The Term Structure of Dividend Risk Premiums

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1 Introduction

The present value of future cash flows is a crucial ingredient to investment decisions. Finding the proper risk-adjusted discount rate for future dividends is therefore one of the central challenges in asset pricing. Gordon [1962] was among the first to show that the discounted value of future dividends coincides with the value of an equity asset, while Lucas [1978] shows that the discounted value of future consumption coincides with total wealth. Following their logic, the price of an equity asset summarizes information on the different growth rates and discount factors applicable to all future dividends. Brennan [1998] was among the first to point out that a theoretical claim on a single dividend paid at a particular point in the future could be valuable to promote rational pricing, revealing the risk-adjusted expected growth rate for a specific horizon.

Both financial markets and the academic literature have come a long way since then. In the early 2000s, several important contributions - see Cornell [1999], Dechow et al. [2000] and Dechow et al. [2004] for early work - have relied on realized returns in the cross-section of stocks to estimate a term structure of equity premiums. The central idea in these studies is based on stocks' different characteristics regarding their dividend distributions. While some stocks promise high dividend payments in the near future, others are expected to pay their dividends in the far future. Under these circumstances, their realized returns can be an indication on the realized term structure of the equity premium. These early empirical studies point towards a premium for low-duration stocks, suggesting a higher discount rate for near-future dividends. At the same time, this finding challenges classical asset pricing models such as Campbell and Cochrane [1999] and Bansal and Yaron [2004], while it motivates theoretical work that accommodates this feature, pioneered by Lettau and Wachter [2007].

Two important contributions in this field have allowed us to get a much more precise estimate of the term structure of dividend discount rates. One is the introduction of dividend futures in financial markets. These financial contracts on a certain stream of future dividends provide us with price information on particular dividends distributed by major stock market indices and individual stocks. The second important contribution is the work of Binsbergen et al. [2012], who were the first to provide a measurement of present values of future dividends from option data. Several studies have since then proposed measurements of risk-adjusted growth rates, see Golez [2014] and Kragt et al. [2018], to name a few. Combined with estimates about future dividend growth, see Binsbergen et al.

[2013] and Binsbergen and Koijen [2017], among others, several studies provide estimates of the respective dividend risk premiums. Findings are mixed, reflecting the sensitivity of the results to the different approaches: While some studies argue for a downward sloping term structure, other studies find an upward slope. Findings about the business cycle behavior of expected premiums, an important question going back to the influential study of Lettau and Ludvigson [2001], are also conflicting, we refer to Bansal et al. [2017] and Gormsen [2018]. My dissertation contributes to this literature. Together with my co-authors, I have developed novel approaches to allow for a fresh perspective on this highly debated topic. We contribute to the literature with a new methodology to obtain model-free estimates of dividend risk premiums from price data and survey estimates on future dividends, thus removing statistical bias emerging from parametric choices. We apply our work to both the U.S. and European market, using both option data and dividend futures data, and analyze the impact of business cycle fluctuations on the respective term structures. Adding to the term structure literature, we derive no-arbitrage conditions and develop a parsimonious affine term structure model to jointly price government bonds, dividend assets and the aggregate equity index.

1.1 Structure of the Thesis

Chapter 2 is based on the working paper 'A Model-Free Term Structure of U.S. Dividend Premiums' of Ulrich et al. [2018]. We introduce a novel approach to obtain an estimate of the dividend risk premium from option price data and survey estimates, model-free and available in real-time. The analysis focuses on the U.S. market, including information about all stocks which have been part in the S&P 500 since January 2004. We evaluate the predictive power of our premium estimate for future excess returns in dividend assets and conclude that the combination of both data sets, options and survey estimates, provides an excellent predictor. Looking at different business cycle variables, we find that investors demand a larger premium for exposure to uncertain dividends during economic contractions, but much more so for near-future dividends then for dividends paid far in the future. This translates into the level of the risk premium term structure moving against the business cycle, while its slope is pro-cyclical. Our analysis also highlights the accuracy of survey estimates on dividends, which complements the rich literature on earnings estimates.

After establishing our methodology to obtain a model-free estimate of the dividend risk premium term structure, we extend our analysis to the European market in chapter 3. We show how to use price information on dividend futures, instead of options, to obtain the risk premium estimates. The index we study is the Euro Stoxx 50, for which dividend futures are traded since August 2008. Compared to our results presented for the U.S. economy, we find a significant upward bias in analyst dividend estimates, which translates into our premium estimate. Yet, the premium estimate turns out to be a strong predictor of returns on dividend futures. Interestingly, we find that returns on dividend futures are positively correlated with the aggregate equity market, contrary to our finding for the U.S. market. Similar to the U.S. market, we show that the term structure of risk premiums is counter-cyclical in its level and pro-cyclical in its slope. We conclude with a brief discussion of the differences and similarities in both markets and the advantages of dividend futures for the analysis of implied dividend risk premiums.

Chapter 4, based on the working paper 'A Macro-Finance Term Structure Model for Bond and Dividend Discount Rates' of Ulrich et al. [2019], introduces a unifying framework to jointly price government bonds, dividend assets and the aggregate equity market in a macro-based term structure model. We establish basic no-arbitrage conditions to price the three asset classes and obtain analytical solutions for the different components of the dividend discount rate, which are the average expected short rate, the bond risk premium and the dividend risk premium. We find that the short-horizon dividend risk premium cannot be captured in an affine model, in which market prices of risk are affine in macro-economic and growth variables alone. With the use of survey estimates as advocated in Kim and Wright [2005] and Kim and Orphanides [2012], we are able to obtain realistic estimates of all term structure components with strong predictive power for their realized counterparts, among them excess returns on dividend assets. As we include a rich set of macro-economic data, we are able to identify their economic drivers and conclude that a Taylor rule based monetary policy achieves strong results, even in recent times of unconventional policies.

2 A Model-Free Estimate of Dividend Risk Premiums

This chapter is based on the working paper 'A Model-Free Term Structure of U.S. Dividend Premiums' of Ulrich et al. [2018], proposing a novel approach to estimate a model-free term structure of dividend risk premiums and applying it to S&P 500 dividends.

2.1 Introduction

As mentioned in chapter 1, 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. The seminal work of Binsbergen et al. [2012] has shown how to use European index options to construct risk-adjusted 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 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. To overcome the problem of incomplete term structures, we apply a smooth Nelson and Siegel [1987] interpolation to both growth rates. 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 dividend growth. Compared to popular models in recent studies on 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 2.2, we derive the dividend risk premium estimate. We discuss our data in section 2.3 and present our findings in section 2.4. In section 2.5, we compare our methodology to alternative approaches in recent literature. Section 2.6 concludes.

2.1.1 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.[1] 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. We also show that a correction of options-implied growth expectations by expected dividend growth from analyst forecasts predicts future dividend returns better than the options-implied growth expectation alone.

[1] 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.

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 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]).[2] 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]).[3] 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

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

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

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 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]).[4] Second, analysts have pay and career related incentives to publish overly optimistic earnings forecasts (e.g. Hong and Kubik [2003]).[5] 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 analyst dividend forecasts for the S&P 500 disappears as the analyst coverage ratio of the total S&P 500 market capitalization approaches 100%.[6]

[4] 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.

[5] 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.

[6] 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.

2.2 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

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

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 corresponding dividend risk premium $z_{t,n}$ make up the discount rate:

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

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].

2.2.1 Dividend Growth Implied by Survey Estimates

The literature relies mainly on time-series models to estimate $g^P_{t,n}$, 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 of

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

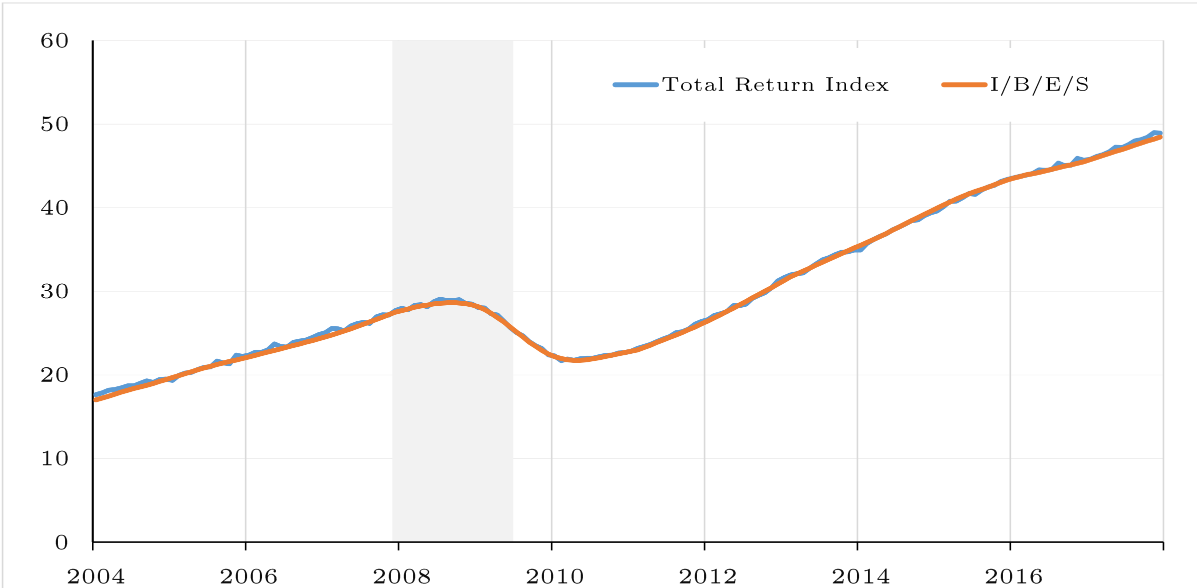
This table contains the sample mean for quantities describing the different Thomson Reuters I/B/E/S dividend estimates made from Jan 2004 - Oct 2017 and the time after the Great Recession. The number of covered companies states for how many companies in the S&P 500 a respective forecast was reported.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

our dividend aggregation, 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,

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

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.

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:

$$g_{t,60}^{P} \equiv E_t^{IBES}\left[g_{t,LT}\right].$$

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 $g_{t,n}^{P}$ 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 2.4.1.

2.2.2 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 2.5.1 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 $P_{t,n}$ be the price of a dividend asset that pays all future dividends up to $t+n$,

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

Put call parity in 'present value' representation reads

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

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

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

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

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

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

2.3 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 $P_{t,n}$ and that pays S&P 500 dividends from t to $t+n$.

2.3.1 Data Source and Data Selection

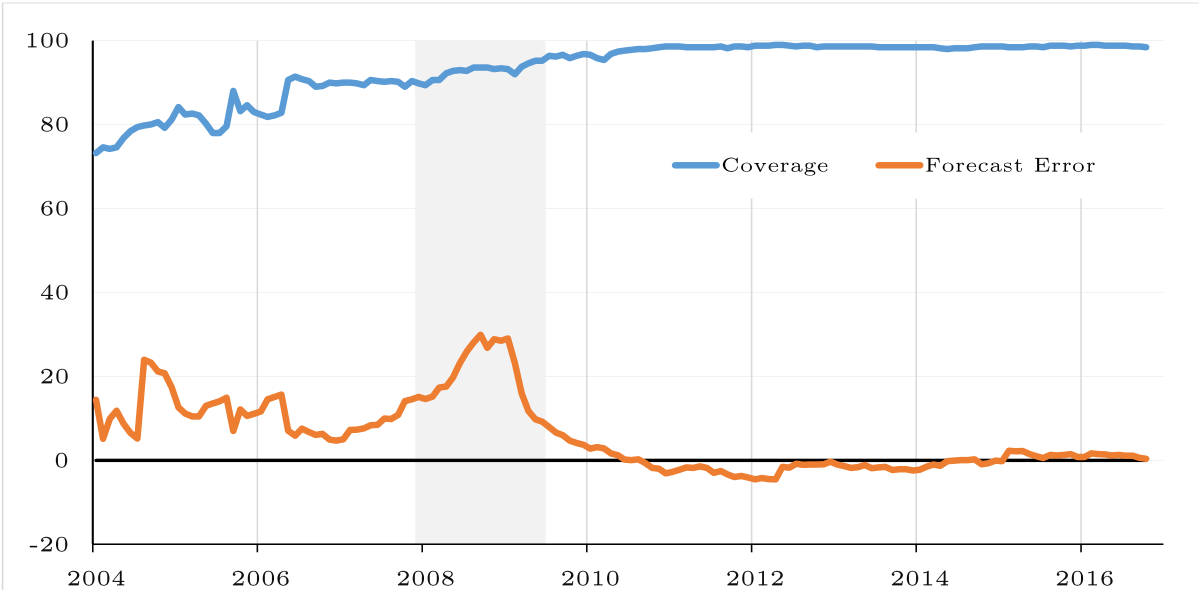
We follow the advice in Hull and White [2013] and proxy the term structure of the risk-free rate, $y_{t,n}$, with the U.S. Dollar Overnight Index Swap (OIS) rate. We take the OIS term structure with maturities of 1 day to 10 years from Bloomberg. Hull and White [2013] advocate the use of overnight rates for derivatives discounting and note that since the Great Recession, the OIS curve has increasingly become the new risk-free rate benchmark among practitioners.

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 Estimates 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

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.

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.

2.3.2 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 $P_{t,n}$. Equation (12) shows how to invest into this asset, whose only future cash flows are the realized dividends between t and $t+n$:

$$-P_{t,n} = p_{t,n} - c_{t,n} + S_t - Ke^{-ny_{t,n}}. \tag{15}$$

Going long the dividend asset $P_{t,n}$ 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 $P_{t,n}$ receives.

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

2.4 Empirical Analysis

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 in 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.

2.4.1 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.

Table 2: Implied Growth and Risk Premium Estimates

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 - Sep 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 - Sep 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

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 - Sep 2017 and the Great Recession in Dec 2007 - Jun 2009. Values are annualized, in percentage terms and rounded to two decimals.

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. The amount of lags in the Newey and West [1987] correction of standard error estimates is based on the heuristic $T^{0.25}$, T being the number of observations; we refer to Greene [2011] for details. 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 $z_{t,12}$.[7] 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 2.5.2 and compare $g^P_{t,12}$ to other popular measures of dividend growth in section 2.5.3.

[7] 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]).

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, where T is the number of observations. The predictions cover the period between Jan 2004 and Oct 2017.

2.4.2 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 $g^Q_{t,n}$ 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.

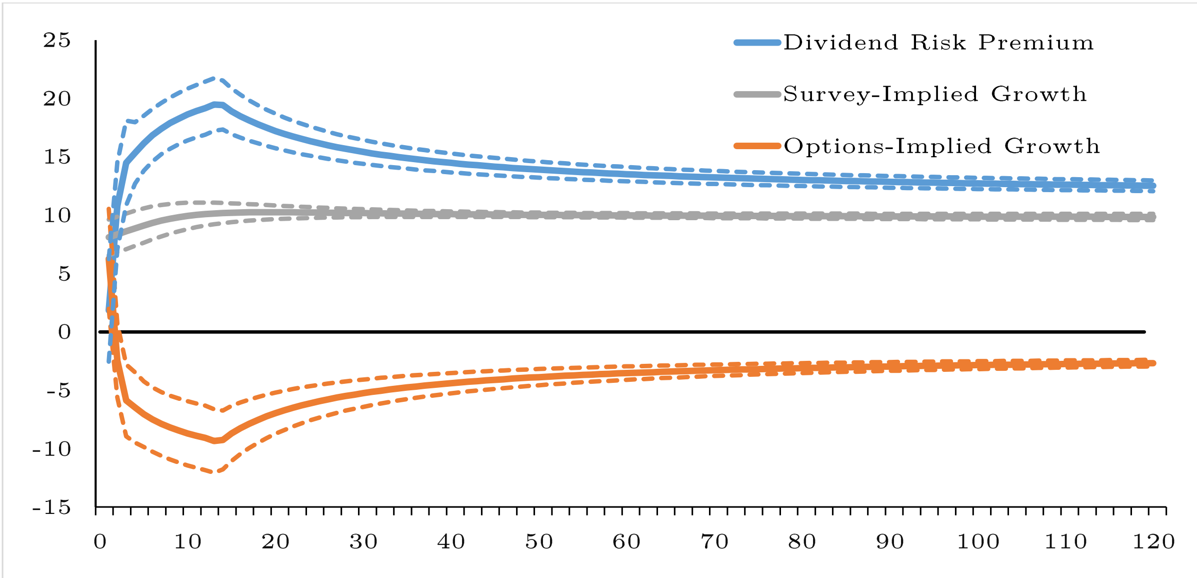
Figure 4 plots the time-series estimates for the one-year, two-year and long term dividend risk premium.

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%.[8]

The importance of dividend risk premium variations in options-implied dividend growth estimates is confirmed in figure 5, which depicts the time-series for $g^Q_{t,12}$, $g^P_{t,12}$ and $z_{t,12}$.

[8] 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 2.4.3.

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



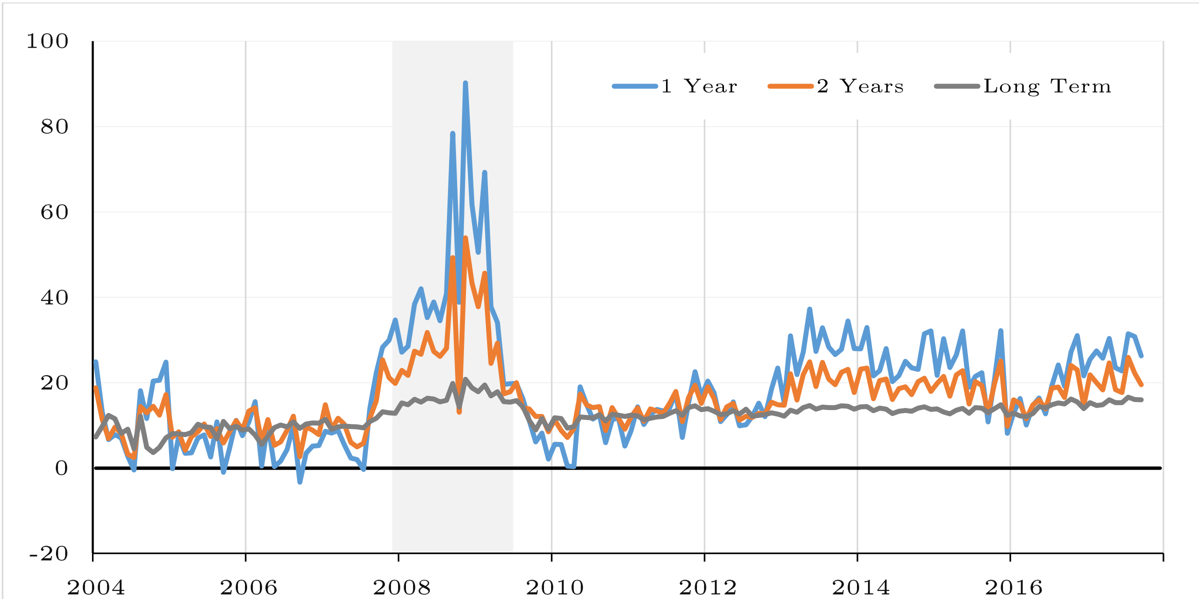
This figure shows the average future dividend growth rate implied by survey forecasts $g^P_{t,n}$ and option-prices $g^Q_{t,n}$, together with the expected dividend risk premium $z_{t,n}$, between Jan 2004 and Oct 2017. Dashed lines indicate two standard errors off the mean estimate. The horizontal axis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

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 $g^P_{t,n}$ and $z_{t,n}$ to the variance in $g^Q_{t,n}$,

$$var(g^Q_{t,n}) = cov(g^Q_{t,n}, g^P_{t,n}) - cov(g^Q_{t,n}, z_{t,n}). \tag{17}$$

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

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.

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 2.4.4.

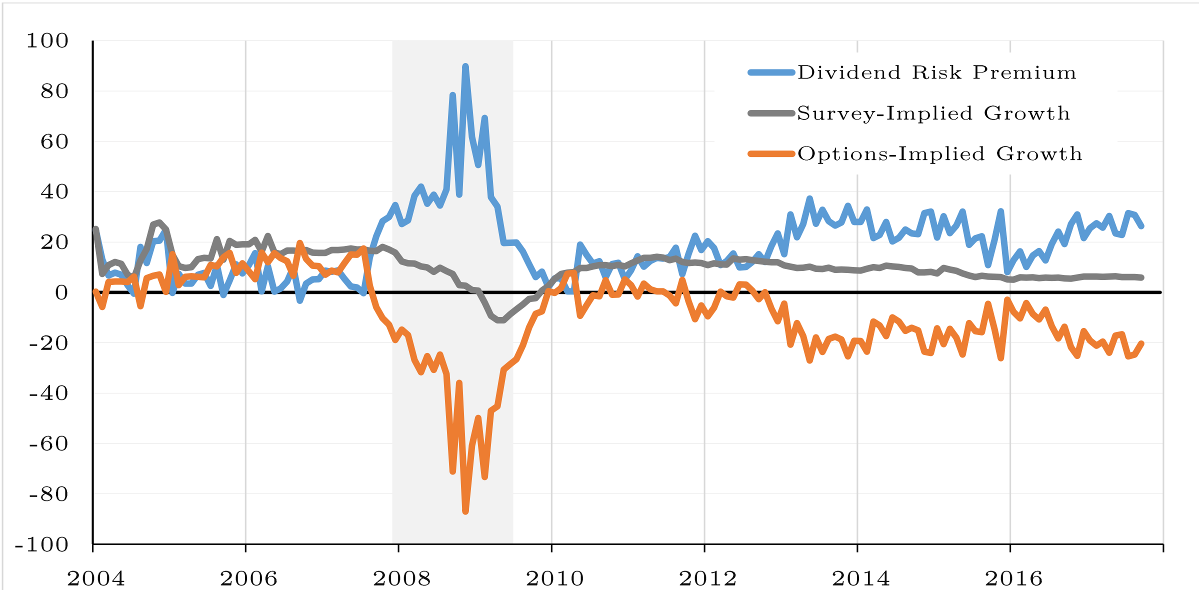
2.4.3 Returns on Dividend Assets

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

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

The holder of the dividend asset with price $P_{t,n}$ is entitled to receive the entire stream of dividends over the holding period h and the present value of the remaining dividends at the

Figure 5: One-year Growth and Premium 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.

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 $P_{t,12}$ to receive the t to $t+12$ dividend stream of the S&P 500,

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

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,

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

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

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

	January 2004 - October 2017							
	α	β_{MKT}	$\beta_{dp^{corr}}$	β_{SVIX}	$\beta_{pd^{strip}}$	β_z	MAE	R^2
$xr^{\infty}_{t,12}$	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

	July 2009 - October 2017							
	α	β_{MKT}	$\beta_{dp^{corr}}$	β_{SVIX}	$\beta_{pd^{strip}}$	β_z	MAE	R^2
$xr^{\infty}_{t,12}$	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:

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

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 according to 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, where T is the number of observations.

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 values 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

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, where T is the number of observations.

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.

2.4.4 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.[9] To formalize the relation of our premium estimates to business cycle variations, we characterize expansionary (contractionary) periods by industrial production 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.

[9] 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.

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

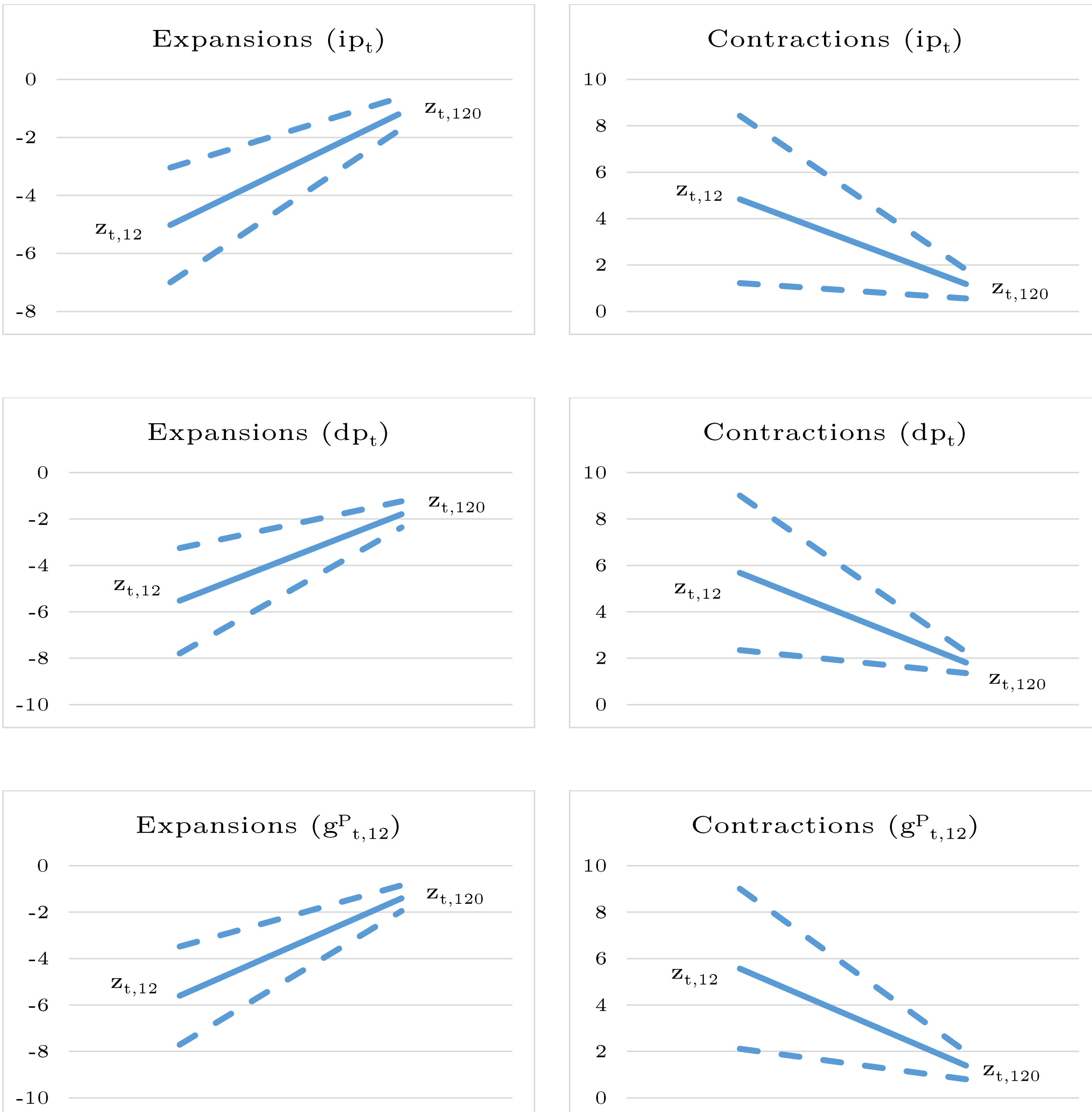
This table contains the risk premium estimates for dividends paid up to 120 months in the future. We report estimates for all data points in the period Jan 2004 - Oct 2017, as well as during expansionary and contractionary times. Expansionary and contractionary times are identified by either the current 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.

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, $X_t \in \{ip_t,\, dp_t,\, g^P_{t,12}\}$,

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

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

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.

Table 7: Regression Statistics - Business Cycle Variables

	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

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, where T is the number of observations. Values for α and R^2 are reported in percentage terms.

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.

2.4.5 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

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.

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 2.4.3 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

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

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

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. Average excess returns and standard deviations are annualized and reported in percentage terms.

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.

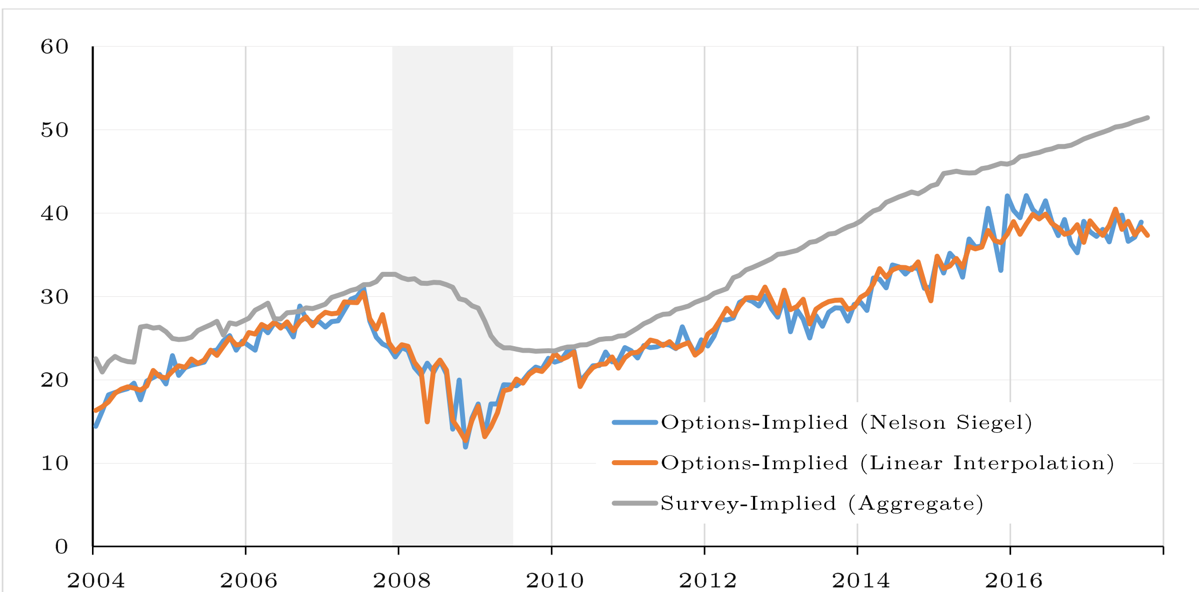
2.5 Comparison to Previous Studies

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. To do so, 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 2.5.1, we show that the choice of the interpolation scheme is irrelevant for short-term estimates. We discuss potential biases in our dividend growth estimates and compare them to findings in previous literature on earnings biases in section 2.5.2. In section 2.5.3, 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 2.5.4.

2.5.1 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.

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.

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.

2.5.2 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 $t+n$,

$$\nu^n_t = \frac{E_t[D_{t+n}] - D_{t+n}}{D_{t+n}}. \tag{24}$$

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.

2.5.3 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,

$$g_{t,t+12} = a^g + b^g X_t + \epsilon^g_{t+12}, \qquad \epsilon^g_{t+12} \sim i.i.d.(0, \sigma^2_g). \tag{25}$$

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

Table 10: Alternative Dividend Growth Estimates

	January 2004 - October 2017			
	a^g	b^g	MAE	R^2
$g^P_{t,12}$	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

	July 2009 - October 2017			
	a^g	b^g	MAE	R^2
$g^P_{t,12}$	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:

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

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 $g^P_{t,12}$ in a model-free way and without look-ahead bias, this means postulating $a^g = 0$ and $b^g = 1$. 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).

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 all five variables dy_t, ey_t, $e_{t,12}$, $e_{t,24}$ and g_t. We find an adjusted R^2 value of 85.1% and significant estimates for the loadings on dy_t, ey_t and g_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.

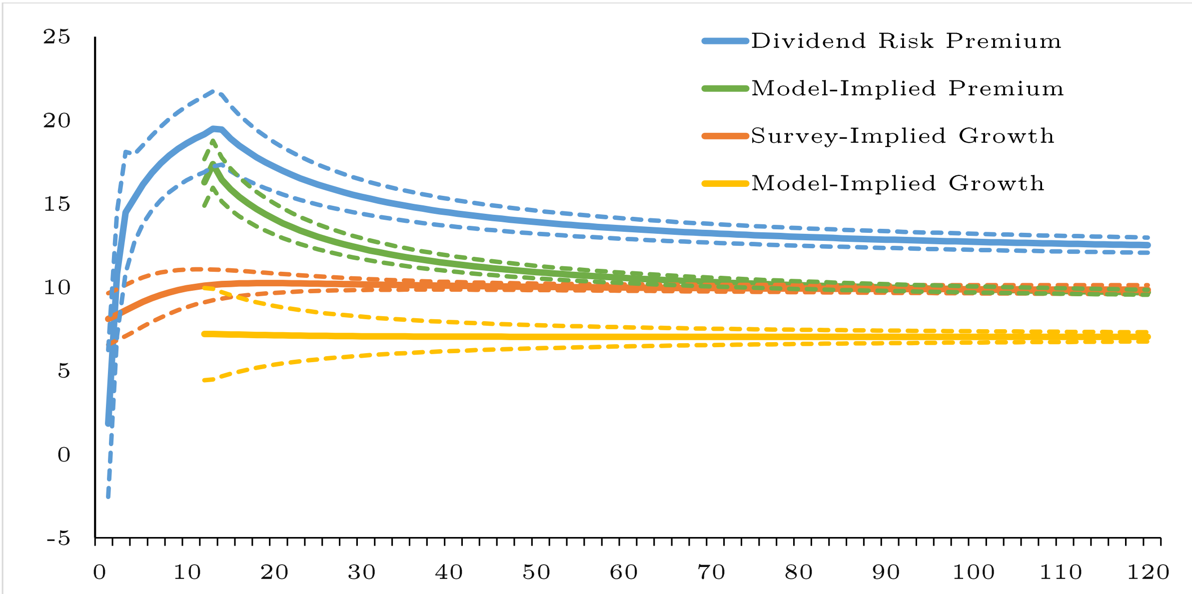
2.5.4 Alternative Measures of Expected Dividend Risk Premiums

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%. The relative spread of 2.7% is not different from zero at the 5% significance level and in line with the insignificant 2.34% bias in aggregate one-year ahead analyst dividend forecasts as documented in table 3.

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 (25). 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

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.

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.

2.6 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

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:

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

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, where T is the number of observations.

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.

3 Implied Premiums in European Dividend Futures

In the previous chapter, we derived a methodology to obtain the term structure of dividend risk premiums from analyst forecasts on dividends and options-implied present values of future dividends. In this chapter, we will extend the analysis of the previous chapter from the U.S. to the European market and show how to incorporate price information from dividend futures instead of options to obtain present values of future dividends.

3.1 Introduction

The introduction of dividend derivatives followed shortly after the work of Brennan [1998], who argued for the usefulness of assets written on single future dividends. First dividend swaps emerged in 2002 and were traded over-the-counter. Early studies, such as Binsbergen et al. [2013], studied this over-the-counter data with a strong focus on the term structure of realized returns. In August 2008, dividend futures on the Euro Stoxx 50 started to be traded at the Eurex Exchange, with maturities of up to ten years. Several studies have since then extended their scope and analyzed not only the American market, but other markets such as the European one, which has become the largest and most liquid market for dividend futures; see Binsbergen and Koijen [2017] and Kragt et al. [2018] for recent studies. Kragt et al. [2018] conclude that a two-factor model is necessary to accurately describe the term structure of risk-adjusted dividend growth rates. The authors find that one factor captures short-term mean reversion, while the second factor reverts at a business cycle horizon, and show that both latent factors are related to various economic and financial variables.

We contribute to this literature with an analysis of model-free premium estimates for the European market, obtained from analyst estimates and exchange-traded dividend futures. Trade prices of Euro Stoxx 50 dividend futures provide us with daily estimates of dividends paid up to ten years in the future. As for S&P 500 constituents, the Thomson Reuters I/B/E/S Estimates Database provides us with analyst estimates on future dividends of the different Euro Stoxx 50 constituents. We closely follow the methodology presented in Ulrich et al. [2018], in which we aggregate single company estimates to a representative index estimate, and construct the term structures of growth under the risk-neutral and empirical probability measure. From their difference, we obtain an estimate of the dividend risk premium term structure.

We aim for a comparison of the European and U.S. dividend market and therefore follow the empirical analysis in Ulrich et al. [2018], focusing on survey-implied dividend growth, return predictability, and the covariation of premium estimates with the broad equity market and business cycle. We find that analyst estimates on dividends imply an overly optimistic dividend growth rate of 7.51% for one-year and 7.59% for long term horizons during the period August 2008 to October 2017. Over the same period, realized one-year dividend growth has been negative on average at -2.85%, as the Euro Stoxx 50 dividends never recovered to their level prior to the Great Recession. Looking at the 67 individual constituents that have been part of the Euro Stoxx 50 index in our sample period, we find that the optimistic bias in the aggregate index is not due to a few outliers, but rather consistent across companies. Contrary to our findings for the S&P 500, one-year dividend growth implied by the derivatives market turns out to be unbiased, while survey-implied growth estimates appear to be strongly upward biased.

We find that this upward bias in analyst growth expectations translates into an upward bias in the implied dividend risk premium. Regarding return variation, our premium estimate turns out to be a strong predictor of future returns in dividend assets, similar to its counterpart in the U.S. market. The rich data set with several trades a day and a clean calculation of the respective returns allows us to study returns on a daily basis. We find that, unlike options-implied dividend assets on the S&P 500, excess returns in Euro Stoxx 50 dividend futures are positively correlated to returns in the underlying index. The business cycle behavior of our dividend risk premium term structure estimate is similar to its U.S. counterpart; we document a counter-cyclical level and pro-cyclical slope.

We summarize our methodology in sections 3.2 and 3.3, describe our data in section 3.4, and present our findings in section 3.5. We conclude with a comparison of our findings for the European and U.S. market in section 3.6.

3.2 Dividend Growth implied by Dividend Futures

A Euro Stoxx 50 dividend future with maturity n pays the dividends which all index constituents paid in the year preceding the expiry of the future. The exact value investors receive is determined by the value of the Euro Stoxx 50 Dividend Points (DVP) Index. This index adds up the dividends paid by all index constituents, without reinvestment, and is reset every year at the third Friday in December. Dividend futures expire on the third Friday in December of a particular year and hence pay all the dividends that were paid between the third Friday of the year prior to expiry and the actual expiry date. We can relate the present values or spot prices $S_{t,n}$ of investors' risk-neutral expectations on these dividends to dividend future prices $F_{t,n}$, as described in Binsbergen et al. [2013],

$$F_{t,n} = S_{t,n} e^{n y_{t,n}}, \tag{26}$$

where $y_{t,n}$ is the risk-free interest rate used to discount a cash flow occurring at time $t+n$. In the previous chapter, we established the relation between the present value and risk neutral dividend (growth) expectations,

$$S_{t,n} = D^Q_{t,n} e^{-n y_{t,n}} = D_t e^{n(g^Q_{t,n} - y_{t,n})}, \tag{27}$$

which reveals that the dividend future price is equal to investors' dividend expectations under the risk-neutral probability measure:

$$F_{t,n} = D^Q_{t,n}. \tag{28}$$

Dividend futures are traded on a daily basis and hence provide us with daily observations of risk-neutral expectations $D^Q_{t,n}$ for different horizons.

In order to estimate a daily measure of dividend growth expectations $g^Q_{t,n}$ from the daily observations of $D^Q_{t,n}$, we need a daily measure of current dividends D_t corresponding to $D^Q_{t,n}$,

$$g^Q_{t,n} \equiv \frac{1}{n} \ln \left(\frac{D^Q_{t,n}}{D_t} \right). \tag{29}$$

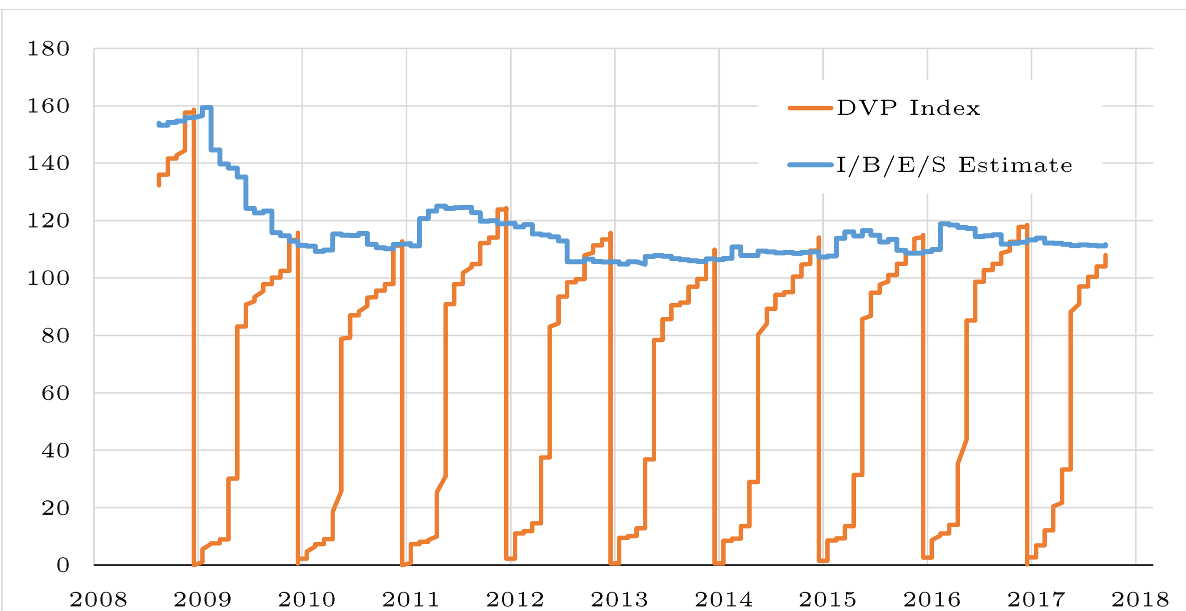
We propose two approximations to obtain an estimate for D_t. The first approximation is the aggregate dividend measure obtained from monthly I/B/E/S data. This measure is, by construction, constant throughout an entire month, which introduces some measurement error if we use it on a daily basis. While our empirical findings are robust to this approximation for D_t, we suggest to calculate a daily measure from the dividends paid by all index constituents over the 365 calendar days prior to t. We obtain this number from the positive increments[10] in the DVP index,

$$D^{DVP}_t = \sum_{i=1}^{364} [DVP_{t-i} - DVP_{t-i-1}]^+. \tag{30}$$

[10]The index is set to zero on the third Friday in December, which is the only negative change during a calendar year and the reason why we cannot simply calculate the difference between DVP_{t-1} and DVP_{t-365} to approximate one year of paid dividends.

We prefer this choice because of several reasons. First of all, the DVP index is also the underlying of the dividend future contracts and hence compares well to $D^Q_{t,n}$. Second, we do not have to adjust for seasonalities induced by clustered dividend payments, as both D^{DVP}_t and $D^Q_{t,n}$ consider a full year of dividend payments. Third, we always include the most recent payment of an index constituent that falls into the last 365 days. We acknowledge that this approach is also susceptible to measurement error, as some firms change the dates of their dividend payments and thus might pay twice in a 365 day interval or not at all. Figure 9 compares the actual DVP Index, which is reset to zero in December of each year, to our aggregate dividend measure from monthly I/B/E/S data. We can see how the DVP index starts at 0 close to the end of a calendar year and increases over the course of a year, approaching the aggregate I/B/E/S measure. The fact that they do not coincide each time that the DVP index reaches its peak in December is owed to the measurement error in both aggregation techniques.

Figure 9: Aggregate Euro Stoxx 50 Dividends



This figure plots the daily Euro Stoxx 50 Dividend Points (DVP) Index and the aggregate estimate for Euro Stoxx 50 dividends paid out over the last 12 months from monthly I/B/E/S reports on single company dividends. Values are in EUR.

We calculate the implied growth rates according to

$$g_{t,n}^{Q} \equiv \frac{1}{n} \ln \left(\frac{D_{t,n}^{Q}}{D_{t}^{DVP}} \right). \tag{31}$$

For every trading day with at least four out of ten observable maturities, we apply a Nelson and Siegel [1987] interpolation to all implied $g_{t,n}^{Q}$ to recover the full maturity spectrum,

$$g_{t,n}^{Q} = \tilde{\delta}_0 + \tilde{\delta}_1 \frac{1 - e^{-n\tilde{\lambda}}}{n\tilde{\lambda}} + \tilde{\delta}_2 \left(\frac{1 - e^{-n\tilde{\lambda}}}{n\tilde{\lambda}} - e^{-n\tilde{\lambda}} \right), \tag{32}$$

where the parameters $\tilde{\delta}_0$, $\tilde{\delta}_1$, $\tilde{\delta}_2$, and $\tilde{\lambda}$ are estimated by least-square methods.

3.3 Implied Premiums and Realized Returns

As shown in section 2.2, the implied premium is the difference between empirical growth expectations $g_{t,n}^{P}$ and risk-neutral growth expectations $g_{t,n}^{Q}$,

$$z_{t,n} = g_{t,n}^{P} - g_{t,n}^{Q}, \tag{33}$$

which we approximate with survey- and future-implied dividend growth. We obtain growth expectations $g_{t,n}^{P}$ under the empirical probability measure from survey estimates, using our approach first implemented with S&P 500 data in the previous chapter. We rely on the Thomson Reuters I/B/E/S Estimates Database, which supplies us with dividend estimates for the constituents of the Euro Stoxx 50 index for different forecast horizons. We find a high coverage ratio for the Euro Stoxx 50, see section 3.4, and hence conclude that our aggregation and interpolation approach detailed in appendix A is well-suited to obtain aggregate estimates for Euro Stoxx 50 dividends.

We calculate the ex-post realized return on every future contract in our sample from the value of the underlying DVP index at maturity $t + n$ and the dividend future price at time t,

$$r_{t,n}^{F} = ln \left(\frac{DVP_{t+n}}{F_{t,n}} \right), \tag{34}$$

which provides us with estimates of the returns the investors received from buy-and-hold investments.

3.4 Data Source and Data Selection

We set the term structure of the risk-free rate, $y_{t,n}$, to coincide with the euro area yield curve estimated and published by the European Central Bank based on AAA-rated euro area central government bonds.[11] The provided Svensson [1994] parameters allow us to obtain any necessary maturity between one and ten years.

Regarding the estimation of survey-implied dividend growth rates, we find the CUSIP identifier of all Euro Stoxx 50 index constituents 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) fiscal year one, two and three (DPS1D, DPS2D, DPS3D), (v) dividend per share median estimate for fiscal year one, two and three (DPS1MD, DPS2MD, DPS3MD) and (vi) the long term operating earnings growth median estimate (LTMD). Notice, we assume that the long term earnings growth forecast coincides with the long term dividend growth forecast and that the one-month ahead expected dividend growth rate coincides with the currently realized dividend growth rate, which we measure as the annual growth in twelve-month trailing dividends. Table 12 contains descriptive statistics which highlight the good coverage in analyst forecasts - on average, more than 98% of the Euro Stoxx 50's market capitalization are covered by fiscal year estimates in the period August 2008 to October 2017.

Table 12: Descriptive Statistics - Analyst Data (Euro Stoxx 50)

Aug 2008 - Sep 2017	FY1	FY2	FY3	Long Term
Number of covered companies	49.21	49.21	49.16	48.70
Coverage of market capitalization	98.16	98.16	98.14	97.15

This table contains the sample mean for quantities describing the different Thomson Reuters I/B/E/S dividend estimates for Euro Stoxx 50 companies. It covers the period from Aug 2008 - Sep 2017, for which we have quotes on dividend futures. The number of covered companies states for how many companies with the respective forecast horizon a forecast was reported. Coverage of market capitalization is a measure for the reported companies' aggregate contribution in percent to the aggregate market capitalization of the Euro Stoxx 50 index.

[11] https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/euro_area_yield_curves

We use Eurex Exchange Euro Stoxx 50 Index Dividend Futures (ISIN DE000A0V8MN0) trade data to obtain future-implied Euro Stoxx 50 dividend growth forecasts $g^Q_{t,n}$. We collect over half a million intra-day trade prices for dividend future contracts during the period August 4, 2008 to September 29, 2017, which translates into 238 trades per trading day on average. Compared to the option market studied in the previous chapter, we find much longer maturities in dividend futures - the longest traded maturity is 3641 days in the Euro Stoxx 50 dividend futures and 1094 days in the S&P 500 options. We provide detailed descriptive statistics in table 13. The average trade size is at 689,934 EUR, the median

Table 13: Transaction Data for Euro Stoxx 50 Dividend Futures

	0	1	2	3	4	5	6	7	8	9
Total amount of trades (M)	51.81	150.88	127.11	86.16	53.45	28.30	14.25	6.12	5.16	3.86
Average trade volume (MM)	1.05	0.72	0.66	0.60	0.58	0.61	0.59	0.57	0.47	0.44
Average trades per day	23	68	58	39	24	13	6	3	2	2
Non-trading days per year	21	3	4	6	11	19	45	88	117	129

This table contains descriptive statistics regarding Eurex trade data on Euro Stoxx 50 Dividend Futures between Aug 2008 and Oct 2017. We split the data set into maturity bands: 0 comprises all traded future contracts with a maturity of up to one year, 1 comprises all traded future contracts with a maturity between one and up to two years, and so on. The total amount of trades is quoted in thousands, average trade volume in million EUR. Average trades per day and days without trading per year are rounded to the nearest integer.

trade size at 165,150 EUR, considering all maturities. The most often traded maturity band is one to two years, with on average 68 trades per day and only three trading days per year without a trade. With an average of two trades per day, the longest maturity of ten years is at the same time the least frequently traded.

We find daily quotes on the DVP index, the underlying to the Euro Stoxx 50 Index dividend futures, in Bloomberg (SX5ED Index), from which we then determine the future-implied growth rates $g^Q_{t,n}$ and future excess returns for every future trade as described in equation (34).

3.5 Empirical Findings

Our empirical findings for the Euro Stoxx 50 document a strong and positive upward bias in aggregate dividend forecasts, which translates into an upward bias in the risk premium estimates. Still, the time series variation in realized one-year dividend growth is well captured by the aggregate one-year survey-forecast and helps, combined with growth implied by dividend futures, to accurately predict their returns. We confirm the on average negative slope of the dividend risk premium term structure, which steepens further during contractionary periods and flattens during business cycle expansions, as documented for the S&P 500 in chapter 2. We also document a strong predictability in hold-to-maturity excess returns on dividend futures, which are positively correlated to returns in the underlying index.

3.5.1 Growth and Premium Estimates

Before we dedicate this section to the analysis of potential biases, we discuss the different term structure estimates documented in table 14. Our estimate of the term structure

Table 14: Implied Growth and Risk Premium Estimates (Euro Stoxx 50)

n	1	2	3	4	5	6	7	8	9	10
$g^P_{t,n}$	7.50	7.55	7.57	7.58	7.58	7.58	7.59	7.59	7.59	7.59
$g^Q_{t,n}$	-8.49	-7.35	-6.34	-5.72	-5.33	-5.06	-4.86	-4.72	-4.60	-4.51
$z_{t,n}$	15.99	14.90	13.91	13.30	12.91	12.64	12.45	12.30	12.19	12.10

This table contains the estimates 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 Aug 2008 - Sep 2017 for various maturities n. The maturities range from one to ten years, based on the maturities of the dividend futures. Values are annualized, in percentage terms and rounded to two decimals.

of survey-implied dividend growth $g^P_{t,n}$ is almost flat, starting at 7.50% at the one-year horizon and reaching 7.59% at the longest reported horizon, five years, from where it stays flat for longer extrapolated maturities. This almost flat term structure is the reason why the negative slope in the risk premium term structure is almost only due to the positive slope in future-implied growth estimates $g^Q_{t,n}$. The estimates for $g^Q_{t,n}$ start at -8.49% for the one-year horizon and increase to -4.51% for the ten-year horizon. Future-implied growth thus contributes most to the negative term premium of -3.89%, the difference between the ten-year, 12.10%, and one-year, 15.99%, dividend risk premium .

Our analysis of S&P 500 constituents and their aggregate values reveals an upward bias in analyst dividend forecast on the single constituents level, which gets smaller on the value-weighted aggregate index level. Regressing one-year future dividend growth on aggregate analyst estimates, we have documented an insignificant regression constant of

-2.34% for the S&P 500, see table 3. We repeat this exercise for the Euro Stoxx 50. As with the S&P 500, we focus on the one-year estimates because our sample is not long enough to test for biases in long term forecasts.

Before we turn to regression results, we briefly look at the constituents of the Euro Stoxx 50. For 62 of the 67 companies that have been part of the index during our sample period, we find a positive prediction error in fiscal year one estimates. The average estimate predicts dividends 10.71% higher than their subsequent realizations. This bias on the company level has an impact on the aggregate growth forecast, as we can see from the difference between the average realized one-year growth, -2.85%, and the average one-year growth estimate, 7.50%. For robustness, we compute the average realized growth from aggregate I/B/E/S data on realized dividends and conclude that the resulting average growth rates are reasonably close to each other at -2.85% (DVP Index) and -3.26% (I/B/E/S).

We compare future-implied dividend growth, survey-implied dividend growth and future realized growth in figure 10. Contrary to the findings for the S&P 500, the figure suggests the existence of a strong upward bias in the aggregate analyst forecast and almost no bias, except for the months that fall into the Great Recession, in future-implied growth.

The following regressions support this finding. We assess whether $g^P_{t,12}$ or $g^Q_{t,12}$ are accurate expectations of future annual dividend growth, denoted as $g_{t,t+12}$, by the following regressions:

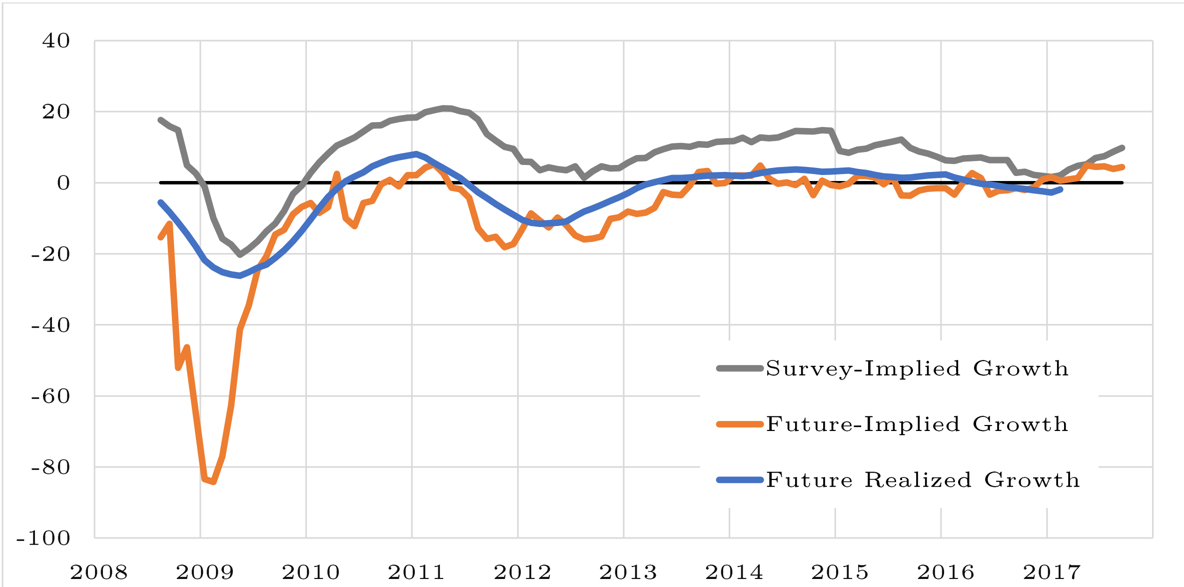
$$g_{t,t+12} = a^g + b^g X_t + \epsilon^g_{t+12}, \qquad \epsilon^g_{t+12} \sim i.i.d.(0, \sigma^2_g), \qquad X_t \in \{g^P_{t,12}, g^Q_{t,12}\}. \tag{35}$$

The results of these regressions are summarized in table 15. Given the short period of time for which we observe future trades, both parameter estimates and adjusted R^2 values are prone to small sample biases. We therefore focus our attention to the intercept estimate a^g, which is insignificant and small (0.35%) for $g^Q_{t,12}$, but significant and large (-10.24%) for $g^P_{t,12}$. This finding is contrary to our findings in chapter 2, where analyst estimates on the S&P 500 appear to be unbiased, and options-implied growth biased. Our survey-implied growth estimates are therefore likely to introduce a significant bias in the risk premium estimates $z^d_{t,n}$.

3.5.2 Economic Fluctuations

Figure 11 documents the average shapes of the dividend risk premium term structure during different states of the economy.

Figure 10: Comparison of Growth Estimates



This figure plots survey-implied growth, future-implied growth and future realized growth for Euro Stoxx 50 dividends with a one-year horizon. Values are in percentage terms and annualized.

We classify each month in our sample into expansion or contraction, according to the current value of annual industrial production growth for the European Union, respective to its sample median.[12] The findings for the Euro Stoxx 50 index are in line with the findings for the S&P 500 index - we detect a counter-cyclical level and a pro-cyclical slope. We conduct a difference-in-mean test for each maturity, where we asses whether the mean estimates of the risk premium are statistically different (our alternative hypothesis) between contractionary and expansionary times. For maturities up to four years, the two-tailed probability of falsely rejecting the null hypothesis of equal means is below 1%. For maturities beyond four years, t-statistics turn out to be too small to reject the null hypothesis with confidence.

3.5.3 Realized Returns and Predictability

Figure 12 contains the future realized excess returns for dividend futures with a maturity between one and two years.

[12]OECD (2019), Industrial production (indicator). doi: 10.1787/39121c55-en

Table 15: Regression Statistics - Dividend Growth (Euro Stoxx 50)

X_t	a^g	b^g	R^2
$g^P_{t,12}$	-10.24 (1.22)	0.86 (0.06)	74.3
$g^Q_{t,12}$	0.35 (1.36)	0.40 (0.06)	62.7

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 futures-implied dividend growth expectations $X_t = g^Q_{t,12}$:

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

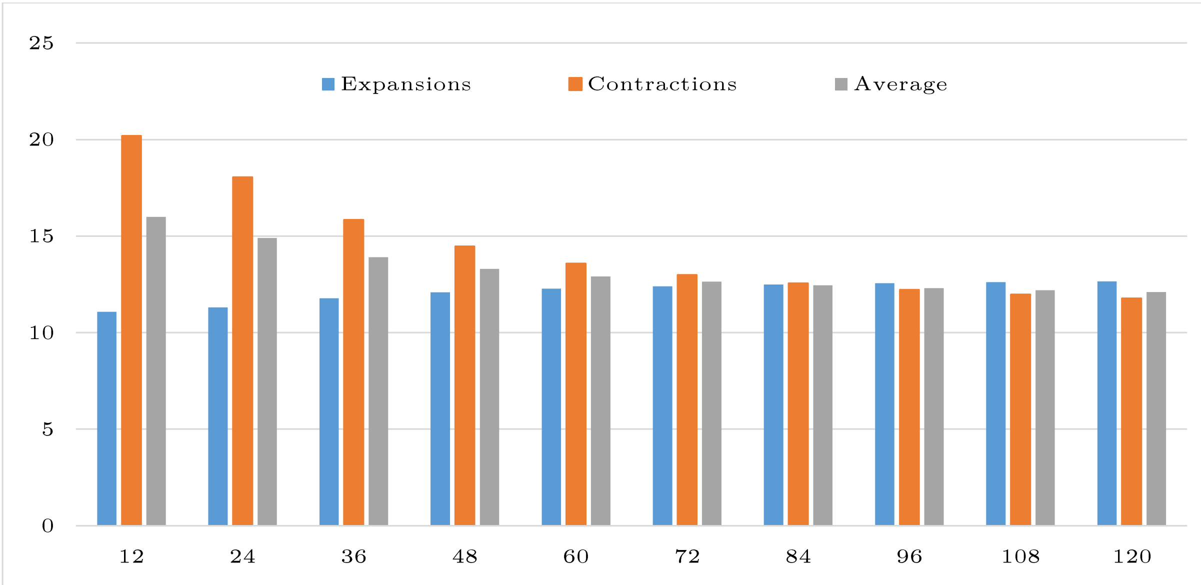
Values for a^g and R^2 are in percentage terms. Newey and West [1987] standard errors with $T^{0.25}$ lags are reported in parenthesis, where T is the number of observations. The predictions cover the Aug 2008 - Sep 2017.

This maturity band is traded multiple times a day and thus provides us with a high number of buy-and-hold returns which we calculate from the trade price and the underlying DVP index. Assuming that survey-implied growth $g^P_{t,n}$ is constant throughout a month, we can approximate the growth expectation corresponding in maturity to every dividend future, and hence the implied premium $z_{t,n}$. From a first visual inspection, this figure suggests the previously mentioned upward bias in the premium estimates, as the implied premium is above the subsequent realized excess return in almost all occasions. We will formalize this in a set of regressions, in which we also assess the predictive power of our premium estimate for subsequent excess returns.

Instead of limiting our analysis to end-of-month data, we consider all trading days in this maturity band. By using actual returns on realized trades, we have no constant maturity, but a maturity which decreases constantly throughout the year. At the third Friday in December, the dividend future gets rolled into the new two-year future. To obtain one return value per day, we take the median value across all realized trades in the same day. Note that we first look at hold-to-maturity returns, then look at day-to-day price changes. Our regressions cover 1503 observations, limited by the amount of trading days with a consecutive trade on the next day.

Our regression results are documented in table 16, we start our predictability analy-

Figure 11: The Changing Shape of the Dividend Risk Premium Term Structure



This figure shows the average risk premium estimates for dividends paid up to 10 years in the future. We report average premiums for Aug 2008 - Sep 2017 and split the sample into expansionary and contractionary times, characterized by the current value of log industrial production growth above and below its median. The horizontal axis displays the maturity of the respective dividends. Values on the vertical axis are in percentage terms and annualized.

sis with the following regression:

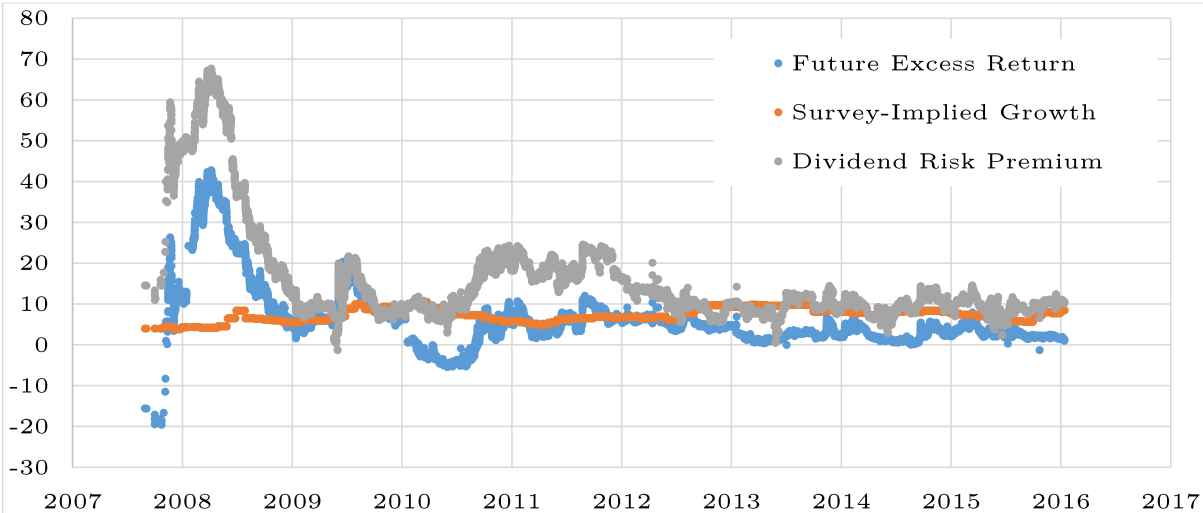
$$xr^F_{t,n} = \alpha + \beta z_{t,n} + \epsilon^F_{t+n}, \qquad \epsilon^F_{t+n} \sim i.i.d.(0, \sigma^2_F), \tag{36}$$

where $xr^F_{t,n}$ is the hold-to-maturity excess return of the dividend future with maturity n between one and two years, calculated according to equation (34) minus the corresponding risk free rate. We regress $xr^F_{t,n}$ on the corresponding risk premium estimate $z_{t,n}$, which reveals a significant upward bias of 2.39% across the entire sample and an adjusted R^2 value of 77.6%, implying that our risk premium approximation is a strong, albeit upward biased, predictor of future returns in dividend futures.

We assess the premium estimates' predictive power for the total excess return in the underlying equity index, also reported in table 16:

$$xr^{SX5E}_{t,n} = \alpha + \beta z_{t,n} + \epsilon^{SX5E}_{t+n}, \qquad \epsilon^{SX5E}_{t+n} \sim i.i.d.(0, \sigma^2_{SX5E}), \tag{37}$$

Figure 12: Trade Data - Dividend Premium Estimates and Future Returns



The blue dots in this figure represent hold-to-maturity excess returns for 15.772 dividend future trades in our sample with a maturity between 1 and 2 years. The gray dots represent the implied dividend risk premium $z_{t,n}$ corresponding to each single trade, the orange dots the survey-implied growth expectation $g^P_{t,n}$ matched to each futures maturity. Values on the vertical axis are in percentage terms and annualized.

where $xr^{SX5E}_{t,n}$ is the buy-and-hold total excess return of the Euro Stoxx 50 over holding period n. For every day with a corresponding trade in dividend futures, we match the holding period to the one in the dividend future to allow for a comparison of the regression results. We find an adjusted R^2 value of 20.7%, which is compared to the estimates for the S&P 500 a significantly different result and suggests that our dividend risk premium estimate has predictive power for the equity index excess return.

We also compute excess returns from day-to-day price changes in the dividend futures. From all trades in the one- to two-year maturity band, we take the median price on a given trading day to calculate the realized daily returns. We then regress the excess returns on the five daily Fama and French [2015] factors for the European market to analyze the contemporaneous correlation to these popular return factors.[13] Table 17 contains the results, of which we want to highlight the significant correlation between dividend future excess returns and the overall market excess return, with an adjusted R^2 value of 23.0%.

[13]Fama/French European 5 Factors [Daily], *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International.*

Table 16: Regression Statistics - Equity and Dividend Returns

	α	β	R^2
$xr^F_{t,n}$	-2.39 (0.63)	0.56 (0.04)	77.6
$xr^{SX5E}_{t,n}$	0.91 (2.61)	0.26 (0.08)	20.7

This table reports regression estimates and adjusted R^2 values for predictive regressions of future equity excess returns $xr^{SX5E}_{t,n}$ and excess returns in dividend futures $xr^F_{t,n}$ realized over holding period n, where n corresponds to the maturity of the dividend future traded on a respective trading day. We regress the future excess returns on the corresponding dividend risk premium estimate $z_{t,n}$:

$$r_{t,n} = a^r + b^r z_{t,n} + \epsilon^r_t.$$

Values for a^r and R^2 are in percentage terms. Newey and West [1987] standard errors with $T^{0.25}$ lags are reported in parenthesis, where T is the number of observations. The sample period is from Aug 2008 - Sep 2017 and covers a total of 15.772 trades.

This findings suggests that contemporaneous returns in Euro Stoxx 50 dividend futures are much closer related to the equity market than returns in S&P 500 dividend assets obtained from option trades.

3.6 Conclusion

In this chapter, we rely on a large set of Eurex Exchange trade data to extend our work in Ulrich et al. [2018]. Trade prices of Euro Stoxx 50 dividend futures provide us with direct estimates of dividends paid up to ten years in the future. As for the American market, the Thomson Reuters I/B/E/S Estimates Database provides us with analyst estimates on future dividends of the different Euro Stoxx 50 constituents. We closely follow the methodology presented in Ulrich et al. [2018], by aggregating single company estimates to a representative index estimate, and construct the term structures of growth under the risk-neutral and empirical probability measure. From their difference, we obtain an estimate of the dividend risk premium term structure.

We conclude this chapter with a brief comparison of the results obtained from options on the S&P 500 and dividend futures on the Euro Stoxx 50. For both markets, we find that the implied risk premium term structures are counter-cyclical in their level and pro-cyclical in their slope. One potential explanation is that investors demand a larger

Table 17: Regression Statistics - Daily Fama and French [2015] Factors

	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	R^2
xr_t^{SX5E}	0.00 (0.00)	0.54 (0.02)	-1.06 (0.07)	0.31 (0.05)	-0.23 (0.09)	-0.24 (0.08)	84.9
xr_t^F	0.00 (0.00)	0.30 (0.06)	0.21 (0.07)	0.07 (0.11)	-0.28 (0.15)	-0.32 (0.12)	23.0

This table reports estimates for regressions of daily index excess returns xr_t^{SX5E} and daily excess returns in dividend futures xr_t^F on the daily European five Fama and French [2015] factors:

$$xr_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{RMW}RMW_t + \beta_{CMA}CMA_t + \epsilon_t^r.$$

We analyze daily excess returns for every trading day with sufficient liquidty to compute a return in dividend futures between Aug 2008 - Sep 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, where T is the number of observations.

premium for exposure to uncertain dividends in times of economic contractions. Our difference-in-mean test suggest that this difference in the level is significant for short term maturities, supporting the idea that investors are more concerned about dividends paid over a business cycle frequency than about dividends paid beyond, potentially assuming that the market will recover over three to five years. While aggregate analyst estimates for the S&P 500 seem to be unbiased, we find a significant positive bias for the Euro Stoxx 50, translating into a bias in the premium estimates. Yet, for both markets, the premium estimate is a strong predictor of returns on dividend assets, at least for the one- to two-year maturity band.

We also want to highlight the several advantages of dividend future data over option data when it comes to the estimation of implied dividend risk premiums. The price of a dividend future corresponds to the expectation on a set of future dividends under the risk-neutral probability measure. This direct measurement of dividend expectations comes without the need to match option trades in put call parity. For several reasons, the matching procedure for option trades is prone to significant measurement error - a slightly asynchronous match between option and underlying quotes can have a large impact on the implied present value, as does the choice of the risk free rate used in put call parity. We can avoid these problems with the use of dividend futures. A second advantage are the longer maturities in dividend futures, which have become more and more frequently traded over the last ten years. In addition, the underlying DVP index facilitates the calculation of realized returns. All these advantages lead us to our recommendation of dividend futures data if one is interested in an estimate of the term structure of risk-adjusted growth or the dividend risk premium. Since 2015, dividend futures for the S&P 500 are exchange-traded and provide an interesting opportunity for future research.

4 A Term Structure Model for Bonds and Dividends

In the previous chapters, we proposed a model-free approach to estimate the term structure of dividend risk premiums. In this chapter, we will derive an affine term structure model which allows us to price bond and dividend markets simultaneously, providing us with a parametric estimate of the dividend risk premium term structure.

4.1 Introduction

Term structure models have a rich history in the bond pricing literature, where they dominate more than four decades of academic research. The empirical literature on dividend or equity pricing, on the other hand, lacks term structure models for one particular reason: a standard equity claim has no determined maturity, less so several maturities which are the corner stones of a term structure. Over time, with the introduction of derivatives, it has become feasible to trade particular future dividends and estimate their respective discount rates. This literature, pioneered by Binsbergen et al. [2012], has made considerable contributions to provide us with parametric (Binsbergen et al. [2013], Bansal et al. [2017], among others) and non-parametric (Ulrich et al. [2018]) estimates of the dividend risk premium term structure. To the best of our knowledge, our paper offers the first affine term structure model to price Treasury bonds, S&P 500 dividend strips and the S&P 500 equity index, allowing us to decompose discount rates into interest rate and dividend risk premiums.

Our empirical analysis reveals several new insights and in other occasions confirms well-known empirical facts. First, our benchmark model describes the asset price, macro and survey data well. The pricing errors of the bond, equity and short-horizon dividend data are comparable to state-of-the-art latent factor models which focus on only one of the asset classes. The reason for the model to fit the data so well is rooted in three reasons. We use survey data about the underlying economy and on asset prices to ensure that long- and short-term components of the fundamental risk factors are well identified. The data on realized asset prices in combination with the macro and survey data ensures that the market prices of risk are well identified. Lastly, we apply economic restrictions to reduce the most general framework to a parsimonious setting, with a reasonable amount of pricing factors to price three asset classes.

Second, we find that a monetary policy rule based on the Federal Reserve's dual mandate - price stability and sustainable employment - enables us to price government bond yields accurately, even in recent times of unconventional monetary policy measures.

Survey data on inflation and unemployment expectations, published by the Federal Reserve, contributes to the identification of our pricing factors.

Third, we show how to incorporate dividend growth into an affine term structure model to obtain a term structure estimate on dividend discount rates. Looking at the full sample for which we have data on dividend strips, 1996 - 2017, we find that the average term structure of dividend discount rates is downward sloping. This is due to an on average negative slope in the dividend risk premium term structure, driven by the two recent recessions. At the same time, we find that the bond term structure is upward sloping (Lettau and Wachter [2007]). Looking at the time before 1996, for which we have no signals on near-future dividends, the term structure of the dividend discount rate cannot be identified. Restricting our benchmark model to have all market prices of risk to be affine in the economic state variables, our macro-only model, leads to large pricing errors in both dividend growth and dividend strips. In order to price dividend strips accurately, we find that the market price of near-future dividend risk is not affine in the underlying economy. The estimated dividend risk premium turns out to predict future returns on dividend strips with high precision.

Our term structure model provides a potential explanation to the empirical observation that short-horizon dividend assets, or dividend strips, earn average excess returns that in a CAPM regression are classified as abnormal, or 'alpha', see Binsbergen et al. [2012] and Ulrich et al. [2018]. Binsbergen et al. [2012] emphasize the implication that dividend strips could be used as an additional asset class to test asset pricing models. We argue that this seemingly odd behavior of risk premiums in dividend strips is based on a market price of dividend risk which is comprised of a long term and a short-term component. The long term component is earned for exposure to long term dividend risk, while the short-term component is earned for exposure to near-future dividend risk. Holding a standard equity claim exposes the investor to short-term, but most of all long term dividend shocks. An investment into dividend strips, on the other hand, exposes the investor almost entirely to near-future, or short-term, dividend shocks. We argue that these shocks are priced with different market prices of risk. While a standard equity investment can be well described with market prices of risk being affine in the underlying economic growth states, dividend strips cannot be priced under this assumption. As these two market prices of risk are weakly correlated, the excess return from an investment in dividend strips is classified as an abnormal return when regressed against the excess return of a standard equity claim.

Section 4.2 presents well-known present value models that allow to derive arbitrage-free discount rates for bonds and dividend assets. Section 4.3 sets up the affine term structure model and derives several model quantities of interest. Section 4.4 introduces several economic restrictions that we apply to bring the model to data. We dedicate section 4.5 to a discussion of our data and estimation methodology and present our findings in section 4.6. We conclude in section 4.7.

4.1.1 Related Literature

Our paper is the first to provide an affine term structure model for options- and survey-implied dividend discount rates, embedded into a state-of-the-art macro-factor term structure model for Treasury bonds and aggregate equity. As such, our model and empirical findings contribute to separate strands of the literature. First, Binsbergen et al. [2012] and Binsbergen et al. [2013] rely on regression tools and realized returns to uncover the average term structure of the dividend risk premium. Our model provides a new tool to extract this term structure. Our approach generalizes the approach of Ang and Liu [2004], who calibrate a quadratic Gordon Growth model to equity data.

We also contribute to the macro-finance bond literature (including Ang and Piazzesi [2003], Ang et al. [2011], Ang et al. [2008], Bauer et al. [2014], Joslin et al. [2013], Joslin et al. [2014], Ludvigson and Ng [2009] and Rudebusch and Wu [2008], among others), showing that an affine bond model with macro risks is very well able to price the U.S. Treasury yield curve with high accuracy, even in recent times of unconventional monetary policy measures. Our strong predictive values for future short rates and bond returns reconcile our work with the work of Kim and Orphanides [2012], who rely on survey expectations to accurately identify dynamics under the empirical and risk-neutral probability measure.

Our work is closest related to Binsbergen et al. [2012], Binsbergen et al. [2013], Binsbergen and Koijen [2017] and Ulrich et al. [2018], who extract the term structure of the dividend risk premium from derivative prices and dividend growth expectations. Relative to these papers, we propose a macro-based no-arbitrage framework with a simple monetary policy rule to explain prices of bonds, equity and dividend strips in a single unifying model.

Also related to our work is the contribution of Kragt et al. [2018], who estimate a term structure of dividend growth using dividend futures; and Filipović and Willems [2017], who jointly estimate interest rate and dividend term structures with a latent discount rate factor and a latent dividend factor. Kragt et al. [2018] show that a two-factor structure, one factor with quick mean reversion and one at business cycle frequency, can explain discount rates implied by dividend futures, but not reconcile the aggregate stock price with dividend strips. Filipović and Willems [2017] estimate a downward sloping term structure for the dividend risk premium embedded in Euro Stoxx 50 dividend derivatives. In contrast to these contributions, our model is based on an economic environment with a monetary policy rule and prices bonds, dividend strips and equity simultaneously.

For the joint modeling of bonds and equity, our model also relates to Ang and Ulrich [2012] and Lemke and Werner [2009], who set-up an affine latent factor model for the term structure of Treasury bonds and the aggregate price of equity. Adding to these contributions, we work with survey expectations to separate between physical and risk-neutral expectations and incorporate dividend strips to study the term structure of the dividend risk premium.

4.2 The Dividend Discount Model

We define the time t present value of a future dividend expected to be distributed in time $t+n$ by

$$S_{t,n} \equiv E_t^Q \left[D_{t+n} e^{-n y^{\$}_{t,n}} \right] \tag{38}$$

where $y^{\$}_{t,n}$ is the risk free bond yield applicable between t and $t+n$, and $\mathcal{Q}$ denotes that we take expectations under the risk neutral probability measure. Dividends are uncertain and expected to grow at a stochastic rate between t and $t+n$, which we define as

$$g^d_{t,n} \equiv \frac{1}{n} ln \left(\frac{E^P[D_{t+n}]}{D_t} \right). \tag{39}$$

We introduce the dividend discount rate $y^d_{t,n}$, which, in addition to the bond yield, compensates investors for exposure to this uncertainty in form of a dividend risk premium $z^d_{t,n}$,

$$y^d_{t,n} \equiv y^{\$}_{t,n} + z^d_{t,n}. \tag{40}$$

This allows us to express the present value under the empirical probability measure $\mathcal{P}$:

$$S_{t,n} = D_t e^{n(g^d_{t,n} - y^d_{t,n})}. \tag{41}$$

A relatively well understood special case of $S_{t,n}$ is the price of a risk-free zero-coupon bond. A risk-free zero-coupon bond with maturity n pays a certain dividend $D_{t+n} = 1\$$ and zero in all other periods. We denote the price of such a risk-free zero-coupon bond as $S^{\$}_{t,n}$,

$$S^{\$}_{t,n} \equiv e^{-ny^{\$}_{t,n}}. \tag{42}$$

The fundamental value of an equity asset coincides with the expected discounted value of all future dividends,

$$S_t = \sum_{n=1}^{\infty} S_{t,n}. \tag{43}$$

By splitting the sum into two components, we can express the equity asset as the sum over near-future dividends and far-future dividends. We characterize near-future dividends as dividends which are expected to be distributed before and at $t+n^*$, and far-future dividends as dividends which are expected to be paid out after $t+n^*$:

$$S_t = \sum_{n=1}^{n^*} S_{t,n} + \sum_{n=n^*+1}^{\infty} S_{t,n}. \tag{44}$$

For near-future dividends, derivative markets provide us with rich information on their present values. Regarding the U.S. market, we obtain price signals from put-call-parity, while other studies use dividend swaps and futures with maturities up to seven years in the future. Several studies have used this information to estimate the term structures of expectations on dividend growth and dividend risk premiums, among them Binsbergen et al. [2012], Binsbergen et al. [2013], and Ulrich et al. [2018], to name a few. The present values of far-future dividends are much less explored, because financial markets do not provide us with information on particular dividends paid far in the future. So far, we only find information about the present values of particular near-future dividends in derivative markets, and the aggregate present value of all future dividends in form of stock prices.

In order to price equity assets, one faces then the challenge to determine present values for dividends paid far in the future, without clear signals on corresponding growth rates $g^d_{t,n}$ and discount rates $y^d_{t,n}$ for $n > n^*$. A common approach to avoid this problem is to assume the existence of a growth and discount rate $\bar{g}^d_t$ and $\bar{y}^d_t$ which are applicable to all future dividends. This facilitates the infinite sum to a geometric series and overcomes the necessity to estimate term-structures for very long (or infinite) horizons. This approach leads to the so-called Gordon growth formula:

$$S_t \approx D_t \sum_{n=1}^{\infty} \frac{(1+\bar{g}^d_t)^n}{(1+\bar{y}^d_t)^n} = D_t \frac{1+\bar{g}^d_t}{\bar{y}^d_t - \bar{g}^d_t}. \tag{45}$$

Our paper shows that this simple approach to price equity is able to reconcile the price information on near-future dividends from derivative markets with equity prices in the aggregate stock market and the underlying economy. To decide on values for $\bar{g}_t^d$ and $\bar{y}_t^d$, we refer to anecdotal evidence in recent literature about long term estimates of risk-adjusted growth rates or equity yields. Gormsen [2018] shows that five- and seven-year equity yields almost coincide across different equity indices, and Bansal et al. [2017] present the term structure of equity yields for the S&P 500 being essentially flat for five years and beyond. Kragt et al. [2018] estimate mean reversion in risk-adjusted growth rates to their long-run mean is broadly measured in half-lives of two to four years across different equity indices, a space of time that comes close to that of a typical business cycle. In chapter 3 of this thesis, we obtain a model-free estimate of the dividend risk premium term structure based on Euro Stoxx 50 dividend futures and find no significant difference between five- and ten-year estimates. We therefore decide to set $\bar{g}_t^d = g_{t,60}^d$ and $\bar{y}^d = y_{t,60}^d$ in the Gordon growth formula, assuming that the five-year values implied by the term-structure estimates are a reasonable proxy for the risk-adjusted growth rate applicable to all future dividends. Our identification of the dividend discount rates relies on present values of near-future dividends extracted from option prices with maturities of up to three years, realized dividend growth and one-year growth estimates, and the dividend yield.

4.2.1 Bond and Equity Yields

As in Binsbergen et al. [2013], we define the equity yield at time t with maturity in $t+n$ as

$$e_{t,n} := -\frac{1}{n} \ln \left(\frac{S_{t,n}}{D_t} \right). \tag{46}$$

Consistent with the bond literature, $e_{t,n}$ collapses to the time t value of a zero-coupon bond yield $y_{t,n}^{\$}$ with maturity in $t+n$ if $D_{t+n} = 1$ and zero otherwise,

$$y_{t,n}^{\$} = -\frac{1}{n} \ln S_{t,n}^{\$}. \tag{47}$$

Prices of zero-coupon claims are directly related to the respective yield,

$$S_{t,n} = D_t e^{-n e_{t,n}} \quad \text{and} \quad S_{t,n}^{\$} = \$1 e^{-n y_{t,n}^{\$}}. \tag{48}$$

The price of a standard equity claim can be expressed in terms of

$$S_t = D_t \sum_{n=1}^{n^*} e^{-ne_{t,n}} + D_t \sum_{n=n^*+1}^{\infty} e^{-ne_{t,n}}, \tag{49}$$

which highlights two insights. First, the zero-coupon equity yield $e_{t,n}$ aggregates information about the expected dividend discount rate and the expected dividend growth rate, both for t to $t+n$. Second, derivatives with price information on dividends paid before time $t+n^*$ identify the short-end of the equity yield term structure (up to n^*), whereas the aggregate stock prices summarizes information about both the short and long-end of the equity yield term structure.

4.3 A Term Structure Model for Bond and Equity Yields

We build our model around a strictly positive pricing kernel with an affine short rate, an affine market price of risk vector and a VAR(1) state dynamic. Let $m_{t,t+1}$ be the log pricing kernel. It takes the form

$$m_{t,t+1} = -r_t - \frac{1}{2}\lambda_t'\lambda_t - \lambda_t'\epsilon_{t+1}^P, \quad m_0 = 0,\, \epsilon_{t+1}^P \sim N(0, I), \tag{50}$$

with λ_t being the column vector of market prices of risk and specified further below, whereas r_t is the short rate which itself is a linear function of the state vector X_t,

$$r_t = \alpha + \beta' X_t \tag{51}$$

where α is a scalar and β is column vector of dimension $K \times 1$, X_t is the time t realization of the $K \times 1$ dimensional state vector.

We assume that X_t follows a Gaussian VAR(1) process under the physical probability measure $\mathcal{P}$,

$$X_t = c^P + \Phi^P X_{t-1} + \Sigma\epsilon_t^P, \tag{52}$$

where c^P is a $K \times 1$ column vector, Φ^P is of dimension $K \times K$ and Σ is a K-dimensional diagonal volatility matrix. We assume dividend growth d_t to be spanned by the state vector,

$$d_t = e_d' X_t, \tag{53}$$

where e_d is a $K \times 1$ column vector that selects dividend growth from the state vector. The column vector of market prices of risk, λ_t, is assumed to be affine in the states

$$\lambda_t = \Sigma^{-1} \left(\lambda_0 + \lambda_1 X_t\right), \tag{54}$$

where λ_0 is of dimension $K \times 1$ and λ_1 is of dimension $K \times K$. The affine market price of risk together with the VAR(1) dynamic for the state vector implies, that the $\mathcal{Q}$ dynamic of the state vector follows a VAR(1),

$$X_t = c^Q + \Phi^Q X_{t-1} + \Sigma \epsilon_t^Q,\ \epsilon_t^Q \sim N(0, I), \tag{55}$$

where c^Q is a $K \times 1$ column vector and Φ^Q is of dimension $K \times K$.

Before we decompose bond and equity yields into their cash-flow and risk premium components, we first derive their equilibrium values.

Proposition (1) [Equity Yield]
The arbitrage-free zero-coupon equity yield at time t with maturity in n periods, for an economy that is characterized by equations (51), (52), (53) and (55), is equal to

$$e_{t,n} = a_e(n) + b_e'(n)\ X_t, \tag{56}$$

where for $n > 0$, the scalar $a_e(n)$ and the column vector $b_e(n)$ are deterministic functions of the underlying economy and fully specified in appendix B.

A zero-coupon bond yield is a special type of equity yield. The following corollary states that explicitly.

Corollary (1) [Bond Yield]
The arbitrage-free zero-coupon bond yield at time t with maturity in n periods, for an economy that is characterized by equations (51), (52), (53) and (55), is equal to

$$y_{t,n}^{\$} = a_y(n) + b_y'(n)\ X_t \tag{57}$$

where $a_y(n)$ and $b_y(n)$ are deterministic functions of the underlying economy and fully specified in appendix B.

4.3.1 Decomposing the Term Structure of Equity Yields

Any zero-coupon equity yield contains information about expected dividend growth and about the respective dividend discount rate. The next corollary summarizes the respective decomposition.

Corollary (2) [Decomposing Equity Yields]
Any zero-coupon equity yield is equal to

$$e_{t,n} = y^d_{t,n} - g^d_{t,n} \quad \text{with} \quad g^d_{t,n} = \frac{1}{n}\sum_{i=1}^{n} E^P_t[d_{t+i}] \tag{58}$$

where $g^d_{t,n}$ is the time t term structure of the expected continuously compounded dividend growth rate with maturity n and $y^d_{t,n}$ is the respective term structure of the continuously compounded dividend discount rate. Both, $g^d_{t,n}$ and $y^d_{t,n}$ are deterministic functions of the underlying economy from equations (51)*,* (52)*,* (53)*,* (55)*. Appendix B contains a detailed derivation of both quantities.*

Since a zero-coupon bond pays a constant (zero) coupon, its respective value for $g^d_{t,n}$ is zero and its respective discount rate equals $y^{\$1}_{t,n}$. This highlights that an equity yield does only coincide with the discount rate if its expected dividend growth rate equals zero. On the other hand, an equity yield is only an unbiased forecast of dividend growth if the dividend discount rate is constant.

The term structure of dividend discount rates, $y^d_{t,n}$, is the sum of three components. First, $y^d_{t,n}$ compensates for the expected average value of the short rate from t to $t+n-1$, which we denote as $r_{t,n}$,

$$r_{t,n} \equiv \frac{1}{n}\sum_{i=0}^{n-1} E^P_t[r_{t+i}].$$

Second, it compensates for the risk that the realized path of the short rate differs from $r_{t,n}$. This compensation is well-known in the fixed-income literature and is usually called interest rate risk premium, which we denote as $z^\$_{t,n}$,

$$z^\$_{t,n} \equiv y^\$_{t,n} - r_{t,n}.^{14}$$

[14] Alternative expressions for the interest rate risk premium are 'duration premium' and 'term premium'. For our context of equity modeling, we prefer the term 'interest rate risk premium' because there is a term / duration structure not only in interest rates but also in dividend growth and the dividend premium.

The sum of $r_{t,n}$ and $z^{\$}_{t,n}$ coincides[15] with the n-maturity default-free zero-coupon bond yield,

$$y^{\$}_{t,n} = r_{t,n} + z^{\$}_{t,n}. \tag{59}$$

Third, $y^{d}_{t,n}$ also compensates for the risk that the realized path of future dividends from t to $t+n-1$ differs from the ex-ante expectation $g^{d}_{t,n}$. This compensation coincides with the zero-coupon dividend risk premium, which we denote as $z^{d}_{t,n}$,

$$z^{d}_{t,n} \equiv y^{d}_{t,n} - y^{\$}_{t,n}. \tag{60}$$

The following corollary summarizes the decomposition of the zero-coupon dividend discount rate curve.

Corollary (3) [Decomposing Dividend Discount Rates]
The arbitrage-free term structure of the dividend discount rate coincides with the sum of three components

$$y^{d}_{t,n} = r_{t,n} + z^{\$}_{t,n} + z^{d}_{t,n}, \quad n > 0 \tag{61}$$

where $r_{t,n}$, $z^{\$}_{t,n}$ and $z^{d}_{t,n}$ coincide with the term structures of the expected average value of the future short rate, the zero-coupon interest rate risk premium and the zero-coupon dividend risk premium; respectively. Each of these term structures is a deterministic function of the underlying economy, characterized by the equations (51)*,* (52)*,* (53)*,* (55) *, and fully specified in appendix B.*

The next chapter imposes economic restrictions onto our most general pricing model to set-up an economy that can be tested empirically.

4.4 Economic Setup

We now explain the economic restrictions that our empirical analysis imposes onto our most general model specification of section 4.3. Starting from an economic setup where all factors have a macro-economic interpretation - our macro-only model - we find that short-term dividend discount rates are not captured and fail to price dividend strips. We respond by introducing one latent variable which allows the market-price of short-term cash flow risk to move independent from the macro-economy - our benchmark model - and succeed in pricing

[15] The negligible convexity term is assigned to $z^{\$}_{t,n}$.

the term structure of discount rates. Our economy follows the macro-finance tradition of Ang and Piazzesi [2003] and Ang et al. [2011], among others, to account for monetary policy that sets the short-rate of the economy as a function of macro-economic fundamentals. It consists of a real, a nominal and an equity financed corporate sector. We capture these sectors via the realized unemployment rate u_t, the realized inflation rate π_t and the realized dividend growth rate d_t. Each growth rate $i \in \{u, \pi, d\}$ consists of a predictable trend component, x^i, and an uninformative noise component ν_i. The noise components ν_π and ν_u will not affect prices and are therefore not put into the state vector. This is consistent with the bond and equity modeling in Lettau and Wachter [2007] and lead to endogenous financial yields that are unspanned by macro risks, an empirical feature of the data that Joslin et al. [2013] have motivated in great detail. Similar to Campbell et al. [2016], we allow the predictable components of unemployment, inflation and dividend growth to be driven by a transitory and a permanent element, ξ and θ, respectively,

$$u_t \equiv u_0 + x^u_{t-1} + \nu_{u,t}, \quad x^u_{t-1} \equiv \xi^u_{t-1} + \theta^u_{t-1}, \quad \nu_{u,t} \sim N(0, \sigma^2_u); \tag{62}$$

$$\pi_t \equiv \pi_0 + x^\pi_{t-1} + \nu_{\pi,t}, \quad x^\pi_{t-1} \equiv \xi^\pi_{t-1} + \theta^\pi_{t-1}, \quad \nu_{\pi,t} \sim N(0, \sigma^2_\pi); \tag{63}$$

$$d_t \equiv d_0 + x^d_{t-1} + \nu_{d,t}, \quad x^d_{t-1} \equiv \xi^d_{t-1} + \theta^d_{t-1}, \quad \nu_{d,t} \sim N(0, \sigma^2_d); \tag{64}$$

where ξ^π_{t-1}, ξ^u_{t-1} and ξ^d_{t-1} are the $t-1$ values of the transitory growth rate components in inflation, unemployment and dividends while θ^π_{t-1}, θ^u_{t-1} and θ^d_{t-1} are the respective permanent growth components in inflation, unemployment and dividends. The respective dynamics are specified further below. The terms π_0, u_0, d_0, σ_π, σ_u and σ_d are positive constants.

We assume that the U.S. central bank (Fed) sets the economy's policy rate r_t as a function of real and nominal trend growth,

$$r_t = r_0 + \delta^\pi x^\pi_t + \delta^u x^u_t, \tag{65}$$

where δ^π and δ^u capture the central bank's unconditional inflation and unemployment policies (Ang and Piazzesi [2003]).

4.4.1 The Macro-Only Model

Both the conditional $\mathcal{P}$ and $\mathcal{Q}$ distribution of bond and equity yields are driven by macro-economic risks in form of x^π_t and x^u_t as well as corporate sector specific risks x^d_t, which we summarize into the state-vector M_t. For convenience of notation and as required by the pricing equations, we introduce a seventh state variable which is mechanically set to be the sum of d_0, ξ^d_{t-1} and θ^d_{t-1}:

$$M_t \equiv \begin{bmatrix} \xi^\pi_t & \theta^\pi_t & \xi^u_t & \theta^u_t & \xi^d_t & \theta^d_t & d_t \end{bmatrix}'. \tag{66}$$

According to the VAR(1) dynamic proposed in (52), we describe the parametric restrictions we apply to allow for a robust and well-identified model. As our state variables have a mean of zero, c^P is a vector of zeros, except for the seventh element, which is set to d_0:

$$c^P_M = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & d_0 \end{bmatrix}. \tag{67}$$

The vector c^Q is free to be non-zero,

$$c^Q_M = \begin{bmatrix} c^Q_{\xi^\pi} & c^Q_{\theta^\pi} & c^Q_{\xi^u} & c^Q_{\theta^u} & c^Q_{\xi^d} & c^Q_{\theta^d} & d_0 \end{bmatrix}, \tag{68}$$

to allow for non-zero market prices of risk which are affine in the state variables:

$$\lambda_t = \lambda_0 + \lambda_1 X_t \qquad \text{with} \qquad \lambda_0 = \Sigma^{-1}(c^P - c^Q), \quad \lambda_1 = \Sigma^{-1}(\Phi^P - \Phi^Q). \tag{69}$$

Regarding Φ^P, we impose a near-unit root on the persistent components θ^π_t, θ^u_t and θ^d_t to identify long-run dynamics, see Campbell et al. [2016] for a similar design. Off-diagonal elements, which allow for Granger-causality among macro-economic states, are set to zero for a convenient estimation. In unreported results, we find that a rich Granger-causality does not improve the pricing of bond or equity term structures.

$$\Phi^P_M = \begin{bmatrix} \phi^P_{\xi^\pi} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \phi^P_{\xi^u} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \phi^P_{\xi^d} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}. \tag{70}$$

Again, to allow for affine market prices of risk, we allow the corresponding elements in Φ^Q to vary,

$$\Phi_M^Q = \begin{bmatrix} \phi_{\xi^\pi}^Q & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \phi_{\theta^\pi}^Q & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \phi_{\xi^u}^Q & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \phi_{\theta^\pi}^Q & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \phi_{\xi^d}^Q & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \phi_{\theta^\pi}^Q & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}. \tag{71}$$

We estimate the diagonal elements of the covariance matrix Σ_M and keep off-diagonal elements at zero.

4.4.2 The Benchmark Model

Our benchmark model adds one state variable to our macro-only model: an independent market price of risk ψ_t for near-future dividend growth. This feature is motivated by the work of Ulrich et al. [2018], who show that survey-expectations ($\mathcal{P}$) cannot explain options-implied expectations ($\mathcal{Q}$) about near-future dividend growth. For a similar design in a bond pricing application, we refer to the work of Bauer and Rudebusch [2017].

We extend the state vector from our macro-only model,

$$X_t = \begin{bmatrix} M_t & \psi_t \end{bmatrix}', \tag{72}$$

and adjust the VAR(1) parameters accordingly. We extend the vectors c_M^P and c_M^Q to

$$c_X^P = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & d_0 & 0 \end{bmatrix} \tag{73}$$

and

$$c_X^Q = \begin{bmatrix} c_{\xi^\pi}^Q & c_{\theta^\pi}^Q & c_{\xi^u}^Q & c_{\theta^u}^Q & c_{\xi^d}^Q & c_{\theta^d}^Q & d_0 & c_\psi^Q \end{bmatrix}, \tag{74}$$

and add the dynamics of ψ_t to Φ_M^Q, resulting in

$$\Phi_X^P = \begin{bmatrix} \phi_{\xi^\pi}^P & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \phi_{\xi^u}^P & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \phi_{\xi^d}^P & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_\psi^P \end{bmatrix}. \tag{75}$$

To ensure the interpretation of ψ_t as a market price of near-future dividend growth risk, we adjust the dynamics under the risk-neutral measure accordingly:

$$\Phi_X^Q = \begin{bmatrix} \phi_{\xi^\pi}^Q & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \phi_{\theta^\pi}^Q & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \phi_{\xi^u}^Q & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \phi_{\theta^\pi}^Q & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \phi_{\xi^d}^Q & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & \phi_{\theta^\pi}^Q & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_\psi^Q \end{bmatrix}. \tag{76}$$

As in the macro-only model, our benchmark model sets Σ to be a diagonal matrix.

4.5 Data and Estimation Methodology

Our sample of monthly data covers the period between January 1965 and December 2017. We confront the model with a rich cross-section of macro-economic, interest rate and equity data. The affine bond literature agrees nowadays that a robust identification of premiums requires the addition of expectations under the physical probability measure $\mathcal{P}$ to the set of measurement equations on which the model is tested.[16] The following thought experiment highlights the issue. Imagine a drop in long term government bond yields. The reason for that drop could be either (i) a reduction of $r_{t,n}$ capturing the expected path of future monetary policy, (ii) a decline in $z_{t,n}^{\$}$ from an increased risk appetite or (iii) a combination of both. Reason (i) is most likely to occur if the economy moves into a recession, whereas

[16]See, among others, Kim and Orphanides [2012], Chernov and Mueller [2012], Chun [2011], Crump et al. [2016].

reason (ii) is most likely accompanied by an economy that recovers.

Including survey forecasts for macro-economic and interest rate quantities into the empirical estimation of the model allows us to identify whether a change in a yield is due to a revision in the expected future path of the economy or whether it is due to a change in risk appetite. We include survey expectations for future inflation, unemployment, dividend growth and Treasury yields in our estimation framework. Survey data for inflation, unemployment and interest rates come from the Survey of Professional Forecasters (SPF). Ang et al. [2008] and Faust and Wright [2013] conclude that these surveys are superior to econometric forecasting methods. The survey data on dividends is constructed from the Reuters I/B/E/S forecast data on dividend growth of S&P 500 constituents, as suggested and tested in De la O and Myers [2017] and Ulrich et al. [2018]. Both studies show independently that these dividend forecasts provide a term structure of unbiased forecasts of future S&P 500 dividend growth rates. Overall, we have 26 measurement equations to identify six state variables.

Our measurement equations for the macro-economy are the SPF forecast on average U.S. CPI inflation with a forecast horizon of one and ten years, which we complement with realized U.S. CPI inflation. We capture the real economy with SPF forecasts on the average U.S. unemployment rate over the next year and the realized U.S. unemployment rate. For unemployment, we did not find long term forecasts such as ten years into the future.

Our financial data covers both survey expectations and data obtained from asset prices. Regarding survey expectations, we add the SPF forecasts for the three-month and ten-year U.S. Treasury zero-coupon bond yields with forecast horizons of one month, one year and ten years as well as aggregate analyst dividend expectations on the S&P 500 with a forecast horizons of one year. The latter is constructed from survey forecasts following the methodology first proposed by De la O and Myers [2017] and modified by Ulrich et al. [2018]. We complement that dividend data with realized dividend growth.

Asset price information are reflected by the one-year, three-year, five-year, seven-year and ten-year U.S. Treasury zero-coupon bond yields, the aggregate S&P 500 dividend yield and prices of short-term dividend assets with maturities of 6, 12, 18, 24, 30 and 36 months obtained from put call parity for CBOE European index options on the S&P 500 (see Binsbergen et al. [2012] and Ulrich et al. [2018]).

All asset price data, except for short-term dividend prices and ten-year bond yields, start in January 1965 and end in December 2017, spanning 636 months. The time series for the ten-year bond yield starts in September 1971. Short-term dividend prices are available since January 1996. The dividend price data of Binsbergen et al. [2012] is available for the period January 1996 to October 2009. We extend the panel of short-term S&P 500 dividend prices, using the methodology proposed by Ulrich et al. [2018], up to September 2017. Survey expectations start later and at different points in time in our sample. Survey data on inflation expectations is available since August 1981 (one-year horizon) and August 1991 (ten-year horizon). The earliest record of unemployment expectations is in November 1968. We include one-year dividend expectations,see Ulrich et al. [2018], starting in June 2003.

We describe the macro, survey and asset market data with six state variables M_t in our macro-only model and seven state variables X_t in our benchmark model. Ang and Piazzesi [2003] compare different specifications in their affine term structure model and conclude that five pricing factors - two macro variables together with three latent factors - are best suited to price the Treasury yield curve while still ensuring robust identification. Adrian et al. [2013] advocate the use of five latent pricing factors to best describe the Treasury yield curve and predict bond returns. Kragt et al. [2018] find that a two-factor structure in dividend growth is necessary to describe the time series dynamic of priced dividend growth in major stock markets. In a principal component analysis, we consider the 13 of the 26 time series for which we have a complete history since January 1996 and find that five factors explain 94% of the cross-sectional variation, six factors explain 97%, and seven factors explain 99%. In the light of these results and previous findings in the term structure literature, we argue that six and seven pricing factors are a reasonable choice. Our results support this choice, with an increased accuracy in our benchmark model compared to the macro-only model, and a robust identification of the model parameters.

4.5.1 Biases in Survey Forecasts

In our empirical design, we rely on information in survey forecasts to improve the identification of parameters describing the empirical dynamics of our pricing factors, we refer to Kim and Wright [2005] and Kim and Orphanides [2012] for important contributions. A large literature is dedicated to the various types of biases in survey forecasts, among them cognitive biases in forecasters and statistical biases through their aggregation. We refer to Lambros and Zarnowitz [1987] and Keane and Runkel [1990] for early work, Abarbanell [1991] and Abarbanell and Lehavy [2003] for work on earnings forecasts, Capistrán and

Timmermann [2009] for work on SPF inflation forecasts, and Kim and Orphanides [2012] for an analysis of the efficiency and biasedness in SPF interest rate forecasts. We briefly discuss statistical properties and evaluate potential biases in the survey data used in our empirical design to the extent that they might be relevant for the interpretation of our results. Regression results are summarized in table 18.

Table 18: Regression Statistics - Biases in Survey Forecasts

$y^{\$}_{t,t+1,120}$	a^y	b^y	R^2
$y^{SPF1}_{t,120}$	-0.06 (0.12)	1.01 (0.02)	93.3
$y^{\$}_{t,t+12,120}$	a^y	b^y	R^2
$y^{SPF12}_{t,120}$	-0.61 (0.17)	1.05 (0.04)	87.5
$d_{t,t+12}$	a^d	b^d	R^2
$d^{IBES}_{t,12}$	-2.34 (2.46)	0.97 (0.19)	43.5
$\pi_{t,t+12}$	a^π	b^π	R^2
π^{SPF12}_{t}	0.77 (0.28)	0.62 (0.08)	31.3
$u_{t,t+12}$	a^u	b^u	R^2
u^{SPF12}_{t}	0.54 (0.30)	0.92 (0.05)	65.0

This table reports regression estimates and adjusted R^2 values for predictive regressions of future realizations corresponding to survey estimates. The first panel shows results for one-year survey-implied dividend growth, the second panel for one-month and one-year forecasts on average ten-year Treasury yields, the third panel for one-year inflation estimates and the fourth panel for one-year unemployment estimates. Values for intercept terms and R^2 are in percentage terms. Newey and West [1987] standard errors with $T^{0.25}$ lags are reported in parenthesis, where T is the number of observations. The predictions cover the period for which the respective forecast is available.

We asses the accuracy of the one-month and one-year forecasts of the average ten-year Treasury yield. Ten-year forecasts exist since 1982 on an annual basis and offer only a few data points. A regression of the average future 10-year Treasury yield $y^{\$}_{t,t+12,120}$ on the SPF one-year forecast $y^{SPF12}_{t,120}$,

$$y^{\$}_{t,t+12,120} = a^y + b^y y^{SPF12}_{t,120} + \epsilon^y_{t+12}, \qquad \epsilon^y_{t+12} \sim i.i.d.(0, \sigma^2_y), \tag{77}$$

results in a significant negative intercept estimate of -61 basis points, which suggests that the median forecaster did not fully anticipate the decline in long term rates that materialized since the 1980s. The one-month forecast horizon has no significant bias during our sample.

Regarding dividend growth expectations, we refer to the findings in Ulrich et al. [2018], who rely on the same panel of analyst dividend forecasts to construct their aggregate dividend growth expectation on the S&P 500. They regress one-year future realized growth $d_{t,t+12}$ on their estimate $d_{t,12}^{IBES}$ for the period January 2004 to September 2017,

$$d_{t,t+12} = a^d + b^d d_{t,12}^{IBES} + \epsilon_{t+12}^d, \qquad \epsilon_{t+12}^d \sim i.i.d.(0, \sigma_d^2), \tag{78}$$

and find a statistically insignificant intercept value of 234 basis points and a slope estimate $\beta^d = 0.97$. Chapter 2 discusses their findings in greater detail.

Turning to inflation, we assess the accuracy and biasedness in the median one-year inflation forecast π_t^{SPF12},

$$\pi_{t,t+12} = a^\pi + b^\pi \pi_{t,12} + \epsilon_{t+12}^d, \qquad \epsilon_{t+12}^d \sim i.i.d.(0, \sigma_d^2), \tag{79}$$

for which we have 142 quarterly observations. We find an intercept estimate of 77 basis points, suggesting that the median forecaster under-predicted one-year inflation on average by 77 basis points. This potential bias decreases to 4 basis points once we discard the first 20 observations, which fall into the high inflation regime of the 1980s.

Since the former Federal Reserve's chairman Ben Bernanke announced a two percent inflation rate target in January 2012, the ten-year (long term) inflation expectation has been very stable with a sample mean of 2.23% and a standard deviation of 0.08%, despite some negative values for realized inflation rates in this period of time. Prior to 2012, volatility in long term inflation expectations was at 0.47%. Both findings suggest that the Federal Reserve has been successful in anchoring inflation expectations close to their quantitative aim for price stability and reducing uncertainty around long term inflation expectations.

Turning to unemployment, we find that one-year forecasts are accurate expectations on future unemployment. The intercept estimate of 54 basis points is not statistically significant and the slope estimate $b^u = 0.92$ cannot be rejected to be different from one at the 5% significance level.

4.5.2 Likelihood

We estimate the model with a combination of Maximum Likelihood and the Extended Kalman Filter. This econometric design has become a standard tool for models like ours, see Chernov and Mueller [2012], Kim and Orphanides [2012] and Feldhuetter and Lando [2008], among others.

We collect all model parameters and volatilities of the measurement errors in a vector θ and all time t measurements in a vector y_t. We further assume pairwise orthogonal Gaussian measurement errors. The resulting log of the joint model-implied likelihood function $f(\theta)$ coincides with

$$\sum_{t=1}^{T} log\left(f(\theta|y_t)\right) = -\frac{T \times n}{2} log(2\pi) - \frac{1}{2}\sum_{t=1}^{T} log|V_{t(\theta)}| - \frac{1}{2}\sum_{t=1}^{T}(y_t - \hat{y}_{t(\theta)})V_{t(\theta)}^{-1}(y_t - \hat{y}_{t(\theta)}) \quad (80)$$

with $n = 26$ measurement equations per time period. Notice, $\hat{y}_{t(\theta)}$ denotes the model-implied quantities that we contrast with the data counterpart y_t, and $V_{t(\theta)}$ denotes the covariance matrix of the fitting errors. Both $\hat{y}_t$ and V_t depend on parameters θ and are computed using the model and the well-known recursions from the Kalman Filter. All model parameters and state variables are estimated by a combination of Maximum Likelihood, the Extended Kalman Filter and a global optimization routine, which together run in C++ on the bwUniCluster, a high performance computing cluster.

4.6 Empirical Findings

Our analysis is centered around the decomposition of the dividend discount rate, as implied by our benchmark model, into its three components: these are short rate expectations, the duration premium and the cash flow premium, as outlined in section 4.3.1. In a first step, we assess how well our model describes the data and highlight two findings. First, a simple Taylor rule setup seems able to reconcile macro-economic developments and the short-rate in times of Quantitative Easing. This suggests that the Federal Reserve's dual mandate of ensuring price stability and sustainable employment has been in line with its monetary policy even in times of unconventional policy measures such as large-scale asset purchases. Second, we find that the average term structure of the dividend discount rate $y_{t,n}^d$ has been downward sloping because of a strong increase in short-term risk premiums $z_{t,n}^d$, a feature which we cannot recover in the macro-only model.

In a second step, we assess the predictive power of our model for each of the involved quantities and conclude that our model provides a realistic decomposition: our model predicts future short-rates well and implies expected returns which are a strong predictor of future bond returns. The future return on the one-year dividend assets is well captured by our dividend risk premium estimate. A decomposition of forecast errors allows us to quantify the contribution of each economic variable to forecast errors in the components of dividend discount rates. We conclude with an impulse response analysis, which quantifies the impact of a shock in an economic variable to each component. Parameter estimates for the benchmark model can be found in table 19.

4.6.1 Empirical Fit and Filtered States

Overall, our benchmark model explains the data, both survey expectations and financial quantities, very well and captures the spikes in short-term dividend prices during the past recessions. Table 20 contains the mean absolute pricing errors for all estimated quantities in both the macro-only and the benchmark model.

Across all maturities, the average absolute pricing error in bond yields is at 7 basis points. To put this into perspective, we refer to Adrian et al. [2013], who price the term structure with five principal components over the period 1987 to 2011 and find an average absolute pricing error of 4 basis points. We argue that both approaches achieve a very good fit - while the focus of Adrian et al. [2013] is on return predictability, we provide an arbitrage-free model for both bonds and equity and focus on economic interpretation. If we isolate the period after the Great Recession, the Taylor rule model leads to very similar pricing errors relative to the entire sample period - the error in the short rate is smaller and bond yield errors increase by 1 basis point on average. Figures 13 and 14 emphasize that our model does not only capture bond yields ($\mathcal{Q}$), but also the survey-based yield expectations ($\mathcal{P}$) to an acceptable degree. The 1-month and 10-year SPF survey forecasts on the average 10-year bond yield are accurately described, and the 10-year and 1-month bond yields, $y^{\$}_{t,120}$ and $y^{\$}_{t,1}$, from secondary market data are well priced. Following the analysis in Kim and Orphanides [2012], we expect to be able to decompose bond yields into expected short rates and duration premiums, which we confirm in a later analysis.

As we illustrate in figure 15, our benchmark model achieves a remarkable fit to both short-term dividend assets and the classical dividend yield. The simple Gordon growth model we use to price the dividend yield reconciles dynamics in dividend growth and equity markets well, as the mean absolute pricing error of 5 basis points suggests. There is an apparent mismatch of survey expectations on dividend growth during the years 2004 to 2008, as figure

Table 19: Parameter Estimates

Taylor rule parameters			r_0		δ^π		δ^u	
			3.88E-03		1.4978		-0.8213	
			-		(158.41)		(-63.52)	
c^P	ξ^π	θ^π	ξ^u	θ^u	ξ^d	θ^d	d	ψ
	-	-	-	-	-	-	**4.68E-03**	-
	-	-	-	-	-	-	-	-
c^Q	ξ^π	θ^π	ξ^u	θ^u	ξ^d	θ^d	d	ψ
	-1.29E-06	4.98E-06	9.76E-05	-3.55E-05	-8.03E-04	-8.63E-05	**4.68E-03**	9.00E-04
	(-0.20)	(5.14)	(1.17)	(-3.57)	(-0.09)	(-14.80)	-	(-0.17)
Φ^P	ξ^π	θ^π	ξ^u	θ^u	ξ^d	θ^d	d	ψ
ξ^π	0.9693	-	-	-	-	-	-	-
	(1672.45)	-	-	-	-	-	-	-
θ^π	-	**1**	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
ξ^u	-	-	0.9671	-	-	-	-	-
	-	-	(280.09)	-	-	-	-	-
θ^u	-	-	-	**1**	-	-	-	-
	-	-	-	-	-	-	-	-
ξ^d	-	-	-	-	0.9510	-	-	-
	-	-	-	-	(629.45)	-	-	-
θ^d	-	-	-	-	-	**1**	-	-
	-	-	-	-	-	-	-	-
d	-	-	-	-	**1**	**1**	-	-
	-	-	-	-	-	-	-	-
ψ	-	-	-	-	-	-	-	0.9988
	-	-	-	-	-	-	-	(2228.93)
Φ^Q	ξ^π	θ^π	ξ^u	θ^u	ξ^d	θ^d	d	ψ
ξ^π	0.9604	-	-	-	-	-	-	-
	(678.85)	-	-	-	-	-	-	-
θ^π	-	1	-	-	-	-	-	-
	-	(4316.33)	-	-	-	-	-	-
ξ^u	-	-	0.7802	-	-	-	-	-
	-	-	(12.16)	-	-	-	-	-
θ^u	-	-	-	0.9897	-	-	-	-
	-	-	-	(1357.17)	-	-	-	-
ξ^d	-	-	-	-	0.0113	-	-	**-1**
	-	-	-	-	(0.03)	-	-	-
θ^d	-	-	-	-	-	1	-	-
	-	-	-	-	-	(6964.69)	-	-
d	-	-	-	-	**1**	**1**	-	-
	-	-	-	-	-	-	-	-
ψ	-	-	-	-	-	-	-	0.0107
	-	-	-	-	-	-	-	(0.03)
$\Sigma\Sigma^\top$	ξ^π	θ^π	ξ^u	θ^u	ξ^d	θ^d	d	ψ
σ_i^2	(5.78E-08)	(2.60E-08)	(9.61E-08)	(3.96E-08)	(9.03E-07)	(1.51E-08)	(3.51E-07)	(1.27E-03)
	(13.48)	(15.74)	(12.44)	(10.62)	(11.38)	(20.83)	(0.00)	(13.13)

This table reports parameter estimates of the benchmark model, obtained for the full sample period Jan 1965 to Dec 2017. Bold values are not estimated. T-statistics, calculated according to appendix E, are given in parentheses and rounded to two decimals.

Table 20: Mean Absolute Pricing Errors

		Economic Variables and Survey Forecasts												
		π_t	π_t^{SPF12}	π_t^{SPF120}	u_t	u_t^{SPF12}	d_t	d_t^{IBES}	$y_{t,3}^{SPF1}$	$y_{t,3}^{SPF12}$	$y_{t,3}^{SPF120}$	$y_{t,120}^{SPF1}$	$y_{t,120}^{SPF12}$	$y_{t,120}^{SPF120}$
1965	MO	123	77	51	24	34	233	264	24	36	125	25	39	69
	BM	121	73	48	27	39	87	330	20	33	112	27	40	67
1996	MO	85	59	48	17	34	417	264	24	32	116	24	41	74
	BM	84	56	44	20	38	165	330	18	30	99	25	42	73
2009	MO	98	70	60	22	36	603	232	31	27	166	21	46	117
	BM	94	70	61	25	39	197	278	19	26	140	22	46	112

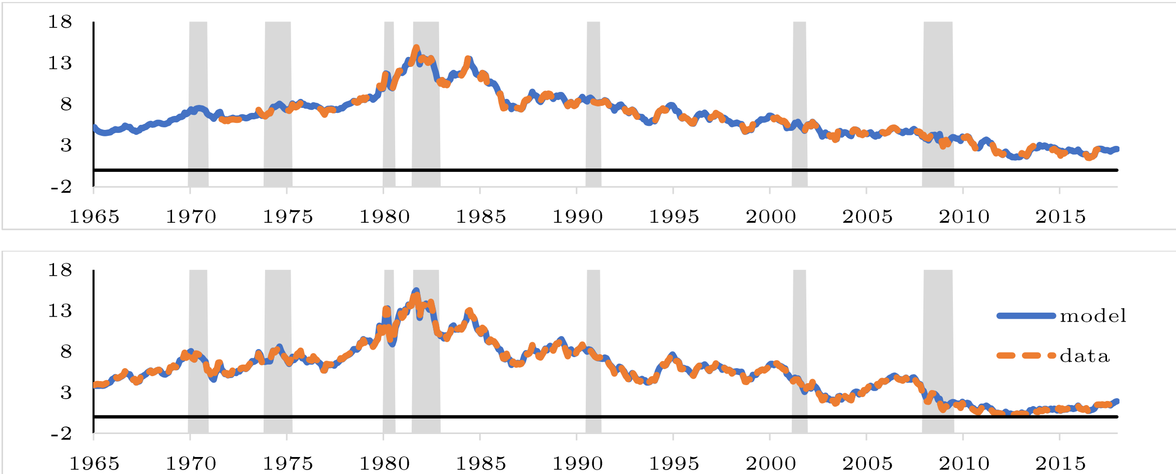
		Bond Yields, Strip Yields and Dividend Yield												
		r_t	$y_{t,12}^{\$}$	$y_{t,36}^{\$}$	$y_{t,60}^{\$}$	$y_{t,84}^{\$}$	$y_{t,120}^{\$}$	$y_{t,6}^{s}$	$y_{t,12}^{s}$	$y_{t,18}^{s}$	$y_{t,24}^{s}$	$y_{t,30}^{s}$	$y_{t,36}^{s}$	y_t^d
1965	MO	48	10	8	7	6	9	26	14	9	7	7	6	5
	BM	45	9	8	7	6	8	7	3	3	3	2	2	5
1996	MO	38	8	8	7	5	8	26	14	9	7	7	6	6
	BM	31	7	8	7	6	8	7	3	3	3	2	2	9
2009	MO	52	9	9	8	6	11	36	20	14	11	9	7	8
	BM	36	7	10	9	6	11	10	3	3	3	3	3	9

This table reports mean absolute pricing errors for all modeled quantities in the macro-only model (MO) and the benchmark model (BM) for the full sample sample period (Jan 1965 to Dec 2017), the time with option data (Jan 1996 to Sep 2017) and the time after the Great Recession (Jul 2009 to Dec 2017). The upper panel reports errors for economic quantities and survey forecasts, the bottom panel contains secondary market data on bond yields and equity quantities. Errors are reported in basis points.

16 shows. This mismatch coincides with a strong upward bias in analyst estimates during the years 2004 to 2008, documented in Ulrich et al. [2018].

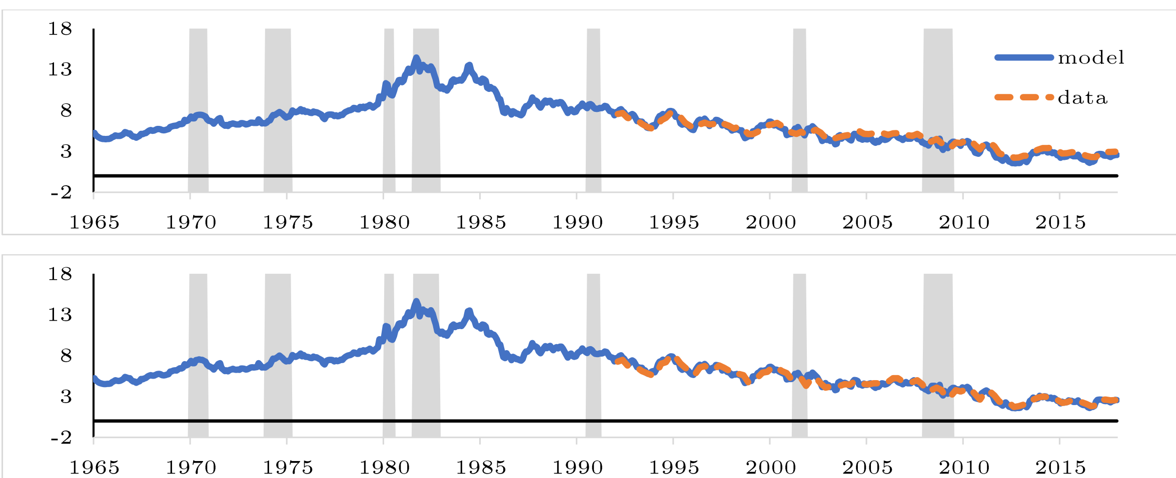
Short-term dividend assets are well priced in the benchmark model, with an average absolute error of 3 basis points across all maturities. Restricting market prices of risk to be affine in the economic state variables does not allow such a good fit, as we can see from the pricing errors in the macro-only model. There, the average absolute error in dividend strip yields amounts to 12 basis points, missing to capture the spikes during the two recent recessions. The mismatch is particularly pronounced at the short-end, with 26 basis points for the six-month maturity. Dividend growth is also barely captured, as the pricing errors are more than twice as large as in the benchmark model (233 versus 87 basis points) - pointing towards the problem of simultaneously matching growth and risk premiums with affine market prices of risk.

Figure 13: Bond Yield Estimates - Market Data



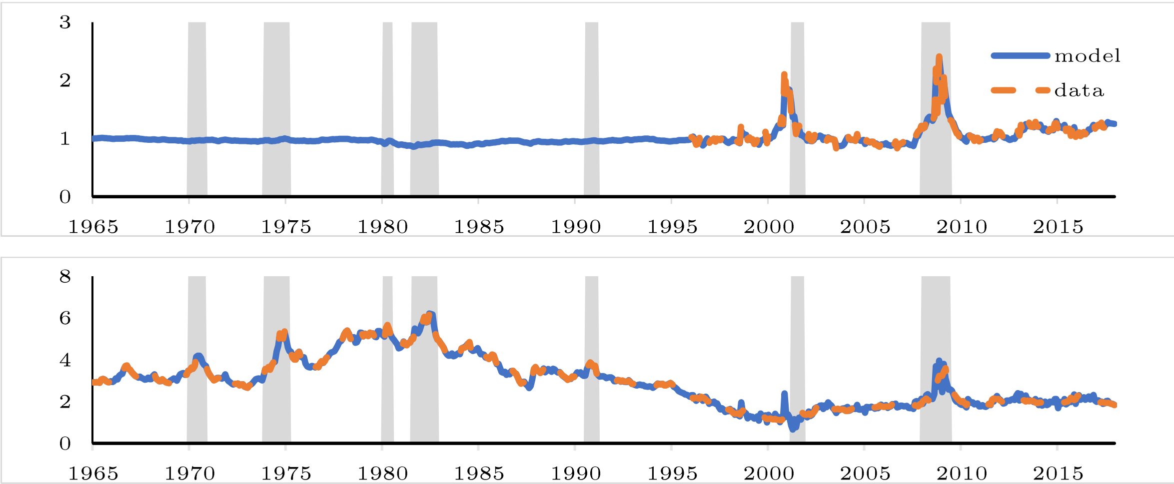
This figure shows the one-year (top) and ten-year (bottom) U.S. Treasury bond yield as in our data (orange dashed line) and implied by our model (blue solid line). Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

Figure 14: Bond Yield Estimates - Survey Expectations



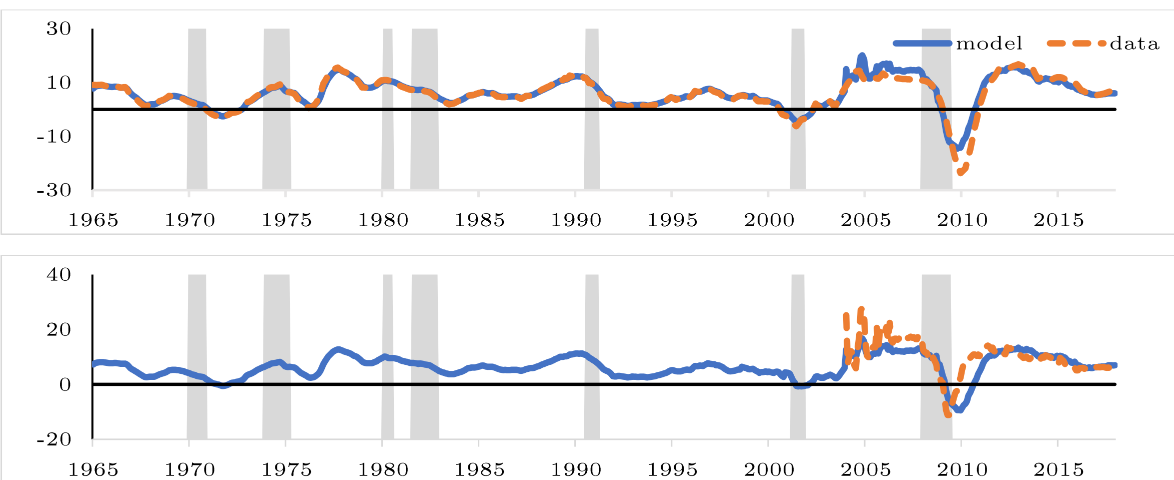
This figure shows the one-month (top) and one-year (bottom) expectations on the average future ten-year U.S. Treasury bond yield as in our data (orange dashed line) and implied by our model (blue solid line). Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

Figure 15: Estimates of Dividend Yields



This figure plots the one-year dividend strip yield and dividend yield as in our data (orange dashed line) and implied by our model (blue solid line). Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

Figure 16: Estimates of Dividend Growth

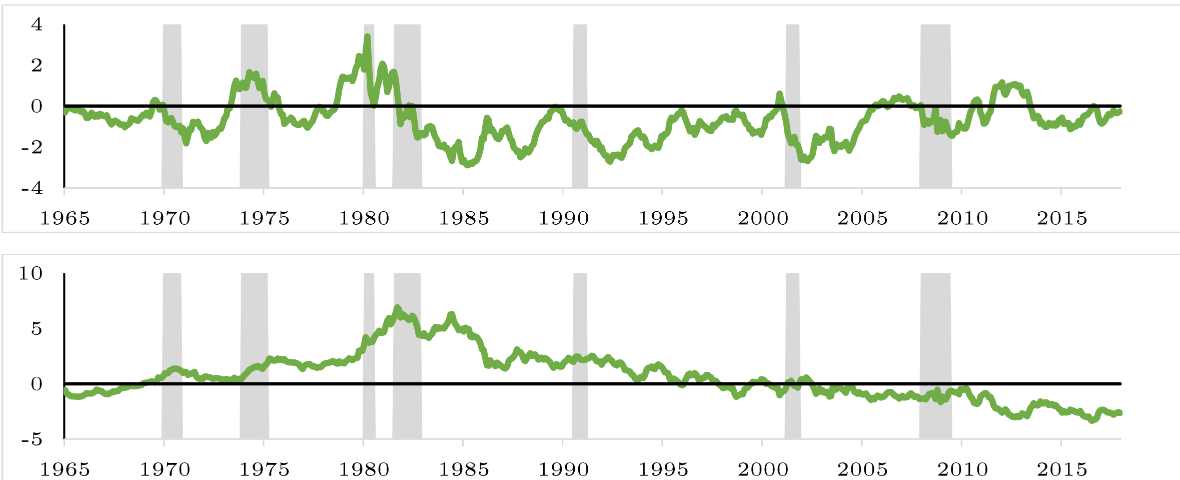


This figure shows the realized dividend growth and one-year dividend growth expectation as in our data (orange dashed line) and implied by our model (blue solid line). Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

The filtered state variables show intuitive features and allow conclusions about the evolution of economic expectations and market prices of risk. As can be seem from figure

17, the permanent component of inflation, θ^{π}, is tent-shaped with a global peak during the high inflation period of the early 1980s and declines ever since.

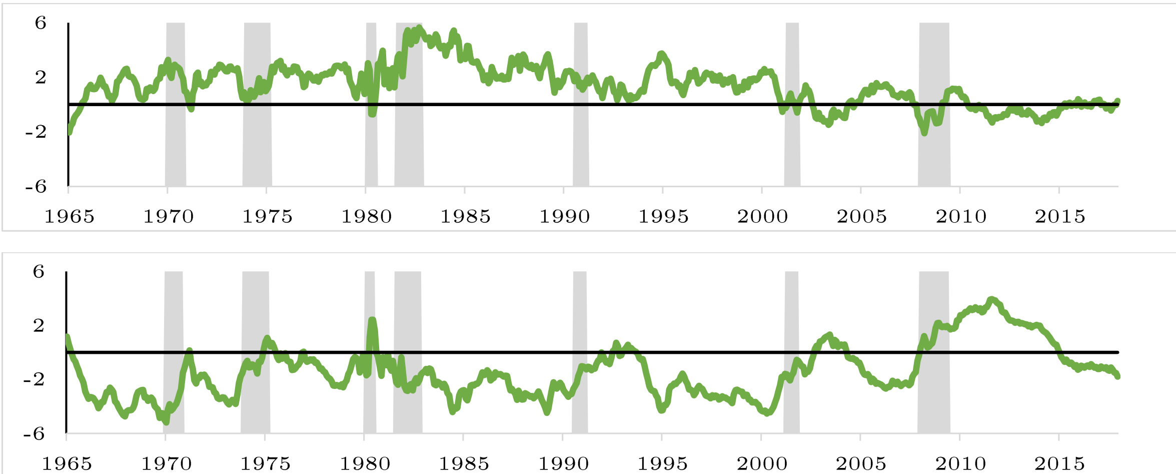
Figure 17: State Estimates - Inflation Components



This figure shows the estimates of the transitory (top) and permanent (bottom) components ξ^{π} and θ^{π} of inflation. Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

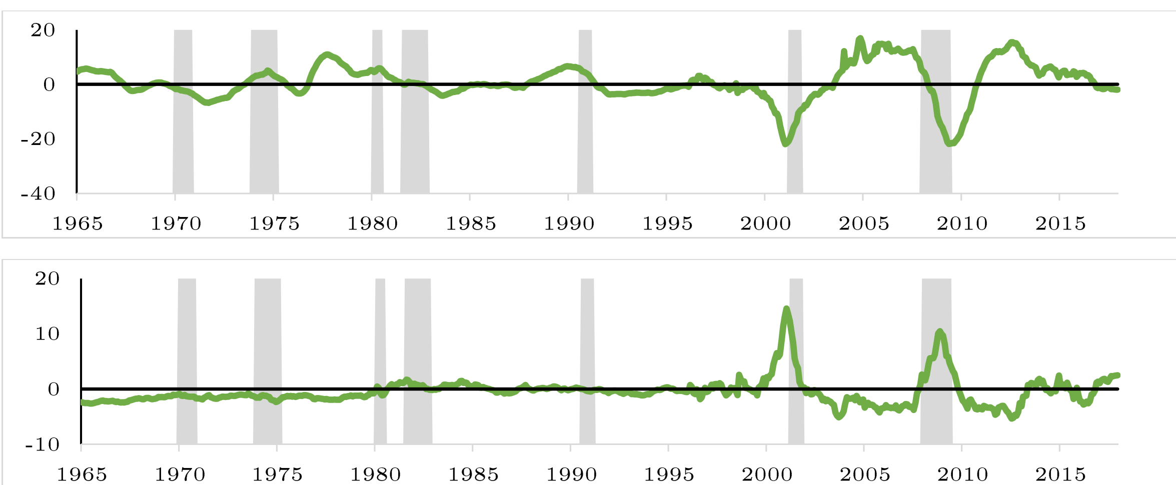
The cyclical inflation component, ξ^{π}, is highest during the recessions prior to the tenure of Paul Volcker and tends to fall during recessions, suggesting that prices are expected to drop temporarily during recessions. In figure 18 we can see that the permanent component in unemployment, θ^{u}, has been highest shortly after recessions and highest after the Great Recession. The cyclical component in unemployment, ξ^{u}, shows increased volatility during recessions, times when short-term labor market uncertainty might increase. Turning to figure 19, the model estimates assign the sharp declines in dividend growth during the past two recessions to sharp and unprecedented drops in the transitory growth component ξ^{d}.
On the other hand, increases in the permanent component θ^{d} in times of dividend cuts might be an indication that the two past recessions were expected to only have a short-term impact on corporate dividends. In figure 20, we see how ψ shoots up into positive territory during the recent two stock market crashes, highlighting large market prices of risk for taking-on short-duration dividend risk.

Figure 18: State Estimates - Unemployment Components



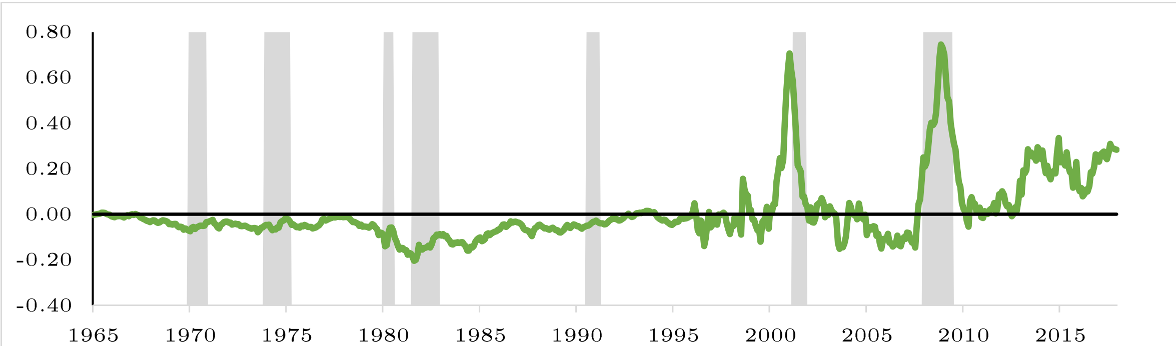
This figure shows the estimates of the transitory (top) and permanent (bottom) components ξ^u and θ^u of unemployment. Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

Figure 19: State Estimates - Dividend Growth Components



This figure shows the estimates of the transitory (top) and permanent (bottom) components ξ^d and θ^d of dividend growth. Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

Figure 20: State Estimates - Market Price of Dividend Risk

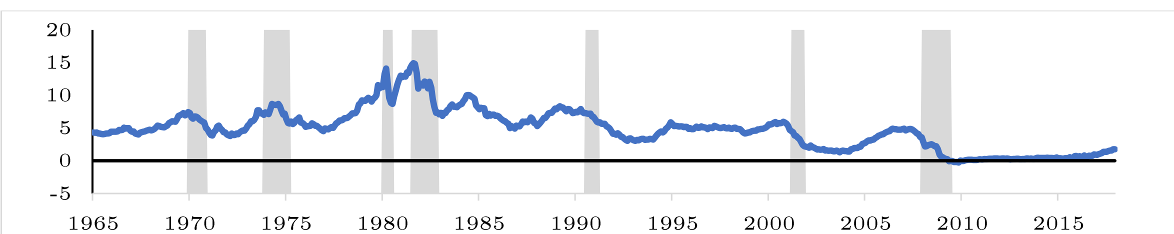


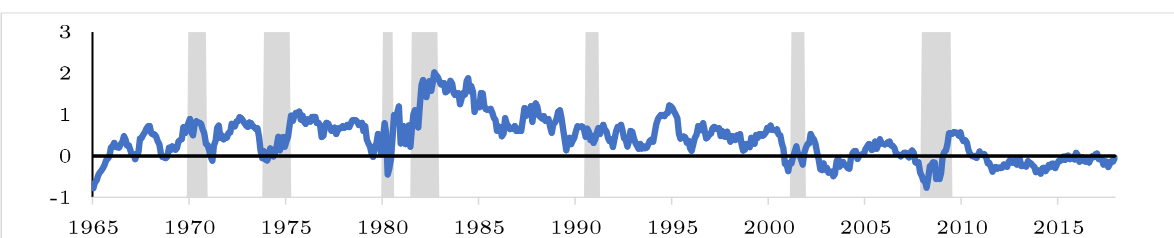
This figure shows the estimate of the market price of short-term dividend risk ψ. Gray shaded areas indicate NBER recessions.

4.6.2 Term Structure Estimates

We present the mean estimates of all components of the dividend discount rate, $r_{t,n}$, $z^{\$}_{t,n}$ and $z^{d}_{t,n}$, together with expected dividend growth $g^{d}_{t,n}$, for different periods within our sample. Table 21 summarizes all the results. Figure 21 illustrates the one-year estimates over the entire sample period for bond related quantities, figure 22 for dividends.

Figure 21: Term Structure Components - Bond Yield Components





This figure shows the estimates of the one-year average expected short rate $r_{t,12}$ (top) and interest rate risk premium $z^{\$}_{t,12}$ (bottom), whose sum is the one-year bond yield. Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

Table 21: Equity Yield Components

T	(1) Entire Sample					(3) Great Recession				
	1y	3y	5y	7y	10y	1y	3y	5y	7y	10y
r	4.83	5.07	5.22	5.31	5.40	1.56	1.79	1.94	2.04	2.13
$z^{\$}$	0.41	0.60	0.72	0.85	1.03	-0.22	0.27	0.77	1.18	1.67
z^d	1.33	1.64	2.60	3.70	5.42	41.56	13.08	9.11	8.27	8.61
g^d	5.79	5.54	5.42	5.35	5.29	5.59	7.88	9.05	9.69	10.22
e	0.75	1.74	3.11	4.50	6.56	37.62	7.44	2.90	1.90	2.26

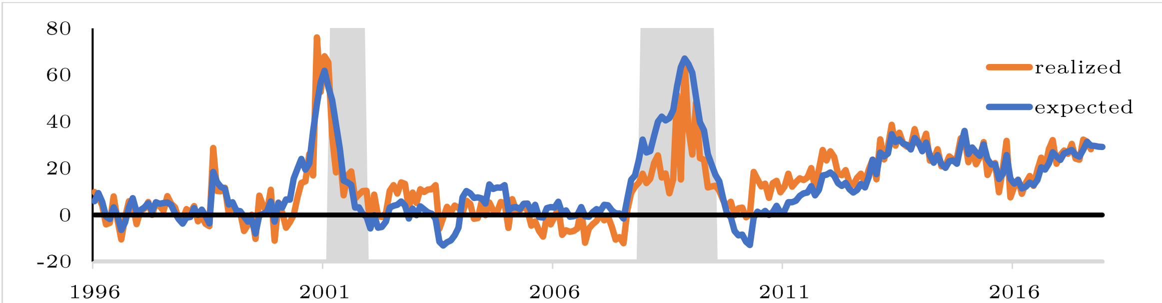
T	(2) Option Sample					(4) Quantitative Easing				
	1y	3y	5y	7y	10y	1y	3y	5y	7y	10y
r	2.40	2.61	2.75	2.84	2.93	0.45	0.62	0.73	0.81	0.88
$z^{\$}$	0.07	0.36	0.64	0.88	1.19	-0.08	0.38	0.83	1.22	1.69
z^d	10.50	5.76	5.22	5.05	6.19	16.87	7.25	6.11	6.17	7.16
g^d	6.40	6.07	5.86	5.81	5.73	6.64	5.84	5.43	5.21	5.02
e	7.04	2.66	2.75	2.95	4.58	10.50	2.34	2.26	2.96	4.70

This table reports the decomposition of model-implied equity yields into risk-free rate r, interest rate risk premium $z^{\$}$, cash flow premium z^d and dividend growth g^d for four different periods in the benchmark model: (1) the entire sample from Jan 1996 to Dec 2017, (2) the entire option sample from Jan 1996 to Sep 2017, (3) the Great Recession between Dec 2007 and Jun 2009 and (4) the time after the Great Recession from Jul 2009 to December 2017. All numbers are expressed in percentage terms.

While both expected short rates and interest rate risk premiums have been upward sloping in all samples under consideration, we find clear differences in their levels. The Federal Reserve has undertaken several measures, commonly referred to as Quantitative Easing, such as the acquisition of mortgage debt and government bonds, to stimulate the economy and stabilize the financial sector. During this period, the 1- and 10-year Treasury bond yields fell to 0.37% and 2.57%. One of the reasons for these low values are the low expected short-rates at 0.45% and 0.88%, more so the interest rate risk premiums at -0.08% and 1.69%. Expected short rates across all maturities have been more than 4 percentage points lower over the years since the Great Recession than their sample averages.

Options-implied present values of near-future dividends are only available since 1996. As they provide us with the information to identify short-horizon dividend risk premiums,

Figure 22: Term Structure Components - Dividends



This figure shows the estimates of the one-year dividend risk premium $z^d_{t,12}$ (top) and the average expected dividend growth $g^d_{t,12}$ (bottom). Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

we focus on the respective period in our analysis. The point estimates suggest a downward sloping term structure of dividend risk premiums for the time with option data availability, from 10.50% for the one-year horizon to 6.19% for the ten-year horizon. The pronounced downward slope is driven by the two most recent recessions, of which the last one was accompanied by a 41.56% premium over the one-year horizon.

4.6.3 Predicting the Economic Environment

While the previous analysis helped to understand the model's capability of matching the data and how it allows us to decompose yields into premium components and short rate expectations, we turn to the question which economic factors drive the different components and how well we can actually predict them. We predict certain model quantities of interest and decompose their forecast errors, which allows us to evaluate each variables contribution, as described in appendix D.

Based on the economic setup described in section 4.4, our model is able to describe economic developments, bond yields and dividend assets. The tractable VAR(1) structure behind our state variables allows us to obtain term structures not only for all the components of the dividend discount rate, but also for expectations on inflation, unemployment and growth. The following analysis will help us to assess the accuracy of our model-implied expectations. We focus on annual forecast horizons and calculate the R^2 values according to Harvey [1989],

$$R^2 = 1 - \frac{var(w_t - \hat{w}_t)}{var(w_t)}, \tag{81}$$

where w_t is the data counterpart to the model-implied value $\hat{w}_t$.

Our model turns out to be an accurate predictor of macro-economic time-series. The model-implied estimate of future annual inflation results in a R^2 value of 29.8%, where future annual inflation is measured as the log-change in the CPI over the next 12 months. We find a R^2 value of 83.1% for future annual unemployment, where we measure future annual unemployment as the average unemployment rate over the next 12 months. This choice comes closest to the methodology behind the Survey of Professional Forecasters. Turning to dividend growth, we measure future annual dividend growth as the log-ratio between dividends paid over the next 12 months and dividends paid over the past 12 months. We find a R^2 value of 21.2% for the entire sample period. We relate this finding to a previous study of Binsbergen and Koijen [2010], who find that their filtered estimates of dividend growth predict annual cash-invested dividends with a similar R^2 value of 13.9% for the period 1946 to 2007.

4.6.4 Predicting Returns in Bond and Dividend Investments

One of the benefits of our Taylor rule model is the straightforward decomposition of bond yields into future expected short rates and the interest rate risk premium. To empirically validate the model-implied $r_{t,12}$, derived from our linear term structure model and VAR(1) dynamic in the state variables (see equation (120) in appendix B), we compute the realized $r_{t,12}$ from the average of short rates over the next 12 months. We find a large R^2 value of 93.4%, which we see as support for the ability of our model to decompose bond yields into $r_{t,n}$ and $z^{\$}_{t,n}$. Besides the high auto-correlation of 96.4% in monthly data, we attribute part of this predictability to the use of survey expectations. On one hand, we use survey data on interest rate expectations to identify the interest rate dynamic under the empirical measure. On the other hand, we relate the short rate to economic expectations, for which we also find survey data. In a next step, we assess the ability of our model to predict returns in bond and equity markets.

We derive the expression for the expected buy-and-hold return over k periods from a zero-coupon bond with maturity n in appendix C,

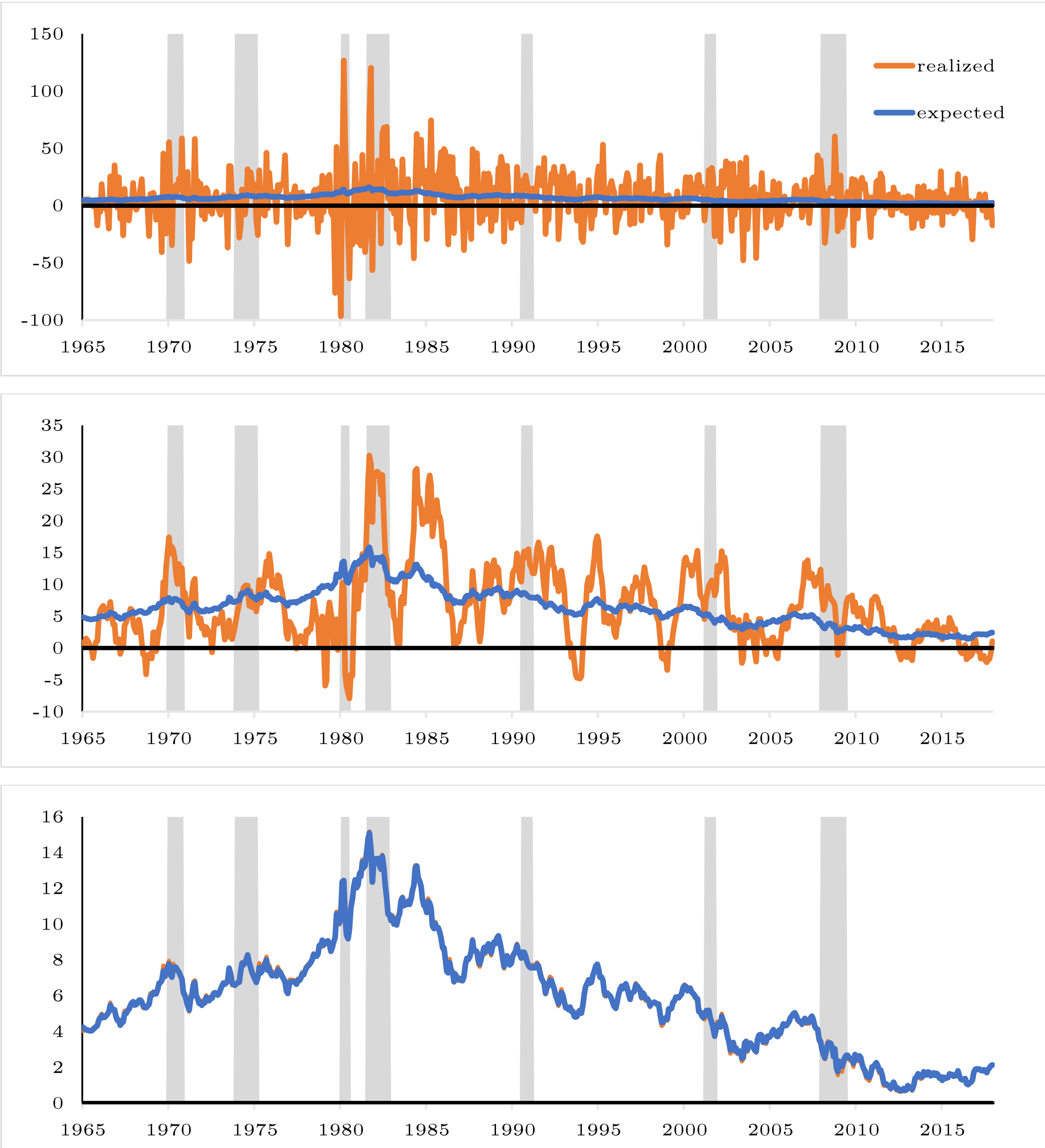
$$E_t[R^n_{t,t+k}] = n\left(a_y(n) + b_y^\top(n)X_t\right) - (n-k)\left(a_y(n-k) + b_y^\top(n-k)E_t[X_{t+k}]\right). \tag{82}$$

The trivial case of a holding period corresponding to the bond's maturity, $n = k$, results in it's yield to maturity as expected return. We predict returns for a bond with a maturity

of five years and two different holding periods, for one month and one year, to asses the predictive power. We compare the expected returns to the realized returns in figure 23. We find that our expected returns share a correlation of 15.3 % for the one-month horizon and 54.0% over the one-year horizon. In addition, the sample averages of expected returns and realized returns are very close to each other, with 6.5% (expected) and 6.7% (realized) in the one-month horizon and 6.4% (expected) and 6.6% (realized) in the one-year horizon.
Turning to dividend assets, we consider both an investment into a one-year dividend strip and the S&P 500. The recent literature has provided empirical evidence on the strong predictability of returns in dividend strips, see Binsbergen et al. [2012] and Ulrich et al. [2018]. Regarding standard equity investments, the S&P 500 has always been the focus of many empirical studies which try to reconcile the dividend price ratio with future returns or dividend growth, starting with Campbell and Shiller [1988]'s accounting identity. A more recent study of Dybvig and Zhang [2018] provides strong empirical evidence that the dividend price ratio is indeed a strong signal for future dividend growth, but not for future equity returns. The empirical findings of our prediction exercise are in line with the findings in these papers. We follow Ulrich et al. [2018] and compare the realized returns from a buy-and-hold investment into the one-year dividend strip to the implied dividend discount rate $y^d_{t,12}$. To earn the return on a one-year dividend strip, the authors propose to replicate the exposure to S&P 500 dividends which will be distributed over the next year by an option strategy. Alternatively, with the introduction of dividend futures, the investment strategy has become much simpler in recent years, as discussed in chapter 3 of this thesis. The return from this strategy is earned by receiving the dividends which get paid throughout the year, and assuming they do not get reinvested for simplicity. We find returns for this strategy since January 1996, the earliest date for which we have option data available. Figure 24 shows the strong similarity between the dividend discount rate and the realized return of the dividend strip. The correlation of 82.9% is in line with estimates in Ulrich et al. [2018], who derive a model-free estimate of the dividend discount rate and report similar predictability results. While our average dividend discount rate estimate has been 12.8% since 1996, the average annual return has been 12.2%.

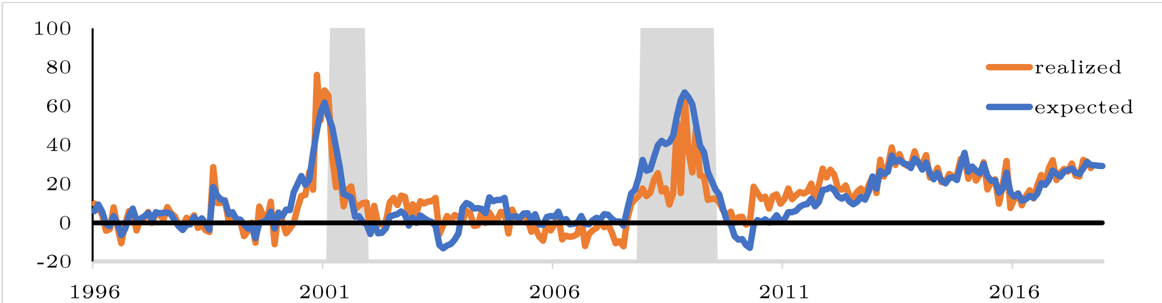
Regarding the S&P 500, we derive the formula for buy-and-hold returns in appendix C. We find little to none predictability over the one-month, one-year or five-year horizon. While the average return estimates at 9.0%, 8.7% and 8.4%, respectively, are close to the average realized returns at around 9.4%, the correlations are at 0.1%, 4.6% and 18.8% over the entire sample period. Figure 25 compares the different estimates to their realized counterparts.

Figure 23: Return Expectations - Five-Year Treasury Bond Investments



This figure shows the model-implied return expectations (blue) for a five-year Treasury bond and the corresponding future realizations (orange) for holding periods of one month (top), one year (middle) and five years (bottom). Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

Figure 24: Return Expectations - Dividend Strip Investments



This figure shows the one-year dividend discount rate estimate and the future one-year return on the one-year dividend strip (orange). Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

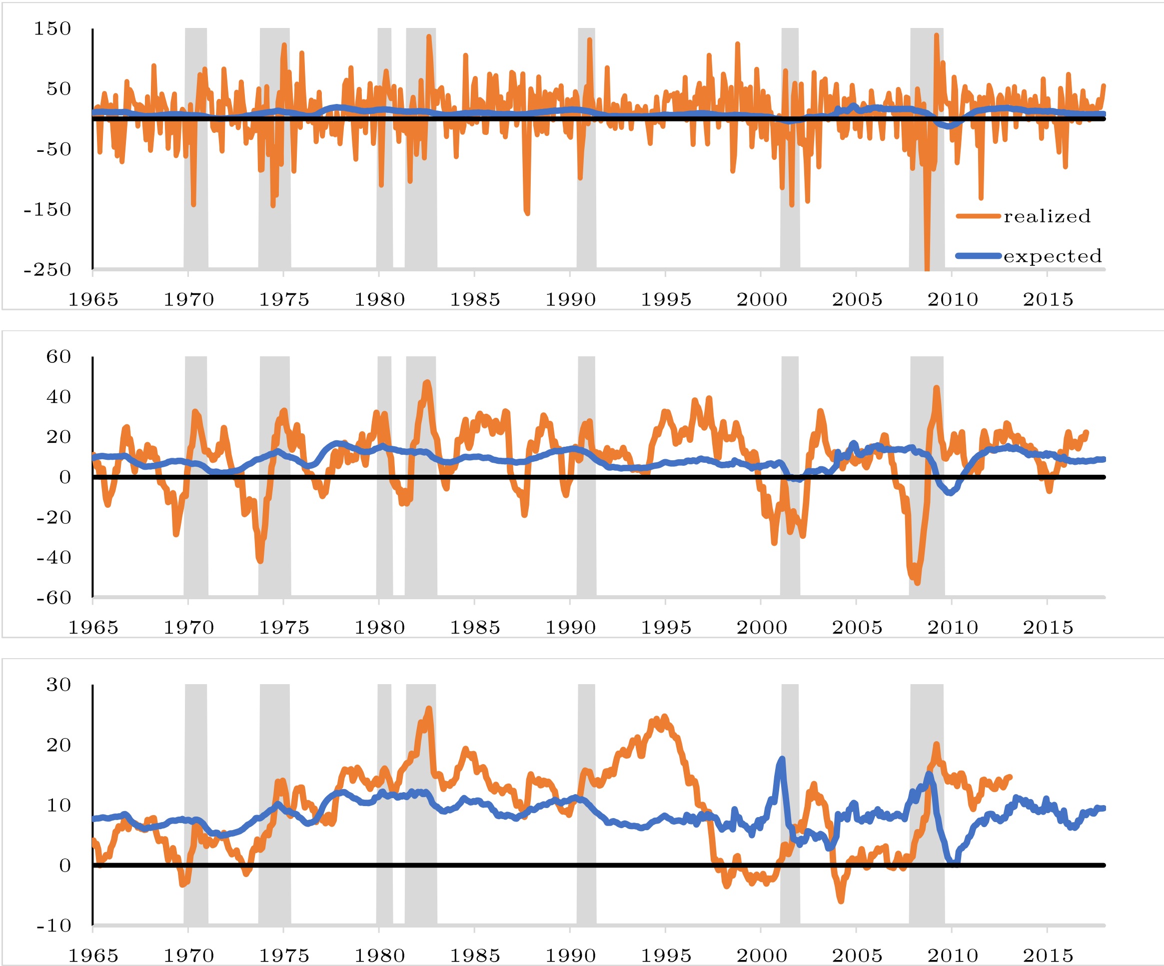
4.6.5 Forecast Error Variance Decompositions

We decompose forecast errors in the term structure components to better understand which macro factors drive short-term and long term forecast errors in $r_{t,n}$, $z^{\$}_{t,n}$, $z^{d}_{t,n}$ and $g^{d}_{t,n}$. For a derivation of our forecast error variance decomposition, we refer to appendix D. We focus on one-month and one-year forecast horizons. Results for selected quantities presented here are summarized in table 22.

We first analyze the forecast error variances in bond yields $y^{\$}_{t,n}$ and their components $r_{t,n}$ and $z^{\$}_{t,n}$. Across all maturities and forecast horizons, we find that bond yield forecast errors stem to approximately two thirds from shocks to inflation expectations and one third from shocks to unemployment expectations. Intuitively, the longer the forecast horizon or maturity of the bond yield, the more contribute long term components θ^{π} and θ^{u}. The error in interest rate risk premium forecasts seems to be largely due to unemployment expectations, as more than 95% of their variance is explained by ξ^{u} and θ^{u}. Errors in short rate expectations, on the other hand, are driven similarly across the four macro states for short horizons and maturities, with a gradual shift towards the long term inflation and unemployment component.

The forecast error variance decomposition for $z^{d}_{t,n}$ highlights that short horizons and maturities are almost exclusively driven by ψ. Shocks to ξ^{d} gain importance as the forecast horizons and maturity increases. This finding underlines the importance of an additional factor, which allows for market prices of risk that are not affine in economic fundamentals.

Figure 25: Return Expectations - Equity Index Investments



This figure shows the model-implied return expectations (blue) for an investment into the S&P 500 and the corresponding future realizations (orange) for holding periods of one month (top), one year (middle) and five years (bottom). Gray shaded areas indicate NBER recessions. Values are in annualized percentage terms.

We end this subsection by studying the forecast error variance of the dividend discount rate $y^d_{t,n}$. The results reflect that the dividend discount rate is the sum of the Treasury bond yield and the dividend risk premium, as it is largely driven by ψ for short horizons and short maturities, with increasing contributions of macro variables for longer horizons and maturities.

Table 22: Forecast Error Variance Decompositions

	One-month forecast horizon						
	ξ^π	θ^π	ξ^u	θ^u	ξ^d	θ^d	ψ
r_{12}	0.28	0.19	0.21	0.31	0.00	0.00	0.00
r_{60}	0.03	0.36	0.02	0.60	0.00	0.00	0.00
$z^{\$}_{12}$	0.04	0.01	0.92	0.04	0.00	0.00	0.00
$z^{\$}_{60}$	0.04	0.00	0.72	0.24	0.00	0.00	0.00
$y^{\$}_{12}$	0.42	0.21	0.07	0.30	0.00	0.00	0.00
$y^{\$}_{60}$	0.19	0.41	0.01	0.39	0.00	0.00	0.00
z^d_{12}	0.00	0.00	0.00	0.00	0.04	0.00	0.96
z^d_{60}	0.00	0.00	0.00	0.00	0.16	0.00	0.84
y^d_{12}	0.01	0.00	0.00	0.01	0.04	0.00	0.94
y^d_{60}	0.04	0.08	0.00	0.07	0.13	0.00	0.68

	One-year forecast horizon						
	ξ^π	θ^π	ξ^u	θ^u	ξ^d	θ^d	ψ
r_{12}	0.23	0.30	0.11	0.35	0.00	0.00	0.00
r_{60}	0.02	0.45	0.01	0.53	0.00	0.00	0.00
$z^{\$}_{12}$	0.05	0.03	0.84	0.08	0.00	0.00	0.00
$z^{\$}_{60}$	0.05	0.00	0.84	0.08	0.00	0.00	0.00
$y^{\$}_{12}$	0.33	0.31	0.02	0.33	0.00	0.00	0.00
$y^{\$}_{60}$	0.13	0.52	0.00	0.35	0.00	0.00	0.00
z^d_{12}	0.00	0.00	0.00	0.00	0.07	0.00	0.93
z^d_{60}	0.00	0.00	0.00	0.00	0.24	0.00	0.76
y^d_{12}	0.01	0.00	0.00	0.01	0.06	0.00	0.92
y^d_{60}	0.02	0.09	0.00	0.06	0.20	0.00	0.64

This table reports estimates for the forecast error variance decomposition for selected financial quantities estimated over the full sample from Jan 1965 to Dec 2017. Values are relative contributions of each state variable to the respective forecast error variance and rounded to two decimals.

4.6.6 Impulse Response Functions

We closely follow the analysis in Ang and Piazzesi [2003] to report the responses in the different discount rate components to movements in the state variables. The methodology is outlined in appendix F. We are interested in the question by how many basis points a financial variable moves following an isolated movement of one standard deviation in one of the state variables. The variables we consider in this analysis are short rate expectations $r_{t,n}$ and interest rate risk premiums $z^{\$}_{t,n}$, whose responses add up to the responses of Treasury bond yields $y^{\$}_{t,n}$. Then we add an analysis of dividend risk premiums $z^d_{t,n}$, which added to

Treasury bond yields give us the responses in dividend discount rates $y_{t,n}^d$. We focus our analysis on the responses in one- and five-year maturities. Table 23 contains selected results which we discuss below.

Table 23: Impulse Responses

$h=1$	Impact one month after impulse						
	ξ^π	θ^π	ξ^u	θ^u	ξ^d	θ^d	ψ
r_{12}	32	25	-23	-17	0	0	0
r_{60}	16	25	-12	-17	0	0	0
$z_{12}^\$$	-3	-2	13	2	0	0	0
$z_{60}^\$$	-3	-1	9	4	0	0	0
$y_{12}^\$$	29	23	-10	-15	0	0	0
$y_{60}^\$$	13	24	-3	-14	0	0	0
z_{12}^d	0	0	0	0	69	1	301
z_{60}^d	0	0	0	0	28	1	58
y_{12}^d	29	23	-10	-15	69	1	301
y_{60}^d	13	24	-3	-14	28	1	58

$h=12$	Impact twelve months after impulse						
	ξ^π	θ^π	ξ^u	θ^u	ξ^d	θ^d	ψ
r_{12}	24	25	-17	-17	0	0	0
r_{60}	13	24	-8	-16	0	0	0
$z_{12}^\$$	-2	-2	10	2	0	0	0
$z_{60}^\$$	-2	-1	6	4	0	0	0
$y_{12}^\$$	22	23	-7	-15	0	0	0
$y_{60}^\$$	11	23	-2	-11	0	0	0
z_{12}^d	0	0	0	0	48	1	288
z_{60}^d	0	0	0	0	20	1	52
y_{12}^d	22	23	-7	-15	48	1	288
y_{60}^d	11	23	-2	-11	20	1	52

This table reports estimates of impulse responses for selected financial quantities estimated over the full sample from Jan 1965 to Dec 2017. Values represent the impact in basis points after a one standard deviation impulse in a particular state variable and are rounded to full basis points.

In accordance with Ang and Piazzesi [2003], we find that short-term Treasury yields are more sensitive to shocks in macro-economic variables than long term Treasury yields. Comparing the one-year to the five-year Treasury yield, we find that the impact of ξ^π and ξ^u

is at least twice as large for the one-year yield across horizons. We find that an increase in inflation expectations affects Treasury yields almost only because of increased expectations about future short rates. A positive shock to unemployment expectations leads intuitively to lower expectations on future short rates, but increases interest rate risk premiums. As the negative effect on short rate expectations is stronger, Treasury yields tend to decrease with an increase in unemployment expectations.

Regarding the dividend risk premium, we find that short maturities are strongly affected by an increasing market price of short-term dividend risk. A shock of one standard deviation in ψ translates into an immediate increase of 301 basis points in the one-year dividend risk premium. The impact on the five-year premium is only about a fifth as large at 58 basis points. The dividend discount rate $y^d_{t,n}$, which is the sum of Treasury bond yield $y^\$_{t,n}$ and dividend risk premium $z^d_{t,n}$, shows intuitively the same behavior as its constituents. While the one-year discount rate $y^d_{t,12}$ reacts strongest to shocks in ψ, the impact of ψ on the five-year discount rate $y^d_{t,60}$ is closer in magnitude to the impact of other economic variables.

4.7 Conclusion

We have derived and estimated the first affine term structure model that jointly prices Treasury bonds, equity and options-implied dividend strips. We have applied the model to U.S. data and find it describes the economy, survey forecasts and asset price data very well. From a pricing perspective, our model fits the asset price data as good as latent factor models that focus on one of the three asset classes, with a reasonable amount of economically meaningful pricing factors. From an economic point of view, our model allows to study the interplay of the economy and price data and to decompose dividend discount rates within an affine term structure model into their economically meaningful components.

Our application to U.S. data reveals several new learning points. We find that a monetary policy rule based on the Federal Reserve's dual mandate - price stability and sustainable employment - allows for an accurate description of government bond yields. Survey data on inflation and unemployment expectations, published by the Federal Reserve, provide us with valuable information about the pricing factors. Based on our predictive exercise regarding economic variables and future short rates, we conclude that the auto-regressive structure behind the state variables is well identified.

The inclusion of dividend growth into our affine term structure model allows us to price claims on dividends. While survey-expectations on dividend growth allow us to identify dynamics under the empirical probability measure, price data on dividends, paid at different points in the future, allows us to estimate risk-adjusted growth rates. In a macro-only specification, where market prices of dividend growth risk are affine in the dividend growth variables, we are not able to reconcile the prices of near-future dividends and the equity index. An additional state variable for the market price of near-future dividend growth risk, on the other hand, improves the pricing and enables us to predict returns on dividend strips with high accuracy.

We leave many interesting further developments to future research. For example, we have analyzed only one special case of our most general model framework. It could be interesting to add stochastic volatility to the model as in Creal and Wu [2017], in particular as volatility in dividend discount rates increases in difficult economic times and as a mechanism to learn about the links between second moment and first moment shocks. Allowing for Granger causality among fundamental risk factors might enable us to better understand interactions between bond and equity markets. Another interesting avenue is the application to the cross-section of equity, as dividend derivatives are also available for individual companies. We leave all of these three interesting extensions to future research.

5 Summary and Outlook

In this thesis, we quantify and analyze the term structure of dividend risk premiums. In chapter 2, we derive a novel approach to quantify the dividend risk premium in the aggregate U.S. stock market, represented by the S&P 500, based on option prices and analyst estimates on future dividends. Our approach is novel in the sense that it is based on real-time and forward-looking data and does not assume a parametric structure in the dividend growth process. Our first important finding contributes to the literature on dividend growth predictability. We cannot reject the hypothesis that our model-free one-year estimate of S&P 500 dividend growth is an unbiased predictor of future realized dividend growth. Combining the growth measure derived from analyst estimates with growth estimates implied by put call parity, we obtain an estimate of 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. 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 term structure slope flattens during business cycle expansions and becomes more negative during business cycle contractions.

In chapter 3, we extend our analysis to the European market. A rich set of intra-day data on Euro Stoxx 50 dividend futures provides us with present values, and hence implied growth rates, of future dividends. We find that growth rates implied by analyst forecasts are upward biased for this market, whose realized growth rates have been negative on average between August 2008 and September 2017. The upward bias in the aggregate growth estimate is not due to a few outliers among the index constituents, we rather find an upward bias for most of the constituents. This introduces an upward bias in our estimate of the dividend risk premium, which nonetheless is a strong predictor of future returns in dividend assets and exhibits a similar business cycle behavior as its U.S. counterpart. While returns on S&P 500 dividend assets earned through put call parity show very little correlation with the equity market, returns on Euro Stoxx 50 dividend futures are positively correlated with the equity index.

In chapter 4, we derive an affine term structure model which jointly prices government bonds and dividend-paying assets. While the affine model is well-established for government bonds, we derive an affine pricing structure for dividend-paying assets by incorporating the dividend growth rate into the state vector. While our model allows for several specifications regarding pricing factors and price signals, we decided to build on the work of Ang and Piazzesi [2003] and Kim and Wright [2005] in our implementation. We use survey-expectations on macro-economic variables, interest rates and dividend growth together with price data to estimate the dynamics of our economic risk factors: inflation, unemployment and dividend growth. The use of survey data and price data allows us to determine the dynamics under the empirical and risk-neutral probability measure, revealing the market prices of risk for each risk factor. Our analysis shows that an affine specification of market prices of risk allows for excellent fits to both price and survey data regarding bond interest rates, but fails to accommodate dividend strips. In an extension to our macro-only model, we show how an independent process for the market price of short-horizon dividend growth risk improves the pricing substantially. Within this benchmark model, the implied return on dividend strips turns out to be a strong predictor of future realized returns.

Our findings open new avenues for future research, in particular regarding the cross-section of stocks. While we dedicated ourselves to the aggregate measures of the U.S. and European stock market, the approaches derived in this thesis can easily be applied to single stocks or industry portfolios, as long as both analyst growth estimates and dividend derivatives or options on the individual companies are available. Our affine term structure model allows us to estimate the common risk factors among bond and equity markets and can easily be applied to regions other than the United States. Several straightforward extensions to our benchmark model, such as Granger causality among risk factors or additional price data, might shed light on the drivers behind the time-varying correlation between bond and equity markets.

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

$$M_t = \sum_i P_{i,t} S_{i,t}. \tag{83}$$

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

$$D_t = \sum_i D_{i,t} S_{i,t}. \tag{84}$$

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:

$$Divisor_t = M_t / S\&P500_t, \qquad Div_t = D_t / Divisor_t. \tag{85}$$

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

$$E_t^P[Div_{t+n}] = E_t^P \left[\frac{\sum_i D_{i,t+n} S_{i,t+n}}{Divisor_{t+n}} \right]. \tag{86}$$

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

$$E_t^P[Div_{t+n}] = \frac{\sum_i E_t^P[D_{i,t+n}]S_{i,t}}{Divisor_t}. \tag{87}$$

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:

$$g_{t,n}^P \equiv \delta_{0,t} + \delta_{1,t}\frac{1-e^{-n\lambda_t}}{n\lambda_t} + \delta_{2,t}\left(\frac{1-e^{-n\lambda_t}}{n\lambda_t} - e^{-n\lambda_t}\right). \tag{88}$$

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

$$g_t^P \equiv \delta^\top L_t \quad \text{with} \quad L_t = (L_{1,t}, L_{360,t}, L_{720,t}, L_{1800,t}) \tag{89}$$

and

$$L_{n,t} \equiv \begin{pmatrix} 1 & \frac{1-e^{-n\lambda_t}}{n\lambda_t} & \frac{1-e^{-n\lambda_t}}{n\lambda_t} - e^{-n\lambda_t} \end{pmatrix}^\top \quad \text{for} \quad n \in \{1, 360, 720, 1800\} \tag{90}$$

to obtain the ordinary least squares solution

$$\delta_t = (L_t^\top L_t)^{-1} L_t^\top g_t^P. \tag{91}$$

Average estimates for our sample can be found in table 24.

Table 24: 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.

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,

$$y_{t,n}^d \equiv \delta_{0,t} + \delta_{1,t} \frac{1-e^{-n\lambda_t}}{n\lambda_t} + \delta_{2,t} \left(\frac{1-e^{-n\lambda_t}}{n\lambda_t} - e^{-n\lambda_t} \right), \tag{92}$$

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 2.3, tailored to our empirical analysis. Average estimates for our sample and option filter can be found in table 24.

B Proofs

B.1 Proof of Proposition (1): Equity Yield

We want to show that

$$e_{t,n} = a_e(n) + b_e'(n) X_t. \tag{93}$$

The proof is by induction. First, for $n = 1$, we define the one period equity yield

$$e_{t,1} \equiv -\ln\left(\frac{S_{t,1}}{D_t}\right) \tag{94}$$

with

$$\frac{S_{t,1}}{D_t} \equiv E_t^Q\left[e^{-r_t}\,\frac{D_{t+1}}{D_t}\right] = e^{-r_t}\;E_t^Q\left[e^{e_d' X_{t+1}}\right] = e^{a_c(1)+b_c'(1)X_t} \tag{95}$$

where

$$a_c(1) = -\alpha + e_d' c^Q \qquad \text{and} \qquad b_c(1) = -\delta + \left(\Phi^Q\right)' e_d. \tag{96}$$

Hence,

$$a_e(1) = -a_c(1) \qquad \text{and} \qquad b_e(1) = -b_c(1). \tag{97}$$

Second, for arbitrary $n > 0$,

$$e_{t,n} \equiv -\frac{1}{n}\ln\left(\frac{S_{t,n}}{D_t}\right). \tag{98}$$

We show by induction that if

$$\frac{S_{t,n}}{D_t} = e^{a_c(n)+b_c'(n)X_t}, \tag{99}$$

it holds that

$$\frac{S_{t,n+1}}{D_t} = e^{a_c(n+1)+b_c'(n+1)X_t}. \tag{100}$$

Note,

$$\begin{aligned}
\frac{S_{t,n+1}}{D_t} &\equiv E_t^Q\left[\frac{D_{t+n+1}}{D_t}\prod_{i=0}^{n} e^{-r_{t+i}}\right] \\
&= E_t^Q\left[e^{-r_t}\frac{D_{t+1}}{D_t}\;\times\;E_{t+1}^Q\left[\frac{D_{t+n+1}}{D_{t+1}}\prod_{i=1}^{n} e^{-r_{t+i}}\right]\right] \\
&= E_t^Q\left[e^{-\alpha-\delta' X_t + e_d' X_{t+1}}\;\times\;e^{a_c(n)+b_c'(n)X_{t+1}}\right],
\end{aligned} \tag{101}$$

where the second equality follows from the law of iterated expectations. Insert the VAR(1) dynamic for X_{t+1}, multiply out terms and put $\mathcal{F}_t$-measurable variables out of the expectation operator:

$$\frac{S_{t,n+1}}{D_t} = e^{-\alpha-\delta' X_t+a_c(n)+(e_d+b_c(n))'(c^Q+\Phi^Q X_t)} \times E_t^Q\left[e^{(e_d+b_c(n))'\Sigma\epsilon_{t+1}^Q}\right]. \tag{102}$$

Taking the expectation of the exponential of a normally distributed variable, we obtain

$$E_t^Q\left[e^{(e_d+b_c(n))'\Sigma\epsilon_{t+1}^Q}\right] = e^{\frac{1}{2}(e_d+b_c(n))'\Sigma\Sigma'(e_d+b_c(n))}. \tag{103}$$

We collect terms that are constant and linear in X_t and match coefficients to solve for the unknown loadings:

$$\begin{aligned} a_c(n+1) =& -\alpha + a_c(n) + (e_d+b_c(n))'c^Q + \frac{1}{2}(e_d+b_c(n))'\Sigma\Sigma'(e_d+b_c(n)), \\ b_c(n+1) =& -\delta + \Phi^Q(e_d+b_c(n)). \end{aligned} \tag{104}$$

Hence,

$$a_e(n+1) = -\frac{a_c(n+1)}{n+1} \qquad b_e(n+1) = -\frac{b_c(n+1)}{n+1}. \tag{105}$$

We proved by induction that

$$e_{t,n} = a_e(n) + b_e'(n)X_t \tag{106}$$

where the deterministic loadings follow the recursions from above.

B.2 Proof of Corollary (1): Bond Yield

Assume a firm was to pay a dividend of \$1 at time $t+n$. The respective equity yield coincides with the time t value of a n-maturity risk-free zero-coupon bond yield

$$y_{t,n}^{\$} \equiv -\frac{1}{n}\ln\left(\frac{S_{t,n}^{\$1}}{\$1}\right) \tag{107}$$

where

$$\frac{S_{t,n}^{\$1}}{\$1} \equiv E_t^Q\left[\$1 \times \prod_{i=0}^{n-1} e^{-r_{t+i}}\right]. \tag{108}$$

The solution to the last equation can be derived by using Equation (93) and setting e_d to zero. Doing so reveals

$$y^{\$}_{t,n} = a_y(n) + b'_y(n)X_t \tag{109}$$

with

$$a_y(n) \equiv a_e(n)|_{e_d \equiv 0} \qquad \text{and} \qquad b_y(n) \equiv b_e(n)|_{e_d \equiv 0}. \tag{110}$$

B.3 Proof of Corollary (2): Decomposition of Equity Yields

We want to show that

$$e_{t,n} = y^d_{t,n} - g^d_{t,n} \tag{111}$$

and start from Proposition (1), which has established that

$$e_{t,n} = a_e(n) + b'_e(n)X_t. \tag{112}$$

We decompose $a_e(n) + b'_e(n)X_t$ into $g^d_{t,n}$ and $y^d_{t,n}$, for all $n > 0$. We first derive $g^d_{t,n}$ using the VAR(1) dynamic under $\mathcal{P}$, followed by getting $y^d_{t,n}$.
We define $g^d_{t,n}$ to be the average future expected dividend growth rate

$$\begin{aligned} g^d_{t,n} &\equiv \frac{1}{n}\sum_{i=1}^{n} E^P_t[d_{t+i}] \\ &= \frac{e'_d}{n} \times \sum_{i=1}^{n} E^P_t[X_{t+i}] \\ &= \frac{e'_d}{n} \times \sum_{i=1}^{n} \left[(I - (\Phi^P))^{-1}\left(I - (\Phi^P)^i\right) \times c^P + (\Phi^P)^i X_t\right] \end{aligned} \tag{113}$$

which in our model coincides with

$$g^d_{t,n} = A_g(n) + B'_g(n)X_t \tag{114}$$

where

$$B'_g(n) \equiv e'_d \times \frac{1}{n}\sum_{i=1}^{n} \left(\Phi^P\right)^i \qquad \text{and} \qquad A_g(n) \equiv e'_d \times \frac{1}{n}\sum_{i=1}^{n} \left[(I - (\Phi^P))^{-1}\left(I - (\Phi^P)^i\right) \times c^P\right]. \tag{115}$$

Turning to $y^d_{t,n}$, such that the following identity holds:

$$y^d_{t,n} - g^d_{t,n} \overbrace{=}^{!} a_e(n) + b'_e(n)X_t, \tag{116}$$

which implies

$$y^d_{t,n} = a_{y^d}(n) + b'_{y^d}(n)X_t \tag{117}$$

with

$$a_{y^d}(n) \equiv [a_e(n) + A_g(n)] \qquad \text{and} \qquad b_{y^d}(n) \equiv [b_e(n) + B_g(n)]\,. \tag{118}$$

B.4 Proof of Corollary (3): Decomposing Dividend Discount Rates

We want to show

$$y^d_{t,n} = r_{t,n} + z^\$_{t,n} + z^d_{t,n} \tag{119}$$

where $r_{t,n}$ is the expected average future path of the policy rate, $z^\$_{t,n}$ is the interest rate risk premium and $z^d_{t,n}$ is the dividend risk premium. We solve sequentially for $r_{t,n}$, $z^\$_{t,n}$ and $z^d_{t,n}$.

Starting from $r_{t,n}$, note that $r_t \equiv \alpha + \delta' X_t$ and $X_t \equiv c^P + \Phi^P X_{t-1} + \Sigma\epsilon^P_t$, $\epsilon_t \sim N(0, I)$. We define

$$r_{t,n} \equiv \frac{1}{n}\sum_{i=0}^{n-1} E^P_t[r_{t+i}] = \alpha + \frac{1}{n}\sum_{i=0}^{n-1} \delta' \left((I - \Phi_P)^{-1}(I - (\Phi^P)^i)c^P + (\Phi^P)^i X_t\right), \tag{120}$$

which can be rewritten as

$$r_{t,n} = a_r(n) + b'_r(n)X_t, \tag{121}$$

where

$$
\begin{aligned}
a_r(n) &\equiv \alpha + \frac{1}{n}\sum_{i=0}^{n-1} \delta' \left((I-\Phi_P)^{-1}(I-(\Phi^P)^i)c^P\right) \\
b_r'(n) &\equiv \frac{1}{n}\sum_{i=0}^{n-1} \delta'(\Phi^P)^i X_t.
\end{aligned}
\tag{122}
$$

Turning to $z^{\$}_{t,n}$, we define the interest rate risk premium as

$$
z^{\$}_{t,n} \equiv y^{\$}_{t,n} - r_{t,n}, \tag{123}
$$

where the first term on the right hand side is derived in Corollary (1). Hence, we conclude

$$
z^{\$}_{t,n} = a_z(n) + b_z'(n)X_t + X_t' h_z(n) X_t, \tag{124}
$$

with

$$
\begin{aligned}
a_z(n) &\equiv a_y(n) - a_r(n) \\
b_z(n) &\equiv b_y(n) - b_r(n).
\end{aligned}
\tag{125}
$$

Finally, we derive $z^{d}_{t,n}$. The term structure of the dividend risk premium follows from

$$
z^{d}_{t,n} \equiv y^{d}_{t,n} - r_{t,n} - z^{\$}_{t,n}. \tag{126}
$$

Corollary (2) derived the expression for $y^{d}_{t,n}$ while we have derived the expressions for $r_{t,n}$ and $z^{\$}_{t,n}$ above. Hence,

$$
z^{d}_{t,n} = a_{z^d}(n) + b_{z^d}'(n)X_t \tag{127}
$$

with

$$
a_{z^d}(n) \equiv a_{y^d}(n) - a_y(n) \qquad b_{z^d}(n) \equiv b_{y^d}(n) - b_y(n). \tag{128}
$$

C Implied Return Expectations

In this section, we derive the expected buy-and-hold returns on equity and bond investments as implied by our term structure model and economic setup.

C.1 Expected Bond Returns

The price $S^{\$}_{t,n}$ of a zero-coupon bond with maturity n at time t is a function of the respective yield to maturity $y^{\$}_{t,n}$,

$$S^{\$}_{t,n} = e^{-ny^{\$}_{t,n}}. \tag{129}$$

The expected cumulative return over the next k periods is defined as

$$E_t[R^n_{t,t+k}] \equiv E_t \left[\sum_{m=1}^{k} ln \left(\frac{S^{\$}_{t+m,n-m}}{S^{\$}_{t+m-1,n-m+1}} \right) \right], \tag{130}$$

which, as we find a telescoping sum, can be simplified to

$$E_t[R^n_{t,t+k}] = E_t \left[ln \left(S^{\$}_{t+k,n-k} \right) \right] - ln \left(S^{\$}_{t,n} \right) = ny^{\$}_{t,n} - (n-k)E_t \left[y^{\$}_{t+k,n-k} \right] \tag{131}$$

A solution for the zero-coupon bond yield exists, in form of a linear function of the state vector,

$$E_t[y^{\$}_{t+m,n}] = a_y(n) + b_y^{\top}(n) E_t[X_{t+m}], \tag{132}$$

such that we can calculate the model implied expected return on the $n-$maturity zero-coupon bond over multiple periods k at each point in time t as

$$E_t[R^n_{t,t+k}] = n \left(a_y(n) + b_y^{\top}(n) X_t \right) - (n-k) \left(a_y(n-k) + b_y^{\top}(n-k) E_t[X_{t+k}] \right). \tag{133}$$

C.2 Expected Equity Returns

Both the future dividends D_{t+m} and prices S_{t+m} of a dividend-paying asset define its future returns. The expected cumulative return over the next k periods is defined as

$$E_t[R_{t,t+k}] \equiv E_t \left[\sum_{m=1}^{k} ln \left(\frac{S_{t+m} + D_{t+m}}{S_{t+m-1}} \right) \right], \tag{134}$$

which we can express more conveniently as

$$E_t[R_{t,t+k}] = \sum_{m=1}^{k} \left(E_t \left[ln \left(\frac{S_{t+m}}{S_{t+m-1}} \right) + ln \left(1 + \frac{D_{t+m}}{S_{t+m}} \right) \right] \right). \tag{135}$$

We rewrite the first term in the expectation,

$$\begin{aligned} E_t \left[ln \left(\frac{S_{t+m}}{S_{t+m-1}} \right) \right] &= E_t \left[ln \left(\frac{S_{t+m}}{D_{t+m}} D_{t+m} \frac{D_{t+m-1}}{S_{t+m-1}} \frac{1}{D_{t+m-1}} \right) \right] \\ &= E_t \left[ln \left(\frac{S_{t+m}}{D_{t+m}} \right) - ln \left(\frac{S_{t+m-1}}{D_{t+m-1}} \right) + ln \left(\frac{D_{t+m}}{D_{t+m-1}} \right) \right], \end{aligned} \tag{136}$$

to conclude our formula for the expected equity return:

$$E_t[R_t(k)] = \sum_{m=1}^{k} \left(E_t \left[ln \left(\frac{D_{t+m}}{D_{t+m-1}} \right) + ln \left(\frac{S_{t+m}}{D_{t+m}} \right) - ln \left(\frac{S_{t+m-1}}{D_{t+m-1}} \right) + ln \left(1 + \frac{D_{t+m}}{S_{t+m}} \right) \right] \right). \tag{137}$$

The first term on the right hand side, dividend growth, can easily be obtained from the state vector,

$$E_t \left[ln \left(\frac{D_{t+m}}{D_{t+m-1}} \right) \right] = d_0 + e_d E_t[X_{t+m}]. \tag{138}$$

The three remaining terms in equation (137) contain all expectations on the future dividend yield or its inverse, which in the Gordon growth formula can be written as

$$E_t \left[ln \left(\frac{S_{t+m}}{D_{t+m}} \right) \right] = E_t \left[ln \left(\frac{1 + \bar{g}^d_{t+m}}{\bar{y}^d_{t+m} - \bar{g}^d_{t+m}} \right) \right], \qquad \text{with} \quad \bar{y}^d_{t+m} > \bar{g}^d_{t+m} > -1. \tag{139}$$

Based on the assumption that a medium- to long term estimate of dividend growth and dividend discount rates with horizon n^* are a good approximation for the Gordon growth formula, $\bar{y}^d_t = y^d_{t,n^*}$ and $\bar{g}^d_t = g^d_{t,n^*}$ with $y^d_{t,n^*} > g^d_{t,n^*} > -1$, we obtain

$$E_t \left[ln \left(\frac{S_{t+m}}{D_{t+m}} \right) \right] = E_t \left[ln \left(\frac{1 + d_0 + e'_d X_{t+m}}{a_e(n^*) + b'_e(n^*) X_{t+m}} \right) \right] \tag{140}$$

which we can express as a difference instead of a quotient:

$$E_t \left[ln \left(\frac{S_{t+m}}{D_{t+m}} \right) \right] = E_t \left[ln(1 + d_0 + e'_d X_{t+m}) \right] - E_t \left[ln(a_e(n^*) + b'_e(n^*) X_{t+m}) \right]. \tag{141}$$

To approximate a random variable $E[ln(x)]$, we use a second-order Taylor expansion around $\mu = E[x]$, which we can do as long as $x \gg 0$, see Teh et al. [2006] for details:

$$E[\ln(x)] \approx \ln(\mu) - \frac{\sigma_x^2}{2\mu^2}. \tag{142}$$

Applied to equation (141), we obtain the following approximation

$$\begin{aligned} E_t\left[ln\left(\frac{S_{t+m}}{D_{t+m}}\right)\right] \approx \quad & ln\left(1 + d_0 + e_d' E\left[X_{t+m}\right]\right) - \frac{e_d' \Sigma e_d}{2\left(1 + d_0 + e_d' E\left[X_{t+m}\right]\right)^2} \\ & - ln\left(a_e(n^*) + b_e'(n^*) E\left[X_{t+m}\right]\right) + \frac{b_e'(n^*) \Sigma b_e'(n^*)}{2\left(a_e(n^*) + b_e'(n^*) E\left[X_{t+m}\right]\right)^2}. \end{aligned} \tag{143}$$

Turning to the last term, we proceed in the same way to solve for the expectation. First, we rewrite the term based on the Gordon growth formula,

$$\begin{aligned} E_t\left[ln\left(1 + \frac{D_{t+m}}{S_{t+m}}\right)\right] = \quad & E_t\left[ln\left(1 + \frac{a_e(n^*) + b_e'(n^*) X_{t+m}}{1 + d_0 + e_d' X_{t+m}}\right)\right] \\ = \quad & E_t\left[ln\left(\frac{1 + d_0 + a_e(n^*) + (e_d' + b_e'(n^*)) X_{t+m}}{1 + d_0 + e_d' X_{t+m}}\right)\right] \\ = \quad & E_t\left[ln\left(1 + d_0 + a_e(n^*) + (e_d' + b_e'(n^*)) X_{t+m}\right)\right] \\ & - E_t\left[ln\left(1 + d_0 + e_d' X_{t+m}\right)\right] \end{aligned} \tag{144}$$

and then use equation (142) to solve for the expectation:

$$\begin{aligned} E_t\left[ln\left(1 + \frac{D_{t+m}}{S_{t+m}}\right)\right] \approx \quad & ln\left(1 + d_0 + a_e(n^*) + (e_d' + b_e'(n^*)) E\left[X_{t+m}\right]\right) \\ & - \frac{(e_d' + b_e'(n^*)) \Sigma (e_d + b_e(n^*))}{2\left(1 + d_0 + a_e(n^*) + (e_d' + b_e'(n^*)) E\left[X_{t+m}\right]\right)^2} \\ & - ln\left(1 + d_0 + e_d' E\left[X_{t+m}\right]\right) + \frac{e_d' \Sigma e_d}{2\left(1 + d_0 + e_d' E\left[X_{t+m}\right]\right)^2}. \end{aligned} \tag{145}$$

D Variance Decomposition of Forecast Errors

We decompose the variance of the model-implied forecast errors into the contribution of each state variable for the financial quantities discussed in chapter 4.6. For all relevant quantities $y_t^{(i)}$, we find a linear dependence on the state vector X_t,

$$y_t^{(i)} = a^{(i)} + b^{(i)} X_t, \tag{146}$$

where both $a^{(i)}$ and $b^{(i)}$ are derived in appendix B for all relevant financial quantities. The k period ahead forecast error of the state vector is

$$\epsilon_t^{X,k} = X_{t+k} - E_t^P\left[X_{t+k}\right] = X_{t+k} - \left((I - \Phi^P)^{-1}\left(I - (\Phi^P)^k\right)c^P + (\Phi^P)^k X_t\right), \tag{147}$$

with a posteriori state estimates being used for X_t. The corresponding covariance matrix is

$$Cov(\epsilon_t^{X,k}) = \frac{1}{T-k-1}\sum_{t=1}^{T-k} \epsilon_t^{X,k}(\epsilon_t^{X,k})^\top. \tag{148}$$

The k period ahead forecast error of model quantity i at time t is given by

$$\begin{aligned} \epsilon_t^{y,k,i} &= y_{t+k}^{(i)} - E_t^P\left[y_{t+k}^{(i)}\right] \\ &\approx a^{(i)} + b^{(i)} X_{t+k} - a^{(i)} + b^{(i)} E_t^P\left[X_{t+k}\right] \\ &= b^{(i)} \epsilon_t^{X,k}. \end{aligned} \tag{149}$$

The variance operator yields

$$Var(\epsilon_t^{y,k,i}) \approx b^{(i)} Cov(\epsilon_t^{X,k})(b^{(i)})^\top. \tag{150}$$

If we assume the shocks to the J state variables to be orthogonal to each other, which implies that the forecast errors of the state vector are uncorrelated, the variance simplifies to

$$Var(\epsilon_t^{y,k,i}) \approx \sum_{j=1}^{J} (b_{t-1}^{(i,j)})^2 Cov(\epsilon_t^{X,k})^{(j,j)} \tag{151}$$

and the contribution of the state variable in the l-th position of the state vector to the variance of the k period ahead forecast error of model quantity i is given by

$$\frac{(b^{(i,l)})^2 Cov(\epsilon_t^{X,k})^{(l,l)}}{\sum_{j=1}^{J}(b^{(i,j)})^2 Cov(\epsilon_t^{X,k})^{(j,j)}}. \tag{152}$$

E Standard Errors

We calculate standard errors for the maximum likelihood parameter estimates $\hat{\theta}$ as outlined in Hamilton [1994] from the numerically derived observed information matrix $\hat{I}$. The log of the Gaussian likelihood function has the following form,

$$\sum_{t=1}^{T} log\left(f(y_t|x_t,\theta)\right) = -\frac{Tn}{2}log(2\pi) - \frac{1}{2}\sum_{t=1}^{T} log|V_{t(\theta)}| - \frac{1}{2}\sum_{t=1}^{T}(y_t - \hat{y}_{t(\theta)})V_{t(\theta)}^{-1}(y_t - \hat{y}_{t(\theta)}), \tag{153}$$

with n data points comprising y_t, model-implied data $\hat{y}_t$, state variables x_t and error covariance V_t. Both $\hat{y}_t$ and V_t depend on parameters θ. The information matrix for a sample of size T from the second derivatives of the log likelihood function is

$$I = -\frac{1}{T}E\left[\sum_{t=1}^{T}\frac{\partial^2 log f(y_t|x_t,\theta)}{\partial\theta\partial\theta'}|\theta=\theta_0\right]. \tag{154}$$

To obtain standard errors, we make use of Engle and Watson [1981] who show that the element (i,j) of I is given by

$$I_{i,j} = \frac{1}{T}\sum_{t=1}^{T}\left[\frac{1}{2}tr\left(V_{t(\theta)}^{-1}\frac{\partial V_{t(\theta)}}{\partial\theta_i}V_{t(\theta)}^{-1}\frac{\partial V_{t(\theta)}}{\partial\theta_j}\right) + E\left(\frac{\partial\hat{y}_{t(\theta)}}{\partial\theta_i}V_{t(\theta)}^{-1}\frac{\partial\hat{y}_{t(\theta)}}{\partial\theta_j}\right)\right] \tag{155}$$

and then drop the expectation operator,

$$\hat{I}_{i,j} = \frac{1}{T}\sum_{t=1}^{T}\left[\frac{1}{2}tr\left(V_{t(\theta)}^{-1}\frac{\partial V_{t(\theta)}}{\partial\theta_i}V_{t(\theta)}^{-1}\frac{\partial V_{t(\theta)}}{\partial\theta_j}\right) + \frac{\partial\hat{y}_{t(\theta)}}{\partial\theta_i}V_{t(\theta)}^{-1}\frac{\partial\hat{y}_{t(\theta)}}{\partial\theta_j}\right], \tag{156}$$

which allows us to obtain standard errors from the square root of the diagonal elements of

$$\frac{1}{T}(\hat{I})^{-1}. \tag{157}$$

F Model Implied Impulse Responses

We derive impulse response functions for every state variable and the financial quantities discussed in chapter 4.6. Our state variables summarized in X_t follow a VAR(1)

$$X_t = c^P + \Phi^P X_{t-1} + \Sigma\epsilon_t. \tag{158}$$

To assess the impact of a one standard deviation shock $\Sigma^{(,k)}$ (being the k-th column in Σ) in variable k on the entire state vector over the next H periods, we compute the difference between two expectations

$$IRF^X_{t,k,h} \equiv E_t[X^{s_k}_{t+h}] - E_t[X_{t+h}] \qquad h \in [1, ..., H] \tag{159}$$

where $X^{s_k}_{t+h}$ denotes the state vector at time $t+h$ after a one standard deviation shock in variable k at time t. Solving for the expectations, we obtain

$$E_t[X^{s_k}_{t+h}] - E_t[X_{t+h}] = (\Phi^P)^h(X_t + \Sigma^{(,k)}) - (\Phi^P)^h X_t = (\Phi^P)^h \Sigma^{(,k)}. \tag{160}$$

Any financial quantity $y^{(i)}_t$ with a linear dependence on X_t can be written in terms of

$$y^{(i)}_t = a^{(i)} + b^{(i)} X_t, \tag{161}$$

we refer to appendix B for detailed derivations regarding all relevant financial quantities. To asses the impact of a one standard deviation shock in state variable k on $y^{(i)}_t$ over the next H periods, we once again compute the difference in expectations

$$IRF^Y_{t,k,h} \equiv E_t[(y^{(i,s_k)}_{t+h}] - E_t[y^{(i)}_{t+h}] \approx b^{(i)} E_t[X^{s_k}_{t+h}] - b^{(i)} E_t[X_{t+h}] = b^{(i)} (\Phi^P)^h \Sigma^{(,k)} \tag{162}$$

and obtain the $h \in [1, ..., H]$ period impulse responses.

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