Duration-Driven Returns*

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Abstract

We propose a duration-based explanation for the major equity risk factors, including value, profitability, investment, low-risk, and payout factors. Both in the US and globally, these factors invest in firms that earn most of their cash flows in the near future. The factors could therefore be driven by a premium on near-future cash flows. We test this hypothesis using a new dataset of single-stock dividend futures, which are claims on annual dividends for individual firms. Consistent with our hypothesis, the expected CAPM alpha on individual cash flows decrease in maturity within a firm, but do not vary across firms for a given maturity.

Keywords: asset pricing, cross-section of stock returns, cash-flow growth, duration, survey expectations, dividend strips.
JEL classification: G10, G12, G40.

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In this paper, we provide a simple framework for understanding the major equity risk factors in asset pricing. We focus our analysis on value, profit, investment, low-risk, and payout factors. These five categories of risk factors have a large impact on stock prices given their high persistence, and they form the basis of leading factor models such as the Fama and French models.[1] Yet the economics behind these factors are not well understood because the factors are hard to relate to common economic fundamentals. We relate the risk factors back to economic fundamentals, and identify the source of their high risk-adjusted returns, by studying the timing of the cash flows of the firms in the risk factors. The analysis centers around the duration of cash flows, which is the value-weighted time to maturity of a firm's future cash flows.

We find that the risk factors invest in firms that have a short cash-flow duration. This finding is illustrated in Figure 1.a, which plots the future cash flows for firms in the long and short leg of each risk factor, averaged across risk factors. Each cash flow is measured by its present value relative to the present value of all the future cash flows. As shown in orange, the firms in the long leg have relatively large near-future cash flows and therefore a short cash-flow duration. The opposite is the case for the firms in the short leg, which are shown in blue. The figure is based on an average of the major risk factors (and its construction is detailed in the sections below), but we obtain similar results for all the individual risk factors on their own. These risk factors thus share a fundamental economic characteristic, the duration of their cash flows, and can accordingly be summarized by a new duration risk factor.

More importantly, the fact that the risk factors invest in short-duration stocks is key to understanding their expected returns. Indeed, previous research on the equity term structure finds that claims on near-future cash flows on the market portfolio have high risk-adjusted returns.[2] A natural extension of this finding is that the firms that produce these near-future cash flows also have high risk-adjusted returns. In fact, we argue that the major risk factors arise as a product of this premium on near-future cash flows.

To understand our argument, note that the expected return on a given stock, or asset, can be written as the value-weighted return on all of its future cash flows:

$$E_t[r_{t+1}] = \sum_{m=1}^{\infty} w_t^m E_t[r_{t+1}^m], \tag{1}$$

[1]For example, Fama and French (2015).

[2]For example, Binsbergen, Brandt, and Koijen (2012), Binsbergen and Koijen (2017).

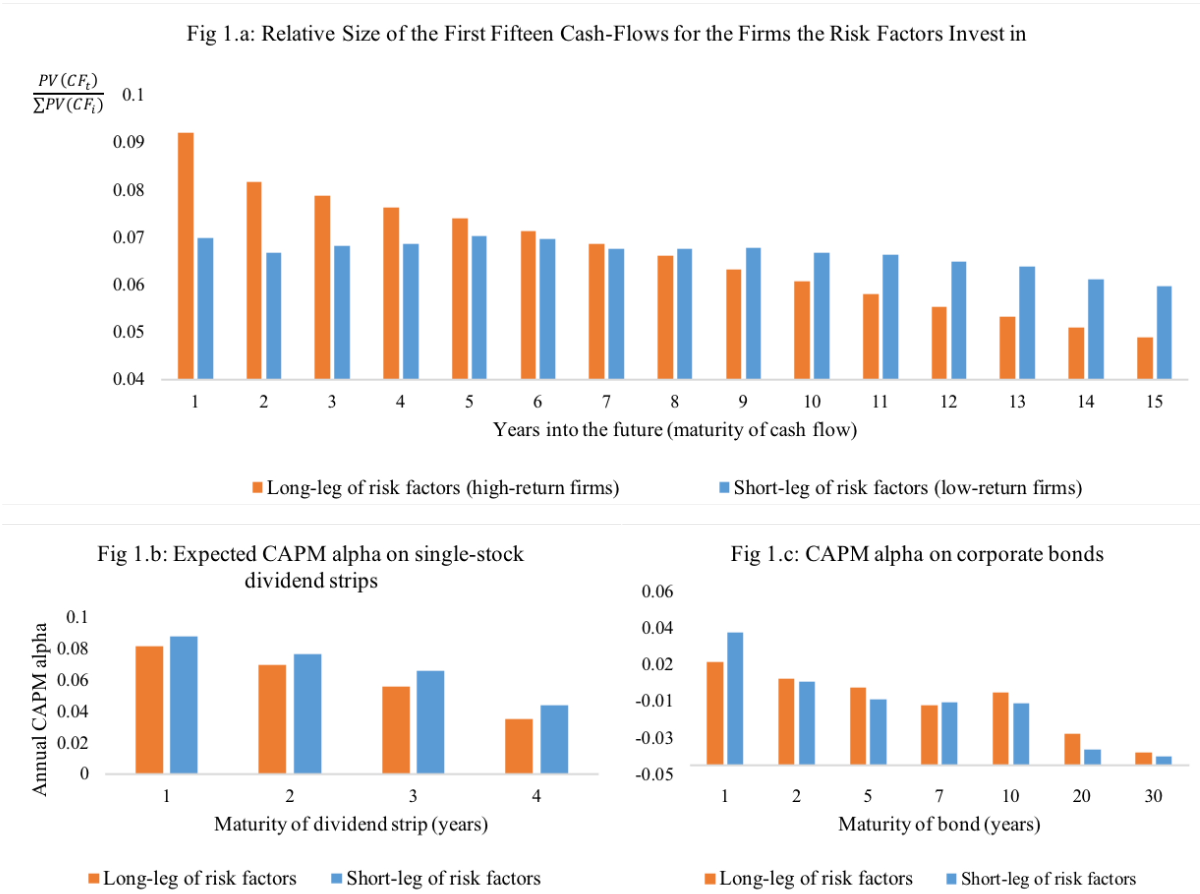

Figure 1: The Timing and Pricing of the Cash Flows of the Major Risk Factors

Figure 1.a shows the relative present value of future dividends for firms in the long and short leg of for a new duration risk factor, which is a combination of the profit, investment, low-risk, and payout factors. The present values are calculated by assuming a nominal discount rate of 10% for all stocks. Figure 1.b shows the CAPM alpha on single-stock dividend strips for firms in the long and short leg of the risk factor. Figure 1.c shows the CAPM alpha of corporate bonds for firms in the long and short leg of the risk factor. The samples are 1929-2018 for Figure 1.a, 2010-2018 for Figure 1.b, and 2002-2016 for Figure 1.c.

where r_{t+1}^m is the one-period excess return on the $t+m$ cash flow and w_t^m is its relative present value ex ante. We argue that, for a given maturity, the risk-adjusted return on cash flows are more or less the same across firms. However, returns decrease in maturity for all firms. Firms with higher weights on near-future cash flows therefore have higher risk-adjusted returns.

We provide direct evidence for such a duration-driven explanation using novel data. We study a dataset of single-stock dividend futures, which are claims to stock level dividends that are paid out during a given calendar year. These are often referred to as dividend strips and can be thought of as the equity equivalent of a zero-coupon bond for an individual firm, only with the face value being the stochastic dividend. These dividend strips allow us to study the return to the individual cash flows of individual firms. Doing so, we find that the risk-adjusted return on individual cash flows decreases with the maturity of the cash flows, but they do not vary systematically across the underlying firms — for instance, the three-year claim on a high-investment firm has the same risk-adjusted return as the three-year claim on a low-investment firm. This finding is illustrated in Figure 1.b, which shows the CAPM alpha on the cash flows of the long and short leg of the risk factors. For both legs of the risk factors, the alphas start at around 8% percent per year for the one-year claim and decrease to around 4% for the four-year claim. More importantly, for each maturity, the risk-adjusted returns are almost the same for both legs of the risk factors.

The results above are based on expected as opposed to realized returns. We calculate expected returns by comparing prices on dividend strips with the expected dividends from analysts. Doing so increases the power of our tests but also leaves open the possibility that analyst have biased expectations. We therefore also look at realized returns. The realized risk-adjusted returns also decrease in maturity, with a similar magnitude as the expected risk-adjusted returns. However power is lower and the effect is only marginally significant. Realized returns also do vary somewhat between firms, with longer-duration firms having lower risk-adjusted returns, but this effect is generally statistically insignificant.

We emphasize that this single-stock dividend market provides an ideal setting for identifying the underlying drivers of returns, which is particularly unusual in studying the cross-section. The fact that cash-flow duration helps summarize major equity risk-factor returns could arise because either (1) duration itself drives returns, or (2) some other firm-level characteristic correlated with duration drives returns. The single-stock dividend futures allow us to hold fixed the characteristics of the firm and vary the maturity of claims on that firm's cash flows, and conversely to hold fixed the cash-flow maturity and vary the firm. We can thus independently vary each of the two possible contributors to the high returns on short- versus long-duration firms. In doing so, we effectively isolate duration itself as the driver of these returns.

The single-stock dividend futures trade in an established market on the Eurex exchange. We observe around €4 billion notional by the end of 2018, which is within the same order of magnitude as the as the market for the index dividend futures studied by Binsbergen and Koijen (2017). The main players in the dividend futures market are financial intermediaries and hedge funds, which are usually considered important for setting prices in the cross-section of stocks (e.g. Adrian, Etula, and Muir, 2014).

We also provide a robustness analysis using corporate bonds. Like the dividend strips, the corporate bonds allow us to study the returns to claims on horizon-specific cash flows of individual firms. The payoff on a corporate bond is dependent on the firm's cash flow at maturity, and the bond is thus approximately a claim on this cash flow, allowing for return comparisons across horizons. The evidence provided by these comparisons is not as direct as the evidence provided by dividend strips, given additional features of corporate bonds (e.g., optionality). But the bonds are available for a longer time series and longer maturities, and they are traded in larger volumes, all of which make them useful for robustness. As summarized in Figure 1.c, we again find that the CAPM alpha on cash flows are similar across firms but decrease in maturity, consistent with a premium on near-future cash flows. While this corporate bond analysis is intended as a robustness check, the consistency of these results with the dividend-strips analysis provides a promising avenue for unifying the cross-section of equity and debt.

We emphasize that all the above results relate mainly to CAPM alphas. In particular, it is the CAPM alpha on stocks, dividend strips, and corporate bonds that decreases in maturity. For equity claims, the expected returns also decrease slightly in maturity, but the effect is insignificant for dividend strips and only marginally significant for stocks.[3] Our organizing fact is thus that near-future cash flows have high returns relative to conventional measures of risk, such as market beta and volatility (leading, respectively, to high CAPM alphas and high Sharpe ratios). Unsurprisingly, longer-duration portfolios have higher market betas; perhaps more surprisingly, their average returns are nearly identical to the average returns on short-duration portfolios, leading to significant alphas on those short-duration portfolios. As noted by Cochrane (2011, p. 1059), "All [cross-sectional] puzzles are *joint* puzzles of expected returns and betas" (emphasis his). Our unifying explanation of the cross-sectional factors we consider is accordingly an explanation of CAPM alphas.

Why do near-future cash flows have high risk-adjusted returns? A natural explanation is that the cash flows are riskier than they appear when measured using conventional

[3]The fact that CAPM alphas decrease in maturity more than expected returns is consistent with the results on the equity term structure, for which the robust finding is that risk-adjusted returns decrease in maturity, whereas the effect on returns is debated. Indeed, Binsbergen, Brandt, and Koijen (2012) find a negative but insignificant relation between expected returns and maturity. Binsbergen and Koijen (2017) also find a negative relation between maturity and expected returns but emphasize that the relation between maturity and risk-adjusted returns is much stronger (cf. Bansal, Miller, Song, and Yaron, 2019).

methods. Indeed, near-future cash flows may appear safe when measured in terms of volatility or market beta but nonetheless be risky in the sense that they are highly exposed to the worst states of the world. For example, Gormsen and Koijen (2020) show that the value of near-future dividends drops by as much as 40% during February and March of 2020 as the coronavirus crisis unfolds. If near-future dividends are highly exposed to such bad economic shocks, it may help explain why their returns are high relative to more-conventional measures of risk (see models by Lettau and Wachter, 2007; Hasler and Marfe, 2016). However, we do not take a strong stand on why near-future cash flows earn a premium: risk pricing (Eisenbach and Schmalz, 2016; Lazarus, 2019), behavioral (Cassella, Golez, Gulen, and Kelly, 2019), or institutional (Belo, Collin-Dufresne, and Goldstein, 2015) mechanisms may all contribute to the premium. Rather, our main contribution is to identify the high return on near-future cash flows as the key driver behind the return to major equity risk factors and to distill these factors into a single fact: firms with short cash-flow duration have high risk-adjusted returns.

Analyzing the duration of the major risk factors further helps us understand the pricing, or valuation ratios, of these factors. Indeed, the valuation ratios are like yields on individual assets, reflecting the hold-to-maturity returns minus hold-to-maturity growth rates. The valuation ratios of stocks with different duration thus summarize equity yields at different horizons, which is to say that they summarize the equity yield curve. We conclude our empirical analysis by constructing this equity yield curve from the book-to-market ratios of long- and short-duration stocks. The slope of the equity yield curve is generally highly correlated with the slope of the bond yield curve, with the exception of a high-inflation period beginning in the late 1970s. In the early sample, from 1929 to 1974, the correlation between the slopes of the equity and bond yield curves is 0.72, and in the late sample, from 1995 to 2018, the correlation is 0.62. During the high-inflation period from 1974 to 1995, the two curves are only weakly correlated, which is natural as the bond yield curve to a large extent reflects inflation expectations that are less relevant for assets with significant real risk, like equities. Separately, the slope of the equity yield curve also predicts the returns to the major equity risk factors, and it predicts the timing of the return on the market portfolio.

Finally, it might be surprising, at first glance, that the major risk factors all share the common economic feature of investing in firms with a short cash-flow duration. We argue, however, that this commonality can be interpreted intuitively. Consider, for instance, firms with low investment and high payout ratios, which are firms that the long legs of the investment and payout factors invest in. Because both of these characteristics imply that the given firms invest only sparsely in future projects, they also naturally imply that the firms will have low growth and thus a short cash-flow duration. Similarly, high-profit firms have short duration because they have large profits today relative to the value of future profits. Firms with high valuation ratios are referred to as *growth* firms precisely because of the high present value of growth opportunities implied by those ratios, and therefore naturally have long cash flow-duration in general (and conversely for firms with low valuation ratios). Finally, a low beta is often a symptom of a short cash-flow duration. Indeed, firms with short cash-flow duration are less exposed to the discount-rate shocks that account for much of the variation in aggregate prices, causing them to comove less with the market and thus have low betas.[4]

The remainder of the paper proceeds as follows. We discuss our relation to previous literature immediately below. Section 1 then explains our data and methodology. Section 2 documents that the major equity risk factors invest in short-duration firms. Section 3 uses this fact to introduce a new duration risk factor, and shows that it summarizes most of the major equity risk factors; that it works well in a broad global sample; and that it provides a meaningful contribution in explaining the cross-section even relative to a large set of previous factors. Section 4 studies single-stock dividend futures and corporate bond returns to isolate duration as a driver of risk-adjusted returns in the cross-section. Section 5 studies the equity yield curve. Section 6 discusses possible economic mechanisms behind our results on duration-driven returns. Appendix A provides additional detail on our data and empirical estimation, and Appendix B studies a simple reduced-form model that can explain our empirical results.

Related Literature: Our paper relates to a literature on duration and the cross-section of stock returns. Much of the previous literature has used duration as an explanation of the value premium: Dechow, Sloan, and Soliman (2004) study an accounting-based measure of cash-flow duration in the cross-section of US stock returns, finding that high-duration stocks have low returns and arguing that their duration measure explains the value premium. Lettau and Wachter (2007) provide a theoretical foundation for this claim. More recently, Weber (2018) shows that the relation between duration and stock returns is stronger when sentiment is higher, and Chen and Li (2018) and Gonçalves

[4]The fact that short-horizon cash flows are less exposed to discount-rate shocks is a feature shared by fixed-income securities. This commonality in part motivates our use of the term *duration* in describing the timing of cash flows accruing to equity-holders, by analogy to its use for fixed-income securities.

(2020) both argue for a duration-based explanation of the profitability and investment premium. Giglio, Kelly, and Kozak (2019), Chen (2020), and Miller (2020) study the slope of the equity term structure in the cross-section of stock returns using different methods.

We provide a series of contributions to this literature. First, we study the timing of cash flows of individual firms and document that the major risk factors all invest in firms with short cash-flow duration. Chen (2017) also studies the timing of cash flows in value and growth firms in the US. Chen finds that the cash flows of value firms actually grow faster those of growth firms when considering a long-history sample in the US, suggesting that value firms are long-duration firms and thereby challenging the duration-based explanation for the value premium. However, this result only holds in the early US sample and we show that it is driven by microcap firms. When excluding the smallest 20% of listed firms, the cash flows of value firms indeed grow slower than those of growth firms, both in the full sample and in the modern sample that we consider. In addition, using international data and data on expectations, we find strong evidence that cash flows grow slower for value firms than for growth firms. Going beyond the value premium, we also analyze the timing of the cash flows for the firms in the profit, investment, beta, and payout factors, finding that all the factors invest in firms with a short cash-flow duration.

Second, we provide direct evidence on the effect of duration using a novel dataset on single-stock dividend futures. Previous research on duration in the stock returns has not been able to determine whether short-duration firms have high returns because of their short cash-flow duration or because of other characteristics of short-duration firms, such as low valuation ratios. Using single-stock dividend futures and corporate bonds, we are able to directly isolate the effect of cash-flow duration on stock returns. We show that the risk-adjusted returns on individual cash flows on individual firms decrease in the maturity of the cash flows and that the return does not vary across firms. These results imply that it is the duration of cash flows, and not other firm-level characteristics, that drive the return premium on short-duration firms.

Third, we introduce a new duration risk factor and provide global evidence on duration risk in the cross-section of stock returns. Finally, we study the equity yield curve that arise from book-to-market ratios of duration-sorted portfolios, and we show that the slope of this yield curve predicts returns to the major risk factors.

We also contribute to the literature on the aggregate equity term structure. Binsbergen and Koijen (2017) document that the risk-adjusted returns on claims to all dividends on the market portfolio decrease in maturity. However, this result could be driven by how the composition of the market portfolio varies over the term structure. We extend the evidence and show that risk-adjusted returns also decrease in maturity for single-stock dividends, implying that the result on the aggregate dividends are not driven entirely by composition effects.

Our paper also relates to a recent literature on the so-called factor zoo.[5] The goal of this literature is to determine which characteristics are most important for predicting returns. The literature achieves this goal mainly through statistical analysis. We differ in our approach and shrink the cross-section based on economic intuition. We use basic economic arguments, coupled with analysis of dividend growth rates and novel dividend futures data, to argue that many of the most prominent characteristics are symptoms of cash-flow duration, and that many cross-sectional anomalies can thus be explained by a duration characteristic, which in turn is consistent with the evidence on the equity term structure of the market portfolio. We do, however, apply the methodology proposed by Feng, Giglio, and Xiu (2020) to assess the contribution of our proposed duration factor relative to a large set of previously proposed factors, and we find that it performs well in this exercise and thus helps explain the cross-section generally.

1 Data and Methodology

1.1 Equities

We study equities in a global sample covering 66,228 stocks in 23 countries between August 1926 and December 2018. The 23 markets in our sample correspond to the countries belonging to the MSCI World Developed Index as of December 31, 2018. Stock returns are from the union of the CRSP tape and the XpressFeed Global Database. All returns are in USD and do not include any currency hedging. All excess returns are measured as excess returns above the US Treasury bill rate. Data needed to construct investment, profit, and payout characteristics are available from 1952.

We study risk factors both in the individual countries in our sample and a in broad global sample. Our broad sample of global equities contains all available common stocks on the union of the CRSP tape and the XpressFeed Global database from 1990 until 2018. For companies traded in multiple markets we use the primary trading vehicle identified by XpressFeed.

[5] See, for instance, Feng, Giglio, and Xiu (2020); Giglio, Liao, and Xiu (2018); Harvey and Liu (2017); Harvey, Liu, and Zhu (2016); Kozak, Nagel, and Santosh (2017).

1.2 Single-Stock Dividend Futures

Single-stock dividend futures are exchange-traded products that give the buyer the right to the dividends per share that go ex-dividend over a given business year (each contract is for 1,000 shares). The futures started trading on the Eurex exchange in 2010, and as of 2018, dividend futures existed for 150 firms with up to five year maturity. The futures are mainly on European firms but also include some of the largest US firms.

We explain the single-stock dividend futures in detail in Section 4.1 but provide a small introduction here. The single-stock dividend futures are similar in nature to the index dividend futures that have become commonly used in asset pricing.[6] The index dividend futures are claims to the dividends on an underlying index, such as the S&P 500 or Euro Stoxx 50. The Euro Stoxx 50 dividend futures market is the most liquid of such index dividend futures markets, with a total notional outstanding of around €12 billion as of mid-2018. By comparison, we observe a total notional of around €4 billion in 2018, suggesting the two markets are of similar order of magnitude. Both markets have around 20,000 contracts traded daily, although the single-stock dividend futures generally trade at 1/10 the price of the index dividends.[7]

There are, however, certain differences between the market for single-stock dividend futures and the market for index dividend futures. Most importantly, almost all trading in the single-stock market takes place off the order book and is then brought onto the order book for risk-sharing purposes. As such, the single-stock dividend futures market inherits many of the features of an over-the-counter market. For instance, pricing is somewhat stale in the dividend futures market. This makes the single-stock dividend futures inappropriate for daily event studies, such as the ones in Gormsen and Koijen (2020). However, for the purposes of this paper, namely measuring expected returns on an annual horizon, potential staleness in prices does not pose a serious problem. We elaborate further on these features of the data in section 4.

We obtain daily prices from Deutsche Borse, which is the owner of the Eurex Exchange. We explain the nature of the data and the steps we take in detail in Appendix A. In short, we match the dividend futures to our equity database using the ISIN. The resulting database has 28,864 firm-month-maturity price observations for 190 different firms. We

[6]See Binsbergen, Hueskes, Koijen, and Vrugt (2013) for an introduction to index dividend futures.

[7]The open interest for index dividend futures in 2018 was around 1 million contracts with an average value of around €12,000, giving a total notional of around €12 billion. Similarly, the open interest on single-stock dividend futures in 2018 was around 4 million contracts with and the average value of the contracts in our matched dataset is €3,000, suggesting a notional of around €12 billion.

explain data in more detail in section 4.

1.3 Bond Returns

We obtain bond returns from WRDS Bond Return database. Our sample includes 23,211 bonds issued by 1,352 US firms and runs from July 2002 to January 2016.

1.4 Expectations

We obtain long-term growth (LTG) expectations from the IBES database, for which data are available 1981–2018. These are defined as annualized expected earnings growth rates over a company's "next full business cycle." In parts of the analysis, we transfer these into cross-sectional percentiles. In other parts, we work with the annualized numerical earnings growth values directly. In all cases we use median estimates for expected dividends.

1.5 Defining Cash-Flow Duration

Macaulay defines cash-flow duration as the weighted-average years to maturity of an asset's expected cash flows:

$$Dur_t = \sum_{i=1}^{\infty} i \times w_{i,t}. \tag{2}$$

The weight $w_{i,t}$ is the present value of the given cash flow relative to the total value of the assets:

$$w_{i,t} = \frac{E_t[CF_{t+i}]/(1+r)^i}{P_t}, \tag{3}$$

where CF_{t+i} is the realized cash flow in period $t+i$, r is the yield to maturity on the asset, and P_t is the price of the asset.

Cross-sectional variation in duration comes from differences in expected cash-flow growth rates and in yield to maturity, or discount rates. We focus mostly on variation coming from differences in growth rates. We do so because the yield to maturity, which is in this case the long-term internal rate of return on a stock, is ex-ante more difficult to observe than expected cash-flow growth. In addition, and more importantly, discount rates are ultimately the variable we are interested in understanding, which precludes us from sorting stocks on differences in duration arising purely from differences in discount rates.

2 A Unifying Theme for the Cross-Section: The Major Risk Factors Buy Low-Growth Firms

We first document that the major risk factors invest in firms with low growth rates. Because these firms have low growth rates, their near-future cash flows are large relative to their distant-future cash flows, which is to say they have a short cash-flow duration.[8]

We focus our analysis on value, profitability, investment, low-risk, and payout factors.[9] We consider commonly used versions of these risk factors, which are based on the following characteristics: high book-to-market, high operating profitability to book equity, a low annual growth in total assets, low market beta, and high payout ratio. The precise definitions of the characteristics can be found in Appendix A. Throughout the paper, we sign all characteristics such that a higher characteristic value implies a higher CAPM alpha.

We first look at the relation between these characteristics and realized growth rates. To do so, we create 50 characteristics-sorted portfolios, 10 for each characteristic. For each portfolio, we calculate the average 15-year growth rates in dividends and earnings. We also calculate the average characteristics of the firms in the portfolios. The methodology for calculating the growth rates is provided in Appendix A. We finally regress the average growth rates onto the average characteristics of the portfolios:

$$\overline{\text{Growth rates}}_i = \beta_0 + \overline{X}_i' B + \epsilon_i, \tag{4}$$

where $\overline{\text{Growth rates}}_i$ is the average growth rate for portfolio i and $\overline{X}_i$ is a row vector containing the five characteristics of the portfolio. For this exercise, all characteristics are measured in cross-sectional percentiles. We consider the 1952-2018 sample as this is the period for which all characteristics are available.

Panel A of Table 1 reports the results of regression (4). The first row uses ex-post

[8]As discussed at the end of Section 1, we abstract here from the effect of discount rates on duration. But as we will argue below, firms with high growth rates in fact also have lower discount rates, which reinforces the positive effect of growth rates on duration.

[9]We consider these risk factors given their prominence in the post–Fama and French (1993) literature, and the fact that their persistence suggests that they are quantitatively important for explaining valuation ratios in addition to expected returns (in contrast to, e.g., momentum or other pricing factors less directly related to firm characteristics). But any such selection is of course subjective, so we consider the applicability of our framework for other anomalies in Section 3 below.

dividend growth rates on the left hand side. These growth rates load negatively on all the characteristics. The next row uses ex-post earnings growth rates on the left hand side. These similarly load negatively on all the characteristics, although the effect is insignificant for profit. Accordingly, these characteristics are all associated with low growth rates.[10]

The parameter estimates in Panel A are large. The right-hand-side variables are measured in cross-sectional percentage points. A one-percentage-point increase in the cross-sectional ranking of, for instance, book-to-market results in a 3% lower average growth rate over the next 15 years. In addition, the R^2 values are around 0.83, suggesting that the five characteristics capture most of the variation in growth across the 50 portfolios.

To get more precise results and more power, we next consider the contemporaneous relation between characteristics and ex-ante expected growth rates from IBES. These expectations are known to embed biases discussed further below. For now, however, we are interested only in the rankings of expected growth rates, as we consider cross-sectional percentile values for this estimation. As documented further below, the IBES-based expectations do correctly rank the firms' growth rates on average.

Panel B of Table 1 documents the univariate correlation between the expected growth rate and the contemporaneous characteristics of the same firm. The long-term expected growth rate is negatively correlated with all the characteristics, in line with the analysis in Panel A.

To go beyond univariate correlations, we run the following panel regression of expected growth rates on contemporaneous characteristics:

$$\mathrm{LTG}_{j,t} = \Gamma_j + X'_{j,t} B + \epsilon_{j,t}, \tag{5}$$

where $\mathrm{LTG}_{j,t}$ is the median expected long-term growth for firm j at time t, and $X'_{j,t}$ is a row vector containing the firm-j characteristics at time t, again both transformed into cross-sectional percentiles. The regressions include firm fixed effects Γ_j.[11] Our baseline analysis uses the number of analysts by firm as regression weights, though we consider alternative specifications as well.

Panel C of Table 1 shows the US results. The LTG expectations load negatively on

[10] We note that these estimates are likely biased upward. The characteristics that predict returns may partly do so because the given firms have overperformed in-sample, which is to say that their dividend growth has been higher than expected. If this was the case, the low future dividend growth of the high-return characteristics would be biased upwards, meaning that the actual relation between characteristics and growth rates is stronger than what we present here.

[11] Given the use of cross-sectional percentile values for all variables, the estimation implicitly incorporates date fixed effects as well.

all the characteristics. This result holds across sample splits, with and without firm fixed effects, and using different regression weights. The R^2 is high in all specifications. The characteristics thus all predict low expected growth rates, even multivariately, and they jointly explain expected growth rates well.

We obtain similar results in our international (non-US) sample, as shown in Panel D of Table 1. In our baseline regressions, weighted by number of analysts, the expected growth rates again load negatively on all of the characteristics. The results are robust to using market-cap weights, but they are not completely robust to removing weights or splitting the sample in the international case.

Figure 2 shows the estimated loadings of expected growth rates on characteristics for each individual country in our sample. The clear majority of the parameter estimates remain negative in each of the countries. Panel B of Figure 2 zooms in on the G7 countries. Again, the estimates all remain negative, with the exception of Japan, where the parameter estimate on investment is positive. Panel C shows the individual characteristics on their own. The negative relation between growth and characteristics appears most robust for the book-to-market and payout ratios.

The long-term growth rates are ideal because we directly link the characteristics to ex ante expectations. By doing so, we avoid drawing our inference based on ex post realized growth, which would be biased to the extent that the characteristics are (at least partly) products of data mining. On the other hand, the IBES expectations figures might themselves be biased and not reflect true consensus earnings-growth expectations. There is indeed evidence — see, for example, Chan, Karceski, and Lakonishok (2003) — that the long-term growth rates suffer from overreaction. However, as documented in the next section, these expectations are not pure noise. Firms with high expected long-term growth do have higher realized ex post growth rates than firms with low long-term growth expectations.[12] This latter property is sufficient for our purposes in this section, as we measure expectations in cross-sectional percentiles and only focus on qualitative relations between growth rates and characteristics.

The results on the book-to-market ratio may seem counter to the findings of Chen (2017), who studies the growth rates of value and growth firms. Chen finds that value firms have lower growth rates than growth firms in his modern sample period (post–1963),

[12]The earlier literature also contested the claim that these expectations had any predictive power over realized growth. We find no support for this claim in the updated data. But we do find some evidence that the expectations tend to be upwardly biased on average, consistent with Chan, Karceski, and Lakonishok (2003).

but that they have higher growth rates in the early sample (1926–1962) and in the full sample. Two points of relation between Chen's results and ours merit comment. First, for this analysis we are also studying the modern sample period (post–1952, or 1981 when IBES data is needed), and our results are thus consistent within this period. Second, and more importantly, the results in the early sample are driven by micro-cap firms. Once we discard the smallest 20% of listed firms, value firms have lower growth rates in the full sample as well, as documented in Appendix Table A1.[13,14]

In conclusion, the major risk factors share a common feature, namely that their long legs all invest in firms with low growth rates relative to their short legs. This result holds when looking at realized growth rates in both dividends and earnings. It also holds when looking at expected growth rates from analyst forecasts, both in the US and internationally.

The firms in the long legs of the risk factors have both low growth rates and high expected returns, leading together to these firms having short cash-flow duration. The stylized fact that the major risk factors buy firms with low growth rates can therefore be restated as the finding that the major risk factors buy firms with short cash-flow duration. In the next sections, we address the asset pricing implications of this new stylized fact.

3 Summarizing the Cross-Section with a Duration Factor

Given that the major risk factors invest in firms with short cash-flow duration, it is natural to expect that the factors' returns can be explained to some extent by a duration factor that similarly invests in short-duration firms. In Section 3.1, we introduce such a duration factor and consider its return and cash-flow properties. In Section 3.2, we show that the factor indeed accounts for a large portion of the major risk factors' returns both in the US and globally. Further, subjecting the factor to the model-selection procedure proposed by Feng, Giglio, and Xiu (2020), we find that it provides a significant marginal contribution in pricing the cross-section relative to a high-dimensional set of preexisting factors.

[13]Micro-cap firms have a strong effect on the results given that Chen (2017) forms portfolios by sorting univariately on book-to-market. This ratio is known to be highly correlated with firm size, implying that some of the portfolios contain mostly micro-cap firms.

[14]Chen (2017) also studies growth rates of "rebalanced" portfolios, which are the usual portfolios studied for purposes of forward-looking expected-return predictions. (The label "rebalanced" as used here is in fact a slight misnomer, as the portfolios are both rebalanced and refreshed every calendar year.) But these portfolios provide little evidence on firm-level growth rates, as discussed on p. 2281 of Chen (2017). Instead, they largely reflect the relative performance of value and growth firms, as shown in Section IV of Chen (2017).

3.1 Factor Construction and Returns

To construct a duration factor, we need ex ante estimates of the duration of different firms. As mentioned, duration is a function of expected growth rates and discount rates. Because discount rates are ultimately the endogenous variable we are interested in explaining, we refrain from sorting on this and sort only on expected growth rates.

We construct a measure of ex ante expected growth rates from the IBES long-term growth expectations. These expectations are useful as they provide direct, ex ante measures of expected growth rates. However, the long-term growth rate expectations are only available for a subset of firms, namely the largest firms, and they are only available from 1981 and onward. To obtain estimated measures of expected long-term growth rates, and thus duration, for the universe of publicly traded firms for the full sample, we use observable firm characteristics along with the estimated loadings on these characteristics from regression (5) to obtain predicted expected growth rates. (As shown in Table 1.C, these characteristics account for a large portion of the variation in expected growth rates in-sample.) Formally, for the 20,422 firms for which we do have analyst expectations, we run the following panel regression from 1981 to 2018:

$$\text{LTG}_{j,t} = \beta_j^0 + X_{j,t}'B + \epsilon_{j,t}. \tag{6}$$

where we use number of analysts as regression weights. We then construct predicted long-term growth expectations for all firms in our sample, including ones for which analyst expectations are not available, as

$$\widehat{\text{LTG}}_{j,t} = \widehat{\beta}_{OP}\text{OP}_{i,t} + \widehat{\beta}_{INV}\text{INV}_{i,t} + \widehat{\beta}_{BETA}\text{BETA}_{i,t} + \widehat{\beta}_{PAY}\text{PAY}_{i,t}, \qquad j \in J, t \in T. \tag{7}$$

We then define our duration characteristic as

$$\text{DUR}_{j,t} = \widehat{\text{LTG}}_{j,t}, \qquad j \in J, t \in T. \tag{8}$$

In estimating our duration characteristic, we exclude the book-to-market characteristic. We do so partly because sorting on book-to-market ratios involves a sort on discount rates, which is the variable we seek to explain. Further, we later use the book-to-market ratios of the duration characteristic to study the equity yield curve, which precludes the use of the book-to-market characteristic in constructing the duration characteristic itself.[15]

[15]We note that including the book-to-market characteristic improves the performance of the duration

Our methodology allows us to construct a duration characteristic for as many firms as possible for as long a time series as possible. It also mitigates potential measurement error in the growth expectations because it discards any variation in growth expectations uncorrelated with fundamentals. The method is, however, an out-of-sample extrapolation by construction.

Table 2 studies returns on ten portfolios sorted on our short-duration characteristic. The portfolio breakpoints are based on NYSE firms and refreshed every year. The portfolios are value-weighted and rebalanced each calendar month. As can be seen in the first row, the average monthly excess returns decrease slightly as duration increases, but the effect is non-monotonic and statistically insignificant. However, the CAPM alpha decreases almost monotonically as the duration increases. This effect is both economically and statistically significant as the long-short portfolio has an alpha of -0.81% per month with a t-statistic of -5.26. As discussed in the introduction, our unifying explanation of the cross-sectional factors we consider is accordingly an explanation of CAPM alphas.

The last row of Table 2 also reports the realized and expected cash-flow growth rates of the portfolios. The expected cash-flow growth rate is based on the long-term growth expectations in the subsample where we have expectations data. Expected cash-flow growth increases monotonically as portfolio duration increases. This effect is mechanical as the the long-term growth expectations form the basis of the duration characteristic on which we sort. More importantly, the realized growth rates of both dividends and earnings also increase monotonically, confirming that the ex-ante expectations contain strong predictive power, and that this predictive power carries through to the out-of-sample fitted expectations. The realized growth rates are for the full sample, so they do not directly compare to the expected growth rates from the 1981-2018 sample. This issue aside, it does appear that the expected growth rates are biased upward relative to the realized growth rates, though this bias does not affect the ranking of portfolios' cash-flow growth rates ex post relative to ex ante.

To put the growth rates in perspective, we calculate realized duration under the assumption that the realized growth rates continue forever and that the discount rate is equal to the realized market portfolio for all stocks. As shown at the bottom of Table 2, the realized duration varies from 15 years for the short-duration portfolios to 59 years for the long-duration portfolio, suggesting that the differences in growth rates lead to sizable differences in cash-flow duration.

factor; results for this analysis are available upon request.

We next construct a duration risk factor using the Fama and French (1993) method. Each June, we sort stocks into six portfolios using breakpoints based on the median market capitalization and the 30th and 70th percentiles of the duration characteristic. In the US, portfolio breakpoints are unconditional and based on NYSE firms. In the international sample, breakpoints are conditional and based on the largest 20% of firms.[16] Portfolios are value-weighted and rebalanced at the end of each calendar month. The factor goes long the short-duration firms and therefore has a positive alpha.

Table 3 analyzes returns on our duration factor in the US and international sample. The US results in Panel A are largely similar to the results in Table 2. The short-duration portfolios have slightly higher average returns than the long-duration portfolios, meaning that our duration factor has positive average returns. This effect is only marginally statistically significant. Much more significant is the finding that the factor has a positive alpha of 0.48% per month with a t-statistic of 5.39. This large alpha is driven neither by the small cap firms nor by the short leg of the portfolio alone. The results is robust across subperiods, as can be seen in Figure 3, which plots the cumulative alpha and return.

The two last rows of Panel A in Table 3 show the expected and realized dividend growth rates of the different portfolios in our duration factor. Both of the long-duration portfolios have realized and expected growth rates above those in the short-duration portfolios. The growth rate for the duration factor is the difference between the growth rates in the long and the short legs of the portfolio. This growth rate is -6.3% when measured using survey expectations and -3.6% when measured using realized growth rates. The realized growth rates are from the full sample whereas the expected growth rates are from the 1981-2018 sample.

Finally, Figure 4 shows the cumulative dividend growth for the short- and long-duration portfolios as a function of time after the portfolio formation period. As can be seen in the figure, the long-duration firms have higher growth rates than the short-duration firms in every year after the formation period. After 15 years, the earnings of the long-duration portfolio have increased by almost 100 percentage points more than the short-duration portfolio. These results verify that our measure of ex ante duration indeed predicts ex post differences in growth rates (and thus duration).

Panel B of Table 3 reports the performance of the duration factor in the global sample. The factor has a positive and statistically significant CAPM alpha of 0.40% per month. Similarly, Figure 5 shows that the factor has positive alpha in 20 out of 23 countries in

[16]We follow standard practice in using conditional breakpoints for the international data given small-sample issues; see, for example, Asness, Frazzini, and Pedersen (2019).

our sample, and that it is statistically significant in 13 of these, despite the sample being quite short in many exchanges. Given that the characteristics that underlie our duration factor are all based on our analysis in the US data, this international evidence mitigates data mining concerns.

3.2 Spanning and Model Selection Tests

We next consider the factor's ability to explain the cross section. First, we use three-factor regressions to ask whether our duration factor summarizes the five major equity risk factors studied in Section 2. For each factor, we regress the returns onto the market, a small-minus-big portfolio, and the duration factor in the following regression:

$$r^i_{t+1} = \alpha^i_{\text{DUR}} + \beta^i_{\text{mkt}}(r^{mkt}_{t+1} - r^f_t) + \beta^i_{\text{smb}} r^{smb}_{t+1} + \beta^i_{\text{DUR}} r^{DUR}_{t+1} + \epsilon_{t+1}, \tag{9}$$

where r^i_{t+1} is the excess return on risk factor i. The small-minus-big factor is based on the six portfolios sorted on duration and size, and it goes long the small firms and short the large firms. Including the size factor does not influence our results much, as our left-hand-side variables are size-neutral by construction. However, without the size factor, the model struggles to explain portfolios that are not size-neutral. On average, small stocks have higher growth rates than large stocks, which means they are long-duration stocks. As such, based on duration alone, one would expect them to have low returns, but empirically the small firms have high returns. This size premium could potentially arise from liquidity effects or from other market microstructure issues related to small firms. But regardless of the origin of this premium, it illustrates that our duration factor of course does not (along with the market) explain the entirety of the cross-section.

Panel A of Table 4 presents results of our factor regressions in the US. The first three columns of Panel A show the results from the CAPM regressions using the market alone. The risk factors all have positive and statistically significant CAPM alphas. In addition, they all have negative CAPM betas.

We next consider the three-factor regressions in the middle columns. The major risk factors all load positively on our duration factor in these regressions. The loadings are statistically significant and the R^2 values increase substantially relative to the CAPM regressions. More importantly, the duration risk factor explains the alpha to the factors as they are all insignificant in the three-factor model.[17]

[17]While the table reports results from the three-factor model including a small-minus-big factor, the

Panel B reports similar results in the global sample. The major risk factors all load on our duration factor. In addition, controlling for the factor substantially increases the R^2 and it explains most of the CAPM alpha to these factors, although the profit factor remains statistically significant.

The duration factor is based on four of the five factors listed in the first column of Table 4. As such, one might think that the relation between the duration factor and these other factors is somewhat mechanical. However, even though the duration factor is long the other factors, the returns to the major risk factors could have been sufficiently negatively correlated, such that one or two of them loaded negatively on our duration factor. The fact that they all load positively on our duration factor suggests a common source of returns. In addition, it is worth noting that our duration factor includes the other factors only because expected growth rates load negatively on all the characteristics behind these factors — if growth rates had loaded positively on one of the characteristics, say profit, the duration factor would have shorted this characteristic. We discuss this issue further below (after Table 5).

The above results suggest that the proposed factor model indeed spans the space of factors we set out to explain. We now consider whether it meets a more significant hurdle: using the machine-learning procedure of Feng, Giglio, and Xiu (FGX, 2020), we test the marginal contribution of the duration factor in pricing a much larger number of test assets, relative to a high-dimensional set of preexisting factors. FGX design their procedure specifically to provide a "conservative and productive way to screen new factors and bring discipline to the 'zoo of factors'" (p. 1359). They propose using a two-pass (or "double-selection") lasso method to select a benchmark set of factors against which a proposed new factor can be compared.[18] Then, estimating the loadings (λ_h, λ_g) in the multivariate cross-sectional regression

$$\overline{r} = \iota_n \alpha + \widehat{\mathrm{Cov}}(r_t, h_t)\lambda_h + \widehat{\mathrm{Cov}}(r_t, g_t)\lambda_g + u, \tag{10}$$

where r_t is an $n \times 1$ vector of test-asset returns, $\overline{r}$ is its time-series average, ι_n is the $n \times 1$ ones vector, h_t is the $p \times 1$ vector of selected factors, and g_t is the proposed new factor, we

duration factor is in fact providing the bulk of the explanatory power and reduction in alpha. The average R^2 value in analogous unreported two-factor regressions, including only the market and the duration factor, is 0.47 (compared to 0.51 for the three-factor results in the table); similarly, the average alpha in these two-factor regressions is 0.04% per month (compared to 0.01% per month in the three-factor case).

[18]The first-pass lasso selects a low-dimensional set of factors useful in explaining the full cross-section, while the second-pass lasso selects additional factors that covary strongly with the proposed new factor, thereby mitigating omitted variable bias. See FGX (2020) for further details.

test whether λ_g is significant. This value represents the loading on the new factor in the stochastic discount factor, and thus its usefulness in explaining the cross section over and above the benchmark factors h_t (Cochrane, 2005). FGX also provide an asymptotically valid inference procedure for testing the significance of the estimated λ_g.

We set $g_t = r_t^{DUR}$, and we use as test assets r_t the same 750 characteristics-sorted portfolios used and provided by FGX.[19] For the "zoo" of possible control factors (from which h_t is selected), we use FGX's library of 150 risk factors, along with our small-minus-big factor constructed from duration-sorted portfolios as in (9).[20] Their test assets and risk factors are available monthly from July 1976 through December 2017, so we restrict attention to this sample period for r_t^{DUR} so that our estimation follows theirs as closely as possible.

Table 5 presents estimation results for $\lambda_g = \lambda_{DUR}$ using the FGX double-selection procedure. The loading λ_{DUR} as presented corresponds to the estimated average excess return, in basis points (bps) per month, for an efficient portfolio with a univariate beta with respect to r_t^{DUR} normalized to one, following FGX. The first column shows that r_t^{DUR} is estimated to have a loading λ_{DUR} of 220 bps per month, which is strongly significant with a p-value below 1%. For comparison, the best-performing factor of the post-2012 factors considered in FGX's empirical application, the Fama and French (2015) robust-minus-weak (RMW) profitability factor, has a scaled SDF loading of 160 bps per month, with a t-statistic of 4.45. The only other post-2012 factor they consider that is significant at the 1% level is the Hou, Xue, and Zhang (2015) profitability (ROE) factor, which has a loading of 77 bps per month ($t = 3.37$).

The second column in Table 5 presents results for λ_{DUR} estimated using only the three Fama and French (1993) factors (FF3) as controls, with respect to the same set of 750 test assets. In this case the estimate for λ_{DUR} is smaller but more precisely estimated, and thus more strongly significant. Finally, the third column includes all 151 other factors in the factor zoo as controls without any dimension reduction, and shows that the OLS estimate of λ_{DUR} remains quite high, and significant at the 5% level.[21]

These tests provide evidence that the duration factor contributes significantly in ex-

[19]We thank the authors for making their data available, and especially for their help with the code used to implement their estimation procedure.

[20]As FGX note on p. 1332, their procedure is meant to "focus on the evaluation of a *new factor*, rather than testing or estimating an entire reduced-form asset pricing model." We thus add our *smb* factor as a possible control factor, so that we are testing only the marginal contribution of our main factor r_t^{DUR}.

[21]The FGX double-selection procedure used in column 1 selects selects 126 factors to include in the cross-sectional regression (10) as controls in h_t (including our duration-based small-minus-big factor).

plaining returns in the cross-section, even in a conservative high-dimensional test. How might this finding arise, given that the duration factor is constructed using sorts based on a linear combination of characteristics used for previously proposed factors? At a statistical level, the portfolio construction using 2×3 sorts means that the duration factor return is not mechanically spanned by other factors' returns: a firm with high profitability may be in the neutral-duration portfolio (i.e., between percentiles 30 and 70 in predicted duration), for example, and thus be a part of neither leg of the duration portfolio.[22] At a deeper level, though, it appears that the duration factor as constructed is exploiting an economically useful combination of the underlying characteristics used in its construction, as discussed above after Table 4. We hope to explore this issue further in future work.

In conclusion, the major equity risk factors all invest in short-duration stocks and can therefore largely be summarized by a new duration factor. This duration factor invests in short-duration stocks and has a high and statistically significant alpha, both in the US and global sample. In addition, it helps explain other anomalies in the cross-section, and it passes a statistically rigorous test for providing a meaningful contribution to explaining the cross-section as a whole relative to prior proposed factors. However, the question remains as to whether the high returns on our duration factor are causally driven by cash-flow duration itself, or if the returns arise because our short-duration characteristic proxies for some other driver(s) of returns, or both. We address this question in the next section using novel data.

4 Duration-Driven Returns: Evidence from Dividend Strips

In this section, we test the hypothesis that the returns to the duration factor, and to short-duration firms more generally, arise because of a premium on near-future cash flows. The starting point for the analysis is the following identity from the law of one price that links the CAPM alpha on individual firms to CAPM alpha on individual cash flows:

$$\alpha_t^i = \sum_{m=1}^{\infty} w_t^{i,m} \alpha_t^{i,m} \tag{11}$$

[22]Further, some of the characteristics we use for $DUR_{j,t}$ have, in previous work, been used to construct factors that employ different portfolio sorts than our 2×3 sorts. For example, the betting-against-beta (BAB) factor constructed by Frazzini and Pedersen (2014) uses the same beta characteristic that we do, but it is constructed using a single (1×2) sort on beta and weights securities by their beta ranking.

where α_t^i is the CAPM alpha on firm i, α_t^i is the CAPM alpha on the $t + m$ cash flow of firm i, and $w_t^{i,m}$ is its relative present value.

Equation (11) shows that firm-level differences in CAPM alphas can arise for two reasons. They can arise because alphas on individual cash flows vary with the maturity of the cash flows (m) or because the alphas on the individual cash flows vary across firms (i), or both.

Our hypothesis is that CAPM alphas decrease with the maturity of the cash-flows. Such a pattern would cause short-duration firms to have relatively high CAPM alphas as they have relatively large weights on near-future cash flows. The alternative hypothesis is that CAPM alphas do not vary with the maturity of the cash flows but instead vary across firms. We separate between these two competing theories using single-stock dividend futures, which offer the ideal lab-like setting to test our hypothesis.

4.1 An Introduction to Single-Stock Dividend Futures

Single-stock dividend futures are claims to individual dividends on individual firms. For instance, the future on the 2021 dividend for Nestlé gives the buyer the right to the dividends paid by Nestlé during the 2021 calendar year. The single-stock dividend futures have traded as dividend swaps in an over-the-counter market since the early 2000s. Starting in 2010, single-stock dividend have traded as a standardized product on the Eurex exchange. Eurex initially offered dividend futures on 50 firms but offer futures on more than 150 firms by then end of 2018. The availability of maturities varies across firms, with the most liquid firms having maturities as far as 7 years.

Most of volume at the Eurex exhcange is over the counter trades that are brought onto the order book through the Eurex OTC trading facilities. The trades are brought onto the order book for risk management purposes. This feature allows us to observe the activity in the over the counter market in a transparent way.

We obtain daily data from Eurex. The data contain information on volume, open interest, and settlement prices. The settlement prices are the end-of-day prices that positions are cleared against in the risk management systems. The prices are either based on traded prices or on a combination of quotes and proprietary models. To ensure that our prices are based on traded prices, we keep track of prices in calendar time and ensure only to update prices on days where we see volume in the market.

To give a sense of the data, Figure 7 plots the price, open-interest, and daily volume for the futures on the 2020 dividends of AXA and Deutsche Bank. The AXA futures are some of the most liquid in our sample whereas Deutsche Bank are some of the least liquid. As shown in the left part of the Figure, the AXA future trades fairly frequently and does not exhibit any dramatic swings over the sample. We also note that there is no sign of a bid-ask bounce.[23] The open interest increases over time, reflecting the growing nature of the market. As shown in the right side of the figure, the Deutsche Bank future trades more rarely, with trades sometimes being several months apart. This makes the claim on Deutsche Bank ill-suited for high-frequency analysis like event studies, but the stale prices are less of an issue when considering annual returns, as we do in the subsequent sections. We will nonetheless keep the issue of stale prices in the illiquid contracts in mind through the rest of the analysis – and ensure that results are not driven by the pricing of the illiquid strips.

Table 6 shows summary statistics for the dividend futures. Panel A reports statistics on annual returns, volume, open interest, and notional outstanding. We calculate annual returns at the end of December each year (as the contracts matures at the end of December). The average returns are around 5% when measured in raw returns and 3.4% when measured in log-returns. These are futures returns, which means they are in excess of the risk-free rate. The average annual volume is 11,392 contracts and the average open interest is 5,300 contracts. A contract is a claim to the dividends paid out on 1,000 shares and trade on average at around €2,000. The average notional outstanding is around €4 million.

Panel B shows summary statistics as they relate to maturity and CAPM betas. The average maturity is 2 years. The average CAPM beta for the individual strip in 0.52. We estimate CAPM betas in regressions of monthly returns on the monthly returns of the market portfolio in the country of incorporation of the underlying firm, accounting for stale prices; see Appendix A for more details. We trim the betas to be between -1 and 1.5.

Panel C addresses the representativeness of the sample. The panel reports the average characteristics of the firms underlying the strips. We measure the characteristics in cross-sectional percent of the characteristics on the full universe of firms in the country where the firm is traded. If the sample was perfectly representative, the average characteristic would be 50 for all the characteristics. Although the sample contains firms with cash-flow duration below average, the sample is generally fairly representative. The main dimension along which it is not is market size, as the sample generally contains only the largest firms

[23] In tests that span all strips, we find no significant evidence that returns on the strips are autocorrelated.

in the universe of firms.

Finally, Figure 8 shows a histogram of monthly returns. The figures excludes all observations where returns are equal to zero. Returns look fairly symmetric, although the have negative skewness and exhibit excess kurtosis.

The single-stock dividend futures are similar in nature to the index dividend futures that have become commonly used in asset pricing.[24] The index dividend futures are claims to the dividends on an underlying index, such as the S&P 500 or Euro Stoxx 50. The Euro Stoxx 50 dividend futures market is the most liquid of such index dividend futures markets, with a total notional outstanding of around €12 billion as of mid-2018. By comparison, we observe a total notional of around €4 billion in 2018, suggesting the two markets are of similar order of magnitude. Both markets have around 20,000 contracts traded daily, although the single-stock dividend futures generally trade at 1/10 the price of the index dividends.[25]

4.2 Expected Returns and CAPM Alphas on Dividend Strips

We begin our analysis of the dividend strips by analyzing the expected return and alphas. For this purpose, we use expected dividends from IBES to estimate the expected yield-to-maturity on a given claim. That is, we calculate expected return and alphas as:

$$E_t[r^{i,m}_{t+m}] = \left(\frac{E_t\left[D^i_{t+m}\right]}{f^{i,m}_t}\right)^{1/m} - 1 \tag{12}$$

where D^i_{t+m} is the analysts' time-t expectations of the dividends paid out at $t+m$ on firm i and $f^{i,m}_t$ is the price of the m-maturity strip on firm i at time t. In mapping the expectations data to the dividend strip data, there is a risk that the expectations might refer to a different traded version of the share than the dividend strips do, leading to misleading expectations. We therefore exclude all observations where the expected return is below -10% or above 30%.

We note that a cleaner way to map the results on the dividend futures to the cross-section of stock returns would been to look at expected one-period returns instead of the expected yield-to-maturity. The expectations data does not allows us to study one-period

[24] See Binsbergen, Hueskes, Koijen, and Vrugt (2013) for an introduction to index dividend futures.

[25] The open interest for index dividend futures in 2018 was around 1 million contracts with an average value of around €12,000, giving a total notional of around €12 billion. Similarly, the open interest on single-stock dividend futures in 2018 was around 4 million contracts with and the average value of the contracts in our matched dataset is €3,000, suggesting a notional of around €12 billion.

returns. However, in the next section we study realized returns, which do allows us to study one-period returns as opposed to yield to maturity.

We further calculate expected CAPM alphas by subtracting the product of the CAPM beta and the expected market risk premium from the expected returns, assuming a market risk premium of 5%:

$$\alpha_t^{i,m} = E_t[r_{t+m}^{i,m}] - \beta^{i,m} \times 5\%. \tag{13}$$

The estimation of the strip-level betas are outlined in Appendix A.

Table 7 shows the results of the following end-of-year panel regressions:

$$y_{t,t+m}^{i,m} = b_2 D_2^m + b_3 D_3^m + b_4 D_4^m + B_1' X_t^{i,m} + B_2' X_t^i + e_t^{i,m}, \tag{14}$$

where $y_{t,t+m}^{i,m} = E_t[r_{t,t+m}^{i,m}]$ or $y_{t,t+m}^{i,m} = \alpha_{t,t+m}^{i,m}$, D_2 to D_4 are maturity dummies for the claims, $X_t^{i,m}$ is a vector of time t strip-level characteristics, and X_t^i is a vector of time t firm-level characteristics. Time t is end of December of a given year.

The leftmost regression in Table has expected returns on the left hand side and on the right hand side it has the the CAPM beta of the strip, the CAPM beta of the underlying firm, and the cash-flow duration of the underlying firm. We find a positive relation between expected returns and both the beta of the strip and the beta of the underlying firm. This finding suggest that betas are priced in the dividend strips and that there is a link between pricing of strips and the risk of the underlying firm. We find no relation between the cash-flow duration of the underlying firm and the expected returns. The regressions control for date and currency fixed effects.[26] We cluster standard errors by date and firm. Clustering instead by date and firm×maturity (denoted in the table by "*Date/Strip*") does not alter the results much.

The next regression instead has the maturity dummies on the right hand side. We find a slightly negative relation between maturity and dummies, in the sense that the loading on the dummies are negative, and increasingly so, for the 3- and 4-year claim. The effect is significant for the 4-year claim. Column 3 augments the regression with the CAPM betas. Doing so intensifies the negative relation between return and maturity, such that the effect is significant both for the 2-year and 3-year claim. This result reflect the notion that CAPM betas increase in maturity, as shown in the rightmost columns of the Table.

[26]The contracts are traded in the currency at which the dividends are paid out, meaning the contracts are in different currencies.

The fourth and fifth columns of Table 7 has CAPM alpha on the left hand side. The CAPM alphas load negatively on the maturity dummies, and increasingly so, suggesting a negative relation between maturity and alpha on the strips. We again find no effect of cash-flow duration of the underlying firm. The results are robust to use notional outstanding as weight, which ensures that the results are not driven by the illiquid strips.

One possible concern about the above analysis is that the significance of the maturity-dummy loadings could be driven entirely by the one-year claim, as the dummies measure whether the returns are significantly lower than the one-year claim. In unreported results, we verify that this is not the case: using the two-year claim as the benchmark does change the results.

4.3 Realized Returns and Alphas on Dividend Strips

Looking at expected as opposed to realized returns bring additional power to our tests but it also leaves open the possibility that analysts' expectations are biased. We therefore also look at realized returns. At the end of each year, we calculate the realized returns from buying a contract and selling it one year later. If the contract has matured upon selling, we use the settlement price as the selling price. For CAPM alphas, we calculate realized alphas as the difference between realized returns and the product of the beta and the realized return on the market where the firm is incorporated:

$$r_{t+1}^{i,m} = \frac{f_{t+1}^{i,m-1}}{f_t^{i,m}} - 1 \tag{15}$$

$$\tilde{\alpha}_t^{i,m} = r_{t+1}^{i,m} - \beta^{i,m} r_{t+1}^{i,MKT} \tag{16}$$

We start by projecting the realized returns onto the ex ante expected returns. Table 8 Panel A shows the results. The slope coefficients are between 0.67 and 0.80, depending on choice of fixed effects and types of returns. We generally cannot reject that the slope coefficients are equal to 1.

We next project the realized returns onto the maturity dummies from the panel regression above. The first two regression in Panel B has the realized returns on the left hand side. We find a largely flat effect between returns and maturity. We next project the realized alphas onto the dummies. Here we find a negative relation between alpha and maturity. The coefficient are almost similar to the ones from the expected alphas, but the significance is substantially weaker given the noise inherent in looking at realized returns. We cluster by date and firm, or alternatively by date and strip (i.e., date and firm×maturity). Clustering at the higher (date and firm) level is more conservative, and yields slightly less-significant results than clustering by date and strip.

Panel C includes the cash-flow maturity of the underlying firm on the right hand side. The results reveal a negative relation between realized alphas and the cash-flow duration of the underlying firm. The effect is marginally significant in one specification. These results contrast to the results on expected returns, where there we found no relation between returns and duration. The discrepancy might reflect noise or it might reflect overoptimistic beliefs. In either case, it suggests that realized returns have been lower than expected for long-duration firms.

Panel D highlights this finding by taking the difference between realized and expected returns on the left hand side. We find no relation between these expectations errors and the maturity dummies. But we do find a negative relation between the expectations errors and the cash-flow duration, again emphasizing that beliefs in this sample have been overoptimistic.

The findings on realized returns suggests that overoptimistic expectations about growth rates of long-duration firms could play a role in explaining the returns on the duration factor. However, such an explanation would also have to account for the negative relation between cash-flow maturity and both realized and expected alphas.

In conclusion, the dividend strips reveal a strong, negative relation between the maturity of the strips and the risk-adjusted return. These results suggest that cash-flow duration play a role in the returns associated with the major risk factors.

4.4 Evidence from Corporate Bonds

We perform a similar exercise using the corporate bonds described in section 1.3. At time t, we sort all firms for which we have bonds into two groups based on firm-level characteristics at time t. We then sort corporate bonds issued by these firms into portfolios based on maturity and study their performance.

Table 9 shows the CAPM alphas for bond portfolios sorted on firm-level characteristics and maturity. The CAPM alpha is the intercept in a regression of equal-weighted excess returns of the portfolio's bonds on the market. We measure excess returns as returns in excess of the return on a Treasury with the same maturity.

Panel A considers portfolios sorted on the duration characteristics and maturity. For both long- and short-duration firms, the alpha decreases in maturity. However, the alpha does not vary across the duration characteristic. Again, these results suggests that the maturity of the cash flows, not firm-level characteristics, are the main driver of risk-adjusted returns. We report similar results in Panel B when sorting on long-term growth rates. Figure 8 shows t-statistics for portfolios sorted on the other firm-level characteristics. None of these characteristics predict differences in the bonds' CAPM alphas, but for all sorts, the alphas decrease in the maturity of the claim.

Our corporate bond analysis is intended as a robustness check for our results on dividend strips. We note, however, that the consistency of these two sets of results suggests a promising avenue for unifying the cross-section of equity and debt in a parsimonious way.

5 The Equity Yield Curve

We next study the book-to-market ratios of long- and short-duration firms. These book-to-market ratios together constitute the equity yield curve. Indeed, Binsbergen, Hueskes, Koijen, and Vrugt (2013) define equity yields as the hold-to-maturity return minus hold-to-maturity growth rates of dividends with different maturities. Similarly, book-to-market ratios of duration-sorted portfolios measure the future expected return and growth rate of firms with different cash-flow duration (Vuolteenaho, 2002).

We calculate the level of the equity yield curve as the average log book-to-market ratio of the four portfolios that constitute the duration factor. Similarly, we calculate the slope of the equity yield curve as the average log book-to-market ratio of the two long-duration portfolios in the duration factor minus the average log book-to-market ratio of the two short-duration portfolios in the duration factor.

Figure 9 plots the slope of the equity yield curve. As can be seen from the figure, the slope is positive in the beginning of the sample. From 1960 and forwards it fluctuates around zero. These results are consistent with cumulative excess returns to our duration factor in Figure 4, where the long-duration stocks have high returns in the early sample.

Figure 9 also plots the slope of the Treasury yield curve, measured as the difference in yields between all outstanding long- and short-duration Treasuries. Because the CRSP tape of Treasury yields does not start until the 1950s, we create our own estimates of these yields in the early sample. We define long-duration Treasuries as all Treasuries with maturity of more than 10 years. We define short-duration Treasuries as all Treasuries with maturity of less than 5 years. We value-weight the yields based on the total value of each outstanding Treasury security.

Panel A of Table 10 shows results from regressions of the slope of the equity yield curve onto the slope of the bond yield curve. For the full sample, considered in the leftmost column, the relation is weak. However, both in the early sample, from 1929 to 1974, and the late sample, from 1995 to 2018, the relation is strong, with R^2 values of 0.65 and 0.59, respectively. It is only during the relatively high-inflation period from 1974 to 1995 that the two slopes are uncorrelated, which is natural, as the slope of the equity yield curve should not be as closely linked to inflation risk premia as the slope of the Treasury yield curve. These results help validate our measure of the equity yield curve.

If the major risk factors invest in short-duration stocks, the slope of the yield curve should predict their returns. We test this hypothesis in Panel B of Table 10, which shows the results of predictive regressions. The dependent variables are the future realized one-year return to the equity risk factors and the dependent variable are the ex ante level and slope of the yield curve. We run rolling monthly regressions and use Newey–West standard errors with 18 lags. As can be seen in the leftmost column of Table 10, the slope of the yield curve predicts future returns to the duration factor. When the yield curve is more downward-sloping, short-duration stocks have relatively higher returns and the duration factor thus has higher returns. The effect is statistically significant. The level of the yield curve does not predict the return to the duration factor. Similarly, we find that the slope of the yield curve predicts negatively the return to the value, profit, investment, low-risk, and payout factors, although the effect is insignificant for value and investment. The R^2 ranges from 0.06 to 0.16. The regressions also include the slope of the bond yield curve, but this is insignificant when controlling for the equity yield curve.

We next test if the equity yield curve predicts the return to the market portfolio. A higher level of the equity yield curve should, all else equal, predict a higher return to the market portfolio over the long run. In addition, if the equity yield curve is more upward sloping, it suggests that this return is expected to be earned in the more distant future rather than the near future.[27] Accordingly, we expect a higher level to predict higher returns and a more upward sloping curve to predict lower returns over a short horizon (less than five years).

The results in Panel B of Table 10 are consistent with this conjecture: a higher yield curve predicts higher returns and a more upward sloping yield curve predicts lower returns. The effect is strongest, and statistically significant, for the four- and five-year horizons. The R^2 is as high as 41% for the five-year return. The slope of the bond yield curve also predicts returns, but it does so with the opposite sign. This reflects the well-known

[27] Gormsen (2018) discusses the effect of the slope of the equity yield curve on the return to the market portfolio.

result in the bond literature that the slope of the bond yield curve predicts the bond term premium. Since the market is a long-duration claim, the bond term premium should carry over to the equity risk premium, which means the slope of the bond term structure should predict the equity risk premium positively.

In conclusion, the valuation ratios on duration-sorted portfolios constitute an equity yield curve. The slope of this yield curve is strongly correlated with the slope of the Treasury yield curve outside a high-inflation period centered around the 1980s. In addition, it intuitively helps predict the return to individual risk factors and the the timing of the return to the market portfolio.

6 Theory: Why Do Near-Future Cash Flows Have High Risk-Adjusted Returns?

We have argued that the major risk factors arise as a result of a premium on near-future cash flows. This result brings promise for asset pricing models. Distilling the major risk factors into a single fact makes it easier to write economic models explaining them. In addition, the central fact that near-future cash flows have high risk-adjusted returns is consistent with the evidence on the equity term structure of the market portfolio (Binsbergen, Brandt, and Koijen, 2012; Binsbergen and Koijen, 2017). Accordingly, one can explain both the major equity risk factors and the pricing of the aggregate market with models in which near-future cash flows have high CAPM alphas.

Why might near-future cash flows have high CAPM alphas? A simple reduced-form explanation is that all dividend claims have the same expected return but that market betas increase in maturity, making CAPM alphas decrease in maturity. The flat expected returns could arise if expected returns are driven by cash-flow risk that is constant over the term structure. The increasing betas could arise if betas are driven by a discount-rate risk that increases in maturity as duration increases (but is unpriced and does not influence expected returns). In the Appendix, we study a model with some of these dynamics based on Lettau and Wachter (2007), which shows that the major risk factors indeed are priced in such a setting. Gonçalves (2017, 2020) makes similar arguments and provides direct evidence on the exposure of near- and distant-future dividends to cash-flow and discount-rate risk.

Providing a structural framework to rationalize this reduced-form finding is a natural step for future research. One could in principle provide structural foundations for both production and demand in such a framework, though our assessment is that demand-side foundations are likely to be more generative for an understanding of the results documented here for at least two reasons. First, recent work has in fact provided multiple plausible sets of firm-side foundations for asset-pricing facts related to the ones we document.[28] Second, our results show that one need not necessarily consider a fully specified model of firm production to understand the cross-section; all relevant firm-level information is summarized by the timing of its expected cash flows, so it is sufficient to treat firms essentially as machines generating cash flows with different duration. Meanwhile, understanding the possible general-equilibrium foundations of a framework in which discount-rate risk is less strongly priced than cash-flow risk — as in Lettau and Wachter (2007), as well as Campbell and Vuolteenaho (2004) — seems a useful avenue for future work.

However, it is worth emphasizing that other mechanisms also could give rise to duration-driven returns. In general, the high premium on near-future cash flows is consistent with any model in which the equity term structure is downward-sloping. For instance, Hasler and Marfe (2016) model an economy with a disaster with quick recovery. In this economy, the short-maturity cash flows are risky because they are more exposed to disaster risk, which creates a downward-sloping term structure. Binsbergen and Koijen (2017) review the literature and discuss additional models that are consistent with these facts.

The high returns to short-duration firms are also consistent with behavioral models, including some models of overreaction. Diagnostic expectations, for instance, imply that people overestimate the growth rates of high-growth firms and underestimate the growth rates of low-growth firms. In such a setting, realized return to low-growth firms will be high. However, this theory cannot explain why the long-maturity claims have lower expected risk-adjusted returns than the short-maturity claims for the dividend futures, and similarly the results presented in Binsbergen, Brandt, and Koijen (2012) and Binsbergen and Koijen (2017). As such, theories of overreaction would have to be accompanied by additional mechanisms to account for all features of the data.

7 Conclusion

We study the economics of the major equity risk factors in asset pricing. Across a broad global sample of 23 countries, risk factors based on value, profit, investment, low-risk

[28]For example, Zhang (2005) points to costly reversibility of firms' investments in explaining the value premium, and Kogan and Papanikolaou (2014) propose an explanation based on growth firms' exposure to capital-embodied technology shocks.

and payout invest in firms with low growth rates. This common feature is sufficiently pronounced that the risk factors can be summarized by a single factor that invests in low-growth firms. The major risk factors thus share a fundamental economic feature and may arise from the same economic explanation. We refer to our new factor as a duration factor. We do so because the firms in the long-leg of the factor not only have low growth rates but also a short cash-flow duration.

We leverage a new dataset on single-stock dividend futures to better understand the economic mechanism behind the return to the duration factor. We test the hypothesis that the high return to the duration factor arises from a premium on near-future cash flows. Consistent with this hypothesis, expected and realized CAPM alphas decrease in the maturity of cash flows for individual firms. Such a pattern generates a premium on short-duration firms because they have higher weight on the cash flows with high alpha, namely the near-future cash flows.

A natural alternative explanation for the risk factor is that short-duration firms simply have higher expected returns on cash flows at any given maturity than long-duration firms. Such a premium could for instance arise from differences in firm-level riskiness. We directly test this alternative hypothesis in our data and find no evidence to support it: the expected return and CAPM alpha on cash flows does not vary across firms with different cash-flow duration.

However, we cannot completely reject the alternative behavioral theory that investors have irrational expectations. While there are no differences across firms in expected return and CAPM alphas, the realized return and alpha on individual cash flows do vary across firms. In particular, long-duration firms have lower realized returns than short-duration firms. This finding is consistent with a theory of overreaction, where the high growth rates on long-duration firms make investors overestimate the expected growth and thereby subsequently be disappointed. We stress, however, that the statistical significance for this finding is very marginal. In addition, this behavioral explanation cannot explain the maturity dimension of CAPM alphas, which exists both in expected and realized returns.

Our results bring identification to a large literature on the role of cash-flow duration in stock returns. Lettau and Wachter (2007) suggests a model in which value firms have high returns because they load more on near-future cash flows – which are modeled to have a high alpha. However, it is not obvious that it is the timing of cash flows that generates the premium on value firms – one could easily imagine that the premium was driven by other characteristics of value firms. Our data allows us to control for firm-level characteristics and study the effect of maturity within a given firm. Doing so, we provide direct evidence for the role of duration not only for understanding the value premium, but also for understanding profit, investment, low-risk, and payout premia.

As of yet, it is unclear why near-future cash flows have high CAPM alphas. A large literature discusses this question (see Binsbergen and Koijen, 2017, for review). The most common explanation is that near-future cash flows are more exposed to cash flow risk, potentially due to mean-reversion in growth rates, as in the Lettau and Wacther (2007). Other explanations revolve around institutional features or non-standard preferences. We do not seek to separate between these theories here.

Going forward, the dataset of single-stock dividend futures can be used to test and discipline new theories of the cross-section of stock returns. Almost any model of the cross-section of stock returns will have implications for the expected returns on individual cash flows, implications that can be tested directly in our data. As such, the data could be useful not only for the tests in this paper but for our continued understanding of the cross-section.

Finally, one limitation of our study is that we only observe near-future dividends. The near-future dividends constitute around 10% of the value of the underlying firms. To understand the full term structure of individual firms, one could potentially extrapolate the results on the near-future dividends using a flexible model as the one studied by Giglio, Kelly, and Kozak (2019). One can discipline such a model by forcing it to price the near-future cash flows we observe and use the model to makes statements about the entire term structure of returns on individual firms.

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A Detail on Data and Estimation

A.1 Cash-Flow Duration

To better understand the drivers of cash-flow duration, it is worthwhile to consider the Gordon Growth Model as a simple example. In the Gordon Growth Model, the expected return and cash-flow growth rates are assumed constant. Under these assumption, the duration of the cash flows is given by:

$$\text{DUR}_{\text{Gordon growth}} = \frac{1}{r - g} \tag{17}$$

where g is the constant growth rates, meaning that the duration is similar to the valuation ratio of the firm.

Equation (17) suggests that assets, or equities, have a long duration if they have a low expected return or a high expected growth rate. As expected returns is the endogenous variable that we are we are ultimately interested in, we use only expected growth rates to estimate the expected duration.

A.2 Measuring Realized Growth Rates

We calculate realized dividend growth rates for characteristic-sorted portfolios following Chen (2017). Each June, we construct portfolio breakpoints based on the most recent characteristics. We then calculate value-weighted portfolio weights for the subsequent 180 months. Using these weights, we calculate sans and cum dividend returns of the portfolio in each month. Using the sans dividend dividend return, we calculate how the value of a $1 investment in each portfolio develops over time, including delisting returns. Using the value of the portfolio, and the difference between the cum and sans dividend return, we calculate the monthly dividends to the portfolio.

More precisely, the value at time $t+s$ of the portfolio formed at period t is given by:

$$V^t_{t+s} = V^t_{t+s-1}(1 + retx^t_{t+s}) \tag{18}$$

where $retx^t_{t+s}$ is the sans dividend return between period $t+s-1$ and $t+s$ to the portfolio formed at time t. The dividends in period $t+s$ of the portfolio formed at period t is then given by:

$$D_{t+s}^{t} = V_{t+s-1}^{t}(ret_{t+s}^{t} - retx_{t+s}^{t}) \tag{19}$$

where ret_{t+s}^{t} is the cum dividend return between period $t+s-1$ and $t+s$ to the portfolio formed at time t.

For each formation period, we calculate the average dividends per \$100 initial investment in each year after formation until year 15. To calculate the dividend growth rate, we calculate the average dividends per year after formation across the different formation periods, and finally calculate dividend growth rates as the growth in the average dividends over the 15 years after formation.

A.3 Measuring Expected Return and Alpha on Dividend Strips

Because the dividend-strips sample is short, it is difficult to estimate the expected returns from the realized returns. Instead, we estimate expected returns by combining prices with the expected dividends on the same firms. That is, we download expected dividends per share from the IBES database and estimate expected returns as

$$E_t[r_{t,t+m}^{i,m}] = \left(\frac{E_t[D_{t+m}^{i,m}]}{P_t^{i,m}}\right)^{1/m} - 1 \tag{20}$$

where $E_t[r_{t,t+m}^{i,m}]$ is the expected return between period t and $t+m$ for the dividend on firm i that is paid out at period $t+m$. The term $E_t[D_{t+m}^{i,m}]$ is the expected value of the dividend at time t and $P_t^{i,m}$ is the price of the dividend at time t. We discard any observation where the expected annualized return is above 30% or below -10%. The expected dividends from IBES generally line up well with realizations: in our dividend strip sample, the loading of the realized dividends on expected dividends is around 0.9 and the correlation between the two is around 0.87, suggesting there is only limited measurement error.

We calculate expected alphas as:

$$\alpha_{t,t+m}^{i,m} = E_t[r_{t,t+m}^{i,m}] - \beta^{i,m}\lambda_{t,t;m}^{Mkt} \tag{21}$$

where $\alpha_{t,t+m}^{i,m}$ is the annualized alpha between period t and $t+m$ for the dividend paid out by firm i in period $t+m$, and $\lambda_{t,t;m}^{Mkt}$ is equal to the market risk premium (in future returns), which we assume is 5%. To calculate the alpha, we further need to estimate

$\beta^{i,m}$. We do so in monthly regressions of the return on the strip onto the market return where we include lags of the market to account for stale prices following Dimson (1979) and Lewellen and Nagel (2006). Following the literature, we impose the restriction that the last three lags have the same slope parameter to reduce the number of parameters. That is, we run the following monthly regression:

$$r^{i,m}_{t,t+1} = \beta^{i,m}_0 + \beta^{i,m}_1 r^{M,e}_{t+1} + \beta^{i,m}_2 r^{M,e}_t + \beta^{i,m}_3 (r^{M,e}_{,t-1} + r^{M,e}_{t-2} + r^{M,e}_{t-3}) + \epsilon^{i,m}_{t,t+1}, \tag{22}$$

where $r^{M,e}_{t+1}$ is the excess return on the market between period t and $t+1$, and we calculate $\beta^{i,m} = \beta^{i,m}_1 + \beta^{i,m}_2 + \beta^{i,m}_3$. Here t is measured in months and the maturity m is measured in years. We round up the maturity of the claim to the nearest integer; since the regressions are monthly, the maturity measured in years are often non-integer. That is, a claim has maturity of n when $12 \times (n-1) <$ maturity in months $\leq 12 \times n$.

When calculating the expected alpha, we estimate yield-to-maturity betas. We calculate these as the average betas over the remaining life of a given strip. When instance, the yield-to-maturity beta of a 3-year claim is the average beta on the 1-year, 2-year, and 3-year strip on the given firm.

A.4 Definition of Equity Characteristics

We define the book-to-market, profit, and investment characteristics following Fama and French (2015). We use the beta characteristic from Frazzini and Pedersen (2014). We follow Asness, Frazzini, and Pedersen (2019) and define payout as the total payout over the last five years divided by total profits over the last five years. Here, payout is measured as net income minus change in book equity from the year before, and total income is sales minus cost of goods sold.

A.5 Sample Periods

We work with four different sample periods in the US depending on data availability. Whenever we need IBES data, the sample starts in 1981. When doing cross-sectional factor analysis, the sample starts in 1963 because that is when the Fama and French five-factor model becomes available. When calculating the relation between growth rates and characterstics, the sample starts in 1952 because this is when compustat data on these characteristics becomes available. Finally, when studying the duration characteristic, the sample starts in 1929 because this is when the first variable needed to construct the characteristic becomes available (market beta).

B Duration-Driven Returns in the Lettau and Wachter (2007) Model

In this section, we show that the major equity risk factors all arise in the Lettau and Wachter (2007) model. In this model, the equity term structure is downward sloping because the cash-flow risk is higher on near-future cash flows than on distant future cash flows, and because discount-rate risk is not priced.

B.1 Model

The economy has an aggregate equity claim with dividends at time t denoted by D_t, where $d_t = \ln(D_t)$ evolves as

$$\Delta d_{t+1} = \mu_g + z_t + \sigma_d \epsilon_{d,t+1}. \tag{23}$$

Here $\mu_g \in \mathbb{R}$ is the unconditional mean dividend growth and z_t drives the conditional mean:

$$z_{t+1} = \varphi_z z_t + \sigma_z \epsilon_{z,t+1}, \tag{24}$$

where $0 < \varphi_z < 1$. Further, $\epsilon_{d,t+1}$ and $\epsilon_{z,t+1}$ are normally distributed mean-zero shocks with unit variance and σ_d, σ_z are their volatilities.

The risk-free rate r^f is constant and the stochastic discount factor is given by

$$M_{t+1} = \exp\left(-r^f - \frac{1}{2}x_t^2 - x_t \epsilon_{d,t+1}\right), \tag{25}$$

where the state variable x_t drives the price of risk:

$$x_{t+1} = (1 - \varphi_x)\bar{x} + \varphi_x x_t + \sigma_x \epsilon_{x,t+1}. \tag{26}$$

The parameter $\bar{x} \in \mathbb{R}^+$ is the long-run average, $0 < \varphi_x < 1$, and $\epsilon_{x,t+1}$ is a normally distributed mean-zero shock with unit variance and σ_x is the volatility. The three shocks have correlations denoted ρ_{dx}, ρ_{dz}, and ρ_{zx}, where $\rho_{zx} = 0$, $\rho_{dx} = 0$, and $\rho_{dz} < 0$, meaning that there is long-run insurance in dividend growth: a negative shock to dividends is over time partly offset by higher dividend growth.

To understand the stochastic discount factor, note that investors are averse towards shocks to dividends, $\epsilon_{d,t+1}$. A negative shock to dividends increases marginal utility and thus increases the value of the stochastic discount factor. The effect of a given shock on the stochastic discount factor depends on the price-of-risk variable x_t, which in this sense can be interpreted as a risk-aversion variable. In addition, shocks to the price of risk and the conditional growth rate z_t are only priced to the extent that they are correlated with the dividend shock.

B.2 Prices and Returns

The analysis is centered around the prices and returns on n-maturity dividend claims. The price of an n-maturity claim at time t is denoted P_t^n and the log-price is denoted $p_t^n = \ln(P_t^n)$. Since an n-maturity claim becomes and $n-1$ maturity claim next period, we have the following relation for prices:

$$P_t^n = E_t\left[M_{t+1}P_{t+1}^{n-1}\right], \tag{27}$$

with boundary condition $P_t^0 = D_t$, because the dividend is paid out at maturity. To solve the model, we conjecture and verify that the price dividend ratio is log-linear in the state variables z_t and x_t:

$$\frac{P_t^n}{D_t} = \exp\left(A^n + B_z^n z_t + B_x^n x_t\right). \tag{28}$$

The price dividend ratio can then be written as

$$\frac{P_t^n}{D_t} = E_t\left[M_{t+1}\frac{D_{t+1}}{D_t}\frac{P_{t+1}^{n-1}}{D_{t+1}}\right] = E_t\left[M_{t+1}\frac{D_{t+1}}{D_t}\exp\left(A^{n-1} + B_z^{n-1}z_{t+1} + B_x^{n-1}x_{t+1}\right)\right]. \tag{29}$$

Matching coefficients of (28) and (29), using (23) and (26), gives

$$\begin{aligned}
A^n &= A^{n-1} - r^f + \mu_g + B_x^{n-1}(1-\varphi_x)\bar{x} + \frac{1}{2}V^{n-1},\\
B_x^n &= B_x^{n-1}\left(\varphi_x - \rho_{dx}\sigma_x\right) - \sigma_d + B_z^{n-1}\rho_{dz}\sigma_z,\\
B_z^n &= \frac{1-(\varphi)_z^n}{1-\varphi_z},
\end{aligned}$$

where $B_x^0 = 0$, $A^0 = 0$, and

$$V^{n-1} = \mathrm{var}\left(\sigma_d\epsilon_{d,t+1} + B_z^{n-1}\sigma_z\epsilon_{z,t+1} + B_x^{n-1}\sigma_x\epsilon_{x,t+1}\right),$$

which provides the solution to the model and verifies the conjecture.

The term B_z^n is positive for all values of $n > 0$, meaning that the price increases relative to dividends when the expected growth rate of dividends increases. Similarly, B_x^n is negative for all values of $n > 0$, meaning that the price relative to dividends decreases when the price of risk is higher.

The simple return on the n maturity claim is denoted $R_{t+1}^n = P_{t+1}^{n-1}/P_t^n - 1$, and the log-return is $r_{t+1}^n = \ln\left(1 + R_{t+1}^n\right)$. The expected excess return is

$$
\begin{aligned}
E_t\left[r_{t+1}^n - r^f\right] + & \frac{1}{2}\mathrm{var}_t(r_{t+1}^n) && (30)\\
&= -\,\mathrm{cov}_t(r_{t+1}^n; m_{t+1}) && (31)\\
&= (\sigma_d + B_z^{n-1}\rho_{dz}\sigma_z)x_t. && (32)
\end{aligned}
$$

Because $\rho_{dz} < 0$ and B_z^n is strictly increasing in maturity n, the expected return decreases in maturity. Accordingly, the term structure of expected equity returns is downward sloping.

B.3 The Cross-Section of Stock Returns

Following Lettau and Wachter (2007), we introduce a cross-section of stocks by assuming the existence of $i = 1, \ldots, N$ firms that each produce a share s_t^i of the aggregate dividends. The share produced by each firm varies deterministically over time as the firms move through their life cycles. The share starts at $\underline{s}$ and grows at g_s each period until the share hits $\bar{s} = \underline{s} \times (1 + g_s)^{N/2}$ after which it decreases by g_s until the share hits $\underline{s}$ and the cycle repeats. The lower bar is set such that the shares sum to one cross-sectionally, meaning that $\underline{s} + \underline{s}(1 + g_s)^{N/2} + \sum_{i=1}^{N/2-1}(1 + g_s)^i\underline{s} = 1$. We assume $N = 200$ firms, meaning each firm has a life cycle of 50 years. The firms are identical except that they are at different points in their life cycle: the first firm starts at $\underline{s}$, the next firm has grown for one quarter, and so forth.

Given no arbitrage, the price of each firm is its share of future dividends times their present value,

$$
P_t^i = \sum_{n=1}^{\infty} s_{t+n}^i P_t^n, \tag{33}
$$

and the one-period return is given by end-of-period price plus the share of the aggregate dividend received at the end of the period, divided by beginning of period price:

$$R_{t+1}^i = \frac{P_{t+1}^i + s_{t+1}^i D_{t+1}}{P_t^i}. \tag{34}$$

To construct equity risk factors, we must calculate the book value of equity. We consider book value of equity as a measure of fundamental value that does not account for time-varying discount rates. Accordingly, we calculate book value as the present value of future dividends discounted using the unconditional average market risk premium. We then calculate investment as quarterly changes in book value, we calculate profitability as the dividends currently earned by the firm dividend by lagged book value of equity, and we calculate book-to-market as the book value divided by market value of equity. In addition, we calculate momentum as the running one-year return (skipping the most recent month), and we calculate betas as rolling three year betas.

B.4 Results in Simulated Data

To study the cross-section of stock returns, we run 1,000 simulations of 700 quarters of artificial data. For each simulation, we sort stocks at each period into equal-weighted quintile portfolios based on profitability, investment, book-to-market, market capitalization, and market beta. We then construct risk factors as long short portfolios based on the first and fifth quintile. For each simulation, we run CAPM regressions and calculate median intercepts and parameter estimates across the simulations. We also calculate the duration of each factor as the difference between the duration of the long and the short leg of the factor. When calculating the duration of the individual firms, we only consider the following 80 quarters of cash flows — for practical reasons, our firms never die, but when calculating the duration of the cash flows we want to ensure that we are not including the cash flows of its subsequent life-cycle, which we would do if looking at all future cash flows. The duration of a firm's cash flows is thus

$$D = \frac{\mathbf{Y}'\mathbf{P}}{\mathbf{e}'\mathbf{P}}, \tag{35}$$

where $\mathbf{Y}' = [0.25, \ldots, 80]$ is a column vector of quarters, $\mathbf{P}$ is a row vector of present values of dividends, and $\mathbf{e}'$ is a column vector with 1/80 in each column.

The CAPM alphas are reported in Table A2. The risk factors based on valuation, profitability, investment, and beta all have positive CAPM alpha of 0.2 to 0.6% per month. Accordingly, our model of the downward sloping equity term structure is able to explain the well known CAPM alpha associated with these characteristics.

The factors have positive alpha because they are all long short-duration stocks and short long-duration stocks. Indeed, as can be seen in the bottom row of Table A2, the duration is between -3 and -14 for the above-mentioned factors. This difference between the duration of the long and the short leg of the factors is large given that we only use 20 years to calculate duration.

In our model, the links between the risk factors and duration are as follows:

- *Profitability*: In our setting, a high profitability firm has high dividends relative to book value, which summarizes the total value of future dividends. If dividends are high today relative to future dividends, it means that the firm is on the peak of its life cycle and therefore has relatively short duration.
- *Investment*: A high investment firm has large growth in book value, meaning it has a large growth in the value of future dividends. Firms with large growth in the value of future dividends are usually in the beginning of their life cycle, and are therefore long-duration stocks.
- *Book-to-market (value)*: A value firm has a low price of future dividends, meaning their discount rate is high. Discount rates are higher for short-duration claims because the equity term structure is downward sloping. Accordingly, value firms tend to have short cash-flow duration. It is worth noting that value firms have short duration only because the equity term structure is downward sloping. Had it been upward sloping, value firms would have had long duration (as long-duration stocks would have had high discount rates and endogenously become value stocks).
- *Size*: Small firms have long duration because they are at the beginning of their life-cycle and are expected to experience a large growth in dividends.
- *Low beta*: In our model, long-duration stocks have high betas because they are more exposed to the discount rate shock, $\epsilon_{x,t+1}$, and the growth rate shock $\epsilon_{z,t+1}$ as seen in equation 30 (the loading on the shocks, B^n_x and B^n_z, both increase in absolute terms in maturity n, although B^n_x increases non-monotonically). Accordingly, a low-beta stock tends to be a short-duration stock.

While the Lettau and Wachter (2007) model of a downward sloping term structure is proposed to explain the value premium, the model appears better suited to explain the profitability and investment premium for multiple reasons. First, the profit and investment factors have larger alphas in our model than the value factor. Second, the return to the profit and investment factors are more directly related to the slope of the equity term structure. Indeed, in a hypothetical upward sloping model, the profit and investment factors have negative expected returns, whereas the value factor still has positive expected returns. The positive expected returns to the value factor remains because the factor now goes long the long-duration stocks (the book-to-market ratio now identifies the long-duration stocks as endogenously cheap stocks with high expected returns). In the empirical section, we take care not to use market prices when estimating duration to avoid this problem of endogenously identifying firms with high expected returns as short-duration stocks.

Table 1
Growth Rates and the Characteristics that Predict Returns

This table shows the relation between future growth rates and the characteristics that predict returns. Panel A shows the results of a regression analysis for 50 characteristics sorted portfolios. The dependent variables are the realized 15-year growth rates of dividends and earnings and the explanatory variables are the average characteristics of the 50 portfolios. Panel B reports the univariate correlations between the expected growth rates and firm characteristics. The expected growth rates are the median long-term growth (LTG) expectations from IBES. Panel C and D reports results from monthly firm level panel regressions. The dependent variable is the long-term growth rates from survey data and the explanatory variables are contemporaneous firm characteristics. Standard errors are two-way clustered across firm and date. All characteristics and survey growth rates are measured in cross-sectional percentiles. The sample is 1952-2018 in Panel A and 1981 to 2018 in Panel B and C.

Panel A: Portfolio level regressions

Dependent variable:	Explanatory variables					
	High value	High profit	Low inv	Low beta	High pay	R^2
Realized 15-year dividend growth rate	**-0.03**	**-0.01**	**-0.04**	**-0.02**	**-0.01**	0.83
	(-2.79)	(-2.26)	(-6.77)	(-3.25)	(-2.49)	
Realized 15-year earnings growth rate	**-0.02**	-0.01	**-0.04**	**-0.02**	**-0.01**	0.84
	(-1.99)	(-0.95)	(-7.92)	(-3.08)	(-2.48)	

Panel B: Firm-level univariate correlations between characteristics and analyst expectations of growth rates

	High BM	High profit	Low invest	Low beta	High pay
Expected growth (LTG)	-0.38	-0.13	-0.26	-0.29	-0.30

Panel C: Firm-level regressions of survey expected growth rates on different characteristics

US Only	Dependent variable: analyst expected growth rates (LTG)					
	(1)	(2)	(3)	(4)	(5)	(6)
High BM	**-0.493**	**-0.544**	**-0.329**	**-0.304**	**-0.282**	**-0.447**
	(-52.86)	(-22.31)	(-27.78)	(-21.24)	(-35.42)	(-51.68)
High profit	**-0.191**	**-0.240**	**-0.053**	**-0.123**	**-0.076**	**-0.201**
	(-21.62)	(-10.25)	(-5.92)	(-9.28)	(-10.68)	(-22.96)
Low investment	**-0.093**	**-0.090**	**-0.036**	**-0.042**	**-0.042**	**-0.075**
	(-16.07)	(-4.71)	(-7.06)	(-8.22)	(-12.23)	(-13.57)
Low beta	**-0.174**	**-0.277**	**-0.029**	**-0.055**	**-0.052**	**-0.131**
	(-18.22)	(-12.40)	(-2.97)	(-5.32)	(-7.66)	(-14.74)
High payout	**-0.262**	**-0.203**	**-0.120**	**-0.086**	**-0.102**	**-0.238**
	(-33.21)	(-7.85)	(-12.90)	(-8.87)	(-15.74)	(-31.87)
Fixed effect	Date	Date	Firm/Date	Firm/Date	Firm/Date	Date
Cluster	Firm/Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date
Weight	Analysts	Market Cap	Analysts	Analysts	None	None
Sample	Full	Full	Early	Late	Full	Full
Observations	539,297	539,297	269,457	269,733	539,225	539,297
R-squared	0.48	0.44	0.81	0.74	0.68	0.33

Table 1 -- Continued
Growth Rates and the Characteristics that Predict Returns

Panel D: Firm-level regressions of survey expected growth rates on different characteristics – International Evidence

Non-US	Dependent variable: analyst expected growth rates (LTG)					
	(1)	(2)	(3)	(4)	(5)	(6)
High value	**-0.167**	**-0.202**	**-0.147**	**-0.138**	**-0.118**	**-0.150**
	(-15.77)	(-9.52)	(-6.14)	(-7.41)	(-9.01)	(-15.69)
High profit	**-0.078**	**-0.092**	-0.054	**-0.232**	**-0.126**	**-0.066**
	(-7.28)	(-3.62)	(-2.07)	(-12.25)	(-9.76)	(-7.14)
Low investment	**-0.027**	-0.007	**-0.021**	**0.028**	0.008	**-0.027**
	(-3.55)	(-0.50)	(-2.10)	(-3.65)	(-1.27)	(-3.98)
Low beta	**-0.058**	**-0.126**	0.023	0.013	-0.004	**-0.053**
	(-5.41)	(-7.16)	(-1.32)	(-0.86)	(-0.34)	(-5.54)
High payout	**-0.144**	**-0.134**	**-0.048**	**-0.040**	**-0.059**	**-0.129**
	(-15.08)	(-7.86)	(-2.79)	(-2.71)	(-5.99)	(-15.00)
Fixed effect	Date	Date	Firm/Date	Firm/Date	Firm/Date	Date
Cluster	Firm/Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date
Weight	Analysts	Market Cap	Analysts	Analysts	None	None
Sample	Full	Full	Early	Late	Full	Full
Observations	290,418	290,418	103,152	187,157	290,343	290,418
R-squared	0.06	0.10	0.49	0.39	0.35	0.04

Table 2
Risk and Return for Portfolios Sorted on Duration

This table shows the risk and return characteristics for ten long-only portfolios sorted on duration and a long-short portfolio. We sort stocks into ten groups based on our measure of ex ante duration. Portfolio weights are value-weighted and rebalanced monthly and the breakpoints are refreshed each June and based on NYSE firms. CAPM alpha is the intercept in a regression of the excess return to the portfolio on the excess return to the market portfolio. We report *t*-statistics in parenthesis under parameter estimates and statistical significance at the five percent level is marked in bold. Sharpe ratios and information ratios are annualized. Excess return and alphas are in monthly percent. Realized duration is calculated based on the assumption that dividend growth rates of the portfolios continue forever and a constant discount rate of 8% per year for all portfolios. Sample is US firms from 1929 to 2018.

	Portfolios sorted on duration										Long/short
	1	2	3	4	5	6	7	8	9	10	10 minus 1
Excess return	**0.68**	**0.68**	**0.61**	**0.67**	**0.71**	**0.80**	**0.69**	**0.72**	**0.66**	0.51	-0.17
	(5.78)	(5.13)	(4.09)	(4.11)	(3.98)	(4.19)	(3.26)	(3.19)	(2.56)	(1.70)	(-0.76)
CAPM alpha	**0.30**	**0.23**	0.09	0.09	0.08	**0.12**	-0.06	-0.08	**-0.24**	**-0.50**	**-0.81**
	(5.13)	(4.38)	(1.81)	(1.95)	(1.50)	(2.23)	(-0.96)	(-1.16)	(-2.70)	(-4.21)	(-5.26)
CAPM beta	**0.63**	**0.74**	**0.86**	**0.95**	**1.05**	**1.12**	**1.25**	**1.32**	**1.48**	**1.67**	**1.05**
	(57.33)	(77.78)	(95.31)	(108.88)	(111.12)	(110.26)	(107.61)	(105.42)	(91.08)	(75.31)	(36.84)
Sharpe ratio	0.61	0.54	0.43	0.43	0.42	0.44	0.34	0.34	0.27	0.18	-0.08
Information ratio	0.54	0.47	0.19	0.21	0.16	0.24	-0.10	-0.12	-0.29	-0.45	-0.56
Adjusted-R^2	0.75	0.85	0.89	0.92	0.92	0.92	0.91	0.91	0.88	0.84	0.56
# of observations	1079	1079	1079	1079	1079	1079	1079	1079	1079	1079	1079
Realized dividend growth rates	2%	3%	4%	4%	4%	4%	5%	5%	6%	7%	
Analyst expected growth rates	7%	8%	9%	9%	10%	11%	12%	13%	13%	16%	
Realized duration	15	17	18	18	20	20	24	28	33	59	

Table 3
The Duration Factor

This table shows the risk and return characteristics for the portfolios that constitute our duration factor. We sort stocks into six portfolios based on ex ante size and duration. The breakpoints are the median market capitalization and the 30th and 70th percentile of duration. Portfolio weights are value-weighted and rebalanced monthly and the breakpoints are refreshed each June and based on NYSE firms. The duration factor is long 50 cent in the two long-duration portfolios and short 50 cent in each of the two short-duration portfolios. CAPM alpha is the intercept in a regression of the risk factor on the excess return to the market portfolio. We report *t*-statistics in parentheses under parameter estimates and statistical significance at the 5% level is marked in bold. Sharpe ratios and information ratios are annualized. Excess return and alphas are in monthly percent. Returns in the US sample are from 1963 to 2018, realized growth is from 1929-2018, and expected growth is from 1981-2018. The global sample is from 1990 to 2018.

	Long duration		Short duration		Duration factor
Panel A: US	Large cap	Small cap	Large cap	Small cap	
Excess return	0.40	**0.61**	**0.56**	**0.92**	0.23
	(1.83)	(2.24)	(3.90)	(5.44)	(1.91)
CAPM alpha	**-0.22**	-0.08	**0.17**	**0.50**	**0.48**
	(-3.89)	(-0.60)	(3.23)	(5.70)	(5.39)
CAPM beta	**1.24**	**1.40**	**0.79**	**0.85**	**-0.50**
	(98.47)	(45.85)	(66.06)	(43.16)	(-24.69)
Sharpe ratio	0.25	0.30	0.52	0.73	0.26
Information ratio	-0.53	-0.08	0.44	0.77	0.73
Adjusted-R^2	0.94	0.76	0.87	0.74	0.48
# of observations	666	666	666	666	666
Analyst expected growth	13.6%	15.9%	8.1%	8.8%	-6.3%
Realized dividend growth	4.3%	5.7%	1.6%	1.7%	-3.6%

	Long duration		Short duration		Duration factor
Panel B: Global	Large cap	Small cap	Large cap	Small cap	
Excess return	0.34	0.32	**0.52**	**0.66**	**0.26**
	(1.18)	(1.04)	(2.57)	(3.08)	(2.03)
CAPM alpha	**-0.12**	-0.14	**0.20**	**0.34**	**0.40**
	(-2.26)	(-1.15)	(3.47)	(3.68)	(4.44)
CAPM beta	**1.17**	**1.19**	**0.81**	**0.80**	**-0.37**
	(94.99)	(42.16)	(61.89)	(38.50)	(-18.12)
Sharpe ratio	0.22	0.20	0.48	0.58	0.38
Information ratio	-0.43	-0.22	0.65	0.69	0.84
Adjusted-R^2	0.96	0.84	0.92	0.81	0.49
# of observations	342	342	342	342	342
Analyst expected growth	11.4%	14.9%	7.3%	8.3%	-5.4%

Table 4
Summarizing the Major Risk Factors with the Duration Factor

This table shows the results of factor regressions in the US sample and in the broad global sample. Each factor is on six portfolios based on ex ante size and the characteristic the portfolio is sorted on. The breakpoints are the median market capitalization and the 30th and 70th percentile of duration. Portfolio weights are value-weighted and rebalanced monthly and the breakpoints are refreshed each June and based on NYSE firms. Each factor is long 50 cent in the two high-characteristic portfolios and short 50 cent in each of the two low-characteristic portfolios, except the SMB factor, which is long the small duration-sorted portfolios and short the large duration-sorted portfolios. We construct global factors as the market-cap weighted average of country specific factors. Three-factor alpha is in the intercept in a regression of the given equity risk factor on the market portfolio, the duration factor, and the SMB factor. CAPM alpha is the intercept in a regression of the risk factor on the excess return to the market portfolio. We report *t*-statistics in parentheses under parameter estimates and statistical significance at the 5% level is marked in bold. The US sample is from 1963 to 2018 and the global sample is from 1990 to 2018.

Panel A: US Sample

Factor	CAPM model			Three-factor model						
	α_{CAPM}	β_{CAPM}	R^2	α_{Three}	β_{Mkt}	β_{Smb}	β_{Dur}	R^2	*LTG*	*# obs*
HML	**0.32**	**-0.14**	0.29	-0.08	**0.14**	**0.36**	**0.63**	0.26	-9.8%	666
	(2.82)	(-5.61)		(-0.73)	(4.27)	(9.42)	(13.42)			
RMW	**0.28**	**-0.11**	0.39	0.10	**0.11**	**-0.10**	**0.42**	0.35	-5.0%	666
	(3.69)	(-6.17)		(1.59)	(5.54)	(-3.95)	(13.94)			
CMA	**0.30**	**-0.15**	0.44	0.07	0.01	**0.21**	**0.36**	0.32	-6.7%	666
	(4.57)	(-9.73)		(1.23)	(0.69)	(9.61)	(13.09)			
BETA	**0.56**	**-0.81**	0.12	0.03	**-0.26**	0.01	**1.08**	0.83	-8.0%	631
	(4.36)	(-28.39)		(0.30)	(-10.33)	(0.43)	(28.97)			
PAYOUT	**0.24**	**-0.32**	0.13	-0.07	-0.01	0.02	**0.62**	0.78	-7.0%	666
	(3.51)	(-20.69)		(-1.54)	(-0.87)	(1.34)	(32.12)			

Panel B: Global Sample

Factor	CAPM model			Three-factor model						
	α_{CAPM}	β_{CAPM}	R^2	α_{Three}	β_{Mkt}	β_{Smb}	β_{Dur}	R^2	*LTG*	*# obs*
HML	0.24	-0.03	0.33	0.01	**0.17**	**0.17**	**0.53**	0.12	-7.8%	342
	(1.86)	(-1.04)		(0.10)	(4.26)	(2.68)	(7.03)			
RMW	**0.35**	**-0.17**	0.62	**0.13**	**0.05**	**-0.15**	**0.57**	0.68	-4.8%	342
	(4.54)	(-9.63)		(2.52)	(2.99)	(-5.90)	(19.07)			
CMA	**0.23**	**-0.09**	0.49	0.08	0.03	**0.21**	**0.31**	0.25	-5.7%	342
	(3.18)	(-5.46)		(1.23)	(1.42)	(6.12)	(7.82)			
BETA	**0.47**	**-0.72**	0.17	-0.05	**-0.23**	**0.10**	**1.26**	0.89	-6.5%	307
	(3.23)	(-22.68)		(-0.65)	(-9.53)	(2.42)	(27.11)			
PAYOUT	**0.24**	**-0.20**	0.34	-0.01	**0.04**	0.00	**0.62**	0.68	-6.7%	342
	(3.16)	(-11.41)		(-0.21)	(2.19)	(-0.05)	(19.85)			

Table 5
Evaluating the Duration Factor's Contribution to the Factor Zoo

This table shows the results from applying the Feng, Giglio, and Xiu (FGX, 2020) machine-learning test for the contribution of the duration factor in explaining the cross-section, relative to a high-dimensional set of potential control factors. The test assets are the same 750 portfolios used by FGX, constructed from 2×3 bivariate sorts of 125 characteristics. The 151 potential control factors are our small-minus-big factor constructed using 2×3 size-duration sorts, along with the 150 factors considered by FGX. Each entry in the first row of the table is a separate estimate for λ_{DUR}, the loading on the duration factor in the stochastic discount factor. The first column ("FGX Double-Selection") uses the benchmark estimator proposed by FGX, a two-pass lasso estimator, to select the control variables in a cross-sectional regression for test-asset returns. The second column ("FF3") uses only the Fama and French (1993) factors as controls in addition to the duration factor. The third column ("No Selection, OLS") uses all possible factors as controls, without any dimension reduction. Following FGX, the estimates are scaled to correspond to an average excess return (in bps per month) estimated from a cross-sectional regression of test assets on the duration and control factors, in which the univariate beta of the test-asset portfolio with respect to the duration factor has been normalized to one. We report *t*-statistics in parentheses under parameter estimates, calculated using the FGX inference procedure, and statistical significance at the 5% level is marked in bold. The sample is from July 1976 to December 2017, matching the availability of test-asset and factor returns used by FGX.

	FGX Double-Selection	FF3	No Selection, OLS
λ_{DUR} (bps)	**220.4**	**81.1**	**227.2**
	(2.84)	(3.20)	(2.20)

Table 6
Summary Statistics on Single-Stock Dividend Futures

This table reports summary statistics for our matched sample on single-stock dividend futures. Single-stock dividend futures are futures prices for dividends paid out in a given calendar-year on a given firm. Panel A reports statistics for realized annual returns on the individual strips. Each contract is for the dividends on 1,000 shares. The price of the contract is measured in local currency, which can be USD, EUR, GBP, or CHE. Panel B shows summary stats on the maturity of the strips and CAPM betas of the strips. The CAPM betas are measured in time-series regressions of monthly returns on the market portfolio in the given country, including lags, as explained in the Appendix. Panel C shows the characteristics of the firms in our sample, measured in cross-sectional percent of the firms listed in same country as the given firm. The sample is from 2010 to 2019.

	# obs	Mean	Sd	Min	Max
Panel A: Returns and prices					
Annual returns	1,508	0.048	0.21	-1	1.32
Annual returns (using settlement prices)	1,508	0.049	0.21	-1	1.32
Annual log-returns	1,497	0.034	0.22	-2.33	0.84
Annual volume	1,748	11,692	41,281	0	1.07e+06
Open interest	1,748	5,383	15,286	1	341,816
Price of contract	1,748	2,127	3,905	0	69,000
Notional (in thousands)	1,748	4,041	6,959	0	71,781
Panel B: Maturity and Betas					
One-year dummy	1,748	0.36	0.48	0	1
Two-year dummy	1,748	0.32	0.47	0	1
Three-year dummy	1,748	0.22	0.42	0	1
Four-year dummy	1,748	0.090	0.29	0	1
Maturity (in years)	1,748	2.04	0.97	1	5
CAPM beta of strip	1,748	0.52	0.84	-1	1.50
CAPM beta of strip (untrimmed)	1,748	1.58	25.3	-86.8	729
# Obs for CAPM beta	1,748	36.4	27.3	2	101
Panel C: Sample Representativeness					
Duration	1,748	38.8	31.0	0.078	100
Book-to-market	1,503	52.3	26.2	2.60	100
Market Cap	1,748	97.2	3.22	74.1	100
Operation profit	1,493	63.5	22.1	4.62	99.9
Investment	1,503	49.8	21.9	2.46	98.5
Beta	1,737	74.3	18.0	7.45	100
Payout	1,474	68.0	21.2	0.39	100

Table 7
Expected Return and Alpha on Single Stock Dividend Futures

This table reports results from panel regressions with expected return and alphas to single stock dividend futures as dependent variables. We calculate expected returns as the expected yield to maturity using expected dividends per share from the IBES database. Alphas are expected returns minus beta times a market risk premium of 5%. Regressions are annual using end-of-December prices. See Appendix for details on how we calculate expected return and betas. In the equations below, *t, i,* and *m* denotes time, firm, and maturity of the strip at time *t* (measured in years). The data are from 2010 to 2019. Standard errors are reported in parentheses.

Panel A: Expected returns and alphas

Expected returns: $E_t\left[r_{t+m}^{i,m}\right] = \left(\frac{E_t[D_{t+m}^{i}]}{f_t^{i,m}}\right)^{1/m}$

CAPM alphas: $\alpha_{t+m}^{i,m} = E_t\left[r_{t+m}^{i,m}\right] - \beta^{i,m} \times 5\%$

Dependent variable	Expected ret	Expected ret	Expected ret	CAPM alpha	CAPM alpha	CAPM beta
2-year dummy		0.00	-0.00	-0.01*	-0.01*	0.42***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.12)
3-year dummy		-0.00	-0.01*	-0.03***	-0.02**	0.81***
		(0.00)	(0.00)	(0.01)	(0.01)	(0.11)
4-year dummy		-0.02***	-0.02***	-0.04***	-0.04***	0.81***
		(0.00)	(0.00)	(0.01)	(0.01)	(0.13)
CAPM beta of strip ($\beta^{i,m}$)	0.01***		0.01***			
	(0.00)		(0.00)			
CAPM beta of firm (β^{i})	0.05**		0.05**			0.59**
	(0.02)		(0.02)			(0.19)
Cash-flow duration of firm	0.00		0.00	0.00	0.00	
	(0.00)		(0.00)	(0.00)	(0.00)	
Observations	1,245	1,255	1,245	1,255	1,255	1,736
R-squared	0.13	0.10	0.14	0.10	0.17	0.20
Fixed effect	Date/Cur	Date/Cur	Date/Cur	Date/Cur	Date/Cur	Date/Cur
Cluster	Date/Firm	Date/Firm	Date/Firm	Date/Firm	Date/Firm	Date/Firm
Weight	None	None	None	None	Notional	None

Table 8

Realized Return and Alpha on the Annual Horizon for Single Stock Dividend Futures

This table reports results from panel regressions with realized return and alphas to single stock dividend futures as dependent variables. A single stock dividend future is the price for the dividend that is paid out in a given year by a given firm. We calculate realized annual returns for each calendar year. We calculate realized alpha as the realized returns minus the product of the realized market return and the beta of the strip. The beta of the strip is estimated in first-stage regressions (see Appendix A for details). In the equations below, *t, i,* and *m* denotes time, firm, and maturity of the strip at time *t* (measured in years). The data are from 2010 to 2019. Standard errors are reported in parentheses.

Panel A: Realized versus expected returns

Expected returns: $E_t\left[r_{t+m}^{i,m}\right] = \left(\frac{E_t[D_{t+m}^{i}]}{f_t^{i,m}}\right)^{1/m}$

Realized returns: $r_{t+1}^{i,m} = f_{t+1}^{i,m}/f_t^{i,m}$

Dependent variable	Realized return	Realized returns	Realized log-return	Realized log-return	Realized return	Realized log-return
Expected return	0.67***	0.75***			0.43	
	(0.17)	(0.17)			(0.29)	
Expected log-return			0.70***	0.80***		0.43
			(0.14)	(0.14)		(0.26)
Observations	1,075	1,075	1,070	1,070	1,075	1,070
R-squared	0.203	0.250	0.171	0.217	0.147	0.158
Fixed effect	Firm	Date/Firm	Firm	Date/Firm	Firm	Date/Firm
Cluster	Date/Firm	Date/Firm	Date/Firm	Date/Firm	Date/Firm	Date/Firm
Weight	None	None	None	None	Notional	Notional

Panel B: Realized returns and alphas

Realized returns: $r_{t+1}^{i,m} = f_{t+1}^{i,m}/f_t^{i,m}$

Realized alphas: $\tilde{\alpha}_{t+1}^{i,m} = r_{t+1}^{i,m} - \beta^{i,m} r_{t+1}^{Mkt}$

Dependent variable	Realized returns	Realized log-returns	Realized alpha	Realized alpha	Realized log-alpha	Realized log-alpha
2-year dummy	0.0039	-0.00081	-0.033	-0.033	-0.037	-0.037*
	(0.019)	(0.016)	(0.025)	(0.023)	(0.023)	(0.019)
3-year dummy	0.013	0.0018	-0.060	-0.060	-0.070*	-0.070*
	(0.031)	(0.028)	(0.040)	(0.041)	(0.038)	(0.037)
4-year dummy	-0.018	-0.035	-0.084*	-0.084*	-0.10**	-0.10**
	(0.035)	(0.033)	(0.042)	(0.043)	(0.043)	(0.042)
Observations	1,500	1,489	1,500	1,500	1,489	1,489
R-squared	0.205	0.164	0.244	0.244	0.213	0.213
Fixed effect	Date/Firm	Date/Firm	Date/Firm	Date/Firm	Date/Firm	Date/Firm
Cluster	Date/Firm	Date/Firm	Date/Firm	Date/Strip	Date/Firm	Date/Strip
Weight	None	None	None	None	None	None

Panel C: Realizations and firm characteristics

Dependent variable	Realized returns	Realized log-returns	Realized alpha	Realized alpha	Realized log-alpha	Realized log-alpha
2-year dummy	0.0043	-0.0028	-0.030	-0.036	-0.042	-0.042
	(0.020)	(0.015)	(0.025)	(0.021)	(0.024)	(0.023)
3-year dummy	0.0076	-0.0048	-0.063	-0.075*	-0.068	-0.068
	(0.033)	(0.028)	(0.041)	(0.035)	(0.037)	(0.038)
4-year dummy	-0.017	-0.036	-0.083	-0.10*	-0.092	-0.092
	(0.035)	(0.034)	(0.046)	(0.046)	(0.069)	(0.069)
Cash-flow duration of firm	-0.00073	-0.0012	-0.0017	-0.0021	-0.0034*	-0.0034*
	(0.0016)	(0.0014)	(0.0015)	(0.0013)	(0.0018)	(0.0017)
Observations	1,507	1,496	1,507	1,496	1,496	1,496
R-squared	0.046	0.039	0.061	0.064	0.082	0.082
Fixed effect	Date/currency	Date/currency	Date/currency	Date/currency	Date/currency	Date/currency
Cluster	Date/Firm	Date/Firm	Date/Firm	Date/Firm	Date/Firm	Date/Strip
Weight	None	None	None	Notional	None	Notional

Panel D: Expectations errors

Dependent variable	Realized returns – Expected returns		Realized log-returns – Expected log-returns	
2-year maturity dummy	0.0062	0.0062	-0.0019	-0.0010
	(0.016)	(0.016)	(0.013)	(0.012)
3-year maturity dummy	0.014	0.014	-0.0053	-0.0047
	(0.031)	(0.031)	(0.029)	(0.029)
4-year maturity dummy	-0.0028	-0.0028	-0.024	-0.024
	(0.031)	(0.031)	(0.034)	(0.034)
Cash-flow duration of firm	-0.0021	-0.0021	-0.0019*	-0.0021*
	(0.0013)	(0.0013)	(0.00098)	(0.0011)
Observations	1,081	1,081	1,076	1,076
R-squared	0.076	0.076	0.067	0.071
Fixed effect	Date/currency	Date/currency	Date/currency	Date/currency
Cluster	Date/Firm	Date/Firm	Date/Firm	Date/Firm
Weight	None	Notional	None	Notional

Table 9
CAPM Alpha on Corporate Bonds

This table reports CAPM alphas for corporate bond portfolios. We sort firms into two groups based on the median firm characteristic. Within each group, we sort all outstanding corporate bonds into portfolios based on maturity. Portfolio weights are equal-weighted and rebalanced monthly. We calculate CAPM alpha as the intercept in a time series regression of monthly excess portfolio returns on the excess market returns. Excess returns are calculated as returns in excess of a treasury claim with the same maturity. The market return is the equal-weighted return across all bonds. We report *t*-statistics below parameter estimates in parenthesis. Bold font marks statistical significance at the 5% level. Alphas are annualized. The sorting is such that the 2-year portfolio, for instance, contains all bonds with maturity between 1 and 2 years. The sample is US firms from 2002 to 2016.

	Maturity of bonds (in years)							
	1	2	5	7	10	20	30	Average
Panel A: Duration								
Short-duration firms	**0.02**	**0.01**	0.00	-0.01	0.00	**-0.02**	-0.03	-0.01
	(5.25)	(2.76)	(0.71)	(-1.41)	(-0.05)	(-3.10)	(-1.94)	
Long-duration firms	**0.03**	0.01	0.00	-0.01	-0.01	**-0.03**	-0.03	-0.01
	(3.75)	(1.13)	(-0.63)	(-1.29)	(-0.92)	(-4.09)	(-1.19)	
Average	0.02	0.01	0.00	-0.01	0.00	-0.03	-0.03	
Panel B: Growth								
Low-LTG firms	**0.03**	0.01	0.00	-0.01	-0.01	**-0.03**	**-0.04**	-0.01
	(4.27)	(1.82)	(0.19)	(-1.85)	(-0.91)	(-3.75)	(-2.30)	
High-LTG firms	**0.02**	0.01	0.00	0.00	0.00	**-0.02**	-0.03	0.00
	(3.53)	(1.67)	(-0.25)	(-1.22)	(0.06)	(-3.11)	(-1.56)	
Average	0.03	0.01	0.00	-0.01	0.00	-0.02	-0.04	
Panel C: Value								
Low BM firms	**0.01**	0.01	0.00	0.00	0.00	**-0.02**	-0.03	-0.01
	(3.53)	(1.64)	(0.89)	(-0.97)	(-0.02)	(-3.37)	(-1.76)	
High BM firms	**0.03**	0.01	-0.01	**-0.01**	-0.01	**-0.03**	**-0.04**	-0.01
	(3.94)	(1.75)	(-0.95)	(-2.04)	(-1.21)	(-3.86)	(-2.20)	
Average	0.02	0.01	0.00	-0.01	0.00	-0.03	-0.04	

Table 10
The Equity Yield Curve

Panel A reports the results of regressions of the slope of the equity yield curve onto the slope of the bond yield curve. Panel B and C report results of predictive regressions. We regress the future realized returns of different risk factors on the ex ante level and slope of the equity yield curve. The level is the equal weighted log book-to-market ratio of the four sub portfolios in the duration factor, and the slope is the average log book-to-market ratio of the long-leg of the two long-duration portfolios in the duration factor minus the average log book-to-market ratio of the two short-duration portfolios in the duration factor. In Panel B, we run monthly regressions of annualized returns. In Panel C, we run monthly regressions with varying holding horizon. We report *t*-statistics based on Newey West standard errors in parentheses under parameter estimates and statistical significance at the five percent level is marked in bold.

Panel A: Equity and bond yield curves

	Dependent variable: slope of equity yield curve			
Sample period:	Full sample	1929-1974	1974-1995	1995-2018
Slope of bond yield curve	**32.74**	**58.02**	11.98	**25.66**
	(4.97)	(12.07)	(1.93)	(5.41)
Adjusted-R^2	0.18	0.65	0.08	0.59
# of observations	1074	546	252	276

Panel B: Predicting risk factors

	DUR	HML	RMW	CMA	Low Risk	Payout
Level of equity yield curve	-0.14	0.07	-0.06	0.01	-0.11	**-0.06**
	(-1.90)	(1.11)	(-1.50)	(0.37)	(-1.35)	(-2.30)
Slope of equity yield curve	**-0.23**	**-0.14**	-0.06	**-0.10**	**-0.25**	**-0.12**
	(-4.08)	(-2.84)	(-1.59)	(-2.77)	(-4.28)	(-3.79)
Slope of bond yield curve	1.02	1.82	0.24	1.62	-0.10	1.31
	(0.47)	(1.17)	(0.25)	(1.50)	(-0.04)	(0.88)
Adjusted-R^2	0.18	0.09	0.06	0.10	0.16	0.16
# of observations	654	654	654	654	619	654

Panel C: Predicting market returns

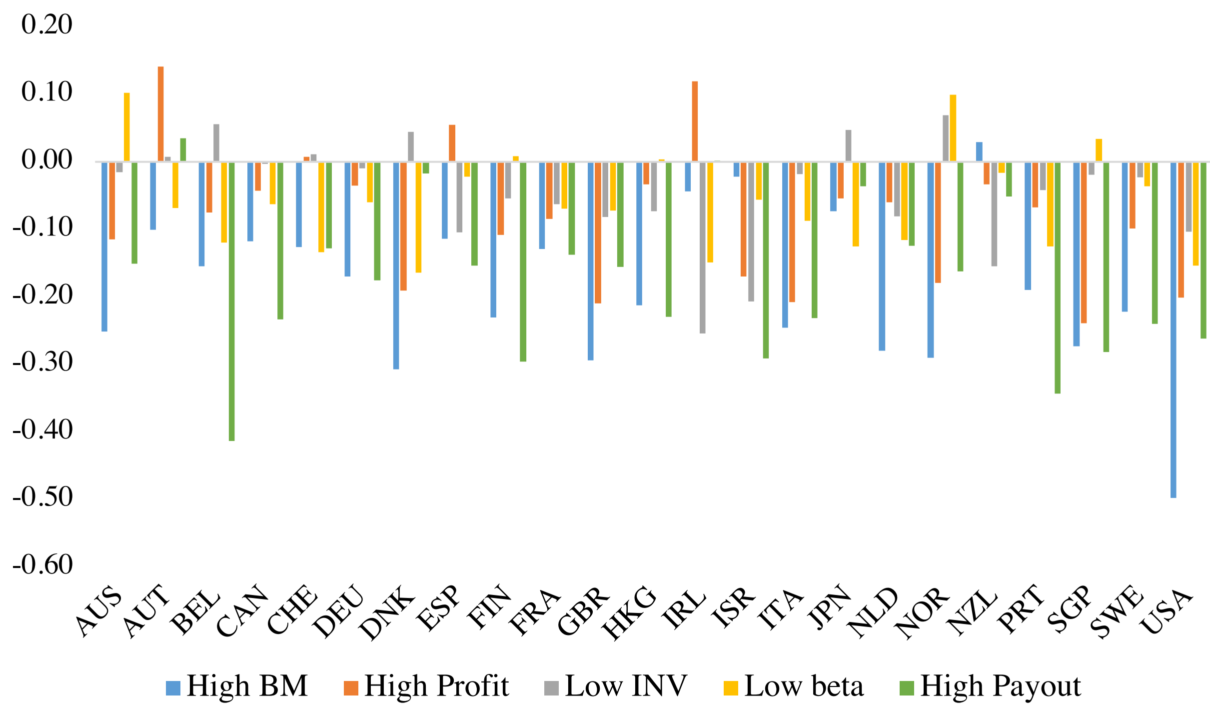
	MKT	MKT	MKT	MKT	MKT
Horizon	1 year	2 years	3 years	4 years	5 years
Level of equity yield curve	**0.17**	**0.29**	**0.37**	**0.55**	**0.85**
	(2.52)	(2.20)	(1.97)	(2.28)	(3.00)
Slope of equity yield curve	0.03	-0.09	**-0.31**	**-0.54**	**-0.74**
	(0.57)	(-0.97)	(-2.57)	(-3.21)	(-3.76)
Slope of bond yield curve	2.22	**9.50**	**18.54**	**28.50**	**35.45**
	(1.26)	(2.75)	(4.78)	(5.95)	(4.87)
Adjusted-R^2	0.08	0.15	0.24	0.35	0.41
# of observations	654	642	630	618	606

Figure 2

Loadings of Expected Growth Rates on Characteristics That Predict Returns: Global Evidence

This figure shows the loading of expected growth rates on characteristics that predict returns. In each country, we regress the expected growth rates on the below characteristics in multivariate panel regressions. In almost all cases, the characteristics that predict high also returns predict low expected growth.

Panel A: All countries



Panel B: G7 countries

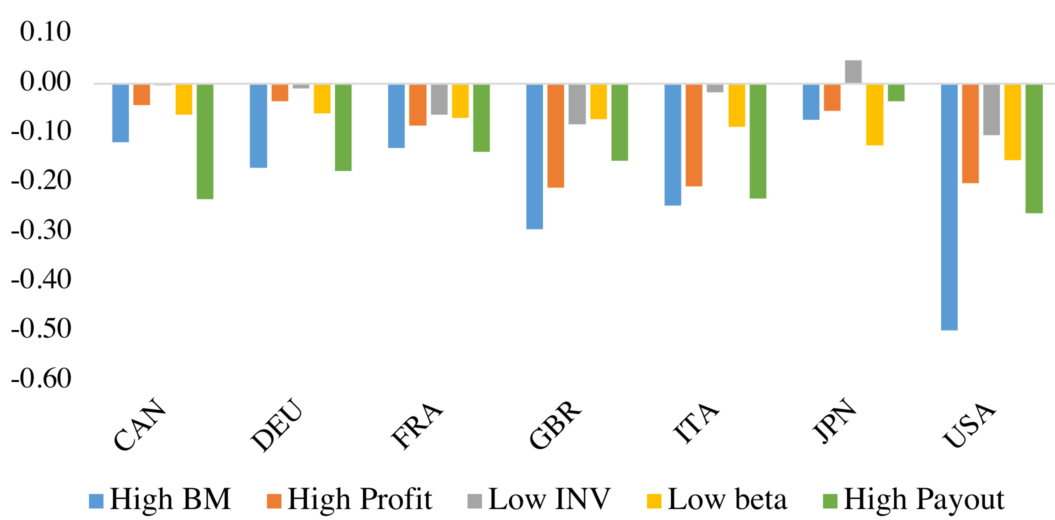


Figure 2 Continued
Loadings of Expected Growth Rates on Characteristics That Predict Returns: Global Evidence

Panel C: Individual Characteristics

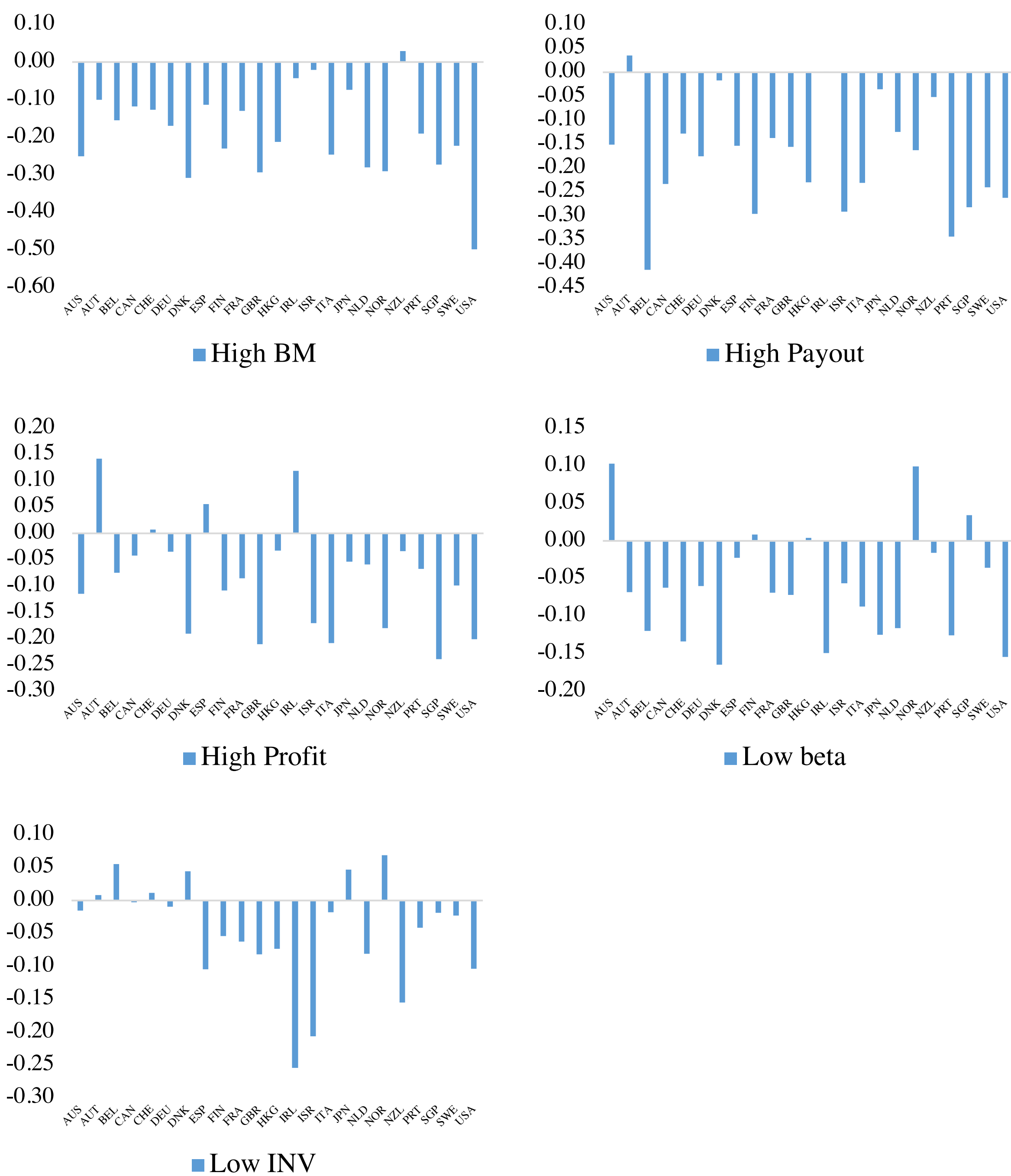


Figure 3
Cumulative return and CAPM alpha to the Duration Factor

This figure shows the cumulative excess return and CAPM alpha to the duration factor. The duration factor is constructed as follows. We sort stocks into six portfolios based on ex ante size and duration. The breakpoints are the median market capitalization and the 30th and 70th percentile of duration. Portfolio weights are value-weighted and rebalanced monthly and the breakpoints are refreshed each June and based on NYSE firms. The duration factor is long 50 cent in the two high-duration portfolios and short 50 cent in each of the two short duration portfolios. The alpha is the return to the duration factor minus the product of duration factor's market beta and the excess return on the market portfolio.

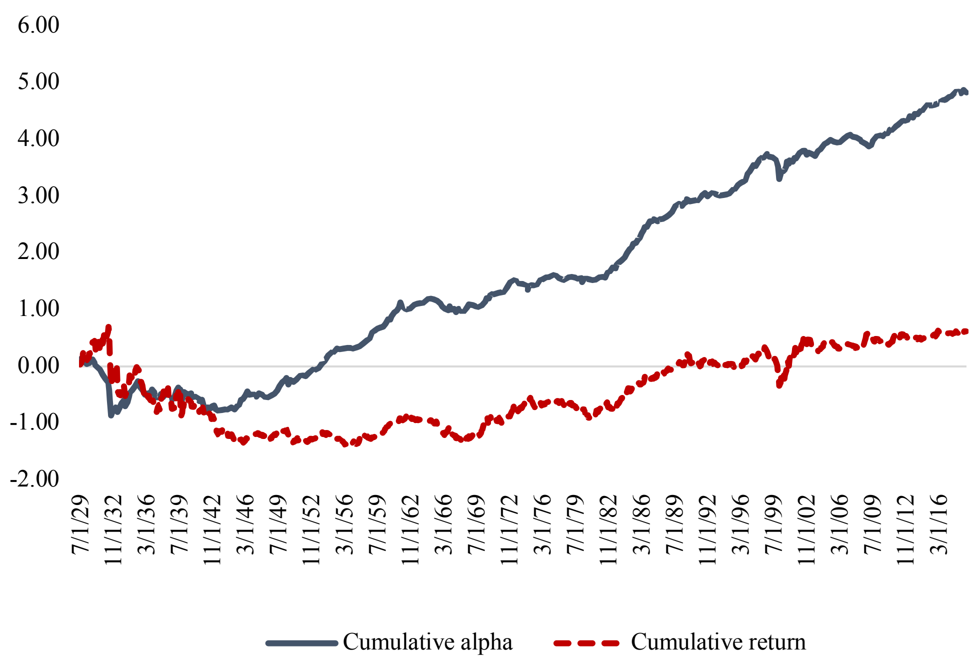


Figure 4
Realized Dividend Growth Rates for Long- and Short-Duration Firms

This figure shows the realized dividend growth rates for the long- and short-leg of our duration factor. We sort stocks into six portfolios based on ex ante size and duration. The breakpoints are the median market capitalization and the 30th and 70th percentile of duration. Portfolio weights are value-weighted and rebalanced monthly and the breakpoints are refreshed each June and based on NYSE firms. The duration factor is long 50 cent in the two high-duration portfolios and short 50 cent in each of the two short duration portfolios. The figure shows the average cumulative growth rate of the two high-duration portfolios per year after formation period and the average cumulative real growth rate of the two low-duration portfolios. The results are based on the 1929-2018 US sample.

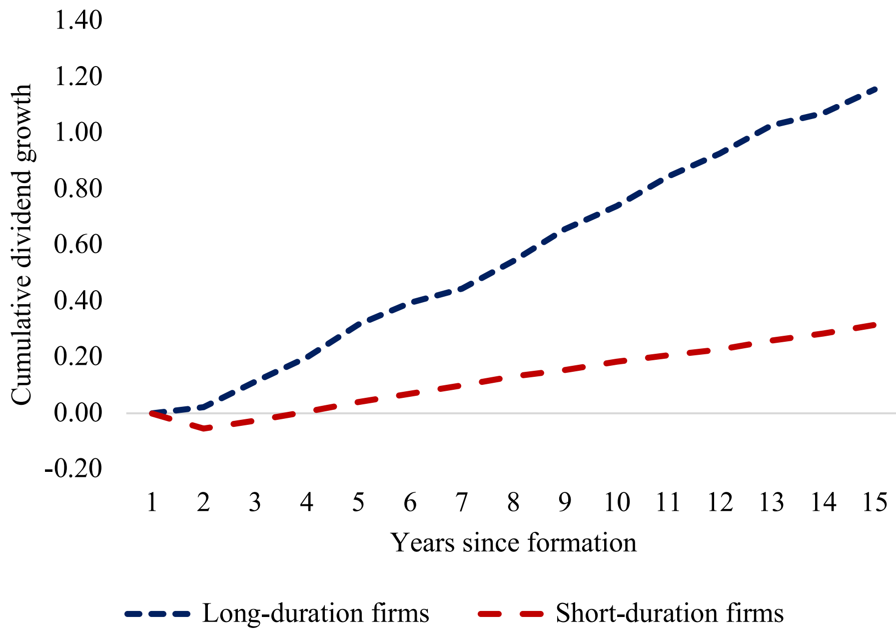
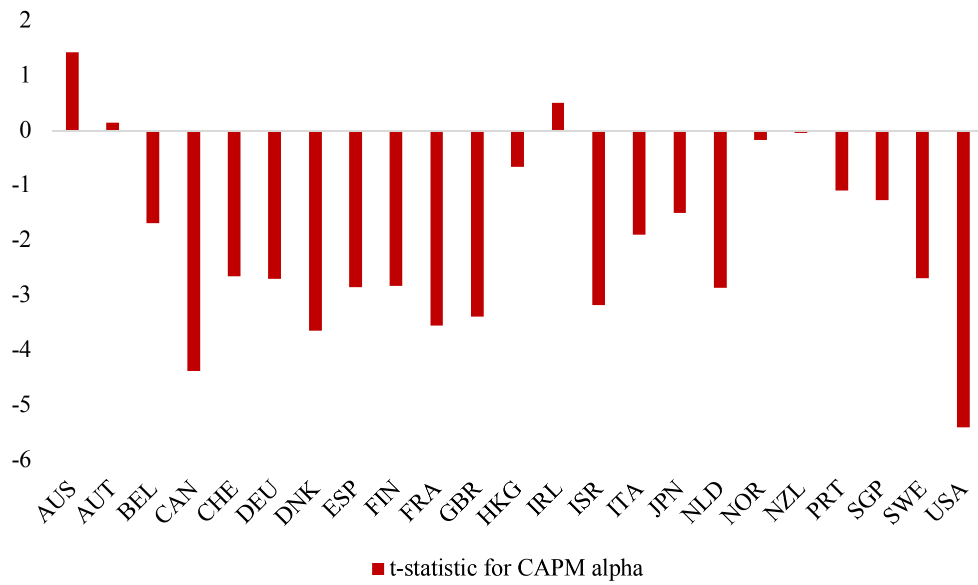


Figure 5
Risk-Adjusted Returns to the Duration Factor around the World

This figure shows the *t*-statistic for the CAPM alpha to the duration factor in different countries. The duration factor is constructed as follows. We sort stocks into six portfolios based on ex ante size and duration. The breakpoints are the median market capitalization and the 30th and 70th percentile of duration. Portfolio weights are value-weighted and rebalanced monthly and the breakpoints are refreshed each June and based on NYSE firms. The duration factor is long 50 cent in the two high-duration portfolios and short 50 cent in each of the two short duration portfolios. The alpha is the intercept in a regression of excess returns to the duration factor on the excess returns to the market portfolio.

Panel A: *t*-statistics on CAPM alpha



Panel B: Information Ratio on CAPM alpha in G7

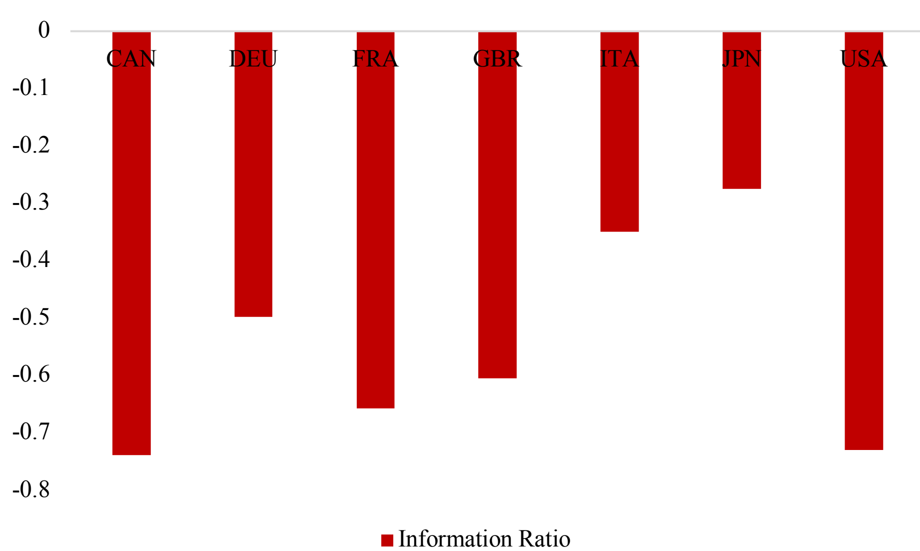
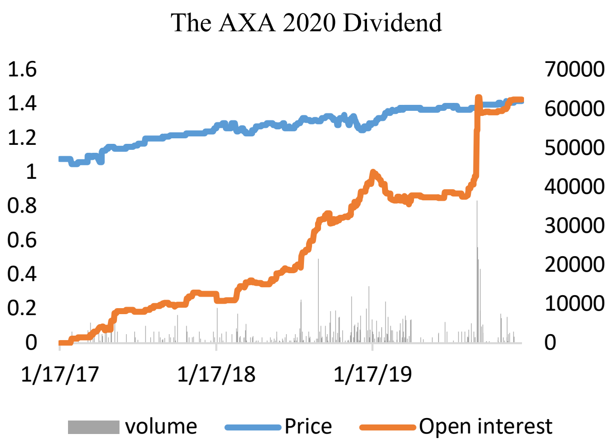


Figure 6
Single-Stock Dividend Futures: Two Examples

This figure shows the price, open interest, and volume for single-stock dividend futures. The left figure shows the future for the 2020 dividend of AXA. Prices are measured in thousands of Euros on the left y-axis and open interest is measured in number of contracts on the right y-axis. Volume shown in bar charts is normalized for ease of reading. The figure to the right shows similar statistics for the future on the 2020 dividend of Deutsche Bank.



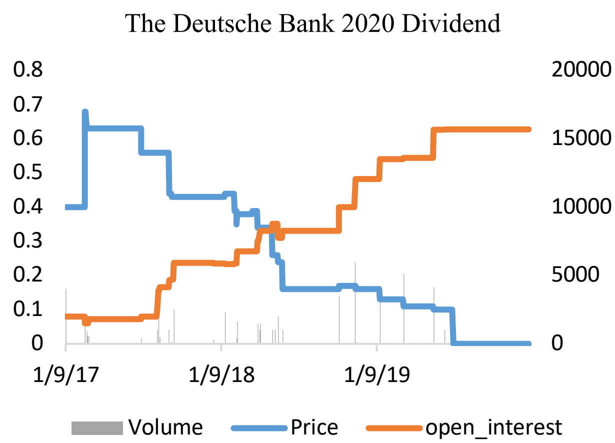


Figure 7
Histogram of Realized Monthly Returns on Dividend Strips

This figure shows a histogram of monthly realized returns on single-stock dividend futures. The figure excludes all observations where monthly returns are zero. The sample is 2010 to 2019.

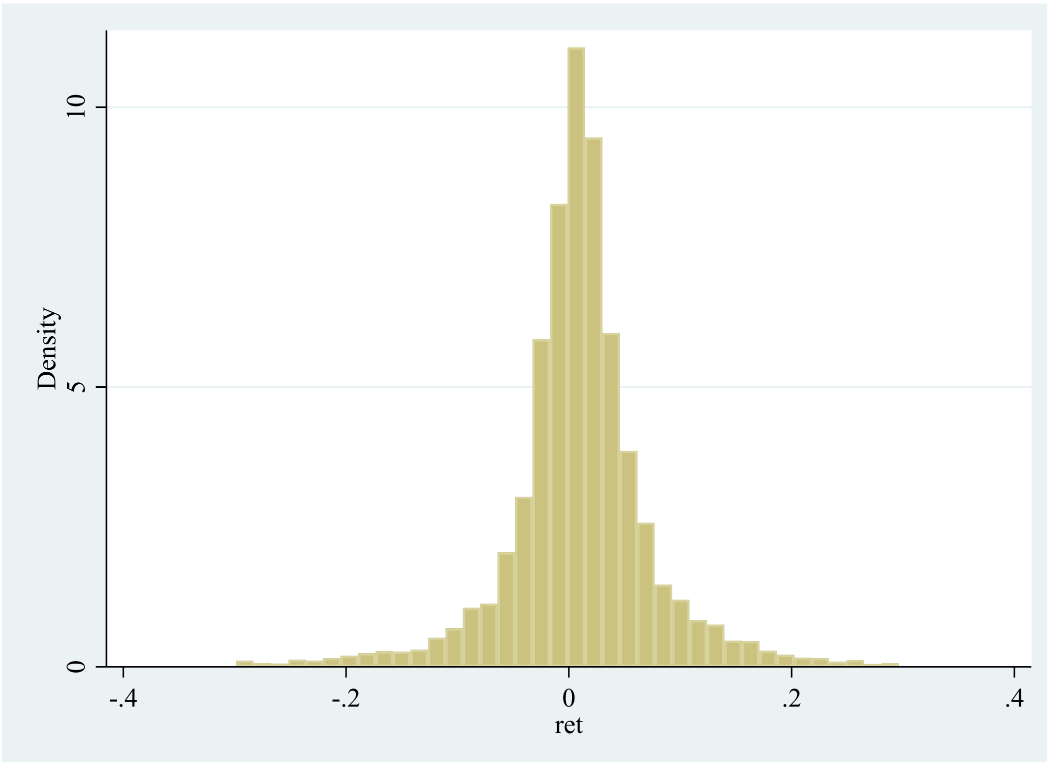


Figure 8
Risk-Adjusted Returns to Corporate Bond Portfolios

This table reports t-statistics for CAPM alphas for corporate bond portfolios. We sort firms into two groups based on the median firm characteristic. Within each group, we sort all outstanding corporate bonds into portfolios based on maturity. Portfolio weights are equal-weighted and rebalanced monthly. We calculate CAPM alpha as the intercept in a time series regression of monthly excess portfolio returns on the excess market returns. Excess returns are calculated as returns in excess of a treasury claim with the same maturity. The market return is the equal-weighted return across all bonds. The sorting is such that the 2-year portfolio, for instance, contains all bonds with maturity between 1 and 2 years. The sample is US firms from 2002 to 2016.

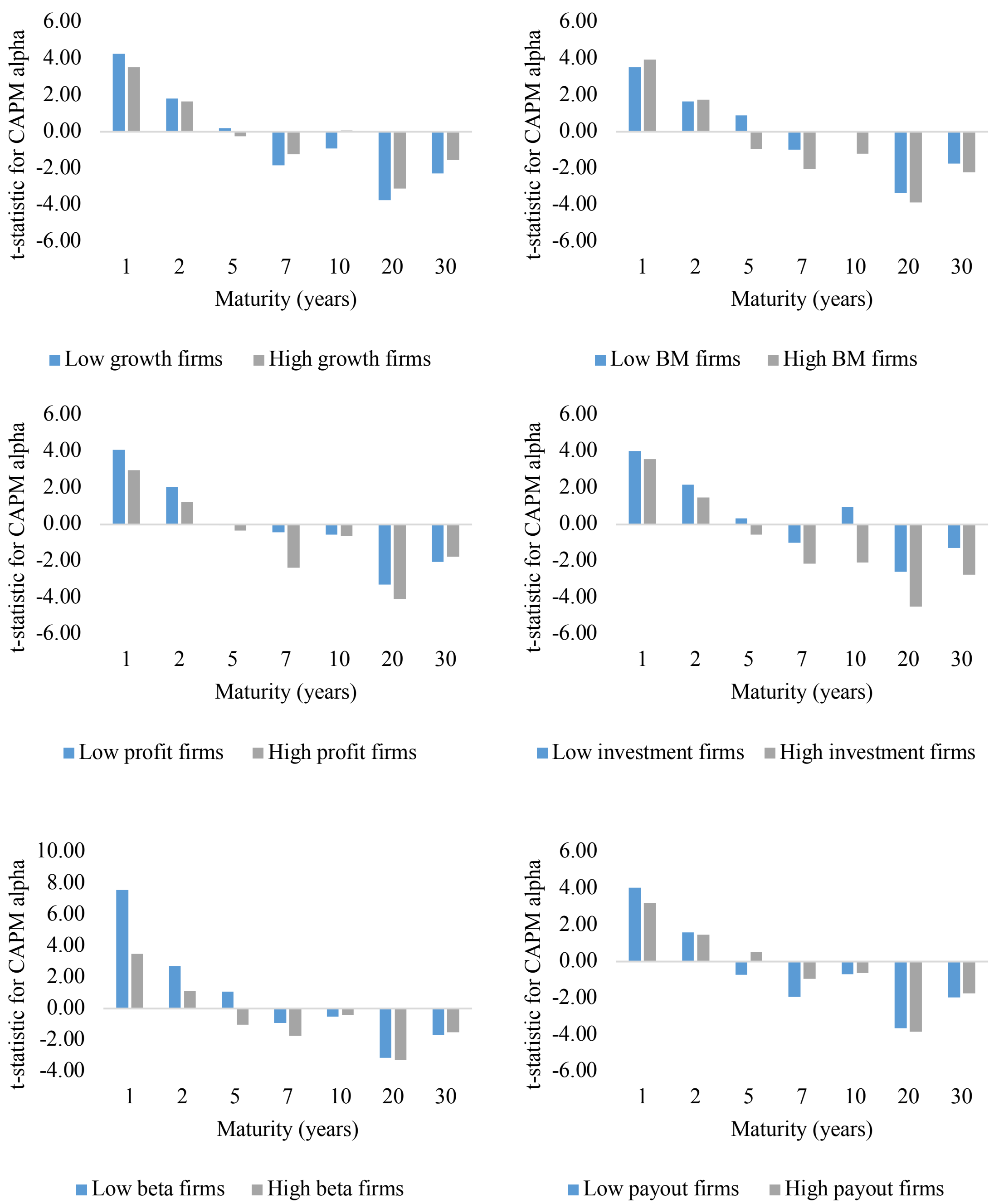


Figure 9
The Slopes of the Equity and Treasury Yield Curves

This figure shows the time series of the slope of the equity yield curve and the slope of the treasury yield curve. The slope of the equity yield curve is the log book-to-market ratio of the long-leg of the duration portfolio minus the log book-to-market ratio of the short-leg of the duration factor. The slope of the treasury yield curve is difference between the long- and short-duration us treasuries. The equity yield curve is measured on the left hand y-axis and the treasury yield curve is on the right hand side.

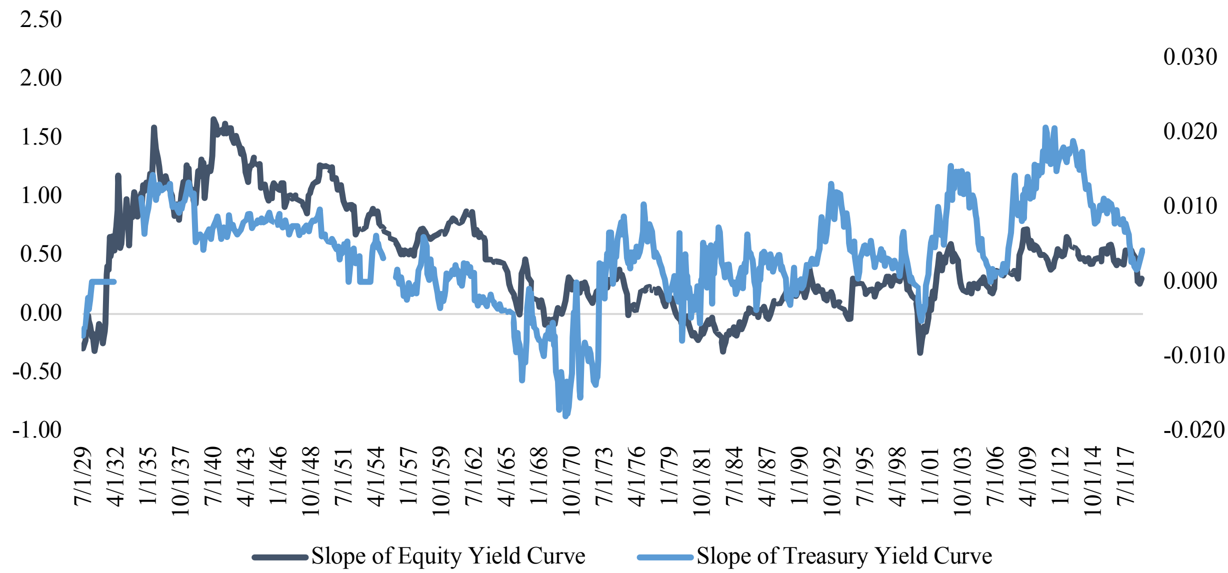


Table A1
Replicating Chen (2017) without Micro-Cap

This table reports the growth rate for value-sorted portfolios calculated following the method in Chen (2017). Panel A shows the results in the modern and full sample including all firms. Panel B reports the results excluding micro-cap (the smallest 20% of firms). Growth firms always grow faster in the modern sample and they also grow faster in the full sample when excluding micro-cap.

Growth Rates of Portfolios Sorted on Book-to-Market Ratios

Panel A: Replication of original study including all stocks

	Modern Sample					Full Sample				
	(growth) 1	2	3	4	(value) 5	(growth) 1	2	3	4	(value) 5
5 years	4%	1%	2%	1%	-1%	3%	2%	2%	3%	5%
10 years	4%	2%	1%	1%	1%	3%	2%	2%	2%	3%
15 years	5%	3%	2%	2%	1%	4%	2%	2%	3%	3%

Panel B: Excluding micro-cap (smallest 20%)

	Modern Sample					Full Sample				
	(growth) 1	2	3	4	(value) 5	(growth) 1	2	3	4	(value) 5
5 years	4%	2%	1%	1%	-1%	3%	2%	1%	2%	2%
10 years	4%	3%	1%	1%	1%	3%	2%	1%	1%	2%
15 years	5%	4%	2%	2%	1%	4%	2%	2%	2%	2%

Table A2

Theory: Equity Risk Factors in a Model with a Downward Sloping Equity Term Structure

This table show the CAPM alpha and duration of equity risk factors in model. The CAPM alpha is the intercept in a regression of return to the risk factor on the market portfolio. The duration measures the difference in the duration of the long- and the short-leg of the factor. The duration of the long- and the short leg is the equal weighted average of the firms in the portfolio. The duration of an individual firm is the value-weighted years to maturity of the firm's expected cash flows over the subsequent 25 years. The table shows the median estimates of 1000 simulations of 700 quarters of data. Alphas are in monthly percent.

	HML	RMW	CMA	Low Risk	DUR
Long-leg:	High B/M	High profit	Low investment	Low beta	High duration
Short-leg:	Low B/M	Low profit	High investment	High beta	Low duration
CAPM alpha	0.24	0.64	0.49	0.43	-0.66
Duration (years)	-3.3	-14.2	-7.5	-5.6	14.7