{t,n}^{Q}$ and implies that near-term dividends pay a small dividend premium, while the dividend premium builds up and peaks at 19% for dividends arriving in 13 months.

Figure 4 plots the time-series estimates for the one-year, two-year and long term dividend risk premium. Especially the short maturity dividend risk premiums vary considerably around their sample mean. The strongest variation arises at the peak of the Great Recession, where $z_{t,12}$ peaks at 89% in November 2008. The respective peak in $z_{t,24}$ happens at the same point in time, but less dramatically at 53%, while the estimate of the long-term dividend risk premium spikes at 19%.[9]

The importance of dividend risk premium variations in options-implied dividend growth estimates is confirmed in figure 5, which depicts the time-series for $g_{t,12}^{Q}$, $g_{t,12}^{P}$ and $z_{t,12}$. It is evident that variations in physical growth expectations are rather slow moving, while variations in dividend risk premiums cause most of the variations in options-implied dividend expectations. The substantial drop in options-implied dividend growth during the Great Recession is mainly due to an upward jump in dividend risk premiums. To formalize this observation, we compute the contribution of both growth expectations $g_{t,n}^{P}$ and $z_{t,n}$ to the variance in $g_{t,n}^{Q}$,

$$var(g_{t,n}^{Q}) = cov(g_{t,n}^{Q}, g_{t,n}^{P}) - cov(g_{t,n}^{Q}, z_{t,n}). \tag{17}$$

At the one-year horizon, we find that growth expectations account for 23% of variation in options-implied dividend growth rates, while variations in the dividend risk premium account for 77%. The dominance of risk premium shocks increases with the maturity of the dividend payment. Figure 4 also highlights that the negative slope for maturities beyond 13 months steepens in times of turmoil. This feature is intuitive, as these business cycle downturns are relatively short-lived, creating uncertainty particularly around near-future dividends and an increased compensation for bearing this risk. Despite the average downward slope for maturities beyond 13 months, there are some instances when the term structure of $z_{t,n}$ seems to be flat or with a positive slope. We have a closer look on the behavior of the term structure during business cycle fluctuations in section 4.4.

[9] The SVIX-implied lower bound for the expected equity risk premium (Martin [2017]) peaks at the same time. We assess the predictive power of the SVIX and our dividend risk premium in section 4.3.

4.3 Returns on Dividend Assets

In this section, we will assess the predictability of returns on dividend assets with different maturities. Dividend assets have a determined maturity, paying the dividends over a certain horizon n and no dividends thereafter. A standard equity asset entitles the investor to receive all future dividends over the life of the firm or index, and can therefore be seen as an asset that pays dividends up to $n = \infty$. We define the return of a dividend asset with maturity n over holding-period h, where $h \leq n$, to be

$$r^n_{t,t+h} := \ln\left(\frac{V_{t+h,n-h} + \sum_{i=1}^{h} D_{t+i}}{V_{t,n}}\right). \tag{18}$$

The holder of the dividend asset with price $V_{t,n}$ is entitled to receive the entire stream of dividends over the holding period h and the present value of the remaining dividends at the end of the holding period. If maturity n and holding period h coincide, the holder receives the entire stream of dividends over the life of the asset, which then matures with a value of zero.

Our analysis focuses on returns of investment strategy A. We also consider returns of the S&P 500 index, a dividend asset with theoretically infinite ($n = \infty$) maturity, to complement our analysis.

Let $xr^{12}_{t,12}$ be the excess return of investment strategy A: The investor pays the price of the one-year dividend asset $V_{t,12}$ to receive the t to $t+12$ dividend stream of the S&P 500, i.e.

$$xr^{12}_{t,12} := \ln\left(\frac{\sum_{i=1}^{12} D_{t+i}}{V_{t,12}}\right) - y_{t,12} \times 12. \tag{19}$$

We now compare how well our model-free dividend risk premium estimate $z_{t,12}$ predicts excess returns of strategy A, relative to other popular measures in recent literature. Among the predictive signals we compare is the realized annual market excess return MKT_t, which by construction has a strong correlation with the realized annual return of the S&P 500, see Fama and French [2015] for details on the time series. We include the one-year corrected dividend price ratio $dp^{corr}_{t,12}$, following the derivation in Golez [2014]. Golez [2014] corrects the standard dividend price ratio of equity for options- and future-implied dividend growth expectations and finds that this variable predicts equity returns significantly better than the standard dividend price ratio. As we do not have futures data, we use his approach to correct the dividend price ratio, but with option data alone. In a third comparison, we consider the one-year $SVIX_{t,12}$ measure of the equity premium derived by Martin [2017]. Martin [2017] argues that the SVIX index, a measure of risk-neutral variance derived from index option prices, provides a lower bound on the equity premium over different investment horizons. His measure shares a positive correlation of 0.29 with our risk premium estimate, and both peak in November 2008. We complement the analysis with the one-year log price dividend ratio of the dividend asset $pd^{strip}_{t,12}$, which as shown by Binsbergen et al. [2012] is a strong predictor for returns on dividend assets.

We regress the monthly return series of $xr^{12}_{t,t+12}$, separately, onto each of the mentioned predictive variables,

$$xr^{12}_{t,12} = \alpha + \beta X_t + \epsilon^d_{t+12}, \qquad \epsilon^d_{t+12} \sim i.i.d.(0, \sigma^2_d), \tag{20}$$

with

$$X_t \in \{z_{t,12},\ MKT_t,\ dp^{corr}_{t,12},\ SVIX_{t,12},\ pd^{strip}_{t,12}\}. \tag{21}$$

Table 4 displays that $z_{t,12}$, $pd^{strip}_{t,12}$ and $dp^{corr}_{t,12}$ are the best predictors of the excess return of strategy A, with predictive R^2 values around 70% and mean absolute errors of approximately 6%.

For two reasons, we now analyze separately the 100 months between the Great Recession and the end of our sample. First, we have insufficient coverage in our analyst forecasts during the first years of our sample, which can lead to inaccurate growth estimates, as figure 2 highlights. Second, we want to see whether the strong predictive power might be due to extreme volatility during the Great Recession. In the lower panel of table 4, we document that survey forecasts substantially add to the predictability of dividend returns,

$$\begin{array}{ccccccc} xr^{12}_{t,12} & = & \underset{(1.13)}{0.73} & + & \underset{(0.04)}{1.01}\, z_{t,12} & + & \epsilon^d_{t+12}, \qquad R^2 = 92.8\%, \end{array} \tag{22}$$

as the β of 1.01, the low mean absolute error of 1.76% and large R^2 of 92.8% suggest. While the results in the lower panel of table 4 point towards a negative effect of insufficient data coverage in the early part of the sample, we acknowledge the possibility that 100 observations of overlapping data might result in inflated R^2 values.

The previous analysis considered the informational content in $z_{t,12}$ about the dividend risk premium for dividend payments within one year. We now ask whether $z_{t,12}$

is useful to predict the return on the S&P 500 over the next 12 months. We define the one-year excess return on the index as

$$xr^{\infty}_{t,12} := \ln\left(\frac{S_{t+12} + \sum_{i=1}^{12} D_{t+i}}{S_t}\right) - y_{t,12} \times 12.$$

Table 4 reports the results of this analysis. Regardless of whether we look at the full sample or the time after the Great Recession, our results document that it is more challenging to predict returns on the index relative to returns on short-term dividend assets. All respective R^2 are zero or close to zero and the respective β's are statistically speaking zero. The best prediction results are associated with the corrected dividend price ratio (Golez [2014]) with an R^2 of 4.1%, and a 1.67 t-statistic for its β estimate.

We also regress both one-year excess returns on the annual five Fama and French [2015] factors MKT_t, SMB_t, HML_t, RMW_t, and CMA_t for our entire sample period and summarize the outcome in table 5. Notice, here we regress current, not future, excess returns on the factors. This analysis allows us to see whether excess returns at the different ends of the term structure can be explained by one or multiple common style factors. We find that 99.6% of the variation in realized S&P 500 excess returns, but only 4.9% of the variation in returns of strategy A are explained by the Fama and French [2015] factors. In addition, none of those factors is a significant explanatory variable for excess returns of strategy A.

4.4 The Impact of Business Cycle Variations

Does the term structure of expected dividend risk premiums fluctuate with the business cycle? Several studies on the term structure of the equity risk premium (see Binsbergen and Koijen [2017] and Gormsen [2018] for recent contributions) consider realized one-year returns during different stages of the business cycle. Unlike realized one-year excess returns, our premium estimates represent expected excess returns earned over the entire life of the dividend asset, similar to the exposition in Bansal et al. [2017]. Our dividend risk premium is conceptually similar to the risk premium in the term structure of bond yields, in the sense that the n-year premium represents the expected excess return earned over the life of the asset.[10] To formalize the relation of our premium estimates to business cycle variations, we characterize expansionary (contractionary) periods by industrial production

[10] A recent bond market study by Crump et al. [2018] shows how survey-forecasts on future short-rates can be used to obtain a forward-looking and model-free estimate of bond risk premiums.

growth being above (below) its sample median. For robustness, we complement industrial production growth ip_t with two alternative measures to determine the current state of the economy: the log dividend price ratio dp_t (see Gormsen [2018]) and our survey-implied growth estimate $g^P_{t,12}$. The results are qualitatively and quantitatively similar, independent of how we measure business cycle variations. We discuss results for a classification according to industrial production growth and refer to table 6 for further results.

We find that the level of the term structure of the dividend risk premium moves counter-cyclically; it falls during expansions and increases during contractions. The top panel of figure 6 quantifies that the short-end (long-end) of the dividend risk premium term structure falls by 4.45% (1.16%) during business cycle expansions, whereas it increases by 4.60% (0.96%) during business cycle contractions. These counter-cyclical movements of the level of the term structure are statistically significant.

We measure the dividend term premium as the spread between the ten-year and one-year premium estimate and find an average of -6.48% over the entire sample. As the dividend term structure steepens further during contractions, we find an average term premium of -10.12% during these periods. The term premium narrows down to -3.09% during business cycle expansions. In order to assess the cyclical behavior of the dividend term premium, we regress it separately on each of our different economic indicators, $X_t \in \{ip_t, dp_t, g^P_{t,12}\}$, i.e.

$$z_{t,120} - z_{t,12} = \alpha + \beta X_t + \epsilon_t, \qquad \epsilon_t \sim i.i.d.(0, \sigma^2). \tag{23}$$

Table 7 reports our different estimates for β. The positive and significant estimate of $\beta = 1.07$ for $X_t = ip_t$ suggests that the on average negative term premium flattens with an increase in production growth and steepens during business cycle contractions. The same pro-cyclical pattern can be found in the regression on the log dividend price ratio, $X_t = dp_t$, where a significant $\beta = -0.35$ suggests an expected further steepening of the negative term premium in times of asset market turmoil. The term premium regression estimate for β when $X_t = g^P_{t,12}$ is not significant, but its positive sign is well in line with the other estimates.

4.5 The Role of Transaction Costs

The annualized Sharpe ratio of investment strategy A has been 1.08 before transaction costs. The analogous Sharpe ratio of investment strategy B has been 1.16.

Naturally, Sharpe ratios drop if one accounts for costs from trading and holding the underlying or for buying and selling options. Table 8 summarizes our findings when including costs into strategies A and B. We find that adding costs to transact and hold the underlying (a total expense ratio of 0.07% per year and an average bid ask spread of 0.01% as they can be found for very liquid ETFs during the entire sample period) reduces the Sharpe ratios of strategy A and B to 0.76 and 0.84, respectively. Sharpe ratios fall further once we include transaction costs for the call and put positions. Using quoted bid and ask prices of the respective calls and puts, we find that the Sharpe ratio of investment strategy A drops to -0.18. Investment strategy B's Sharpe ratio remains large at 0.72, which statistically speaking, using Opdyke [2008] standard errors, is significantly larger than a buy and hold investment in the index, achieving a Sharpe ratio of 0.36 over the same period. Investment strategy B produces such high Sharpe ratios even when accounting for transaction costs because the dividend risk premium is a good predictor of the future dividend excess return, see section 4.3 for details.

Once we use actual bid and ask option prices in its inference, we immediately reflect trading costs in our investment decision. Including the trading costs leads to fewer trade executions at the beginning of our sample, when bid ask spreads in options and borrowing costs were higher than at the end of the sample. Higher bid ask spreads lead to a higher options-implied present value of future dividends. This translates into higher growth expectations under the risk neutral measure than with small bid ask spreads and the implied dividend risk premium is hence more often negative, a signal not to engage in the trade. With higher option market liquidity over the past few years, the bid ask spread plays a minor role and has led to significantly higher returns at the end of our sample. The large difference between survey-implied and options-implied growth expectations during the crisis resulted in relatively cheap short-term dividend assets, such that the strategy was able to generate profits during the financial turmoil of 2008. We also compute the average excess return, standard deviation and Sharpe ratio for investment strategy A where we invest into the next $k \in \{6, 12, 18, 24, 36\}$ months of dividends, holding each asset until maturity. The results are displayed in table 9 and confirm our previous findings. Independent of the precise maturity of the investment strategy, the Sharpe ratios are of similar magnitude. The average excess returns do also provide evidence for a downward sloping term structure of dividend risk premiums.

5 Comparison to Previous Studies

To the best of our knowledge, we are the first to provide a model-free and real-time estimate of the dividend risk premium for different maturities. We depart from standard approaches commonly seen in the literature, such as econometric models for dividend growth and linear interpolation of options-implied values. In section 5.1, we show that the choice of the interpolation scheme is irrelevant for short-term estimates. Section 5.2 is dedicated to the impact of a different discount rate on our results. We discuss potential biases in our dividend growth estimates and compare them to findings in previous literature on earnings biases in section 5.3. In section 5.4, we compare the survey-implied estimate $g^P_{t,n}$ to popular econometric measures of future dividend growth and conclude that survey-implied growth estimates are superior in terms of mean absolute prediction errors and variance explained. We compare our dividend risk premium estimates to Binsbergen et al. [2013] in section 5.5.

5.1 Alternative Interpolation Schemes

Linear regressions or linear interpolations between neighboring points are often sufficient to infer desired maturities and applied in related work, such as Martin [2017] and Binsbergen et al. [2012]. If term structures are not simply linear, e.g. characterized by level, slope and curvature, these approaches might be inaccurate. In addition, these approaches might not be able to capture information in the available maturities to extrapolate longer maturities reasonably well. The Nelson and Siegel [1987] interpolation scheme, on the other hand, succeeds in this and is of similar simplicity, which is why it is well established in the fixed income literature (see Diebold and Li [2006]) and our method of choice. We compare our results obtained with this approach to a simple linear interpolation and conclude that the differences at the short-end, in particular the one year estimates, are negligible. Figure 7 illustrates the implied present values from both approaches for a horizon of one year and compares these to aggregate survey estimates. The average present values across the entire sample period are USD 26.85 for the linear interpolation, USD 26.90 for the Nelson and Siegel [1987] scheme and USD 33.44 for the aggregate survey estimates. These values lead to an average difference in implied dividend risk premiums of 0.03%. We therefore conclude that our hump-shaped pattern and magnitude of options-implied dividend growth over short to mid-term horizons is robust to the choice of the interpolation scheme.

5.2 Alternative Risk Free Rates

In this paper, we follow the arguments of Hull and White [2013] with regard to the choice of the risk-free interest rate. The replication strategy for the present value of future dividends, we refer to equation (15), involves a short-position K in the money-market. Using rates such as LIBOR, which since the Great Recession are subject to a substantial credit risk component, would project the borrower's credit risk into the estimate of the present-value of future dividends. Therefore, among practitioners, the OIS curve has increasingly become the new risk-free rate benchmark (Hull and White [2015]).

In this section, we will discuss alternative estimates of the dividend risk premium when using LIBOR rates as the risk-free rate. We replicate all relevant figures in the online appendix to this paper and restrict our analysis to the most important results.

With an increased spread between LIBOR and OIS rates, we find a substantial impact on the magnitude of the option-implied present value of future dividends, and hence the dividend risk premium, since the Great Recession. We report average estimates in the lower panel of table 2. The difference in one-year premium estimates is on average 12.8%, and 3.0% in long-term estimates.[11] Regarding the predictive power of the dividend risk premium for returns on the one-year dividend asset,

$$xr_{t,12}^{12} = \alpha + \beta z_{t,12} + \epsilon_{t+12}^{d}, \qquad \epsilon_{t+12}^{d} \sim i.i.d.(0, \sigma_d^2), \tag{24}$$

we find that it decreases from 71.1% in the case of OIS to 42.1% in the case of LIBOR discounting. The difference between the dividend risk premiums obtained with OIS and LIBOR, $z_{t,12}^{OIS} - z_{t,12}^{LIBOR}$, turns out to be highly correlated with the LIBOR-OIS spread, sharing a correlation of 79% over the entire sample. We see this as a potential reason for the lower predictive power in the case of LIBOR discounting, as $z_{t,12}^{LIBOR}$ might partially reflect credit risk.

For LIBOR discounting, we find the same counter-cyclical pattern in the level of the term structure as for OIS discounting documented in figure 6. Regarding the slope of the term structure, which we regress on the different business cycle variables,

$$z_{t,120} - z_{t,12} = \alpha + \beta X_t + \epsilon_t, \qquad \epsilon_t \sim i.i.d.(0, \sigma^2), \tag{25}$$

[11] This sizable difference exceeds the LIBOR-OIS spread because it gets magnified in put call parity, see equation (15), as one has to borrow cash K in the money market at the risk free rate.

we find that point estimates share the same sign for ip_t and dp_t, as can be seen in table 7, but are insignificant in the case of LIBOR discounting.

5.3 Biases in Survey Estimates

The magnitude of our dividend risk premium estimate depends on the magnitudes of the risk-neutral and physical dividend growth expectations. Our model-free estimate of the latter relies on an aggregation of survey estimates on fiscal year dividends. A potential bias in survey estimates would directly enter our estimate of the dividend risk premium. While we find no evidence in existing literature on biases in dividend estimates, a large body of accounting literature investigates forecast errors and biases in earnings estimates. Theories suggest that incentives and cognitive biases such as overconfidence lead analysts to overestimate future earnings, see Brown [1993], Daniel and Titman [1999] and Kothari [2001], among others. Abarbanell and Lehavy [2003] find that previous evidence on forecast biases is mixed and inconclusive because distributional asymmetries in forecast errors make inference of biases problematic. They analyze 33.548 quarterly earnings forecasts and find that median forecast errors are zero, but that mean forecast errors are large due to tail asymmetries. Similar results can be found across a range of commercial data providers (Abarbanell and Lehavy [2002]), among them I/B/E/S. To test for biases in our dividend estimates, we first calculate forecast errors in all available non-zero fiscal year end estimates of all companies which have been part of the S&P 500 since January 2004. Then we look at our interpolated one-year measure $g^P_{t,12}$ of survey-implied growth expectations, which can be seen as the value-weighted average of single company estimates.

We define the forecast error ν^n_t with horizon n at time t as the percentage deviation between forecast $E_t[D_{t+n}]$ reported at time t and corresponding dividends D_{t+n} paid at time $t+n$,

$$\nu^n_t = \frac{E_t[D_{t+n}] - D_{t+n}}{D_{t+n}}. \tag{26}$$

A positive forecast error implies that the estimate was higher than actual dividends. Across all 947 companies in our sample, for which we have 81.419 non-zero estimates, we find a small median forecast error of -0.24%. If we isolate the period after the Great Recession, this number barely changes to -0.27%. Similar to Abarbanell and Lehavy [2003], who look at earnings estimates, we find large mean forecast errors for both periods, 10.72% and 5.58% respectively, due to a strong tail asymmetry in the error distribution. The implications of this finding for our aggregate measure depend on the distribution, as we only select companies who are current constituents of the S&P 500 and value-weight their estimates.

Figure 2 visualizes the overall finding of our analysis: the estimates relevant for our aggregate measure have become very accurate since the Great Recession, but exhibit positive errors before. We find a correlation of -60% between forecast errors and coverage ratio, suggesting that early errors might, at least to some extent, be due to insufficient coverage. Since the Great Recession, the median forecast error is at -0.48%. The average forecast error is even closer to zero at -0.25%. We argue that these errors are fairly small and conclude that an aggregation of analyst estimates can produce an accurate forecast of dividend growth for the aggregate index. We will now compare how alternative measures of expected growth compare to ours and affect our risk premium estimate.

5.4 Alternative Measures of Growth Expectations

The literature on dividend growth discusses a great amount of forecasting models with mixed evidence on growth predictability, see Lettau and Ludvigson [2005], Ang and Bekaert [2007], Chen [2009], Binsbergen and Koijen [2010], Chen et al. [2012], Binsbergen et al. [2013], Maio and Santa-Clara [2015] and Golez and Koudijs [2018] for recent studies. In all of these studies, estimates of usually one-year dividend growth are formed based on a parametric assumption, which is not the case for the survey-implied growth expectation $g^P_{t,12}$.

Two important studies in this field, Ang and Bekaert [2007] and Binsbergen et al. [2013], find strong predictability of S&P 500 dividends through bivariate regressions. Ang and Bekaert [2007] detect significant predictability of future cash flow growth rates by log dividend yields dy_t and log earnings yields ey_t (the bivariate Lamont [1998] regression). The results from a set of predictive regressions in Binsbergen et al. [2013] suggests that a pair of equity yields, e_{t,n_1} and e_{t,n_2}, predicts dividend growth better than several other commonly used linear models. To complement the analysis, we form expectations based on an AR(1) process in annual dividend growth g_t. This way, we include the variables (earnings yield, dividend yield, equity yields, and past dividends) which we encounter most often in the recent literature on dividend growth.

We gather data to calculate the log dividend yield dy_t and log earnings yield ey_t of the S&P 500 from the S&P 500 Composite Dividend Yield (DS DY) and Price Earnings Ratio (DS PER) as reported on Thomson Reuters Datastream. We calculate equity yields with $n_1 = 12$ and $n_2 = 24$ from our option data and complement our sample starting in 2004 with data provided by Binsbergen et al. [2012].

We estimate the two bivariate and one univariate regressions described above,

$$g_{t,t+12} = a^g + b^g X_t + \epsilon^g_{t+12}, \qquad \epsilon^g_{t+12} \sim i.i.d.(0, \sigma^2_g). \tag{27}$$

Table 10 documents the results of these regressions for the entire sample period and the time with almost perfect company coverage in our analyst forecasts. We find that survey-implied growth estimates capture 59.2% and 94.7% of the variance in future dividend growth respectively, more than any of the parametric models. The mean absolute errors associated with the survey-implied growth estimate are at least 10% smaller than for the parametric models.

We find that the estimates based on the Lamont [1998] regression come closest to survey-implied estimates. The Lamont [1998] regression and the equity yields regression have a correlation of 67% and 64% with $g^P_{t,12}$ respectively, forecasts based on past growth still 50%. To see which time series variables best predict survey-implied growth expectations, we regress $g^P_{t+1,12}$ on variables dy_t, ey_t, $e_{t,12}$, $e_{t,24}$, g_t and $g^P_{t,12}$. We find an adjusted R^2 value of 86.1% and significant estimates for the loadings on dy_t and g^P_t. Regressing $g^P_{t+1,12}$ on $g^P_{t,12}$ alone produces an adjusted R^2 value of 83.2% and a significant loading of 0.89. This highlights that the incremental explanatory power of the additional variables is marginal.

5.5 Alternative Measures of Expected Dividend Risk Premiums

We relate our estimate of the dividend risk premium term structure to the findings of the influential study by Binsbergen et al. [2013], who propose a VAR(1) structure behind a pair of equity yields to estimate a term structure of dividend growth. Given the term-structure of options-implied dividend growth, we compute the dividend risk premium term structure once with survey-implied growth estimates and once with their parametric estimates. The parametric estimates for dividend growth begin at a horizon of 12 months. As can be seen in figure 8, both dividend risk premium term structures are downward sloping beyond a maturity of one year. The dividend risk premium we obtain with the help of survey-implied growth forecasts peaks at 19.0%, while the dividend risk premium we obtain with the help of parametric growth forecasts peaks at 16.3%. We conduct a difference-in-mean test and reject the hypothesis of equal means at the 5% significance level.

We now present findings about the predictive power of alternative dividend risk premium estimates for one-year dividend excess returns. As predictors we are going to consider $g^Q_{t,12}$, $z_{t,12}$ and the dividend risk premium estimates implied by the three parametric growth models from equation (27). The estimation results are found in table 11. The analysis distinguishes between the full sample and the period after the Great Recession to ensure that results are not affected by insufficient coverage of analyst forecasts or the Great Recession. Regarding the full sample, we find that the choice of the growth forecast for constructing the dividend risk premium has a small impact on the predictive R^2. This does not come as a surprise, as the positive correlations between the different growth estimates and the inferior role of $g^P_{t,12}$ in the variance decomposition, see equation (17), suggest. For the period after the Great Recession, we find that the growth estimate matters. The highest R^2 of 92.8% is achieved for our dividend risk premium estimate, whereas the R^2 for the predictor $g^Q_{t,12}$ falls to 58.8%. The other predictors generate R^2's in the range of 60% to 80%. These results underline the superiority of $z_{t,12}$ for predicting one-year dividend excess returns for the period after the Great Recession.

6 Conclusion

We estimate the model-free term structure of the dividend risk premium by combining two data sets with different information about future dividends. The first data set, the Thomson Reuters I/B/E/S Estimates Database, provides us with survey-implied expectations on future dividends for single companies over multiple horizons. We estimate dividend growth for the aggregate equity index, the S&P 500, and cannot reject the hypothesis that future realized dividends are survey-implied dividend expectations plus noise. The second data set, comprised of intra-day CBOE option trade data, provides us with put and call prices on the S&P 500. We exploit put call parity to infer options-implied dividend expectations over the life of the respective option pair. A smooth interpolation allows us to infer a spectrum of maturities for both growth estimates and hence the term structure of the dividend risk premium. We use this model-free term structure to provide new insights about its shape and its business cycle behavior.

We find strong evidence for the superior predictive ability of our new dividend risk premium estimate for future returns on dividend assets. For the period after the Great Recession, our one-year dividend risk premium estimate is an unbiased predictor of the future one-year dividend return and explains 92.8% of its variation. We identify that this predictive superiority, relative to existing dividend risk premium estimates in recent literature, stems from the accuracy of aggregate analyst dividend forecasts.

As to business cycle variations, we document that the level of the dividend risk premium term structure moves counter-cyclically, whereas its slope moves pro-cyclically. This means that both short- and long-horizon dividend risk premiums increase during business cycle contractions and fall during expansions. Yet, the on average negative slope (Binsbergen et al. [2012]), measured as the spread between long-horizon and short-horizon dividend risk premiums, flattens during business cycle expansions and becomes more negative during business cycle contractions. Moreover, we find that short-horizon dividend risk premiums react stronger to business cycle shocks than long-horizon dividend risk premiums.

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A Term Structure of Aggregate Dividend Forecasts

Regarding the aggregation of single stock dividend forecasts to the index level, we closely follow the work of De la O and Myers [2017]. They provide an excellent description of the aggregation in their appendix, which we summarize in section A.1. The Nelson and Siegel [1987] estimations to infer the term structure of dividend growth and options-implied dividend yields are outlined in sections A.2 and A.3 .

A.1 Aggregate Dividend Estimation

The market capitalization of an index constituent i is the product of shares outstanding $S_{i,t}$ and price per share $P_{i,t}$. The aggregate market capitalization M_t of all index constituents reads

$$M_t = \sum_i P_{i,t} S_{i,t}. \tag{28}$$

The dividends paid by all S&P 500 constituents are calculated from $S_{i,t}$ and ordinary dividends per share $D_{i,t}$,

$$D_t = \sum_i D_{i,t} S_{i,t}. \tag{29}$$

Standard & Poor's adjust the market capitalization M_t by a divisor, such that the index value is not affected by changes in the constituents or number of shares outstanding. Observing the index level and market capitalization of all constituents, one can back out the divisor and calculate adjusted dividends, corresponding to the index level:

$$Divisor_t = M_t / S\&P500_t, \qquad Div_t = D_t / Divisor_t. \tag{30}$$

The same logic applies to the calculation of an aggregate dividend expectation. Let $E_t^P[D_{i,t+n}]$ denote the expectation for ordinary dividends paid by company i at time $t+n$ under the physical probability measure. The aggregate expectation, adjusted by the divisor, reads

$$E_t^P[Div_{t+n}] = E_t^P \left[\frac{\sum_i D_{i,t+n} S_{i,t+n}}{Divisor_{t+n}} \right]. \tag{31}$$

Assuming that people do not expect changes in constituents or shares outstanding to affect the price-dividend ratio allows one to use current shares outstanding $S_{i,t}$ and the current divisor $Divisor_t$ in the previous formula

$$E_t^P[Div_{t+n}] = \frac{\sum_i E_t^P[D_{i,t+n}]S_{i,t}}{Divisor_t}. \tag{32}$$

Table 1 highlights that dividend estimates are available for a large subset of all constituents. Since July 2009, the fiscal year estimates in particular cover approximately 98% of the total market capitalization of the S&P 500 on average. This leads to the second assumption: firms with an expected dividend are a representative sample for the aggregate index. Based on these two assumptions, the above formulas can be used to infer aggregate dividend expectations from time t share prices, shares outstanding and available dividend expectations on the single stock level.

A.2 Dividend Growth Term Structure Estimation

Based on the previously mentioned aggregation of single stock dividend forecasts to an index dividend forecast, we find ourselves with estimates for two specific horizons: 12 months and 24 months as described in De la O and Myers [2017]. In addition, we consider the long term earnings growth estimate and set it to a horizon of 60 months. The estimated term structure is very robust to a choice beyond 60 months, as different estimations have shown. To achieve a reasonable estimate of the very short end, we approximate the 1 day expectation with current dividend growth, defined as the annual growth in 12 month trailing dividends. These four point estimates, all defined in terms of daily maturities, $g_t^P = (g_{t,1}^P \; g_{t,360}^P \; g_{t,720}^P \; g_{t,1800}^P)^\top$, provide us with information about different points of the term structure of dividend growth - in total for 166 months between January 2004 and October 2017. For every t, we estimate the following equation for all available n simultaneously:

$$g_{t,n}^P \equiv \delta_{0,t} + \delta_{1,t}\frac{1-e^{-n\lambda_t}}{n\lambda_t} + \delta_{2,t}\left(\frac{1-e^{-n\lambda_t}}{n\lambda_t} - e^{-n\lambda_t}\right). \tag{33}$$

The estimation is performed as a grid search for parameter λ_t. For every point in the grid, or every value of λ_t, we obtain a closed form solution for parameters $\delta_t = (\delta_{0,t} \; \delta_{1,t} \; \delta_{2,t})^\top$ which minimizes the root mean squared pricing error between model implied growth rates $\hat{g}_{t,n}^P$ and observed growth rates $g_{t,n}^P$. To ease notation, we rewrite the model

$$g_t^P \equiv \delta^\top L_t \quad \text{with} \quad L_t = (L_{1,t}, L_{360,t}, L_{720,t}, L_{1800,t}) \tag{34}$$

and

$$L_{n,t} \equiv \begin{pmatrix} 1 & \frac{1-e^{-n\lambda_t}}{n\lambda_t} & \frac{1-e^{-n\lambda_t}}{n\lambda_t} - e^{-n\lambda_t} \end{pmatrix}^\top \quad \text{for} \quad n \in \{1, 360, 720, 1800\} \tag{35}$$

to obtain the ordinary least squares solution

$$\delta_t = (L_t^\top L_t)^{-1} L_t^\top g_t^P. \tag{36}$$

Average estimates for our sample can be found in table 12.

A.3 Implied Dividend Yield Term Structure Estimation

The estimation of the parameters λ_t, $\delta_{0,t}$, $\delta_{1,t}$ and $\delta_{2,t}$, which describe the term structure of dividend yields at time t, i.e.

$$y_{t,n}^d \equiv \delta_{0,t} + \delta_{1,t}\frac{1-e^{-n\lambda_t}}{n\lambda_t} + \delta_{2,t}\left(\frac{1-e^{-n\lambda_t}}{n\lambda_t} - e^{-n\lambda_t}\right), \tag{37}$$

follows the same approach, the grid search, as outlined in section A.2. The main difference is in the data. While we face a set of fixed maturities n in the estimation of growth rates, the maturities when estimating options-implied dividend yields varies with t. This is because the maturities of outstanding options vary from day to day. In addition, we filter option trades according to the criteria outlined in section 3, tailored to our empirical analysis. Average estimates for our sample and option filter can be found in table 12.

B Tables

Table 1: Descriptive Statistics - Analyst Data

January 2004 - October 2017	Q1	Q2	Q3	Q4	FY1	FY2	FY3	Long Term
Number of covered companies	419	412	402	389	469	468	432	472
Coverage of market capitalization	83.44	82.18	80.13	77.52	93.79	93.49	85.84	94.70
July 2009 - October 2017	**Q1**	**Q2**	**Q3**	**Q4**	**FY1**	**FY2**	**FY3**	**Long Term**
Number of covered companies	459	455	448	438	492	492	483	470
Coverage of market capitalization	91.66	90.94	89.26	87.73	98.38	98.21	96.40	93.92

This table contains the sample mean for quantities describing the different Thomson Reuters I/B/E/S dividend estimates made from Jan 2004 - Oct 2017 and the time after the Great Recession. The number of covered companies states for how many companies in the S&P 500 a respective forecast was reported. Coverage of market capitalization measures the reported companies' aggregate contribution to the market capitalization of the S&P 500.

Table 2: Descriptive Statistics - Implied Growth and Risk Premium Estimates

Based on OIS rates

μ	$g^P_{t,12}$	$g^P_{t,24}$	$g^P_{t,LT}$	$g^Q_{t,12}$	$g^Q_{t,24}$	$g^Q_{t,LT}$	$z_{t,12}$	$z_{t,24}$	$z_{t,LT}$
Jan 2004 - Dec 2017	10.07	10.22	9.87	-8.91	-6.10	-2.67	19.00	16.33	12.52
Great Recession	3.60	7.33	10.74	-39.59	-22.35	-5.86	43.19	29.68	16.59

σ	$g^P_{t,12}$	$g^P_{t,24}$	$g^P_{t,LT}$	$g^Q_{t,12}$	$g^Q_{t,24}$	$g^Q_{t,LT}$	$z_{t,12}$	$z_{t,24}$	$z_{t,LT}$
Jan 2004 - Dec 2017	6.33	2.95	1.73	17.29	9.42	1.79	14.08	7.99	2.93
Great Recession	8.45	4.23	0.57	20.03	12.01	2.28	18.50	11.05	1.99

Based on LIBOR rates

μ	$g^P_{t,12}$	$g^P_{t,24}$	$g^P_{t,LT}$	$g^Q_{t,12}$	$g^Q_{t,24}$	$g^Q_{t,LT}$	$z_{t,12}$	$z_{t,24}$	$z_{t,LT}$
Jan 2004 - Dec 2017	10.07	10.22	9.87	3.87	1.33	0.30	6.21	8.90	9.56
Great Recession	3.60	7.33	10.74	-9.42	-8.74	-1.67	13.02	16.07	12.41

σ	$g^P_{t,12}$	$g^P_{t,24}$	$g^P_{t,LT}$	$g^Q_{t,12}$	$g^Q_{t,24}$	$g^Q_{t,LT}$	$z_{t,12}$	$z_{t,24}$	$z_{t,LT}$
Jan 2004 - Dec 2017	6.33	2.95	1.73	12.59	7.59	1.58	10.01	6.24	2.54
Great Recession	8.45	4.23	0.57	16.83	9.74	2.06	14.51	7.50	1.75

This table contains the sample mean and standard deviation for dividend growth expectations $g^P_{t,n}$ and $g^Q_{t,n}$ under the empirical and risk-neutral probability measure and the dividend risk premium $z_{t,n}$ in the period Jan 2004 - Oct 2017 and the Great Recession in Dec 2007 - Jun 2009. The upper panel reports estimates based on OIS rates, the lower panel based on LIBOR rates. Values are annualized, in percentage terms and rounded to two decimals.

Table 3: Regression Statistics - Dividend Growth

X_t	a^g	b^g	R^2
$g^P_{t,12}$	-2.34 (2.46)	0.97 (0.19)	43.5
$g^Q_{t,12}$	10.72 (0.83)	0.39 (0.06)	53.2

This table reports regression estimates and adjusted R^2 values for predictive regressions of future realized dividend growth on survey-implied dividend growth expectations $X_t = g^P_{t,12}$ and options-implied dividend growth expectations $X_t = g^Q_{t,12}$:

$$g_{t,12} = a^g + b^g X_t + \epsilon^g_{t+12}, \qquad \epsilon^g_{t+12} \sim i.i.d.(0, \sigma^2_g).$$

Values for a^g and R^2 are in percentage terms. Newey and West [1987] standard errors with $T^{0.25}$ lags are reported in parenthesis. The predictions cover the period between Jan 2004 and Oct 2017.

Table 4: Regression Statistics - One-Year Returns on Dividend Assets

	α	β_{MKT}	$\beta_{dp^{corr}}$	β_{SVIX}	$\beta_{pd^{strip}}$	β_z	MAE	R^2
January 2004 - October 2017								
$xr^{\infty}_{t,12}$	8.00 (3.68)	0.05 (0.19)					10.68	0.0
$xr^{12}_{t,12}$	16.30 (2.08)	-0.13 (0.11)					10.59	2.0
$xr^{\infty}_{t,12}$	0.61 (0.43)		0.13 (0.11)				11.64	2.6
$xr^{12}_{t,12}$	-1.85 (0.21)		-0.50 (0.05)				6.16	69.6
$xr^{\infty}_{t,12}$	5.38 (2.66)			0.77 (0.69)			10.47	1.0
$xr^{12}_{t,12}$	8.59 (3.23)			1.67 (0.51)			10.42	10.7
$xr^{\infty}_{t,12}$	8.19 (2.02)				-0.02 (0.15)		10.61	0.0
$xr^{12}_{t,12}$	9.31 (1.03)				-0.65 (0.07)		6.11	70.1
$xr^{\infty}_{t,12}$	10.70 (2.82)					-0.12 (0.20)	10.64	0.5
$xr^{12}_{t,12}$	0.20 (1.73)					0.79 (0.09)	6.41	71.1

	α	β_{MKT}	$\beta_{dp^{corr}}$	β_{SVIX}	$\beta_{pd^{strip}}$	β_z	MAE	R^2
July 2009 - October 2017								
$xr^{\infty}_{t,12}$	13.41 (1.61)	-0.01 (0.07)					5.83	0.0
$xr^{12}_{t,12}$	19.53 (2.33)	0.04 (0.19)					7.37	0.0
$xr^{\infty}_{t,12}$	0.52 (0.26)		0.10 (0.06)				5.79	4.1
$xr^{12}_{t,12}$	-1.56 (0.20)		-0.43 (0.05)				3.74	69.1
$xr^{\infty}_{t,12}$	10.26 (2.80)			0.82 (0.57)			5.83	2.2
$xr^{12}_{t,12}$	30.66 (3.09)			-2.83 (0.86)			6.24	24.1
$xr^{\infty}_{t,12}$	13.77 (1.77)				0.04 (0.13)		5.83	0.0
$xr^{12}_{t,12}$	11.93 (1.45)				-0.77 (0.09)		3.88	64.1
$xr^{\infty}_{t,12}$	13.85 (2.46)					-0.03 (0.13)	5.82	0.0
$xr^{12}_{t,12}$	0.74 (1.13)					1.01 (0.04)	1.76	92.8

This table reports estimates for predictive regressions of index excess returns $xr^{\infty}_{t,12}$ and excess returns $xr^{12}_{t,12}$ on the one-year asset over the next 12 months on different predictive variables F_t:

$$xr^n_{t,12} = \alpha + \beta_F F_t + \epsilon^r_t, \qquad \epsilon^r_t \sim i.i.d.(0, \sigma^2_r).$$

We analyze future annual excess returns for every month between Jan 2004 - Oct 2017 and the time after the Great Recession. The predictive variables F_t comprise the one-year market excess return MKT_t as in Fama and French [2015], the one-year corrected dividend price ratio $dp^{corr}_{t,12}$ according to Golez [2014], the one-year $SVIX_{t,12}$ measure of the equity premium derived by Martin [2017], the one-year log price dividend ratio of the short term asset $pd^{strip}_{t,12}$ presented by Binsbergen et al. [2012] and our one-year dividend risk premium $z_{t,12}$. Values for α, mean absolute errors and adjusted R^2 are in percentage terms. Newey and West [1987] standard errors with $T^{0.25}$ lags are reported in parenthesis.

Table 5: Regression Statistics - Fama and French [2015] Style Factors

	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	R^2
$xr^{\infty}_{t,12}$	-1.80 (0.31)	1.04 (0.02)	-0.25 (0.03)	0.06 (0.02)	0.01 (0.03)	-0.04 (0.02)	99.6
$xr^{12}_{t,12}$	12.05 (3.15)	0.26 (0.15)	0.02 (0.32)	-0.14 (0.22)	0.21 (0.32)	-0.23 (0.29)	4.9

This table reports estimates for regressions of current index excess returns $xr^{\infty}_{t,12}$ and excess returns $xr^{12}_{t,12}$ on the annual five Fama and French [2015] factors:

$$xr^{n}_{t,12} = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{RMW}RMW_t + \beta_{CMA}CMA_t + \epsilon^{r}_{t}.$$

We analyze annual excess returns for every month between Jan 2004 - Oct 2017. Values for α and adjusted R^2 are in percentage terms. Newey and West [1987] standard errors with $T^{0.25}$ lags are reported in parenthesis.

Table 6: The Dividend Risk Premium Term Structure and the Business Cycle

Entire Sample	12	24	36	48	60	72	84	96	108	120
Average Premium	19.00	16.33	14.79	14.00	13.51	13.19	12.95	12.77	12.63	12.52
Standard Deviation	14.08	7.99	5.72	4.59	3.96	3.56	3.30	3.12	3.00	2.93

Expansions	12	24	36	48	60	72	84	96	108	120
Average Premium (ip_t)	14.45	13.50	12.63	12.16	11.88	11.70	11.58	11.48	11.41	11.36
Average Premium (dp_t)	12.49	12.14	11.48	11.12	10.90	10.76	10.66	10.58	10.53	10.49
Average Premium ($g^P_{t,12}$)	15.37	14.27	13.10	12.52	12.18	11.95	11.80	11.68	11.59	11.52
Standard Deviation (ip_t)	9.19	5.08	3.75	3.18	2.89	2.73	2.64	2.59	2.57	2.55
Standard Deviation (dp_t)	10.10	5.36	3.82	3.16	2.84	2.67	2.58	2.54	2.53	2.53
Standard Deviation ($g^P_{t,12}$)	10.28	6.09	4.19	3.45	3.07	2.85	2.72	2.65	2.60	2.57

Contractions	12	24	36	48	60	72	84	96	108	120
Average Premium (ip_t)	23.60	19.37	16.87	15.71	14.99	14.50	14.14	13.87	13.65	13.48
Average Premium (dp_t)	24.19	19.92	17.45	16.29	15.58	15.10	14.75	14.49	14.28	14.11
Average Premium ($g^P_{t,12}$)	24.29	19.59	17.15	15.97	15.24	14.74	14.38	14.10	13.88	13.70
Standard Deviation (ip_t)	17.49	10.36	6.69	5.21	4.37	3.83	3.47	3.22	3.05	2.92
Standard Deviation (dp_t)	16.93	10.02	6.24	4.71	3.82	3.24	2.85	2.58	2.38	2.24
Standard Deviation ($g^P_{t,12}$)	16.82	10.16	6.58	5.13	4.28	3.74	3.36	3.10	2.91	2.77

This table contains the risk premium estimates for dividends paid up to 120 months in the future. We report estimates for all data points in the period Jan 2004 - Oct 2017, as well as during expansionary and contractionary times. Expansionary and contractionary times are identified by either the current value of the log industrial production growth (ip_t), the log dividend price ratio (dp_t) or survey-implied growth expectations ($g^P_{t,12}$) relative to their sample median. We also report standard deviations. Values are annualized, in percentage terms and rounded to two decimals.

Table 7: Regression Statistics - Business Cycle Variables

Based on OIS rates

	α	β	R^2
ip_t	-7.20 (1.82)	1.07 (0.53)	17.0
dp_t	-14.41 (4.56)	-0.35 (0.12)	24.9
$g^P_{t,12}$	-11.14 (4.10)	0.46 (0.30)	5.4

Based on LIBOR rates

	α	β	R^2
ip_t	3.14 (1.18)	0.29 (0.35)	1.7
dp_t	-3.86 (3.13)	-0.11 (0.07)	3.7
$g^P_{t,12}$	3.61 (2.41)	-0.03 (0.19)	0.0

This table shows the relation of the slope of the dividend risk premium to business cycle variables. It reports the parameter estimates α, β and R^2 values from the following regressions:

$$z_{t,120} - z_{t,12} = \alpha + \beta X_t + \epsilon_t, \qquad \epsilon_t \sim i.i.d.(0, \sigma^2).$$

We consider different business cycle variables X_t over our sample period (Jan 2004 - Oct 2017): the log industrial production growth ip_t, log-dividend price ratio dp_t, and expected dividend growth $g^P_{t,12}$. Newey and West [1987] standard errors with $T^{0.25}$ lags are reported in parenthesis. The upper panel reports estimates based on OIS rates, the lower panel based on LIBOR rates in the calculation of the dividend risk premium. Values for α and R^2 are reported in percentage terms.

Table 8: The Role of Transaction Costs

Excess Return	No Trading Costs	Index Replication	Index Replication + Option Trading
No signal	14.25	10.46	-3.93
$z_{t,12} > 0$	14.95	11.18	6.36
Standard Deviation	No Trading Costs	Index Replication	Index Replication + Option Trading
No signal	13.23	13.75	13.37
$z_{t,12} > 0$	12.86	13.34	8.86
Sharpe Ratio	No Trading Costs	Index Replication	Index Replication + Option Trading
No signal	1.08 (0.07)	0.76 (0.07)	-0.18 (0.09)
$z_{t,12} > 0$	1.28 (0.06)	0.84 (0.07)	0.72 (0.13)
Skewness	No Trading Costs	Index Replication	Index Replication + Option Trading
No signal	0.23	0.16	-0.11
$z_{t,12} > 0$	0.32	0.25	-0.30
Trade Executions	No Trading Costs	Index Replication	Index Replication + Option Trading
No signal	154	154	154
$z_{t,12} > 0$	149	149	79

This table reports descriptive statistics for investments into the one-year dividend asset over the period Jan 2004 - Oct 2017. We compare average excess returns, standard deviations, Sharpe ratios, skewness and the amount of monthly trade executions for two different investment strategies. The first strategy invests into the short term dividend asset at the end of each month, the signal based strategy only invests if the implied premium is positive. We also consider trading costs, both the replication of the index and the actual bid-ask spreads in necessary option trades. We report Opdyke [2008] standard errors in parenthesis. Returns and standard deviations are annualized, in percentage terms and rounded to two decimals.

Table 9: The Term Structure of Buy-and-Hold Dividend Returns

	6	12	18	24	30	36	S&P 500
Average Excess Return	14.50	14.25	12.68	11.18	9.85	11.12	6.44
Standard Deviation	35.69	13.23	10.50	9.69	9.48	10.97	17.17
Sharpe Ratio	0.41	1.08	1.20	1.15	1.04	1.01	0.37

This table reports descriptive statistics for buy-and-hold excess returns from investments into dividend assets realized after January 2004 with different investment horizons n. Each strategy is executed as long as the investment horizon allows for its evaluation. We interpolate between all available maturities to synthetically create the constant maturities of 6, 12, 18, 24, 30 and 36 months. We add the returns from a buy-and-hold investment in the S&P 500 for comparison. Average excess returns and standard deviations are annualized and reported in percentage terms.

Table 10: Alternative Dividend Growth Estimates

	a^g	b^g	MAE	R^2
January 2004 - October 2017				
$g_{t,12}^P$	0.00	1.00	4.97	59.2
g_t	4.10 (2.25)	0.41 (0.16)	5.43	17.2
dy_t, ey_t	-1.87 (0.44)	-0.57 (0.10), 0.09 (0.07)	5.48	40.7
$e_{t,12}, e_{t,24}$	11.18 (1.14)	0.57 (0.20), -1.50 (0.38)	5.72	27.9

	a^g	b^g	MAE	R^2
July 2009 - October 2017				
$g_{t,12}^P$	0.00	1.00	1.99	94.7
g_t	7.29 (1.46)	0.32 (0.11)	3.71	33.4
dy_t, ey_t	-0.32 (0.55)	-0.30 (0.13), 0.25 (0.04)	2.83	30.1
$e_{t,12}, e_{t,24}$	10.51 (1.90)	0.01 (0.21), -0.20 (0.38)	4.28	2.1

This table reports parameter estimates and adjusted R^2 values for regressions of future realized dividend growth on a set of predictor variables X_t:

$$g_{t,12} = a^g + b^g X_t + \epsilon_{t+12}^g, \qquad \epsilon_{t+12}^g \sim i.i.d.(0, \sigma_g^2).$$

The first row shows the mean absolute error and predictive R^2 we obtain when we predict future dividend growth with our survey-implied growth estimate $g_{t,12}^P$ in a model-free way and without look-ahead bias, this means postulating $a_{is}^g = 0$ and $b_{is}^g = 1$. The predictive variables for the univariate regression is past annual dividend growth g_t. For the bivariate regressions, we follow Ang and Bekaert [2007] and Binsbergen et al. [2013] and rely on the log dividend yield, the log earnings yield and a pair of equity yields. Values for a^g, the mean absolute error and R^2 are in percentage terms. Newey and West [1987] standard errors with $T^{0.25}$ lags are reported in parenthesis. The regressions span $T = 166$ months in the period between Jan 2004 and Oct 2017 (upper panel) and $T = 100$ months in the time with almost perfect company coverage in our analyst estimates (lower panel).

Table 11: Alternative Dividend Risk Premium Estimates

January 2004 - October 2017					
X_t	$z_{t,12}$	$z^{g}_{t,12}$	$z^{dy,ey}_{t,12}$	$z^{e_{12},e_{24}}_{t,12}$	$g^{Q}_{t,12}$
b_z	0.79 (0.09)	0.67 (0.07)	0.83 (0.08)	0.76 (0.09)	-0.65 (0.07)
R^2	71.1	75.2	67.2	67.1	70.4

July 2009 - October 2017					
X_t	$z_{t,12}$	$z^{g}_{t,12}$	$z^{dy,ey}_{t,12}$	$z^{e_{12},e_{24}}_{t,12}$	$g^{Q}_{t,12}$
b_z	1.01 (0.04)	0.73 (0.05)	0.91 (0.16)	0.77 (0.13)	-0.72 (0.11)
R^2	92.8	77.8	66.9	56.5	58.8

This table reports parameter estimates and adjusted R^2 values for regressions of future realized excess returns on a set of risk premium estimates X_t:

$$xr_t^{12} = a^z + b^z X_t + \epsilon^z_{t+12}, \qquad \epsilon^z_{t+12} \sim i.i.d.(0, \sigma_z^2).$$

The alternative premium estimates are based on options-implied growth $g^Q_{t,12}$ and the alternative dividend growth estimates implied by the three linear models we consider: based on past growth g_t, based on dividend and earnings yields dy_t and ey_t, and based on a pair of equity yields $e_{t,12}$ and $e_{t,24}$. A direct comparison to $g^Q_{t,12}$ shows whether a particular growth estimate adds value in the return predictions. We separately study the entire sample period (upper panel) and the period with almost perfect company coverage in our analyst estimates (bottom panel) of alternative growth measures. R^2 values are in percentage terms. Newey and West [1987] standard errors with $T^{0.25}$ lags are reported in parenthesis.

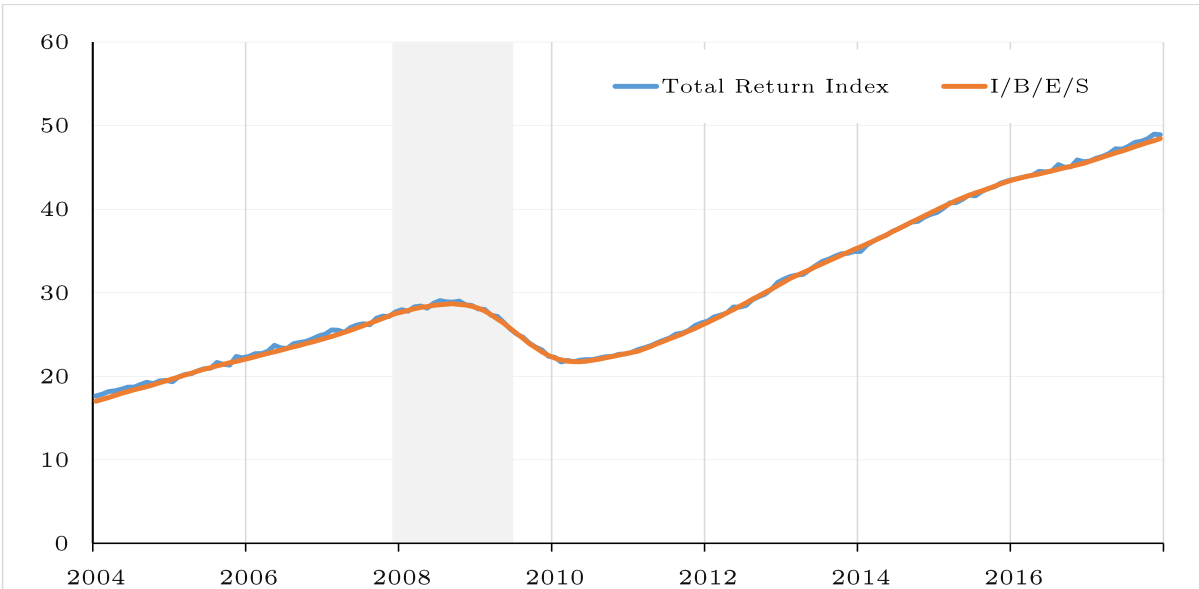
Table 12: Average Nelson Siegel Estimates

	$\bar{\lambda}$	$\bar{\delta}_0$	$\bar{\delta}_1$	$\bar{\delta}_2$
Survey-Implied Dividend Growth	0.2672	10.3640	1.3215	-6.9261
Options-Implied Dividend Yields	0.0182	0.0206	-0.0098	3.5601

This table reports the average estimates for the two Nelson and Siegel [1987] interpolations we use to infer the full term structure of survey-implied dividend growth rates and options-implied dividend yields. The sample period is Jan 2004 - Oct 2017.

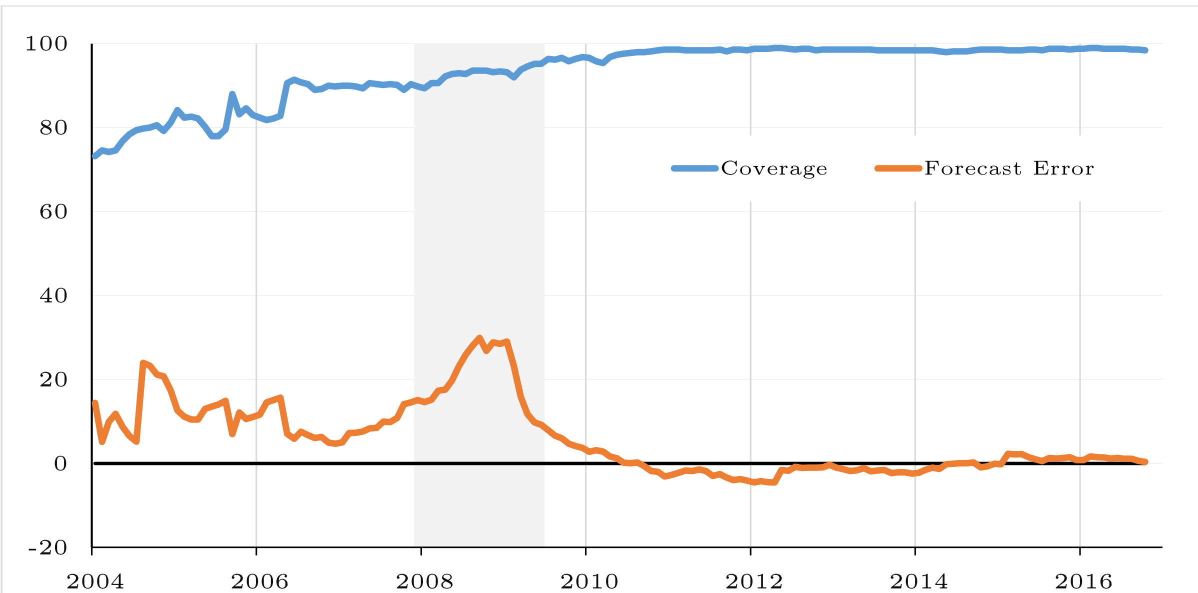
C Figures

Figure 1: One-Year Trailing Dividends



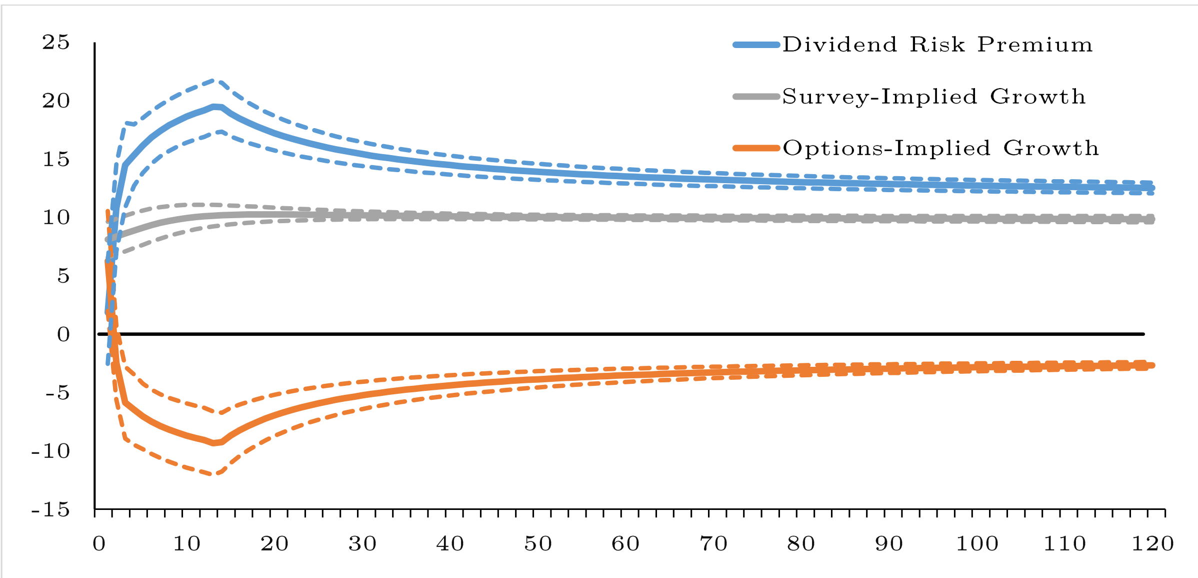
This figure shows one year of trailing S&P 500 dividends obtained from return differences between the total return and normal return index and our aggregate value from I/B/E/S reports. The gray shaded area indicates the Great Recession. Values are in U.S. Dollar.

Figure 2: S&P 500 Coverage Ratio and Aggregate Dividend Forecast Error



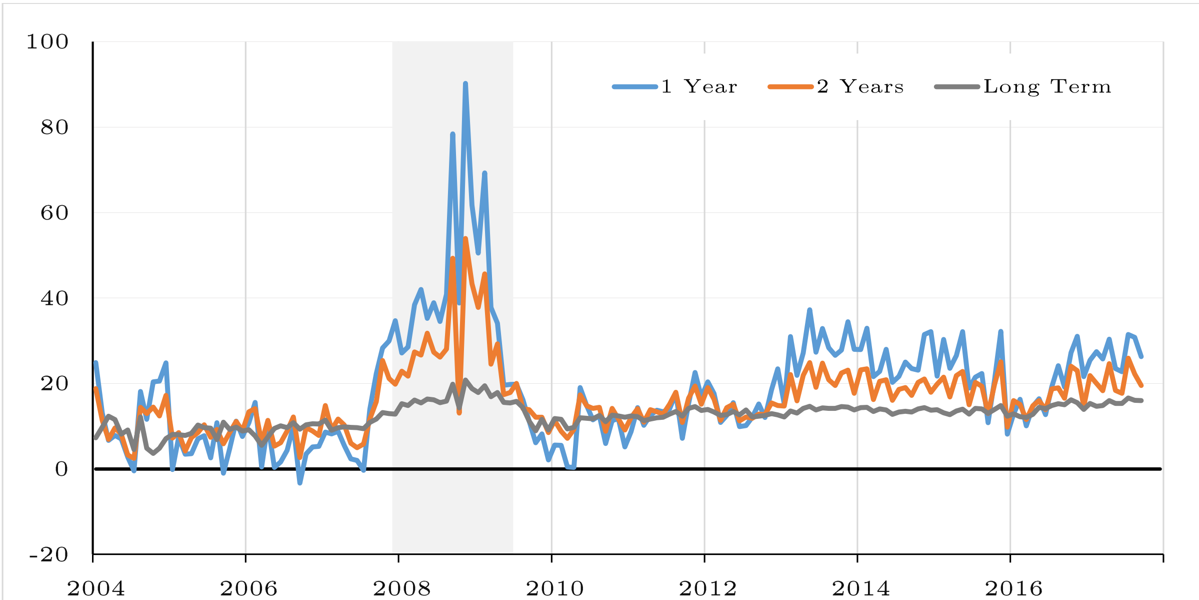
This figure shows the coverage of the S&P 500 market capitalization by aggregate analyst forecasts of fiscal year one dividends and the aggregate forecast error. Values are in percentage terms. The gray shaded area indicates the Great Recession.

Figure 3: Term Structure of Expected Growth and Dividend Risk Premium



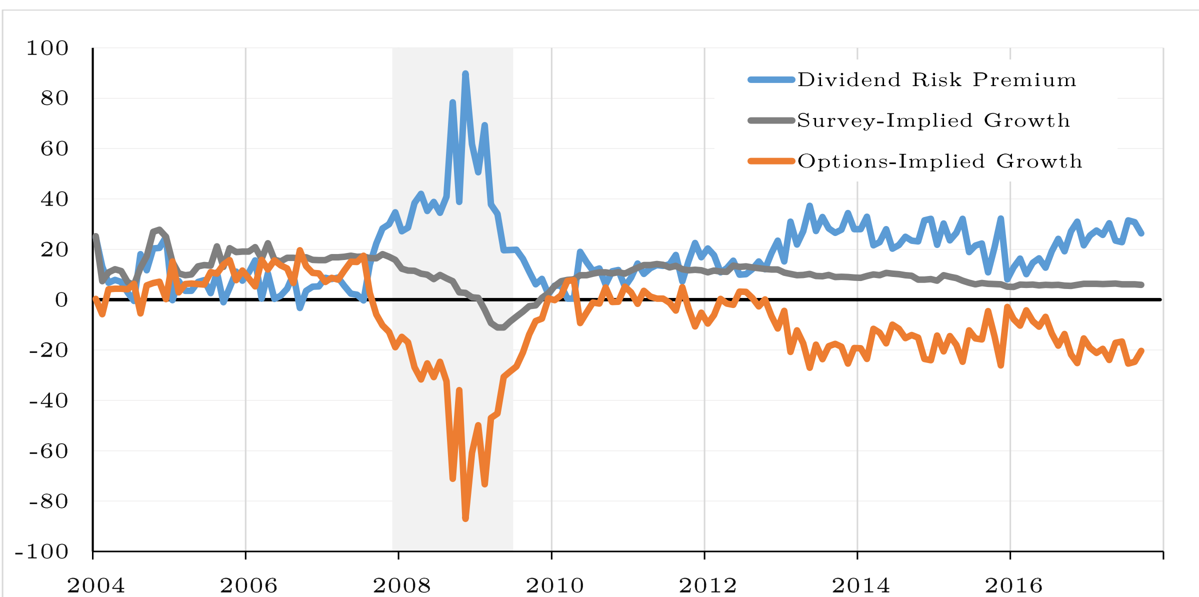
This figure shows the average future dividend growth rate implied by survey forecasts $g_{t,n}^{P}$ and option-prices $g_{t,n}^{Q}$, together with the expected dividend risk premium $z_{t,n}$, between Jan 2004 and Oct 2017. Dashed lines indicate two standard errors off the mean estimate. The horizontal axis displays the maturity in months. Values on the vertical axis are in percentage terms and annualized.

Figure 4: Dividend Risk Premium Estimates



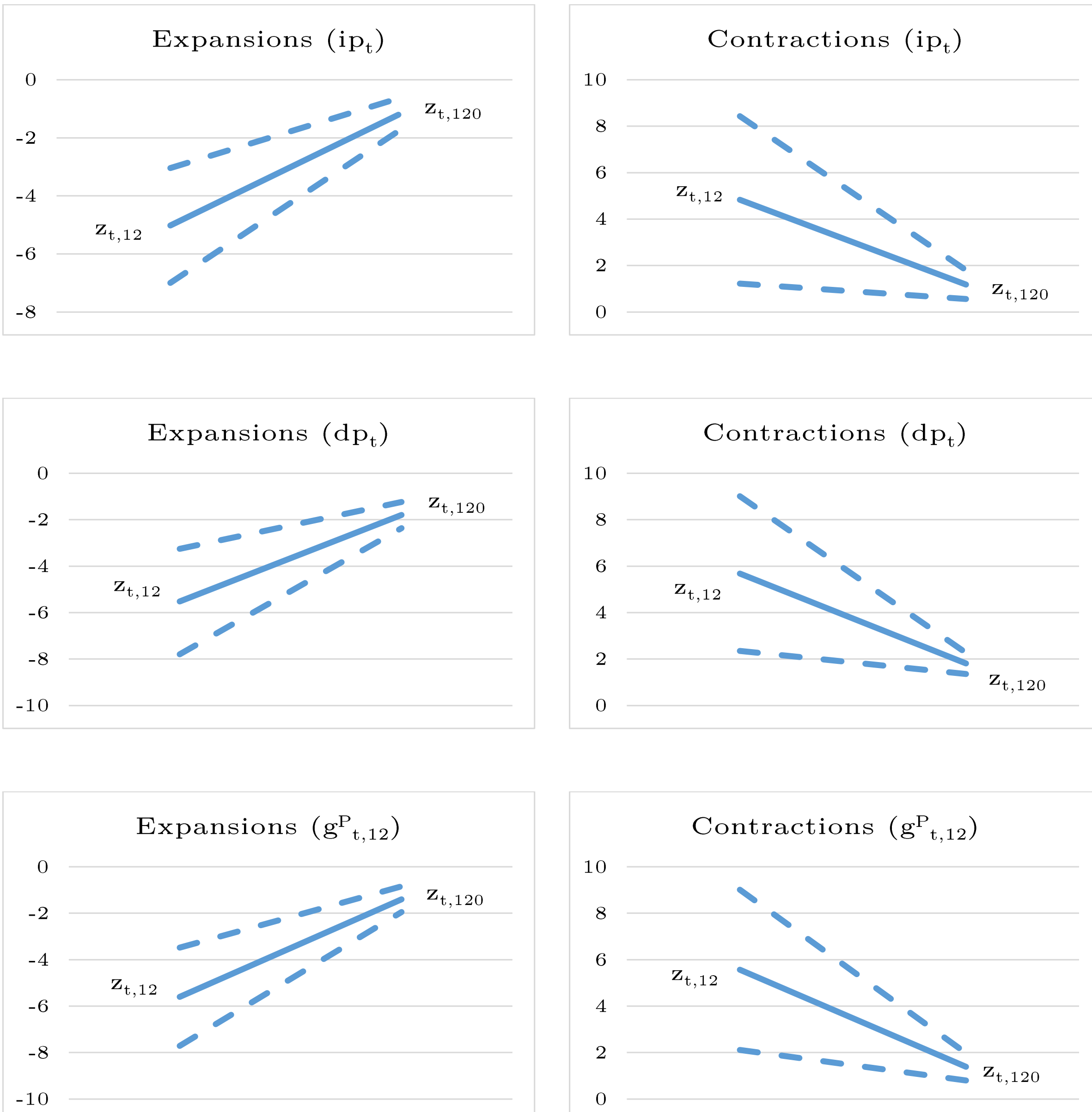
This figure shows the one-year, two-year and long term risk premium estimates for S&P 500 dividends. The gray shaded area indicates the Great Recession. Values are in percentage terms and annualized.

Figure 5: One-year Estimates



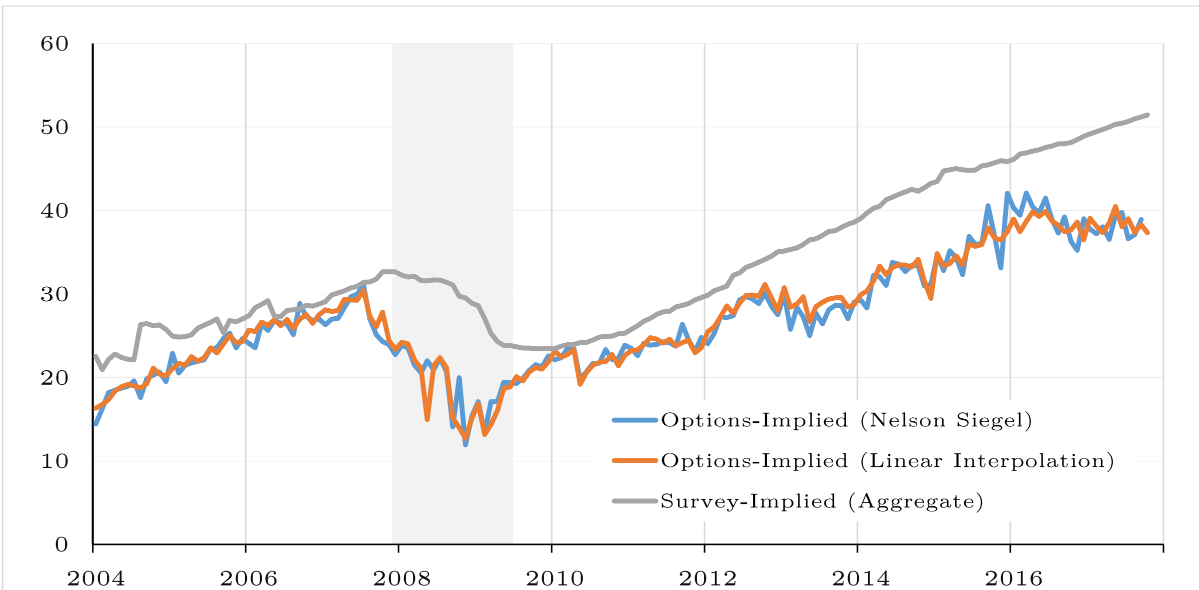
This figure shows the survey-implied growth, options-implied growth and risk premium estimates for S&P 500 dividends. The gray shaded area indicates the Great Recession. Values are in percentage terms and annualized.

Figure 6: Fluctuations in Expected Dividend Risk Premiums



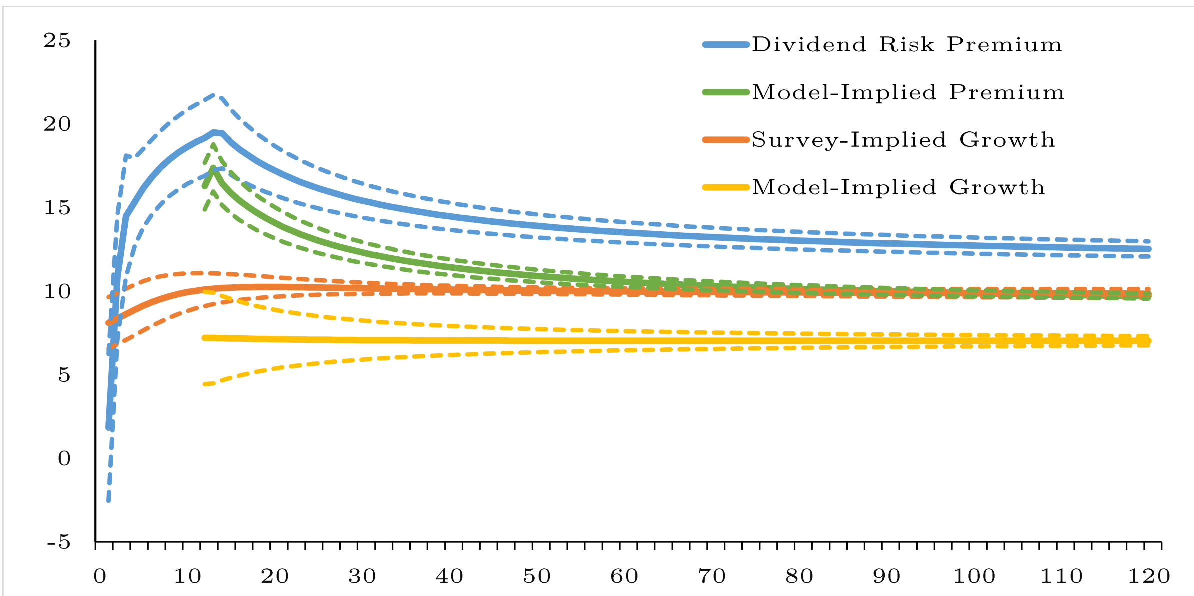
This figure shows the average deviation from the sample average in expected one-year ($z_{t,12}$) and ten-year ($z_{t,120}$) dividend risk premiums during business cycle expansions and contractions. We classify expansions (contractions) according to the current state of log industrial production growth (ip_t), the log dividend price ratio (dp_t) and survey-implied growth expectations ($g^P_{t,12}$) relative to their respective sample median. Values are in percentage terms; dashed lines represent two standard error bounds.

Figure 7: One-Year Dividend Expectations



This figure shows options-implied present values of future dividends, interpolated linearly (orange) and with a Nelson and Siegel [1987] approach (blue), next to survey estimates (gray). The gray shaded area indicates the Great Recession. Values are in U.S. Dollar.

Figure 8: Comparison to Alternative Term Structure Estimates



This figure shows our survey-implied dividend growth (orange) and dividend risk premium (blue) estimates, together with estimates obtained from a parametric model for dividend growth (yellow) as proposed by Binsbergen et al. [2013] and the resulting premium estimate (green). We consider the entire sample period between Jan 2004 and Oct 2017. Dashed lines indicate two standard errors off the mean estimate. The horizontal axis displays the maturity in months. Values on the vertical axis are in percentage terms and annualized.