The Implied Equity Term Structure*

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Abstract

We propose a new methodology to estimate the equity term structure, based on the cross-section of stock prices and the implied cost of capital approach. Specifically, instead of focusing on the realized returns of maturity-specific dividend assets, we imply the term structure of expected returns based on observed market prices and projected firm-level cash flows. Using US data for 1980-2021, we find an unconditionally upward sloping term structure of risk premia with rich cross-sectional patterns. Namely, large and growth firms exhibit an upward sloping term structure, whereas the smallest and value firms mostly have a downward sloping term structure. We also detect that the slope of the term structure changes from negative to positive in the late 1990s for the largest firms, as well as that the slope tends to flatten out or even invert in recessions. Thus, using a direct measure of ex-ante returns, we are able to provide new evidence on the debated properties of the equity term structure.

JEL-classification: G10, G12

Keywords: Cross-section, Equity term structure, Implied cost of capital

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1 Introduction

An active literature studies and measures the expected returns on equity dividend assets with different maturities. The properties of the term structure of equity risk premia have far reaching implications for at least three key reasons. To begin with, it is a direct test of competing theoretical asset pricing models as they mostly imply a flat or positive relationship between the maturity of an asset and its expected return. Second, the risk premium term structure is vital to understanding the aggregate cost of capital and NPV calculations which may be driving companies' and investors' decisions at the micro level. Third, there is evidence suggesting that many documented anomalies (Cochrane (2011) 'factor zoo'), such as the value premium, may be captured or tamed by the differences in cash flow duration across firms (Dechow, Sloan & Soliman (2004), Weber (2018), Gormsen & Lazarus (2022)). In light of these arguments, it is crucial to find a precise measurement of the equity term structure.

In our paper, we propose a new methodology that tackles the inherent empirical challenges of measuring equity risk premia across different maturities. The idea of the procedure is straightforward: we project expected cash flows and estimate discount rates that bring the model price of the firm's equity as close as possible to the observed market value. In the implied cost of capital literature this is normally done by identifying one discount rate specific to the firm (e.g. Pástor, Sinha & Swaminathan (2008), Li, Ng & Swaminathan (2013)). In some sense, this is equivalent to assuming no commonality across observations which could further improve the precision of the estimation procedure. Hence, such a firm-level analysis limits the precision of estimates and, most importantly, leaves no degrees of freedom to recover maturity-specific rates. For these reasons, we diverge from the implied cost of capital literature by imposing some similarity across firms based on observable characteristics (e.g. size, book-to-market, credit risk) and use the cross-sectional variation in cash flows and prices to identify maturity specific risk premia. As a starting point, we assume that discount rates are the same across all firms, but vary with maturity. In this way we can focus on the pricing differences purely driven by the timing and size of cash flows. However, we subsequently allow these discount rates to be portfolio-specific and potentially flexibly modelled as any function of firm characteristics as long as the rates are not entirely firm-specific.

The key value of our method is that it delivers equity term structure estimates over the last 40

years that are neither based on (noisy) realized returns nor assume a specific asset pricing model. We achieve this by combining insights from two strands of the literature: the cross-sectional studies on the realized returns of portfolios with different cash flow durations (e.g. Dechow et al. (2004), Weber (2018)) and the implied cost of capital literature (Pástor et al. (2008), Li et al. (2013)). The key advantage of the first branch of literature is that the U.S. cross-section of stock prices and fundamentals spans a much longer sample (1980-2021 in our case) as compared to the option contracts and dividend strip futures data used in the seminal work of van Binsbergen, Brandt & Koijen (2012) and van Binsbergen, Hueskes, Koijen & Vrugt (2013). The longer sample is particularly important when studying the dynamics of the equity term structure over the business cycle. Moreover, the liquidity of the dividend derivative markets may pose problems, especially in such short samples (Bansal, Miller, Song & Yaron (2019)). The sparse and only recent coverage of firm-level dividend strips also limits a thorough estimation of the equity term structure in the cross-section.[1] Yet, the realized equity returns used in cross-sectional studies are also subject to the critique of non-stationarity and large degrees of noise (Fama & French (2002)). Also, firm duration may be correlated with other drivers of expected returns, which makes it nontrivial to identify the duration effect. For these reasons, instead of averaging realized returns, we resort to the implied cost of capital literature and imply the expected returns using constructed cash flow forecasts and observed market prices. In other words, we combine the best of two worlds without explicitly assuming a specific asset pricing model (as in Giglio, Kelly & Kozak (2022)). As shown later, our approach allows us to discover novel cross-sectional patterns.

We now explain our methodology in more detail. We augment the mean-reverting cash flow model of Dechow et al. (2004) with IBES forecasts data on sales, return on equity (ROE) and earnings-per-share (EPS). In this manner, we are able to include a richer investors' information set and capture more flexible cross-maturity cash flow patterns than standard mean-reversion models alone.[2] Given these forecasts, we are able to estimate the short-, intermediate- and long-maturity discount rates by imposing a parsimonious Nelson-Siegel type functional form often applied in the fixed income

[1] Gormsen & Lazarus (2022) are amongst the first to study the interesting market of single-stock dividend futures. Their sample starts, however, only in 2010 and covers only 180 different stocks.

[2] Cash flow mean-reversion models, applied in Dechow et al. (2004) and Weber (2018), are based on immediate and relatively fast mean-reversion that stifles most of the cross-maturity variation in firms' cash flows. As a consequence, the resulting cash flow duration proxies have small dispersion and estimated expected returns are mostly explained by the book-to-market ratios only. Since the empirical evidence does not support immediate reversion to the steady state across all firms, we incorporate IBES analyst forecasts for the first 2-5 years, in a similar vein as in Gebhardt, Lee & Swaminathan (2001) and Claus & Thomas (2001).

literature (Nelson & Siegel (1987)). Specifically, by including just 3 parameters for the level, slope and decay, we are able to capture a wide array of monotonically increasing or decreasing term structures.

Our first main finding is that, when we apply our method to the full sample of stocks, the aggregate equity term structure's slope is positive. However, we also find substantial cross-sectional differences in risk premium term structures. For most portfolios sorted on size, book-to-market and credit risk the term structure remains upward sloping. But for small value firms and small firms with high credit risk, we document a downward sloping term structure. This novel result illuminates the role of cross-sectional characteristics not only for the level of expected returns (Fama & French (1993)), but also for the shape of the term structure. This is a powerful insight because the empirical success of asset pricing models may depend on the sample of firms one is looking at. On the one hand, aggregate market risk premia are increasing with maturity as canonical habit (Campbell & Cochrane (1999)) and long run risk models (Bansal & Yaron (2004)) predict. On the other hand, to our knowledge, there is no equilibrium model which could match the cross-sectional patterns that we observe (as well as Giglio et al. (2022) document in their recent work). Thus, our findings reveal a new dimension to analyze and explain.

Our empirical analysis also shows that there is substantial time series variation in the equity term structure slope. In recessions, the term structure remains upward sloping but does become flatter, with short-term discount rates rising and long-term discount rates falling. This is consistent with the results of Bansal et al. (2019) and Giglio et al. (2022), who also detect countercylicality of short term risk premia, at least at the annual frequency.[3] On the other hand, our findings challenge Gormsen (2020) who, at the market level, finds a countercyclical term premium implying that most of the variation is driven by changes in long term rates. In contrast, our estimates reveal that most of the time variation comes from the short and intermediate maturity risk premia. Moreover, we do not find evidence that in recessions the variation is so large that it can create an inversion of the term structure slope at the aggregate market level.

As mentioned above, we also perform the estimation for different credit rating groups. We find a positive slope for all investment-grade firms, but a flat term structure for speculative grade firms.

[3]The equity risk premia here is measured using hold-to-maturity returns.

Moreover, we also find that the level of expected returns is decreasing monotonically with the creditworthiness of the issuer, a result which is intuitive, but often undetected in the distress risk literature using realized returns (Campbell, Hilscher & Szilagyi (2008)). When we perform double sorts on credit rating and size, we find that the smallest and least creditworthy firms actually exhibit a downward sloping risk premium term structure. This suggests that firms with high exposure towards short-term transient risk may be driving the puzzling negative relationship between the maturity of the cash flow and its expected return. We also apply our method to industry portfolios and find positive slopes for all industries, except for the steel works industry.

The key limitation of our approach is that it relies on projections of firm's future cash flows. We therefore perform a range of robustness checks on these cash flow projections and show that our qualitative findings persist in a wide array of robustness tests and alternative specifications. First, we implement van Binsbergen, Han & Lopez-Lira (2022)'s estimates of the analyst forecast biases to correct for documented optimism in IBES consensus estimates. Second, we consider time-varying long-term cash flow growth rates proxied by the Survey of Professional Forecasters' (SPF) predictions on long-term inflation and real GDP growth rates. Third, we average cash flow forecasts across different models, cap them, and exclude the most extreme size and book-to-market portfolios to alleviate the possible impact of outliers. None of these extensions affect the upward sloping pattern of the aggregate market equity risk premia. Perhaps not surprisingly, there are some indications that the decreasing term structure slope among the smallest value firms is dampened by additional filters and cash flow refinements. This means that some of the extreme patterns indeed come from estimation noise or small subsets of exceptional firms, but are not washed out entirely. On a similar note, we also perform the estimation with perturbed cash flow reversion parameters and different forecasting horizons which reveal another interesting relationship: the slope of the implied term structure does depend on the assumed persistence of cash flow growth rates. For moderate to high levels of mean reversion, which includes our mean reversion estimates, the recovered term structure is upward sloping. In turn, with very slow mean reversion the slope can flip sign. Thus, one should be careful when drawing conclusions without accounting for the uncertainty that shrouds the cash flow persistence estimates. Interestingly, in most regressions our cash flow reversion estimates generate slower reversion compared to the existing literature (Dechow et al. (2004) and Weber (2018)). We provide evidence that cross-sectional characteristics, such

as ROE and sales growth, converge slower in the medium to distant horizon than in the first few years.

The paper contributes to the empirical asset pricing literature aiming to measure the shape of the equity term structure. We find empirical support for the negative slope among the smallest value and high-risk firms, however, for larger firms the evidence conforms with Bansal et al. (2019)'s findings. This carries substantial ramifications for theoretical research since it finds suggestive evidence supporting the classical theoretical asset pricing models of Campbell & Cochrane (1999) and Bansal & Yaron (2004), at least for large firms. On the other hand, our results challenge the current frameworks in the cross-sectional dimension as, to our knowledge, there is no microfounded model that can generate different equity term structures across firms sorted on book-to-market, size and credit rating. Moreover, this paper questions the existence of the documented credit risk anomaly (Campbell et al. (2008)).

The closest study to our paper is Giglio et al. (2022). They also estimate term structures in cross-sectional portfolios. They find that small (value) firms have a flat (downward sloping) risk premia pattern, whereas for the big (growth) firms the slope is upward sloping. Moreover, Giglio et al. (2022)'s findings conform with the idea that the unconditional equity term structure is upward sloping (mildly in their case), but it inverts in recessions. Even though we share similar insights, their paper is based on a fundamentally different approach. They assume a reduced form model for the pricing kernel (in the light of Lettau & Wachter (2007)) and fit its parameters to the principal components of realized returns. In contrast, we make assumptions about cash flows and imply ex-ante expected returns without assuming a specific asset pricing model. In this way, our methodology provides new degrees of freedom and a perspective that contributes to the ongoing debate in the equity term structure literature.

Finally, this paper is different from the studies that rely on the realized returns of duration portfolios (Weber (2018), Gormsen (2020)). Our approach does not suffer from the mechanical correlations of duration with the book-to-market ratio as we focus on the model-implied prices of firms. At the same time, our method is internally consistent - we use the same discount rate curve throughout the optimization.[4]

[4] A common feature of duration portfolio studies is employing a flat (time-invariant) term structure to create duration measures eventually leading to the downward-sloping patterns in realized returns.

The structure of the paper is as follows. Section 2 describes the identification strategy and methodology. It also expands on the relative advantages and restrictions of the proposed framework over the existent studies. Section 3 presents the data, whereas section 4 elaborates on the estimation techniques applied. Section 5 outlines the results and key comparisons with the literature. Section 6 contains robustness checks, and section 7 contains a summary and final remarks.

2 Implying Discount Rates

As outlined, our method relies on three main components - the pricing equation, cash flow forecasts and the functional form for discount rates. In the following sections, we discuss the identifying assumptions in greater detail.

2.1 Pricing equation

At time t the value of firm i's equity can be described by this discounted cash flow equation:

$$\sum_{m=1}^{\infty} \frac{E_t[CF_{i,t+m}]}{(1+r_{i,t,m})^m} = P_{i,t} \tag{1}$$

where $CF_{i,t+m}$ is the free cash flow accruing to the company's shareholders[5], $P_{i,t}$ is the market value of equity, and $r_{i,t,m}$ is the maturity-specific (zero-coupon) discount rate. We assume that at some year T the firm reaches its steady-state where expected cash flows grow at the rate of g_t, and $r_{i,t,m}$ converges to $r_{i,t,T}$. In other words, both the term structure of cash flow growth rates and discount rates remain flat beyond this maturity. Given this, one can simplify this infinite sum to:[6]

$$\sum_{m=1}^{T} \frac{E_t[CF_{i,t+m}]}{(1+r_{i,t,m})^m} + \frac{E_t[CF_{i,t+T+1}]}{(1+r_{i,t,T})^T (r_{i,t,T}-g_t)} = P_{i,t} \tag{2}$$

In the base specification, we follow Dechow et al. (2004) and Weber (2018) and set g_t to 6%, which equals the long-term average nominal GDP growth rate. As shown later, allowing for time variation in g does not affect the results. Similarly, based on the literature, we fix the forecasting horizon T at

[5] An equivalent formulation of (1) is the well-known Gordon growth dividend discount model where $CF_{i,t+m}$ is the dividend payment. Implicitly, we assume that the fundamental value of the listed firms is non-negative - a condition which, except for a small fraction of firms, is satisfied in the data.

[6] More formal derivations are included in Appendix E.

15 years.[7] For robustness, alternative horizons are also considered and the qualitative conclusions seem to hold as long as the forecasting horizon is distant enough for firms to reach their steady states. That is, with a more persistent cash growth rate process one may need to increase T to reach stable results.

The key identifying assumption is that the discount rate curve $\{r_{i,t,m}\}_{m=1:T}$ is constant across some set of firms. In the implied cost of capital literature, equation (2) delivers a firm-specific discount rate $r_{i,t}$. However, this leaves no degrees of freedom to identify maturity-specific discount rates. To address this challenge, we group firms into characteristic portfolios and impose that all firms in the same group (i.e., portfolio I) share the same discount rates $\{r_{I,t,m}\}_{m=1:T}$. Effectively, the identification of discount rates relies on the cross-maturity variation of cash flows within the portfolio of firms.

2.2 Cash flow forecasts

The key ingredients in the estimation procedure are cash flow forecasts. Following Dechow et al. (2004) and others, we deduce the dynamics of CF's from the identity:[8]

$$CF_t = \underbrace{E_t}_{\text{earnings}} - \underbrace{(BE_t - BE_{t-1})}_{\text{reinvestments}} = BE_{t-1} \times (ROE_t - \%BE_t) \tag{3}$$

where BE stands for the book value of equity, $\%BE$ denotes its growth rate, and ROE is the return on equity. Since Nissim & Penman (2001) documented that the growth rate of sales is a better predictor for book equity growth than most other accounting variables, for the rest of the paper we proxy $\%BE$ by the growth rate of revenues.

In order to forecast ROE and sales growth, a common approach in the literature is to assume mean-reverting processes and use those projections to forecast cash flows (Dechow et al. (2004), Weber (2018), Chen & Li (2018)). It is a parsimonious but restrictive approach as all variation in cash flows is attributed to initial differences across firms which dissipate at the rate of reversion parameters. If the researcher underestimates the cash flow persistence, all firms quickly converge

[7] The forecasting horizon of 15 years is used by Dechow et al. (2004), Li et al. (2013), and Weber (2018), amongst others.

[8] To be precise, this identify is true when clean surplus accounting holds. To a large extent, this is empirically supported (Dechow et al. (2004)).

to the steady state and there are no meaningful differences between, for instance, highly profitable and loss making firms which eventually leads to the poor identification of short-term and long-term risk premia. As this scenario is empirically unrealistic (e.g. loss-making firms often take years to break even), one way to address this is to incorporate analyst forecasts to the first years of cash flow predictions (similarly to Claus & Thomas (2001), Gebhardt et al. (2001), Li et al. (2013)). This allows for more flexible patterns arising from different firm life cycles, and for more accurate depiction of investor beliefs. Needless to say, the analyst projections also alleviate the concern that our results are highly correlated with the initial book-to-market ratios (as in Dechow et al. (2004) and Weber (2018)) and provide additional cross-sectional variation in the estimation of long- versus short-term discount rates. Of course, analyst forecasts may carry some biases or additional noise too, and for this reason we later investigate specifications where cash flow forecasts are averaged across different approaches and find that the main results remain intact.

Based on the arguments mentioned above, we model cash flows in two stages. First, for the 1-5 year horizon, depending on the data availability, we extract information from the median analyst forecasts. Second, starting from the last year of analyst data availability until period T, we follow the same mean-reverting process as in Dechow et al. (2004) and Weber (2018). The key modeling choices of these two stages are discussed below.

Stage one: Analyst forecasts

The estimation procedure benefits from the short and medium horizon forecasts available from IBES by introducing more cross-firm variation. However, the empirical challenge of using IBES forecasts is that they are predominantly available for the earnings-per-share (EPS) measure and there is very little information on the ROE side.[9] To circumvent these data deficiencies, we complement the available forecasts with implied ROE forecasts from median EPS forecasts, which almost triples our sample and data range. If we assume that the number of shares remains fixed, we can proxy the ROE forecasts by the median EPS forecasts divided by the forecasted BE values per share. In a similar spirit, we also imply the revenue growth projections from the level of revenue forecasts. The exact steps in which we construct our projections are described in Appendix A.

[9]The availability of ROE forecasts is limited to 2001-2014 period with relatively few instances in the early years. The level of revenue forecasts is accessible starting from 1992 with much larger coverage across firms. Yet, EPS forecasts date back to 1976 with the largest coverage of around 60,000 observations.

This procedure results in a wide heterogeneity across firms in their ROE and sales growth patterns (Table I). This is particularly valuable for ROE forecasts because empirically ROE mean reverts more slowly than sales growth meaning that most cross-sectional cash flow differences can be explained by this variable. One potential concern is that these implied forecasts have nothing to do with the true forecasts. However, as shown in Table II, the correlation between implied and actual ROE forecasts is high, reaching $70-80\%$ at shorter horizons, and it remains at roughly 50% for 5 year maturities. Moreover, when comparing the distribution of ROE forecasts with implied ones (Table I), one can notice similar means and medians with slightly larger standard deviations and tails of the distribution. Overall, it seems that the procedure delivers a good approximation, however, tighter filters and forecast averaging across alternative models may help to purge some noise and extremities from the estimation (see Section 6).

Stage two: Mean-reverting process

Starting from year 6 or the last available horizon of IBES forecasts, we assume similar mean-reverting processes for ROE and sales growth as in Dechow et al. (2004) and Weber (2018):

$$\begin{aligned} ROE_t &= 0.12 + 0.81(ROE_{t-1} - 0.12) \\ BE_t &= 0.06 + 0.41(BE_{t-1} - 0.06) \end{aligned} \tag{4}$$

Both AR(1) coefficients (0.41 for BE and 0.81 for ROE) are chosen based on the pooled OLS regressions using 3-year lags in the full Compustat sample over 1964-2019 (the third row of Table III). The equations state that ROE converges to the long-run cost of capital of 12%; $\%BE$ is proxied by sales growth, which also reverts to the assumed long-term nominal growth rate of 6% (g). Both 12% and 6% are chosen based on the full sample historical averages, as in Dechow et al. (2004) and Weber (2018).

Table I: Analyst forecasts

The table below summarizes the implied sales growth, ROE and actual ROE forecasts in our merged Compustat-CRSP-I/B/E/S sample over 1980-2021. The implied sales growth forecasts are calculated as the growth rate in median I/B/E/S sales forecasts. The implied ROE forecasts are constructed by dividing median EPS forecasts by projected book value of equity (assuming that it grows at a sales growth rate). Horizon specifies the future financial year for which the forecasts are recorded. To alleviate outliers, all forecasts are winsorized at a 2.5 and 97.5% level.

Implied sales growth forecasts						
Horizon	p5	p50	p95	mean	sd	N
1	0.00	0.10	0.57	0.15	0.15	29577
2	-0.01	0.09	0.64	0.16	0.18	15211
3	0.00	0.10	1.07	0.22	0.28	6648
4	0.00	0.10	1.31	0.25	0.36	4991
ROE forecasts						
Horizon	p5	p50	p95	mean	sd	N
1	-0.04	0.15	0.41	0.16	0.12	12495
2	0.00	0.16	0.41	0.18	0.11	12313
3	0.03	0.17	0.53	0.20	0.13	7064
4	0.07	0.18	0.41	0.20	0.12	469
5	0.08	0.18	0.51	0.23	0.18	279
Implied ROE forecasts						
Horizon	p5	p50	p95	mean	sd	N
1	-0.24	0.11	0.54	0.13	0.17	50696
2	-0.09	0.13	0.63	0.17	0.16	47685
3	0.01	0.15	0.75	0.20	0.18	36051
4	0.02	0.17	0.86	0.23	0.21	31952
5	0.02	0.18	0.97	0.25	0.24	30940

Table II: Correlation between actual and implied forecasts

The table below summarizes the correlation between the actual ROE forecasts and implied ones for different forecasting horizons. The ROE forecasts are available only for 2001-2014.

Years	1	2	3	4	5
Corr	0.79	0.72	0.66	0.58	0.51
N	12479	11843	6798	454	269

The key difference here with previous research is that we employ different regressions that lead to much higher reversion coefficients (in other words, much slower mean reversion). Dechow et al. (2004) find a coefficient for ROE equal to 0.57, and 0.24 for sales growth; Weber (2018) obtains 0.41 for ROE and 0.24 for sales growth. Both studies estimate the annual AR(1) coefficients using annual pooled OLS regressions over the full sample starting in 1964. Yet, these estimates are sensitive to filters applied and, as illustrated in Figure C.I for the ROE and sales growth quintile portfolios, they

are biased downwards due to the very quick initial mean-reversion and slow decay afterwards. In fact, similar pooled regressions where we use more distant lags of 3 to 5 years to estimate the AR(1) coefficient or tighter winsorization of the sample reveal that the true mean reversion for ROE (sales growth) is likely to be in the 0.74-0.84 (0.41-0.53) range (Table III).[10] Since we aim to predict the long term behaviour of firm's cash flows (and short-term patterns should be mostly captured by the analyst forecasts), we conclude that slower mean reversion is more empirically plausible, especially for longer horizons.

Table III: AR coefficient estimates

The table presents the estimated AR coefficients from different pooled OLS regressions. The first five rows represent estimates using the full Compustat sample over 1964-2021, whereas the last 3 rows - merged Compustat-CRSP-I/B/E/S sample spanning 1980-2021. The second and third rows describe regressions where both ROE and sales growth are winsorized at 5% and 95% levels and ROE is capped at -100% (some firms incur losses exceeding their book value of equity). Rows four, five, seven and eight present specifications where the first order autoregressive coefficient is estimated using more distant lags. All AR coefficients are standardized to 1-year maturity. The standard errors (SE) are clustered by year. For longer lag regressions, the Delta theorem is applied to compute the AR(1) coefficient standard errors.

	ROE				Sales growth			
	AR(1)	SE	R2	N	AR(1)	SE	R2	N
Full Compustat sample	0.009	0.009	0.003	190261	0.000	0.000	0.000	234721
Winsorize (5% and 95%)	0.727	0.017	0.431	190261	0.226	0.015	0.055	234721
Cap ROE at -100%	0.720	0.012	0.473	190261				
3 years lag	0.810	0.009	0.241	151445	0.413	0.017	0.006	193541
5 years lag	0.846	0.007	0.158	123611	0.536	0.025	0.002	161360
Merged sample	0.693	0.020	0.475	37267	0.284	0.034	0.094	37934
3 years lag	0.778	0.017	0.217	28230	0.502	0.028	0.022	29019
5 years lag	0.825	0.012	0.144	22459	0.592	0.034	0.008	23164

In the robustness section we also consider alternative autoregressive coefficient magnitudes. While small perturbations do not affect the results much, larger shifts in mean reversion can indeed alter the qualitative conclusions.

2.3 Functional form for equity risk premia

Our framework is flexible in modeling different types of heterogeneity in firm discount rates. Nevertheless, since the m period cash flow is not expected to be much different from the $m+1$ period

[10] We also explored specifications with multiple lags and moving averages, however, the additional terms often were not statistically significant. For this reason, we keep the parsimonious AR(1) model as our base specification.

cash flow, the discount rates for similar maturities will be strongly correlated, and estimating them separately would lead to large standard errors and noisy estimates. For this reason, we choose the Nelson-Siegel (NS) functional form (Nelson & Siegel (1987)), often used to model fixed income yield curves, as it is both sufficiently rich in capturing different discount rate curve patterns and parsimonious in the number of parameters:[11]

$$r_{I,t,m} = r^f_{t,m} + \beta_{1,I} - \beta_{2,I}\Big[\frac{1 - exp(-m/\lambda)}{m/\lambda}\Big] \tag{5}$$

As we see in (5), we take into account the term structure of risk-free rates, $r^f_{t,m}$, by proxying it with the US zero coupon bond yield curve. This allows us to directly focus on the level of risk premia rather than total discount rates, and introduces aggregate time variation in our base scenario case. Importantly, for maturities $m > T$, both the risk premia and total discount rates are assumed to be constant, i.e. for all $m > T$ we have $r_{t,m} = r_{t,T}$.

Rather than reporting the parameter estimates, in the analysis below we mainly report two key aspects of the risk premium term structure: the *level* of the 15-year risk premium and the *slope*, defined as the difference between the 15-year and 5-year risk premium. As discussed below, given the typical duration levels of US firms, identifying the risk premiums at the very short end (1-4 years) is difficult, which is why we define the slope using the 15-year and 5-year maturity points.

The parameter λ captures the curvature of the equity term structure and is notorious for being difficult to estimate (e.g. you can always simultaneously increase the short rate and decay to achieve a similar overall effect). Thus, for the rest of our analysis we will fix it to economically plausible values (i.e. we set $\lambda = 4$ as it introduces some curvature for the smooth convergence to the long-run levels). In Appendix C, we verify that our results remain similar when we use other values for λ (Figure C.III).

[11] In this version, we do not include the hump-term as it is known to be highly correlated with other parameters. Thus, the term structure of risk premiums is either monotonically increasing or decreasing - an assumption which can be relaxed in future work.

3 Data

The analysis is performed using US data over the 1980-2021 period. Even though all required variables are observable as of 1976, we start in 1980 since from that year onwards we have a cross-section of more than 500 firms per year. This is important since our approach requires substantial cross-sectional variation, especially since we also perform analyses where we split the cross-section in several portfolios. The balance sheet information comes at the yearly frequency. Stock price data and balance sheet data, as well as historical credit ratings and S&P500 index composition, are obtained from Compustat-CRSP. Supplementary book equity data is collected from Kenneth French's website. The median analyst forecasts are from Thomson Reuters I/B/E/S summary database, whereas historical constant maturity (zero-coupon) yields are from Gürkaynak, Sack & Wright (2007). Historical GDP and NBER recession periods can be accessed from St. Louis FED, and the long-term inflation and real GDP growth expectations come from the survey of professional forecasters collected by the Philadelphia FED.

We construct our book equity measure following Davis, Fama & French (2000).[12] We measure book equity (and other historical accounting variables) using the most recent financial year results prior to the valuation month (June). Similarly, the market cap is calculated as the price times the number of shares outstanding at the end of the valuation month (June). Both prices and shares outstanding come from CRSP. June is chosen as the valuation month because it guarantees that most of the financial statement information has already arrived to the market, and analyst forecasts are mostly covering the upcoming financial years. To reduce potential extremities, we keep only those I/B/E/S median forecasts that were generated by more than 1 analyst. Adding to that, in order to alleviate liquidity concerns, we exclude the smallest 20% market cap firms on a year by year basis. Following Weber (2018), utilities (4900<= SIC<5000) and financials (6000<=SIC<7000) are dropped from the sample, as well as firms that are not listed on one of the major stock exchanges (NYSE, AMEX and Nasdaq). Finally, since we value the total equity size of each firm, we exclude all mismatches larger than 5% between Compustat and CRSP database market caps.[13] These filters leave us with 79,537 Compustat-CRSP firm-year observations over the 1950-2021 period. After

[12] Observations with negative book equity are excluded.

[13] Differences in end of the year market caps between Compustat and CRSP records may lead to a severe mispricing in our model. For this reason, we exclude all observations with large discrepancies that potentially indicate multiple classes of traded or non-traded shares.

merging with I/B/E/S, the final sample consists of 50,712 firm-year observations over the period 1980-2021. More details on the filters and sample construction are provided in the Appendix.

In terms of summary statistics, the final sample is representative of the broader Compustat-CRSP dataset. As reflected in Table IV, the estimation sample consists of larger firms (with median market cap of USD 722 mln. as compared to USD 260 mln. in Compustat-CRSP) as larger firms tend to be more frequently covered by analysts. Nevertheless, financial ratios, such as ROE or dividend payouts, have almost identical distributions in both samples. The only exception is the BM ratio which is slightly lower in the final sample (median of 0.43 vs 0.49) because larger firms tend to have higher valuation ratios. Since most financial ratios have large outliers due to small denominators, we winsorize ROE (including sales growth) at the 5% and 95% level on a yearly basis.

Table IV: Summary statistics

The table compares the Compustat-CRSP-I/B/E/S sample used for the analysis with a broader Compustat sample obtained after standard filtering procedures (as in Weber (2018)). Sales, book and market equity are presented in millions of USD. ROE, sales growth, book-to-market, earnings-per-share and dividend payout ratio are all presented in units. The dividend payout ratio is calculated similarly as in Li et al. (2013) - the total dividend paid divided by net income (in case it is positive). The ROE is defined as current earnings before extraordinary items divided by lagged book equity. To alleviate outliers, ROE and sales growth are winsorized at a 2.5 and 97.5% level.

IBES-Compustat 1980-2021						
	p5	median	p95	mean	std	N
Sales	22	583	13846	3597	13800	50712
Book equity	27	314	7102	1894	8054	50712
Market equity	71	773	20633	5578	29186	50712
Sales growth	-0.19	0.10	0.78	0.17	0.29	49036
ROE	-0.44	0.11	0.40	0.08	0.23	48161
B/M	0.08	0.42	1.37	0.55	0.61	50712
E/P	-0.19	0.04	0.13	0.00	0.31	50712
Payout	0.00	0.00	0.86	0.16	0.27	50712
Compustat 1980-2021						
	p5	median	p95	mean	std	N
Sales	6	254	9264	2401	11167	79537
Book equity	8	139	4511	1268	6515	79537
Market equity	19	317	12737	3665	23464	79537
Sales growth	-0.21	0.10	0.78	0.16	0.30	73370
ROE	-0.47	0.10	0.39	0.06	0.24	72207
B/M	0.08	0.46	1.59	0.61	0.77	79537
E/P	-0.24	0.04	0.15	0.00	0.40	79537
Payout	0.00	0.00	0.85	0.15	0.26	79537

4 Estimation

We estimate model parameters β_1 and β_2 by minimizing the squared relative pricing error between the firm's total market capitalization and model valuation. Specifically, the squared pricing error for firm i at time t can be expressed as:

$$\phi_{i,t} = \Big(\sum_{m=1}^{T} \frac{E_t[CF_{i,t,t+m}]/P_{i,t}}{(1+r_{t,m})^m} + \frac{E_t[CF_{i,t,t+T+1}]/P_{i,t}}{(1+r_{t,T})^T (r_{t,T} - g_t)} - 1)^2 \tag{6}$$

where $r_{t,m}$ is a function of β_1 and β_2 as in equation (5).

In the baseline scenario, we estimate β_1 and β_2 by minimizing the sum of the squared pricing errors over the whole sample:

$$\underset{\beta_1,\beta_2}{argmin} \sum_t \sum_i w_{i,t} \phi_{i,t} \tag{7}$$

where $w_{i,t}$ is the weight assigned to firm i in year t.

The main criterion is thus how well the chosen risk premia parameters fit the cross-section of stock prices. This estimation procedure can be seen as a joint calibration of model values to market prices where observations with the largest weight or highest pricing deviations attain more importance. We choose to use a value-weighting scheme for the estimation, to focus the estimates towards economically sizable firms and to prevent large pricing errors for small firms from dominating the estimation procedure. We do impose that each observation year has the same weight in the estimation procedure, to prevent later years with higher market values from dominating the results. Later we provide results based on size sorts to analyze differences between small and large firms.

Clearly, differences in cash flow term structures across firms are a necessary condition for identification. In Figure C.1 of Appendix C we graph the distribution of firm's equity durations, where these durations are calculated using our benchmark risk premium estimates. The graph shows that there is indeed substantial cross-firm variation in durations, with a substantial number of firms having durations below 10 years or above 20 years, respectively.

Finally, to alleviate concerns that there are firms whose valuation our model cannot capture well,

we winsorize the sample at 2.5% and 97.5% based on the model implied internal rate of return of a stock. This step effectively excludes firms with extremely high or low valuation ratios (for instance, companies in severe financial distress) that are challenging to value with standard fundamental value models. In this way, without too much loss of generality (most stocks excluded are smaller ones with extreme ROE and sales growth rates), we reduce the impact of outliers.

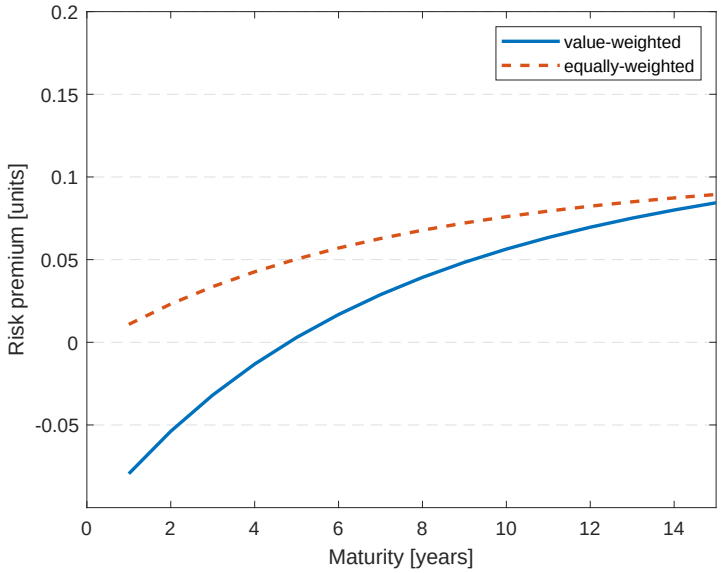
5 Results

5.1 Market-wide estimates

We start with the panel of firms over the full sample period, 1980-2021. We allow for a time-varying risk-free rate term structure and assume the same equity risk premium term structure for all firm-year observations. Later, we extend the setup by allowing for cross-sectional and time-series variation.

The baseline results unveil a clear pattern - the aggregate stock market has an upward sloping term structure of risk premia. This can be seen from Figure I. The long-term risk premia flatten out and approach a constant level of roughly 7-8%. Given that most value of the market is concentrated in the intermediate and long-term horizon, this should represent the unconditional equity risk premium to some extent. Figure I also shows that risk premium estimates are below zero for maturities of 4 years and shorter. As discussed above, given that equity durations are typically above 5 years, identifying the very short end of the risk premium term structure is difficult and the negative premiums at the short end effectively follow from the extrapolation that is inherent in the Nelson-Siegel specification. We therefore mainly focus on the difference between the 5-year and 15-year maturity points in our discussion. Figure I shows that our benchmark estimates generate a slope difference of about 8%, which is substantial. The qualitative finding of a positive slope is confirmed in many specifications below, meaning that, everything else equal, investors have a preference for shorter maturity cash flows. We also present results for an estimation where we equally weight all squared percentage pricing errors of firms. In this case, smaller firms likely dominate the estimation results. Figure I shows that we still obtain an upward sloping term structure, but with a flatter slope and higher short-term premiums. The size sorts presented below confirm the size effect.

Figure I: Full-sample term structure of equity risk premia



Note: The graph depicts the estimated equity risk premium term structure over the full sample for the benchmark value-weighted case, and for a case where we equally weight all firms in the estimation. Compustat-CRSP-I/B/E/S sample: 1980-2021.

Our finding that the equity term structure is upward sloping is consistent with the predictions of well-known theoretical asset pricing models, such as habit (Campbell & Cochrane (1999)) and long-run risk (Bansal & Yaron (2004)). Following their logic, the long-term cash flows are more sensitive to discount rate shocks and contain more uncertainty, therefore, the short maturity risk premium should be lower.

At first sight, our findings seem to go against those of van Binsbergen et al. (2012) and subsequent studies using dividend asset returns (van Binsbergen et al. (2013) and Gormsen (2020)). van Binsbergen et al. (2012) are the first to document the unusually high realized returns on short-maturity dividend strips relative to the total S&P 500. To compare our predictions as closely as possible, we build a sample by tracking down the firms which were constituents of the S&P 500 index in the valuation month. Adding to that, we limit our sample to 1996-2008, as in van Binsbergen et al. (2012).[14] However, we discover a very different pattern: consistent with our full-sample results the implied term structure is upward sloping (Appendix Figure C.IV). This seems to contradict the findings of van Binsbergen et al. (2012). However, in the latter study, the short-maturity rates

[14]The match between samples is not perfect since, on average, we have only 250-300 S&P500 firms in our sample. The main reason is that we exclude financials and utilities, which constitute roughly 150 firms of the index.

are measured using options of maturities up to 2 years. Yet, this is exactly the range where our estimates are the least precise and mostly extrapolated from the intermediate maturities. Thus, it is possible to have a U-shaped term structure which could accommodate both features - the downward sloping pattern for very short maturities and an upward-sloping curve starting from intermediate years. Based on the information embedded in the cross-section of stock prices and fundamentals alone, we cannot reliably test this hypothesis.

Other studies use realized stock portfolio returns to identify the term structure. Weber (2018) sorts stocks on their duration and finds a negative term structure of returns. Giglio et al. (2022) use an asset pricing model to describe the cross-section and dynamics of stock returns and find that, on average, the term structure of risk premiums is close to flat. The difference with our ex-ante return patterns could for example be due to trends or structural changes in the term structure of risk premiums, in which case realized returns will differ from ex-ante returns.

5.2 Size and book-to-market sorts

We then proceed by estimating the term structure for quintile portfolios, sorted on size or book-to-market (Table V). For the size sort, we find a positive slope for all quintiles, with the largest firms having the steepest term structure. Remarkably, the level estimates, which represent the 15-year risk premium, are all around the 8-9% mark without any clear correlation with the quintile of the size distribution. It thus appears that small firms have much higher short-term risk premia than large firms, whereas the long-term rates are almost indistinguishable. It is important to note that the size of a firm is not a parameter in our model affecting the forecasted cash flow growth rates which means that observed patterns are much more likely to capture investor preferences rather than our modeling choices alone. Our results are thus consistent with the extensive literature that documents a size effect in realized returns.[15] Based on our estimates, all of this premium comes from the short- and intermediate-maturity cash flows (our baseline estimates suggest that roughly 50% of firm value comes from the forecasting horizon cash flows). Quantifying the realized return premium in our sample requires careful modeling of time-series variation in risk premia and the proper weighing of cash flows.

[15] Giglio et al. (2022) report that the size premium over the last 50 years was 0.8%.

Table V: Size and book-to-market portfolios

The table shows the estimation results within size and book-to-market quintiles formed on a yearly basis. The first row always represents the level (i.e. 15-year risk premium) and the second row - slope estimates (15 minus 5-year risk premium spread). Size is defined as price times the number of shares outstanding at the end of valuation month (June). Compustat-CRSP-I/B/E/S sample: 1980-2021. Risk premia are measured in annual percentages.

Quintiles		Size	BM
Low	level	0.087	0.088
	slope	0.052	0.150
2	level	0.085	0.088
	slope	0.109	0.130
3	level	0.081	0.091
	slope	0.118	0.108
4	level	0.084	0.086
	slope	0.145	0.083
High	level	0.088	0.086
	slope	0.117	0.036

Our results are also consistent with the findings of Giglio et al. (2022), who report an upward sloping term structure of (forward) risk premia for large firms and a much flatter term structure for small firms. Similar to our findings, large firms have the lowest short-term discount rates according to their estimates.

It thus seems that investors have a preference for short-maturity cash flows generated by large firms. This could be consistent with the intuition that the majority of small cap stocks are young firms that are exposed to short-term fluctuations priced by investors. Yet, if the firm survives long enough, it matures and evolves similarly as large firms whose dynamics are largely explained by the long-run risks. Even though we do not explicitly model this transition process and the associated risks, additional tests with business cycles and credit risk support this story.

We then turn to the sorts on the book-to-market ratio. The recent literature finds contradicting evidence regarding growth and value stocks. Even though the value anomaly is empirically sizable (2% based on Giglio et al. (2022)), there is still much debate on whether the value premium is a compensation for risk, and if so, what the nature of these risks may be. Recent studies find that the value anomaly may be captured by the duration of firms' cash flows which combined with a

downward-sloping term structure would give rise to the value premium (Lettau & Wachter (2007), Weber (2018), Gormsen & Lazarus (2022)). In order to test this aspect, we sort stocks every year in 5 quintiles and re-estimate the model for each of these portfolios. The key finding is that for all portfolios we find an upward sloping term structure (Table V). One can notice that long-maturity rates are similar at 8% to 9% per year. Yet, similarly as with size, there is a strong monotonic relationship between the slope and BM quintiles. High book-to-market (value) stocks have the smallest slope estimate and thus the highest short-term risk premiums, suggesting that these firms are more exposed to (systematic) short-term risk than low book-to-market (growth) stocks. These results are also in line with Giglio et al. (2022). Similarly to size, the value premium comes from the short- and intermediate-maturity cash flows. The level estimates suggest only a 0.2% difference in long-term risk premia. Such a slight difference can also be justified by firms' tendency to revert in their characteristics over time. After 15 years, most growth firms are likely to be very similar to the value firms.

Our findings suggest that the value premium arises from the pricing of short maturity cash flows. The sheer fact that the value premium is detected is not surprising given that there is far more variation in cross-sectional BM ratios relative to observable economic variables affecting the fundamental value of a firm. This is often the key reason why the implied cost of capital estimations generate a value premium. What we add to this is that this value effect is mainly driven by pricing of short term cash flows.

In order to isolate the pure size and BM effects, we analyze double sorts where first observations are assigned to three size and then to three BM portfolios. The obtained results are presented in Table VI. In this case, we find substantial positive slopes for all portfolios except for the smallest value stocks, which exhibit a substantial negatively sloped term structure. The results potentially can be linked to transient short-term risks that distressed firms face if one assumes that the smallest and most extreme value firms are those close to default. Overall, we see that both larger firms and firms in the value domain have more positively sloped term structures, where the effect is largest in the book-to-market direction. Looking at the level estimates (the 15-year risk premium), we again see that these are fairly stable across portfolios.

Table VI: BM-Size double sorts

The table shows the estimation results within 3 book-to-market (BM) and size portfolios formed over the full sample. The data is first sorted on BM ratios and then on size. The first row always represents the level (i.e., 15-year risk premium) and the second row - slope estimates (15 minus 5-year risk premium spread). Compustat-CRSP-I/B/E/S sample: 1980-2021. Risk premia are measured in units.

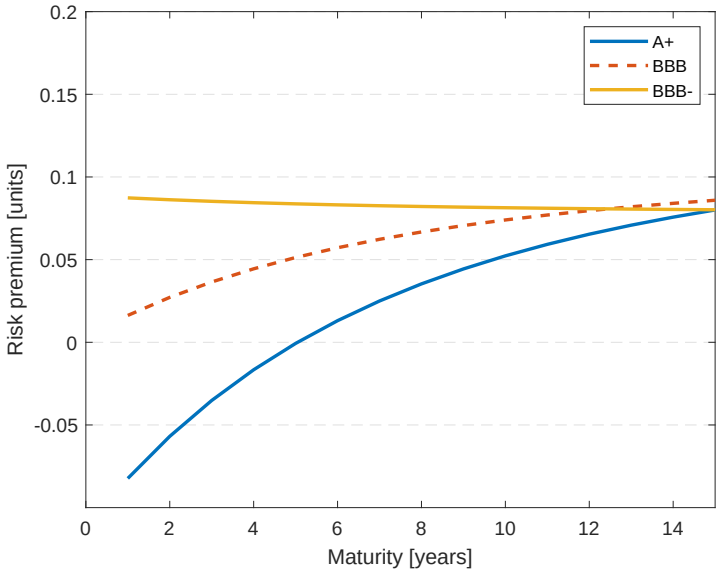
		Size terciles		
BM terciles		Low	2	High
Low	level	0.077	0.076	0.091
	slope	0.121	0.161	0.158
2	level	0.075	0.075	0.092
	slope	0.093	0.115	0.121
High	level	0.091	0.088	0.090
	slope	-0.071	0.037	0.052

5.3 Credit risk

Many articles have analyzed how realized equity returns differ across firms with different credit risk. Our approach allows us to analyze the ex-ante returns for firms with different credit risk, and to see how the term structure of equity is related to credit risk. Thus, building on this existing work, we proxy the credit risk by the S&P issuer's long-term credit rating. Due to data availability, the sample shrinks substantially. We therefore aggregate all issuers into 3 broader categories: above BBB+ (3,865 observations), between BBB+ and BBB- (4,166), below BBB- (6,790). The first two are investment grade ratings, whereas the last one is classified as speculative.

The results in Figure II show that the term structure strongly depends on the credit rating. Firms with higher credit rating have, on average, lower short- and intermediate-maturity discount rates and a positively sloped term structure, while speculative grade firms have essentially a flat term structure of risk premia. This again corresponds to the intuition that such firms are more exposed to short-term risks. The finding that risk premia increase as credit risk increases is not trivial as many studies cannot detect this pattern using realized returns (Campbell et al. (2008)).

Figure II: Credit ratings



Note: The figure presents the estimated equity risk premia term structure in different S&P credit rating portfolios. A+ group contains all credit ratings above and including an $A-$ rating. BBB group includes all $BBB+$, BBB and $BBB-$ rated firms. Finally, BBB- includes all non-investment grade ratings. Compustat-CRSP-I/B/E/S subsample: 1985-2018.

We then perform double sorts, first sorting on the credit rating and then on size (Figure C.V). We see that small stocks with a speculative credit rating have a downward sloping term structure. Given that it is only the small stocks exhibiting this pattern, this supports the company's life cycle story where small, low-rated companies have high short-term risk, and either default or survive and become larger and less risky.

5.4 Time-variation

Recent empirical research has analyzed the variation of the equity term structure using realized returns. Gormsen (2020) finds that the slope of the curve is countercyclical - in bad times, the long maturity premium is higher than short maturity, and vice versa. On the other side, Bansal et al. (2019) base their analysis on hold-to-maturity returns and argue that the slope is procyclical. One potential cause for these contradicting findings is that the realized returns are known to be very noisy and one may need far longer samples than the data allows to detect changes.[16] For this

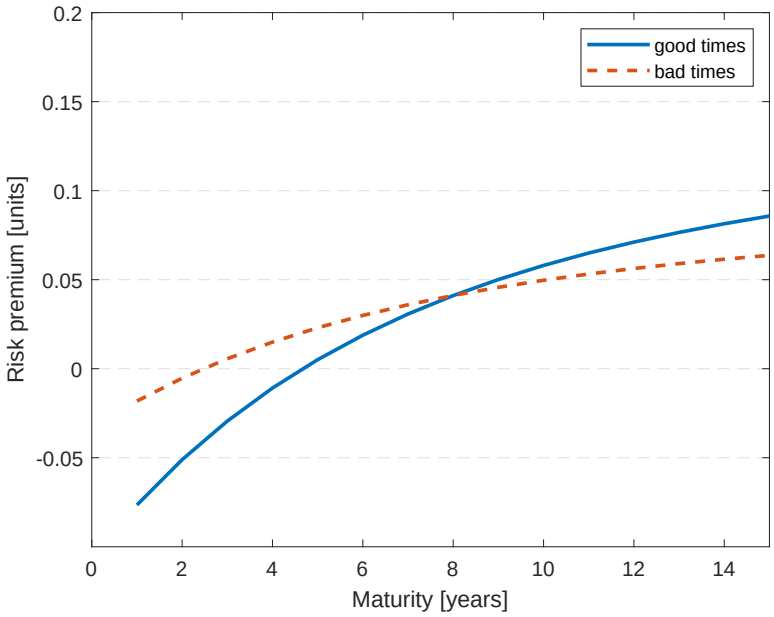
[16] In fact, both realized one period and holding-to-maturity returns in short samples may struggle to distinguish time variation in the level of the equity risk premium from time variation in the slope. However, this concern in our

reason, we shed our perspective based on ex-ante expected returns.

To inspect the variation of equity risk premia over time and across business cycles, we use the NBER recession dummy which equals 1 if at least one month in the valuation year is classified as the NBER recession. Note that the ex post nature of the NBER recessions does not affect the qualitative implications of our results because, if there is any substantial change in the shape of the term structure, this should have occurred in the most severe episodes.

Figure III depicts the risk premia estimates in both NBER recessions and expansions. Periods with high economic prosperity are concurrent with very small or even negative short maturity premia estimates and relatively high long maturity rates. In contrast, the recessions are associated by rising short term rates and slightly decreasing long maturity premia. Still, in both recessions and expansions the term structure remains upward sloping. Our results are thus closest to Bansal et al. (2019), since we both find the most positive slope in expansions, though we do not find evidence for a negative slope in recessions as in Bansal et al. (2019).

Figure III: Good and bad times



Note: The graph depicts the estimated equity risk premia term structure in NBER recessions (dashed red line) and normal times (solid blue line). The year is classified as an NBER recession if at least 1 month in that year is considered to be a recession by the NBER. Compustat-CRSP-I/B/E/S sample: 1980-2021.

methodology is less of an issue because we identify short- and long- maturity returns based on the relative changes in the pricing of short and long cash flow duration firms, including the fact that our Nelson-Siegel specification allows for time-varying levels of risk premiums. Adding to that, we look at relatively long samples starting from 1985 that should, to a substantial degree, attenuate measurement errors.

5.5 Market risk exposures

We investigate if exposures to the market are somewhat related to the upward-sloping term structure that we document. For instance, if the analysts form their expectations using the CAPM, our measure of cash flow duration is likely correlated with the market beta. This argument relies on the assumption that analysts both correctly price and forecast firm's cash flows. Alternatively, different horizon cash flows can merely reflect increases in the quantity of systematic risk, even though the price of risk remains constant. To test that prediction, we construct a model-based cash flow duration, $Dur_{i,t}$, based on the projected cash flows, our baseline discount rate term structure estimates, and the model price of a firm ($\tilde{P}_{i,t}$):

$$\begin{aligned} Dur_{i,t} &= \sum_{m=1}^{\infty} m \frac{E_t[CF_{i,t+m}]}{(1+r_{I,t,m})^m} \frac{1}{\tilde{P}_{i,t}} \\ &= \sum_{m=1}^{T} m \frac{E_t[CF_{i,t+m}]}{(1+r_{I,t,m})^m} \frac{1}{\tilde{P}_{i,t}} + \left(1 - \sum_{m=1}^{T} \frac{E_t[CF_{i,t+m}]}{(1+r_{I,t,m})^m} \frac{1}{\tilde{P}_{i,t}}\right) \left(T + \frac{1+r_{I,t,T}}{r_{I,t,T}-g}\right) \end{aligned} \tag{8}$$

This model of cash flow duration parallels the one used in Weber (2018) and Chen & Li (2018), with the exception that we use the model price of a firm and the estimated term structure for discounting. Then, we sort firms into duration quintiles each June and form value-weighted portfolios.[17] Given their returns, we are able to calculate portfolio β^{CAPM}. The results are displayed in Table VII.

Table VII: Betas of duration portfolios

The table presents the (monthly) realized return betas for duration quintiles. To sort firms into portfolios, we use the value weighted term structure estimates from our baseline to compute the cash flow duration for each firm. Each June the portfolios are rebalanced based on the most recent duration estimate. The standard errors (in the brackets) are computed using the Newey-West procedure with a 6-month lag. Compustat-CRSP-I/B/E/S sample: 1980-2021.

	Low	2	3	4	High
α	0.006***	0.006***	0.005***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
β	0.957***	0.997***	1.038***	0.948***	0.979***
	(0.023)	(0.033)	(0.025)	(0.035)	(0.038)

We notice that there is no clear pattern in market betas across the duration quintiles. β^{CAPM} increases from 0.96 to 1.04, moving from the lowest to middle duration portfolio. Afterwards, the

[17] The average firm in our estimation sample displays a cash flow duration of roughly 15 years. The median duration in each duration quintile is 7.5, 10, 12, 15.5, and 28.5 years, respectively. For an average firm, the present value of the first 15 years of cash flows makes up roughly 55% of the total model firm value.

pattern disappears.[18] Thus, such differences in market betas cannot explain our term structure results since even a 0.1 increase in market beta would realistically correspond to a 0.4-0.6% slope in the term structure. In future research, we will examine if other documented anomalies display a stronger link to these duration portfolio returns.

6 Robustness

6.1 Biases in cash flow expectations

The literature documents that analyst forecasts entail biases which can, in turn, affect our estimates of risk premia. Recent empirical work highlights that the biases tend to increase with maturity (van Binsbergen et al. (2022), Cassella, Golez, Gulen & Kelly (2023)), at least for the first few years. Moreover, there is some evidence that analysts overreact/underreact to information contributing to known cross-sectional anomalies (Bordalo, Gennaioli, Porta & Shleifer (2019)). All these errors can distort our estimates if the investors have different expectations from the analyst (or introduce a wedge between subjective and objective risk premia). In order to take this into account, we implement van Binsbergen et al. (2022)'s estimates of analyst biases in our cash flow forecasts. Specifically, we correct all ROE forecasts for the biases in EPS forecasts.[19] However, since van Binsbergen et al. (2022) focus only on the first 2 years of forecasts, we make a simplifying assumption that for years 2-5 the bias stays constant. Afterward, it dwindles at the speed of cash flow reversion.

The summary statistics of analyst biases are presented in Table C.I, where each EPS bias is normalized by the firm's stock price. On average, the bias is positive and increasing with maturity. One-year cash flows display a bias of roughly 1%, whereas the two-year bias stands at close to 2.5%. However, it appears that the bias is particularly extreme in recessive economic times when the errors jump to 2.3% for one-year and to 5% for two-year forecasts. Thus, van Binsbergen et al. (2022)'s estimates suggest that the analyst are overly optimistic about the severity or duration of recession periods.

[18] Most market betas fall below 1 as our sample is constituted of predominantly larger firms (the average β^{CAMP} is 0.96).

[19] In that sense, we investigate the most extreme scenario of analyst biases. If there was the same-direction bias in sales growth, the bias would cancel out. We can see that from equation (3).

The results with corrected cash flow forecasts are displayed in Figure C.VI. The correction has not altered the quantitative conclusions much - the slope remains positive both for value and equal weighting schemes. On the other hand, quantitatively, the short-maturity risk premia become even smaller. It is an expected result, given that a positive bias would mean that cash flows and discount rates should decrease to deliver similar valuations. Even though the bias is increasing for the first few years, in our specification, the bias eventually dissipates. In order to reverse the slope, the bias has to keep steeply increasing with maturity, even at very long maturities. To our knowledge, nobody has provided such empirical estimates of long-term biases, and minor cash flow distortions do not seem to affect our qualitative conclusions.

6.2 Time-varying g

The cash flow modeling hinges on the assumption that cash flows converge to some steady state g over time. As outlined in the general version of the model, g_t can be made time-varying. This would take into account changes in the growth expectations and inflation - two key macroeconomic variables that may capture phenomena such as structural shifts or secular stagnation. One possibility is to follow Li et al. (2013) who proxy g_t with the average sample nominal GDP rate up to the valuation year. As shown in Appendix C, the benchmark result of an upward sloping aggregate term structure is very robust to using this time-varying g. We also exploit market expectations about the long-term inflation and real GDP trends. Specifically, we incorporate the Federal Reserve survey of professional forecasters data which dates back to 1982 for long-term inflation and to 1992 for real GDP. Mixing inflation forecasts with the average realized real GDP growth rate or real GDP inflation forecasts does not affect the full sample estimates: we again find an upward sloping term structure. Overall, it appears that differences in the steady state growth rate do not generate shifts in the term structure as much as changes in the cross-section of stock prices.

6.3 Cash flow forecast averaging

Considering that our findings may be driven by particular filters or noisy cash flow forecasts, we investigate alternative procedures. The generic insight is that, regardless of additional refinements, we always find upward sloping aggregate term structure estimates with in most cases an even more positive slope compared to the benchmark results (Table C.II).

First, we average cash flow forecasts between our model and the simple mean-reversion approach, as in Dechow et al. (2004) and Weber (2018), which should reduce the impact of outliers. The findings again show a strong positive slope at the aggregate market level. We also introduce a more intricate weighting of these two different models where each forecast i is assigned a score based on the likelihood of such cash flow to materialize:

$$w_i = \frac{\phi(forecast_i; \mu, \sigma)}{\sum_{k=1}^{2} \phi(forecast_k; \mu, \sigma)} \tag{9}$$

In order to determine the likelihood, we assume that cash flows are normally distributed with the mean of 0.75% and standard deviation of 19.7% (empirical sample statistics). For instance, if one of the forecasts is very far from the prior mean of 0.75%, then all the weight is attributed to the more conservative forecast. On top of that, we cap the maximum (minimum) cash flow at 100% (-100%) of firm's value. All these steps should smooth out the extremities. As we see from the second row, all this averaging does not affect much our baseline results. The same holds if we winsorize the sample at 5% and 95% percentiles of model internal rate of return (the third, fourth, fifth rows). Finally, we exclude the most extreme size and book-to-market portfolios, and again find a positively sloped term structure.

6.4 Persistence of cash flows

Concerns about the methodology may also point at the cash-flow reversion process itself. Given the estimates we employ, most of the firms reach their steady state growth rate in 6-10 years. In order to test if the reversion is driving the qualitative results, we rerun our base estimation with perturbed ROE and sales growth reversion parameters (Table VIII). The general tendency is that for small and moderately high mean reversion coefficients the term structure slope is positive. However, very large coefficients can lead to a downward sloping curve. The switch in the slope is an interesting finding that outlines the importance of taking into account the uncertainty surrounding these estimates. One can even speculate that strong biases in investor beliefs may give a rise to the puzzling relationships documented in van Binsbergen et al. (2012). However, in the range of our mean reversion estimates (0.74-0.84) the estimated term structure is upward sloping.

The persistence of cash flow reversion matters in two significant ways. When the firm's transition

to the steady state is very short, all firms behave similarly irrespective of their initial differences in growth rates and profitability. As a result, the pricing differences across firms would be largely affected by the initial book-to-market ratios across firms, as in Dechow et al. (2004) and Weber (2018). Thus, the identification of short- versus long-run risk premia would be weaker and estimates are naturally much more noisy and extreme. On the other hand, the persistence can affect which firms earn a higher expected return. Largely profitable firms tend to have most of their value in the immediate and intermediate future since all firms later converge to the same steady state. A decrease in the speed of cash flow mean reversion (higher AR coefficient) would unilaterally increase their expected return. On the other hand, the unprofitable firms (the flip side of profitable firms) may experience a decrease in expected return due to much more persistent losses (the relationship is not entirely clear if there are non-monotonicities). This can potentially shed some light on why the term structure ultimately depends on the persistence parameters.

To conduct a similar experiment, we also alter the forecasting horizon to 10 and 20 years, and assume different steady state growth rates for g. As outlined in Table IX, this again generates two insights. Firstly, it appears that as long as the forecasting period is long enough for the convergence to occur, the slope sign remains unchanged. Although the magnitude of estimates does depend on the forecasting horizon (as more and more value of the firm is attributed to the terminal horizon), the slope of the equity term structure does not. Second, the steady state rate only mildly affects the slope estimates, except for the high growth and short horizon combination. Yet, a long-term cash flow growth rate of 9% is both rather exceptional and convergence at 10 years horizon is unlikely to fully occur. Overall, the qualitative results seem quite robust to the selection of g and T.

Table VIII: Sensitivity of NS estimates

The table presents the sensitivity of slope and level estimates to changes in ROE and sales growth reversion parameters governing the cash flow dynamics. In all specifications below, the equilibrium cash flow growth rate g and forecasting horizon T are set to 6% and 15, respectively. For brevity, the level estimates are excluded from the table. The negative slope estimates are shaded in dark grey. Compustat-CRSP-I/B/E/S sample: 1980-2021.

slope		AR(1) ROE					
		0.4	0.5	0.6	0.7	0.8	0.9
AR(1) sales	0.2	0.20	0.19	0.17	0.15	0.10	0.01
	0.3	0.19	0.18	0.17	0.14	0.10	0.01
	0.4	0.19	0.18	0.16	0.14	0.09	-0.01
	0.5	0.17	0.16	0.15	0.12	0.08	-0.03
	0.6	0.15	0.14	0.13	0.10	0.05	-0.06

level		AR(1) ROE					
		0.4	0.5	0.6	0.7	0.8	0.9
AR(1) sales	0.2	0.09	0.09	0.08	0.08	0.08	0.09
	0.3	0.08	0.08	0.08	0.08	0.08	0.09
	0.4	0.08	0.08	0.08	0.08	0.08	0.09
	0.5	0.08	0.08	0.08	0.08	0.08	0.09
	0.6	0.08	0.08	0.08	0.08	0.08	0.09

Table IX: Sensitivity of NS estimates

The table presents the sensitivity of slope and level estimates to changes the equilibrium cash flow growth rate g and forecasting horizon T. In all specifications below, the ROE and sales growth mean reversion parameters are set to 0.81 and 0.41, respectively. For brevity, the level estimates are excluded from the table. The negative slope estimates are shaded in dark grey. Compustat-CRSP-I/B/E/S sample: 1980-2021.

slope		T		
		10	15	20
g	0.03	0.05	0.07	0.08
	0.06	0.03	0.08	0.10
	0.09	-0.02	0.08	0.11

level		T		
		10	15	20
g	0.03	0.07	0.05	0.05
	0.06	0.09	0.08	0.09
	0.09	0.12	0.12	0.12

6.5 Industry portfolios

As a final robustness check we perform another cross-sectional sort, where we sort stocks into the 15 Fama-French industries. Because, arguably, the technology sector has changed most substantially over our sample period, we separate technology firms into a separate category following Barron, Byard, Kile & Riedl (2002). In Table C.III the term structure estimates are shown. Again we find largely positively sloped term structures. Only for the steel works industry the slope estimate

is negative. In addition, the level estimates (the 15-year risk premium) are fairly stable across industries. While almost all slope estimates are positive, we do see substantial variation across industries in the size of the slope estimate. It seems that consumer-oriented industries have the steepest term structures. At the same time, this variation may be partially due to estimation noise, since we split the cross-section into 16 portfolios in this analysis.

7 Conclusion

The empirical literature documenting the properties of the term structure of expected equity returns is divided. The prediction of the seminal asset pricing models that longer maturity assets contain more systematic risk was put to test by a series of papers by van Binsbergen et al. (2012), van Binsbergen et al. (2013), van Binsbergen & Koijen (2017). Specifically, the price data in options and dividend strips markets seem to embed a downward-sloping equity term structure meaning that most established models are not in line with empirics. Nevertheless, the evidence is not without controversy due to relatively short historical samples, containing two extreme crashes in 2001 and 2007-2008, which makes the realized returns noisy proxies of the unconditional average expected returns. The challenge is further exacerbated by liquidity effects in derivative markets (Bansal et al. (2019)).

This paper proposes a new methodology to estimate the term structure of equity risk premia based on ex-ante returns. We do so by exploiting the cross-sectional heterogeneity across firm cash flow forecasts and combining them with the implied cost of capital approach. Rather than sorting into duration portfolios and looking at noisy realized returns, we estimate the risk premium term structure by minimizing errors between the discounted cash flow model price of the firm's equity (in the spirit of Dechow et al. (2004)) and the observed market prices. To incorporate as much identifying variation as possible, we augment Dechow et al. (2004) with the information extracted from the IBES analyst forecasts. Our approach does not require prices of dividend assets and can thus be implemented for longer sample periods, 1985 – 2019 in our estimation for the U.S. market. Also, our approach allows us to investigate cross-sectional and time-series variation in risk premium term structures.

Our baseline results show that the equity term structure is upward sloping at the aggregate level, consistent with predictions of classical asset pricing theories such as Campbell & Cochrane (1999) and Bansal & Yaron (2004). However, we also find substantial undocumented heterogeneity between small and large, value and growth firms, with small value firms exhibiting a downward sloping term structure.

We do find evidence that the term structure becomes flatter during recessions, but it remains upward sloping also in these periods. Adding to that, in this paper we cast some light on how credit risk is priced in firms. The implied discount rates are monotonically increasing with credit risk, proxied by the credit ratings, and are particularly high for speculative grade firms. In addition, for the latter firms the term structure is flat or slightly downward sloping for small firms, indeed capturing the idea that these firms either go bust in the upcoming years or survive long enough and transition into higher rated firms. All in all, our ex-ante measure of returns does not support the credit risk anomaly detected in realized returns (Campbell et al. (2008)).

In sum, our key contribution is to develop and implement a coherent framework that merges the cross-section of stock prices and implied cost of capital approach to recover the term structure of equity risk premia. For the modeling cash flows we closely follow the original framework of Dechow et al. (2004) and Weber (2018), and amend it with the information extracted from analysts' forecasts. In doing so, we incorporate more heterogeneity in cash flow expectations, necessary to identify separate horizon discount rates, while at the same time keeping the parsimonious structure of the expected cash flow process. However, we diverge from Dechow et al. (2004) and Weber (2018) by not looking at the realized returns of different duration portfolios, but instead implying the expected returns. As shown, this step allows to flexibly measure ex-ante returns and inspect the cross-sectional and time-varying properties of equity term structure.

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3.A Cash Flow Forecasts

1. Integrating analyst forecasts

We employ and modify the analyst data in the following way:

1. as in Li et al. (2013), we construct the constant maturity median forecasts for revenues, ROE and EPS as a weighted average between year $t+m$ and $t+m+1$ forecasts. This step accounts for the differences in financial years across firms creating discrepancies in timing of cash flows and their discounting. More details on this procedure are provided in Appendix A.2.

2. if a firm has revenue forecasts, we used them for the 1-5 year growth rate of book equity projections (depending on the availability). Namely, we calculate the m'th year sales growth rates as $forecastSALE_{t+m}/forecastSALE_{t+m-1}-1$. If a firm has a non-missing IBES long-term growth rate forecast for sales, we extrapolate all remaining missing values for the 2-5 year horizon using this rate. All resulting sales growth rates are additionally winsorized at 5 and 95% level.

3. if a firm has ROE forecasts, we used them for years 1-5 (depending on the availability). If the forecasts are not available, we proceed with step 4. All ROE forecasts are winsorized at 5 and 95% level.

4. if EPS forecasts are available when ROE are not, we perform the following exercise. For years 1-4, we projected the book value of equity using the mean-reverting sales growth process with an AR coefficient of 0.41 and long-term mean of 6% (à la Dechow et al. (2004) and Weber (2018)). Again, if a firm has a non-missing long-term growth rate forecast for EPS and the last forecast value was positive, we extrapolated all remaining EPS missing values for the 2-5 year horizon using this rate. Then, we implied the ROE forecasts for maturity m using this formula: $EPS_{t+m} * \#shares_t/BE_{t+m-1}$.[20]. All the implied forecasts are winsorized at 5 and 95% level.

[20] The historical number of shares outstanding is assumed to remain fixed in the future.

2. Constant maturity forecast

Forecasts are interpolated using this principle:

$$12monthForecast = w * FY1 + (1 - w) * FY2 \tag{10}$$

where $FY1$ and $FY2$ are the current and subsequent financial year I/B/E/S forecasts and w stands for the number of months left until the realization of current financial year cash flow divided by 12. Since we have forecasts for up to 5 years, we repeat the same procedure for 24, 36, and 48 month forecasts.

Following Li et al. (2013), for the last available year of forecasts we apply this rule to extrapolate the constant maturity forecast:

$$24monthForecast = 12monthForecast * g \tag{11}$$

where g is the implicit growth between $FY1$ and $FY2$ forecasts. To reduce the effect of outliers, we winsorize this g at 5 and 95% level. Clearly, if $FY1$ and $FY12$ switch signs, the growth rates become ill-defined. Therefore, we do not apply this rule for those cases.

The underlying assumption is that firm cash flows realize at the end of the firm's financial year. Because most firms have their financial year ending on Dec 31, we choose June as a valuation month.

As a result of this procedure, the sample shrinks from roughly 65,000 to 53,000 observations. The main reason is that this method requires at least 2 years of forecast data which is not available for all firms in the IBES database.

Data Filters

There are 3 key dates in the I/B/E/S summary database:

- *statpers* - the date on which the forecasts are summarized in this database (e.g. 18 Dec 2014)
- *fpedats* - the end date of the forecasting period (e.g. 31 Dec 2014)
- *anndatsact* - the date when the actuals, i.e. financial statements, for that forecasting period

were announced (e.g. 30 Jan 2015)

Filters:

1. The valuation date is June. Thus, only forecasts available in this month are used.

2. We account for potential mistakes by: i) dropping all observations where the forecast record day (*statpers*) is later than the announcement day of actuals (*anndatsact*); ii) dropping all observations where the forecast record day (*statpers*) exceeds the corresponding forecasting period end date ($fpedats$) by more than 4 months (122 days)[21]. The idea is that forecasts announced after the actual financial statements are no longer forecasts. Adding to that, it should be impossible to observe a 2-year forecast on 18 Jun 2014 for a financial year ending on 31 Jun 2014.

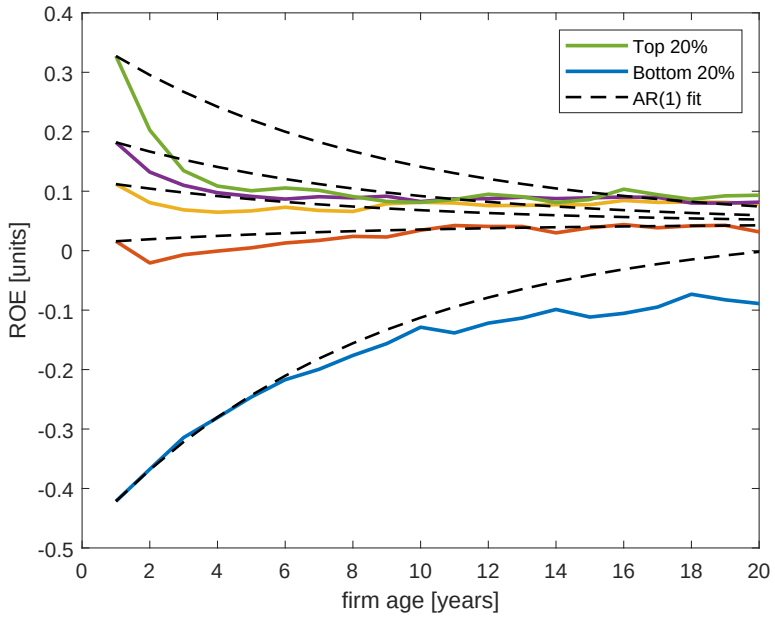
3. We keep firms that have forecasts denominated in US dollars. This filter deletes double entries and eliminates concerns that the reporting currency in I/B/E/S does not match the balance sheet data in Compustat (which is important for measures like EPS, but not for ROE though).

4. In case more than one forecast measure is used, we follow the conservative approach and i) always choose the latest announcement date of actuals across measures, ii) delete all observations where the forecasting period end dates do not match across measures.

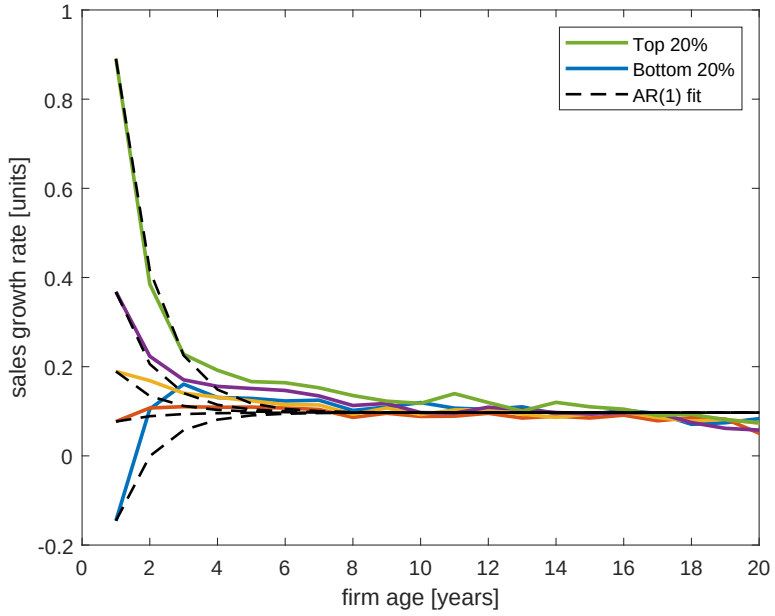
[21] The filter is also applied to all mismatches between 1-5 year actual and implied forecasting period end dates calculated as $statpers + forecastinghorizon$.

3.B Additional Tables and Figures

Figure C.I: ROE and Sales growth quintile portfolios



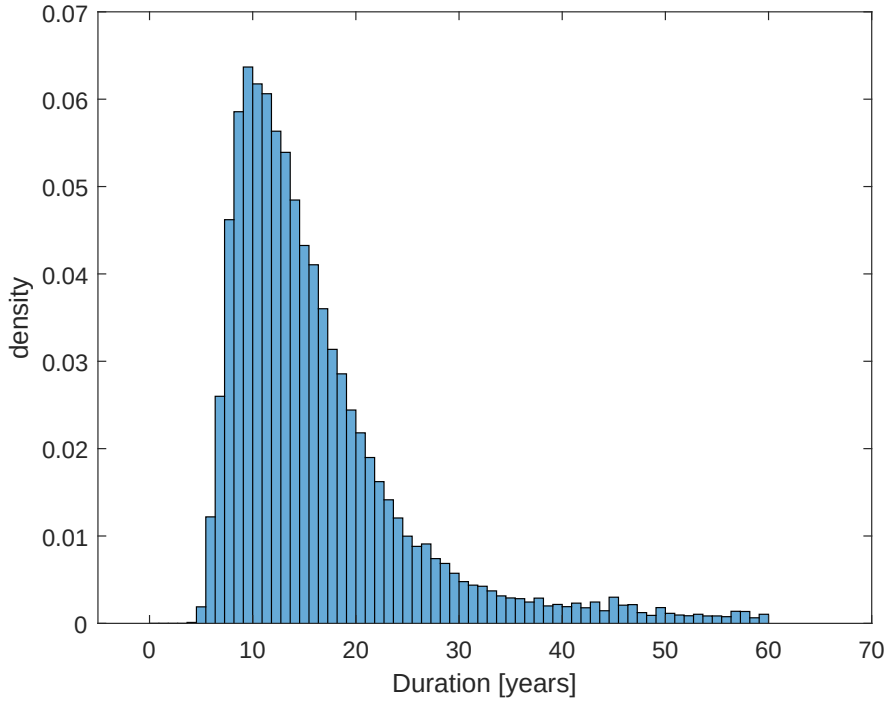
(a) ROE quintiles



(b) Sales growth quintiles

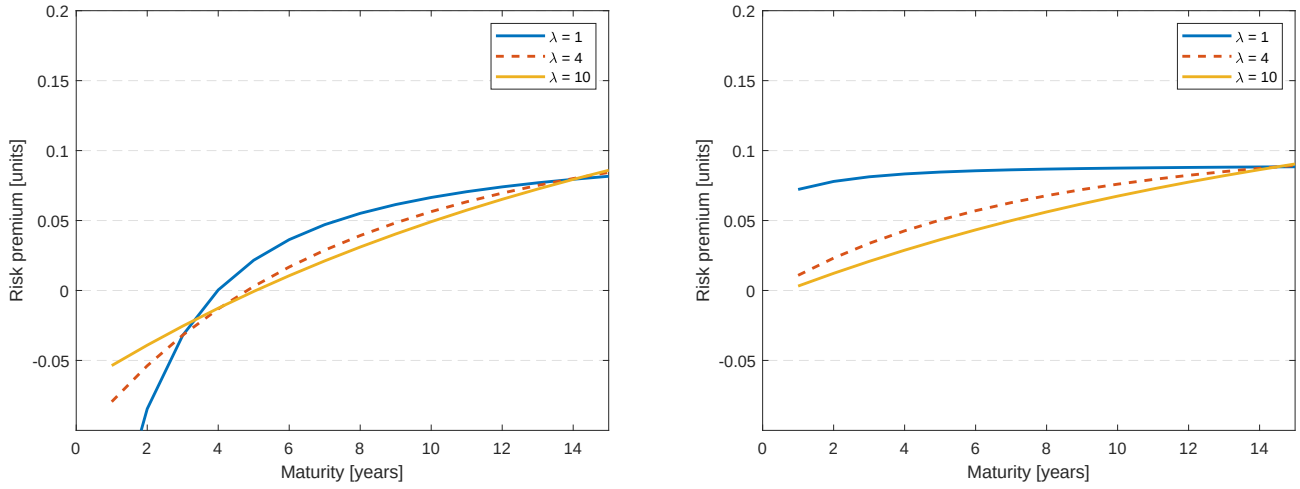
Note: The graph shows the term structure of firm's ROE and sales growth across firm age. Each solid line represents an average of the ROE (sales growth) quintile formed when the age equals 1. The age is proxied by the first occurrence of the firm in the Compustat database. Each dashed line represents the least squares fit of an AR(1) model, where AR(1) for ROE and sales growth portfolios equal to 0.89 and 0.40 respectively. Sample range: 1964-2021.

Figure C.II: Duration distribution



Note: The figure illustrates the year-firm cash flow duration distribution in the merged Compustat-CRSP-I/B/E/S sample (1980-2021). In order to calculate the cash flow duration, we use the model value of a firm, as in equation (2), and the equity term structure estimates from Figure I. For illustrative purposes, the duration is capped at 60-years.

Figure C.III: Sensitivity to λ

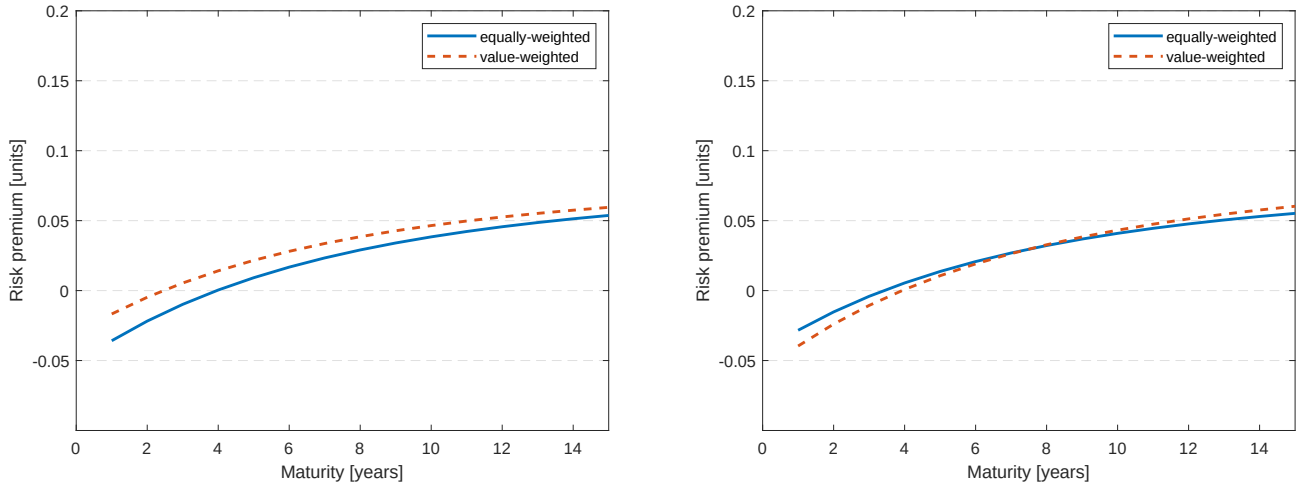


(a) Value weighting

(b) Equal weighting

Note: The figures illustrates the sensitivity of baseline estimates to changes in the decay parameter λ. Compustat-CRSP-I/B/E/S subsample: 1980-2021.

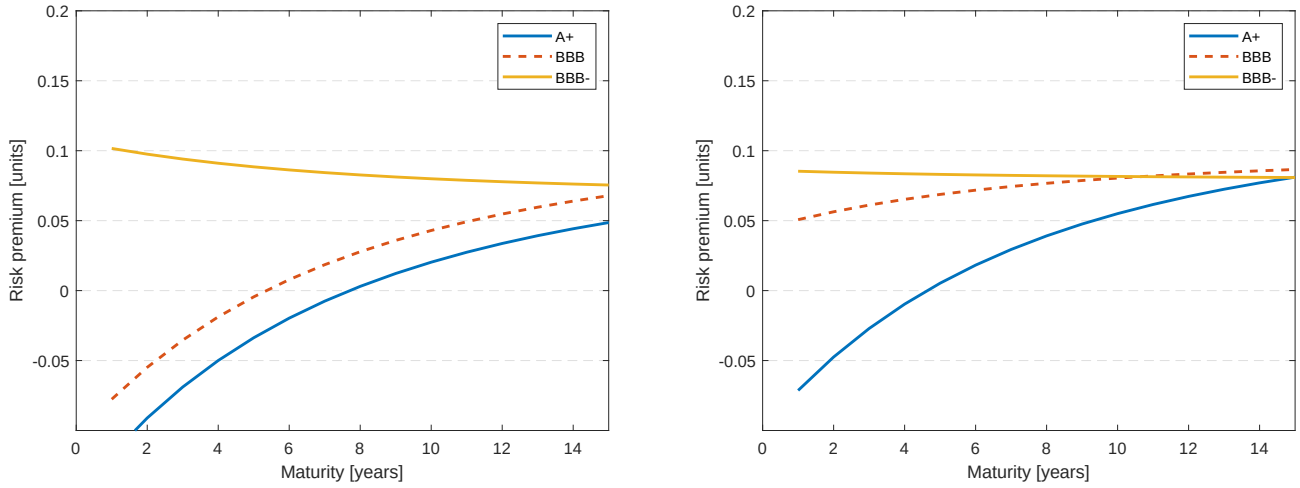
Figure C.IV: van Binsbergen, Brandt & Koijen (2012) sample



(a) Top size quintile (b) S&P500 firms

Note: The figures depict the estimated equity risk premia term structure in the van Binsbergen et al. (2012) sample proxied by the top size quintile firms (left graph) or the $S\&P500$ index firms in our sample (right graph). The blue solid line represents the benchmark value-weighted results, whereas the red dashed line presents results where we equally weight firms in the estimation. Compustat-CRSP-I/B/E/S subsample: 1996-2008.

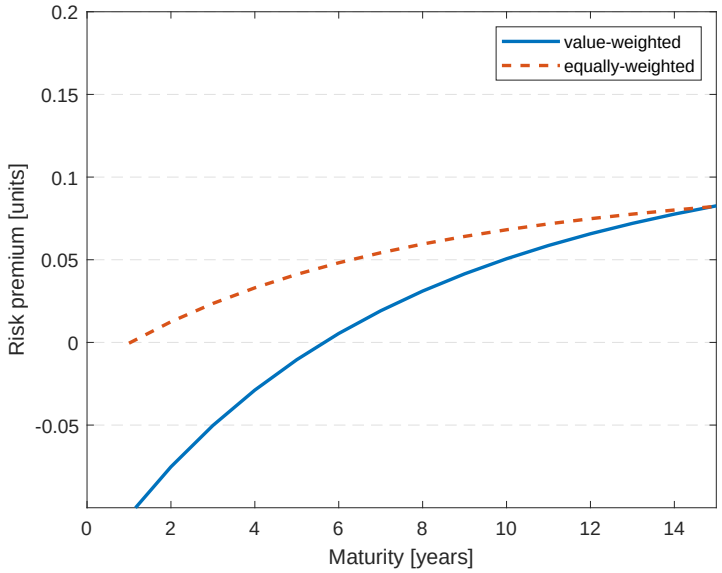
Figure C.V: Double sorts on credit rating and size



(a) small firms (b) large firms

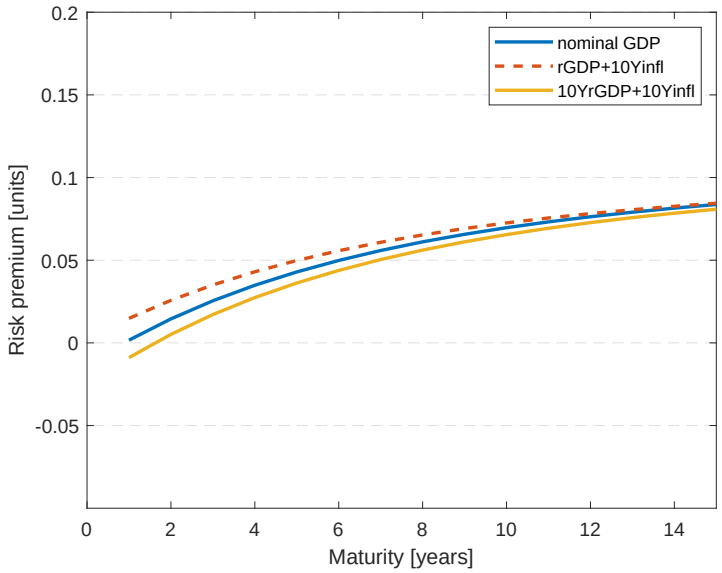
Note: The figures present the estimated equity risk premia term structure in different credit rating and size portfolios. The observations are first sorted based on the S&P credit rating and then split into two median size portfolios. A+ group contains all credit ratings above and including an $A-$ rating. BBB group includes all $BBB+$, BBB and $BBB-$ rated firms. Finally, BBB- includes all non-investment grade ratings. Compustat-CRSP-I/B/E/S subsample: 1985-2018.

Figure C.VI: Cash flows with corrected analyst bias



Note: The figure presents the estimated equity risk premium term structure with corrected analyst forecasts. The correction is made by using estimates from van Binsbergen et al. (2022) (the procedure is described more thoroughly in Section 6.1). Compustat-CRSP-I/B/E/S sample: 1980-2021.

Figure C.VII: Time-varying g



Note: The figures illustrate equity term structure estimates using alternative proxies for the long-term cash flow growth rate g. The blue line represents estimates where g equals the average nominal GDP growth rate up to year t, as in Li et al. (2013) (Compustat-CRSP-I/B/E/S sample: 1980-2021). The red dashed line approximates g with the average real GDP growth rate up to year t plus the long-term (10Y) inflation forecasts (Compustat-CRSP-I/B/E/S subsample: 1982-2018). The yellow line measures g as a sum of the long-term (10Y) real GDP and long-term (10Y) inflation forecasts (Compustat-CRSP-I/B/E/S subsample: 1992-2021).

Table C.I: Analyst forecast bias in EPS

The table presents the average bias, its standard error, and the number of observations of analyst EPS forecast biases obtained from van Binsbergen et al. (2022). The standard errors are clustered by time dimension. Compustat-CRSP-I/B/E/S sample: 1980-2021.

	Analyst bias					
	1-year			2-year		
	mean	SE	N	mean	SE	N
Full sample	0.009	0.002	40,292	0.025	0.003	37,861
Normal times	0.006	0.001	34,683	0.021	0.003	32,486
NBER recessions	0.023	0.008	5,609	0.050	0.010	5,347

Table C.II: Additional filters and model averaging

The table presents the sensitivity of level and slope estimates to alternative filters and cash flow models. The first and the second row stand for scenarios where cash flow forecasts are averaged across two approaches (the mean-reversion model and the augmented version with I/B/E/S forecasts) using the equal-weighting scheme or weights based on the normal distribution, where the mean and the standard deviation are based on the empirical values. The third row represents the case where the estimation sample is trimmed at the higher level of 5th and 95th percentile of the sample IRR. The forth and the fifth rows describe scenarios where different procedures are combined. Finally, the last row summarizes the results when the estimation is performed excluding the most extreme book-to-market portfolios within each size quintile. Compustat-CRSP-I/B/E/S subsample: 1980-2021.

	level	slope
1) cash flows equally averaged	0.086	0.165
2) cash flows averaged using normal dist	0.089	0.189
3) trimmed at 5% and 95% sample IRR	0.087	0.097
combination of 1) & 3)	0.086	0.175
combination of 2) & 3)	0.089	0.200
excluding extreme BM portfolios	0.087	0.201

Table C.III: Industry analysis

The table presents the estimation results within Fama-French 15 industries. The technology industry classification is constructed separately following Barron et al. (2002). Weight denotes the market cap weight of the industry-specific observations in the total sample. All Fama-French industries are sorted based on the slope estimates, and negative slopes are highlighted in gray. Compustat-CRSP-I/B/E/S subsample: 1980-2021.

	level	slope	weight
Transportation	0.09	0.04	0.04
Oil and Petroleum Products	0.08	0.05	0.10
Steel Works Etc	0.08	0.06	0.01
Other	0.08	0.06	0.32
Automobiles	0.09	0.07	0.02
Mining and Minerals	0.08	0.07	0.01
Chemicals	0.08	0.10	0.02
Textiles, Apparel and Footware	0.07	0.11	0.01
Machinery and Business Equipment	0.09	0.12	0.13
Construction and Construction Materials	0.08	0.12	0.02
Fabricated Products	0.07	0.12	0.00
Food	0.08	0.14	0.05
Consumer Durables	0.07	0.16	0.01
Drugs, Soap, Prfums, Tobacco	0.10	0.17	0.12
Retail Stores	0.09	0.18	0.04
Technology	0.09	0.10	0.37

3.C Other Derivations

Notice that an m-maturity cash flow of firm i at time t:

$$\mathbb{E}_t[CF_{i,t+m}] = \mathbb{E}_t[CF_{i,t+m-1}(1 + growth_{i,t+m})]$$

where $growth_{i,t+m}$ is the growth rate of cash flows from period $t+m-1$ to $t+m$ ($m \geq 1$). We can rewrite this expression in terms of cash flow $CF_{i,t}$:

$$\begin{aligned}\mathbb{E}_t[CF_{i,t+m}] &= \mathbb{E}_t[\mathbb{E}_{t+m-1}[CF_{i,t+m-1}(1 + growth_{i,t+m})]] = \mathbb{E}_t[CF_{i,t+m-1}\,\mathbb{E}_{t+m-1}[1 + growth_{i,t+m}]] \\ &= \mathbb{E}_t[CF_{i,t+m-1}(1 + g_{i,t+m})] = CF_{i,t}\prod_{s=1}^{m}(1 + g_{i,t+s})\end{aligned}$$

where $g_{i,t+s} \equiv \mathbb{E}_{t+s-1}[growth_{i,t+s}]$ is the conditional expected growth rate of cash flows from period $t+s-1$ to $t+s$.

Since we make an assumption that all firms after T years converge to the same equilibrium growth rate g_t, for $m > T$, the expression simplifies to:

$$\mathbb{E}_t[CF_{i,t+m}] = CF_{i,t}\prod_{s=1}^{T}(1 + g_{i,t+s})(1 + g_t)^{m-T} = \mathbb{E}_t[CF_{i,t+T}](1 + g_t)^{m-T}$$

This implies that the present value of cash flows after year T is just:

$$\sum_{m=T+1}^{\infty}\frac{E_t[CF_{i,t+m}]}{(1 + r_{i,t,T})^m} = \frac{E_t[CF_{i,t+T+1}]}{(1 + r_{i,t,T})^T(r_{i,t,T} - g_t)}$$

and the equation (2) follows.