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Duration-Driven Returns

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ABSTRACT

We propose a duration-based explanation for the premia on major equity factors, including value, profitability, investment, low-risk, and payout factors. These factors invest in firms that earn most of their cash flows in the near future and could therefore be driven by a premium on near-future cash flows. We test this hypothesis using a novel data set of single-stock dividend futures, which are claims on dividends of individual firms. Consistent with our hypothesis, the expected Capital Asset Pricing Model alpha on individual cash flows decreases in maturity within a firm, and the alpha is not related to the above characteristics when controlling for maturity.

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

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

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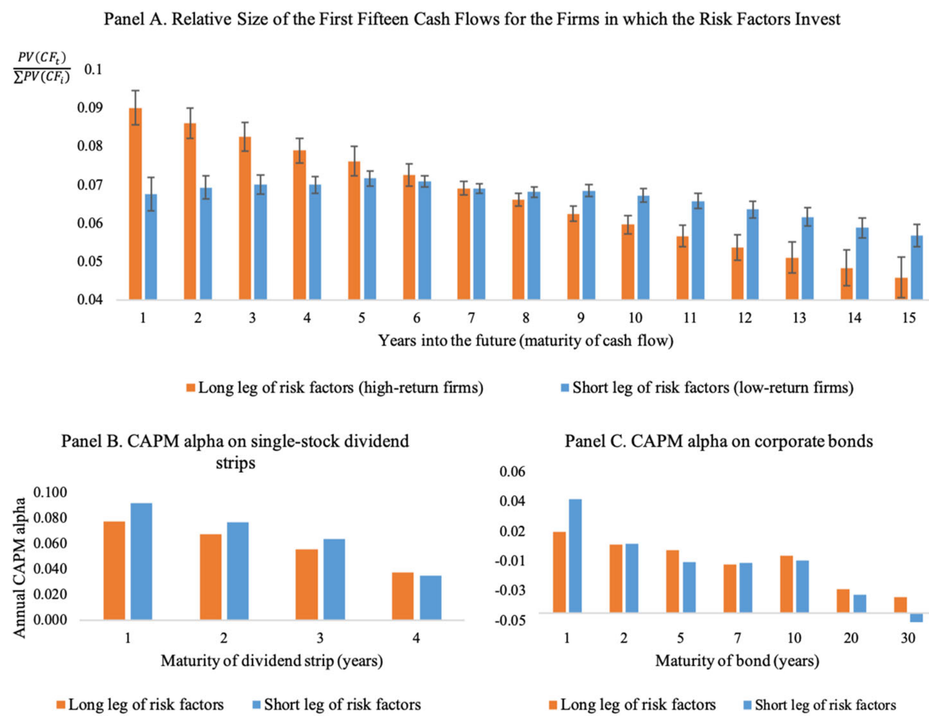

Figure 1. The timing and pricing of the cash flows of the major risk factors. Panel A shows the relative present value of future dividends for firms in the long and short legs of a duration risk factor, which is a combination of the profit, investment, low-risk, and payout factors. All present values are calculated using a nominal discount rate of 10%. Standard error bars (±1 SE) are computed using the delta method and the procedure in Chen (2017, Appendix A), which accounts for serial correlation and cross-correlation across portfolio × maturity using the Driscoll-Kraay estimator with 15 lags. Panel B shows the Capital Asset Pricing Model (CAPM) alpha on single-stock dividend strips for firms in the long and short legs of the risk factor. Panel C shows the CAPM alpha of corporate bonds for firms in the long and short legs of the risk factor. The samples are 1929 to 2019 for Panel A, 2010 to 2019 for Panel B, and 2002 to 2016 for Panel C.

risk-adjusted returns, by studying the timing of the cash flows of the firms in the portfolios of 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, Panel A, which plots future cash flows for firms in the long and short legs of each risk factor, averaged across risk factors. Each cash flow is measured as 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 holds for the firms in the short leg, which are shown in blue. The figure is based on an average of the major risk factors (its construction is detailed in the sections below), but similar results obtain for each of the individual risk factors considered. 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.

The fact that the risk factors invest in short-duration stocks is key to understanding their expected returns. 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 near-future cash flows on individual firms also have high risk-adjusted returns. Indeed, 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,

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

where r_{t+1}^m is the one-period excess return on the $t+m$ cash flow and w_t^m is its ex ante relative present value. Our hypothesis is that, for a given maturity, risk-adjusted returns on cash flows are more or less the same across firms. However, the 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 of such a duration-based explanation using novel data. We study a data set of single-stock dividend futures, which are claims to stock-level dividends that are paid out during a given calendar year. These claims 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 returns to the individual cash flows of individual firms. We find that the risk-adjusted return 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 value firm has the same risk-adjusted return as the three-year claim on a growth firm. This finding is illustrated in Figure 1, Panel B, which shows the CAPM alpha on the cash flows of the long and short legs of the risk factors. For both legs of the risk factors, the alphas start at around 8% per year for the one-year claim and decrease to around 4% for the four-year claim. Moreover, for each maturity, the risk-adjusted returns are almost the same for both legs of the risk factors.

As this exercise shows, the single-stock dividend futures allow us to hold fixed all of the characteristics of a given firm and vary only the maturity, or duration, of claims on that firm's cash flows, and conversely to hold fixed the cash-flow maturity and vary the firm characteristics. The dividend futures thus allow us to directly identify a relation between duration and stock

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

returns that cannot be explained by firm-level characteristics. We provide further details on this strategy in Section IV. This type of identification is unique within the cross-section of stock returns, as we usually cannot obtain model-free identification of the role of a given characteristic.

The single-stock dividend futures trade in an established market on the Eurex exchange. We observe around € 4 billion notional outstanding by the end of our sample in 2019, which is on the same order of magnitude 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 institutions, which are often considered important in price determination in the cross-section (e.g., Adrian, Etula, and Muir (2014)).

We also provide a robustness analysis using corporate bonds. Like the dividend strips, corporate bonds allow us to study the returns to claims on horizon-specific cash flows of individual firms. The payoff on a corporate bond depends 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, which makes them useful for robustness. As summarized in Figure 1, Panel C, we again find that the CAPM alphas on cash flows are similar across firms but decrease in maturity, consistent with a premium on near-future cash flows. We note that while this corporate bond analysis is intended as a robustness check, the fact that these results are consistent with those of the dividend-strips analysis suggests a promising possible avenue for unifying the cross-section of equity and debt.

We emphasize that all of the results above 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, 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 to high CAPM alphas and high Sharpe ratios).[4] As noted by Cochrane (2011, p. 1059), "All [cross-sectional] puzzles are *joint* puzzles of expected returns and betas" (emphasis his). Our unifying

[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 (Bansal et al. (2021)).

[4] 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 these short-duration portfolios.

explanation of the cross-sectional factors we consider is accordingly an explanation of CAPM alphas.

We next address why near-future cash flows have high CAPM alphas. A natural explanation is that near-future cash flows are riskier than their market betas suggest. For example, Gormsen and Koijen (2020) show that the value of near-future dividends dropped by as much as 40% during February and March of 2020 at the outbreak of the coronavirus crisis, substantially more than suggested by their unconditional betas. If near-future dividends are highly exposed to such bad economic shocks, this may help explain why their returns are high relative to more conventional measures of risk.[5] We address this possibility by studying the consumption risk in duration-sorted portfolios. We find that the market-adjusted returns on short-duration firms are positively exposed to consumption risk, while the market-adjusted returns on long-duration firms are negatively exposed to consumption risk. This finding suggests that consumption risk may play a role in the premium on near-future cash flows and thus the premium on the duration factor.[6]

However, the data also do not rule out the possibility of an additional behavioral driver that is unrelated to a premium on near-future cash flows. Indeed, while we find no relation between firm characteristics and expected CAPM alphas on the dividend strips, we do find a relation between firm-level growth rates and realized CAPM alphas. In particular, dividend strips for high-growth firms (long-duration firms) have low realized CAPM alphas, even controlling for maturity. Such a negative relation between growth rates and realized alphas is consistent with theories of overreaction in which investors overestimate the expected growth rates on high-growth firms (La Porta (1996), Bordalo et al. (2019)). The relation between growth rates and realized alphas is generally statistically insignificant but it nonetheless leaves open the possibility that the duration factor is not only driven by a premium on near-future cash flows, but also behavioral overreaction plays a role.

Finally, at first glance, it might be surprising 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 is intuitive. Consider, for instance, firms with low investment and high payout ratios, that is, 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 imply that these 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 thus naturally have long cash-flow duration in general (and conversely for

[5] See models by Lettau and Wachter (2007) and Hasler and Marfe (2016).

[6] Alternative explanations of why the premium on near-future cash flows exists include risk pricing (Eisenbach and Schmalz (2016), Lazarus (2022)), behavioral (Cassella et al. (2019)), or institutional (Belo, Collin-Dufresne, and Goldstein (2015)) mechanisms.

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, leading them to comove less with the market and thus have low betas.[7]

The remainder of the paper proceeds as follows. We discuss our relation to previous literature immediately below. Section I explains our data and methodology. Section II documents that the major equity risk factors invest in short-duration firms. Section III uses this fact to combine the major risk factors into a new duration risk factor and shows that this factor summarizes most of the premia on major equity risk factors, it works well in a broad global sample, and it provides a robust and meaningful contribution in explaining the cross-section even relative to a large set of previous factors. Section IV studies single-stock dividend futures and corporate bond returns to isolate duration as a driver of risk-adjusted returns on the duration factor. Section V studies the economic mechanisms behind our results on duration-driven returns. Finally, Section VI concludes.

Related Literature: Our paper relates to a literature on duration and the cross-section of stock returns. Dechow, Sloan, and Soliman (2004) study a measure of cash-flow duration in the cross-section of U.S. stock returns. Lettau and Wachter (2007) provide a model in which the value premium is explained by the short cash-flow duration of value firms. 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 (2021) argue for a duration-based explanation of the profitability and investment premia. We provide a series of contributions to this literature as explained below.

First, we directly link five major characteristics to duration by studying their relation to cash flow growth, highlighting that these characteristics are similar along a key dimension.[8] This similarity is sufficiently pronounced that the characteristics can be combined into, and in large part explained by, a single duration factor.[9] We provide evidence that this risk factor price long-run returns well, that it is priced in a broad global sample, and that it can be at least partly explained by exposure to consumption risk.

[7] 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.

[8] Previous research by Chen (2017) has studied the growth rates of the firms in the value factor. Chen finds that value firms grow faster, not slower, than growth firms, which challenges the duration-based explanation for the value premium. However, this result only holds in the early U.S. 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. See Section II.C for detail.

[9] The finding helps explain why the different risk factors often subsume each other in factor regressions, a finding that has caused debate in the asset pricing literature ((Fama and French (2016), Bali et al. (2017), Liu, Stambaugh, and Yuan (2018), Asness et al. (2020)).

Second, and crucially, we provide identification of the role of duration. Previous studies have documented a correlation between duration and returns, but there is no evidence that duration actually influences returns. That is, it is unclear whether short-duration firms have high alpha because of the cash-flow duration or because of other characteristics associated with short-duration firms, such as low valuation ratios. Unlike other papers in prior literature, we directly identify an effect of duration using dividend strips, as discussed in detail in Section IV. This point is important not only for the literature on duration but also for the literature on the cross-section more generally: to our knowledge, no prior study has been able to obtain model-free identification of a proposed risk factor.

More generally, the dividend strips allow us to study the returns on individual cash flows. Hansen, Heaton, and Li (2008) emphasize the importance of studying individual cash flows separately, but the lack of data has challenged this approach. The dividend strips fill this gap, allowing for more careful analysis of asset pricing dynamics. Almost any model of the cross-section is going to make predictions about prices of individual cash flows of individual firms; going forward, such predictions can now be tested and disciplined by data.

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.[10] 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, which implies that the results on aggregate dividends are not driven entirely by composition effects. More generally, our paper contributes to the role of duration in understanding stock prices (Binsbergen (2020)).

Our paper also relates to a recent literature on the so-called factor zoo.[11] 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.[12] We use basic economic arguments, together with analysis of dividend growth rates and novel dividend futures data, to argue that a range of the most prominent characteristics are symptoms of short-duration cash flows, and that many cross-sectional anomalies can thus be explained by

[10] Miller (2020), Chen (2020), and Giglio, Kelly, and Kozak (2020) study the slope of the equity term structure in the cross-section of stock returns using different methods. In addition to the literature review in Binsbergen and Koijen (2017), see also Andrews and Gonçalves (2020), Cejnek and Randl (2020), and Gormsen (2021) for evidence on aggregate term structures.

[11] See, for instance, Feng, Giglio, and Xiu (2020), Giglio, Liao, and Xiu (2021), Harvey and Liu (2017), Harvey, Liu, and Zhu (2016), and Kozak, Nagel, and Santosh (2020).

[12] We do, however, use the Feng, Giglio, and Xiu (2020) test to assess the contribution of our duration factor relative to previous factors, and it performs well in this test; see Section IV of the Internet Appendix, which is available in the online version of this article on *The Journal of Finance* website.

a duration characteristic, which, in turn, is consistent with the evidence on the equity term structure of the market portfolio.

I. Data and Methodology

A. Equities

We study equities in a global sample covering 67,842 stocks in 23 countries between August 1926 and December 2019. The 23 markets in our sample correspond to the countries belonging to the MSCI World Developed Index as of December 31, 2019. 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 U.S. 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 in a broad global sample. Our broad sample of global equities contains all available common stocks in the union of the CRSP tape and the XpressFeed Global database from 1990 until 2019.

B. Single-Stock Dividend Futures

We obtain daily prices on single-stock dividend future from Deutsche Borse, which is the owner of the Eurex Exchange on which the futures trade. The sample runs from 2010 to 2019 and contains 190 different firms. We match the underlying firms of the dividend futures to our equity database using the International Securities Identification Number (ISIN). We explain the nature of the data and data handling in detail in Section IV and Appendix B.

C. Bond Returns

We obtain bond returns from the Wharton Research Data Services (WRDS) Bond Return database. Our sample includes 23,211 bonds issued by 1,352 U.S. firms and runs from July 2002 to January 2016.

D. Expectations

We obtain long-term growth (LTG) expectations from the Institutional Bankers' Estimate System (IBES) database, for which data are available from 1981 to 2019. These expectations are defined as annualized expected earnings growth rates over a company's "next full business cycle." In some analyses, we convert these values into cross-sectional percentiles, while in other analyses, we work with the annualized numerical earnings growth values directly. In all cases, we use median estimates for expected dividends.

E. Defining Cash-Flow Duration

Macaulay (1938) defines cash-flow duration as the weighted-average years to maturity of an asset's expected cash flows,

$$Dur_t = \sum_{m=1}^{\infty} i \times \omega_t^m. \tag{2}$$

The weight ω_t^m is the present value of the given cash flow relative to the total value of the assets,

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

where CF_{t+m} is the realized cash flow in period $t+m$, r is the yield to maturity on the asset, and P_t is the price of the asset. The weights ω_t^m are slightly different from the weights in equation (1); the weights ω_t^m are based on present values that are calculated using the yield on the equity, whereas the weights w_t^m in (1) are based on the prices of the individual cash flows (i.e., using cash-flow-specific discount rates).

As can be seen in equation (3), cross-sectional variation in duration comes from differences in expected growth and discount rates. The higher the growth rate and the lower the discount rate, the larger the weight on the distant future cash flows and the longer the duration.

As discount rates are ultimately the variable we seek to explain, we focus most of our analysis on variation in duration that comes from variation in growth rates. Indeed, the analysis in Section II focuses on understanding the timing, or growth rate, of cash flows. Similarly, the duration characteristic that we introduce in Section III is, in fact, a growth rate characteristic. In the analysis of dividend strips in Section IV, the timing and duration of cash flows is conveniently the same as the strips only have one payment.

II. The Timing of Cash Flows for the Major Risk Factors

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 ceteris paribus are large relative to their distant-future cash flows.[13]

We focus our analysis on value, profitability, investment, low-risk, and payout factors.[14] We consider commonly used versions of these risk factors, which

[13] As discussed at the end of Section I, 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.

[14] 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). But any such selection is, of course, subjective, so we consider the applicability of our framework for other anomalies in Internet Appendixes D and E.

are based on the following characteristics: high book-to-market, high operating profitability to book equity, low annual growth in total assets, low market beta, and high payout ratio. 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 start this section with an analysis of realized growth rates. We then move on to expected growth rates.

A. Realized Growth Rates

We first look at the relation between characteristics and realized growth rates. To do so, we create 50 characteristics-sorted portfolios, 10 for each characteristic. For each portfolio i and year t, we calculate growth rates in dividends and earnings from year t to $t+15$ and regress them on the vector of time-t characteristics $X_{i,t}$:

$$\text{Growth rate}_{i,t,t+15} = \beta_0 + X_{i,t}'B + \epsilon_{i,t}. \tag{4}$$

The methodology for calculating growth rates is provided in Appendix A. For this exercise, all characteristics are measured as percentiles of the firm-level cross-sectional distribution in t and then aggregated to the portfolio level, and we include time fixed effects in the regression. We consider the 1963 to 2019 sample and to align with Fama and French (1993), time t is the end of July of the given year.

Panel A of Table I reports the results of regression (4). The first row uses ex post dividend growth rates on the left-hand side. These growth rates load negatively on all the characteristics, though the effect is insignificant for investment. The next row uses ex-post earnings growth rates on the left-hand side. The results are similar, with beta now insignificant and with the loading on investment now positive but still insignificant. Given the noise in earnings, the R^2 in the earnings-growth regression is much lower than that of the dividend-growth regression in the first row (0.05 versus 0.38). These results provide suggestive evidence that the characteristics are associated multivariately with low growth rates, with the more predictable dividend growth rates yielding somewhat stronger results.

In both cases, however, the results in Panel A may be biased upward: these characteristics may predict returns in part because the firms in high-return portfolios have overperformed in-sample, generating higher cash-flow growth than expected. If this were the case, the actual relation between characteristics and expected growth rates would be more strongly negative than presented here. In addition and perhaps more importantly, these results are only at the portfolio level, which limits statistical power.[15] We thus move next to a firm-level analysis using ex ante expectations data.

[15] A firm-level analysis with realized growth rates would be subject to survivorship bias issues, particularly at such a long horizon. The analysis above is thus intended as a first-pass summary.

Table I

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 reports results of a panel regression for 50 characteristic-sorted portfolios. The dependent variables are the realized 15-year growth rates of dividends and earnings and the explanatory variables are the characteristics of the 50 portfolios. The regressions include time fixed effects. 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. Panels C and D report 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. All characteristics and survey growth rates are measured in cross-sectional percentiles. Standard errors are two-way clustered across firm and date. We report t-statistics below the parameters and statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The sample is 1963 to 2019 in Panel A and 1981 to 2019 in Panels B through D.

Panel A: Portfolio-Level Regressions

	Explanatory Variables					
Dependent variable:	High Value	High Profit	Low Inv	Low Beta	High Pay	R^2
Realized 15-year dividend growth rate	−0.01***	−0.02**	−0.00	−0.02***	−0.02***	0.38
	(−2.74)	(−2.07)	(−0.16)	(−4.35)	(−4.57)	
Realized 15-year earnings growth rate	−0.10**	−0.07**	0.11**	−0.01	−0.06**	0.05
	(−2.22)	(−2.50)	(1.99)	(−0.33)	(−2.49)	

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

Continued

Table I
Continued

Panel C: Firm-Level Regressions of Survey Expected Growth Rates on Different Characteristics

	Dependent Variable: Analyst Expected Growth Rates (LTG)					
U.S. Only	(1)	(2)	(3)	(4)	(5)	(6)
High BM	−0.490***	−0.511***	−0.445***	−0.334***	−0.331***	−0.328***
	(−53.60)	(−21.63)	(−53.21)	(−34.10)	(−27.53)	(−22.54)
High profit	−0.197***	−0.293***	−0.212***	−0.095***	−0.056***	−0.168***
	(−22.61)	(−9.554)	(−24.70)	(−11.40)	(−6.230)	(−11.42)
Low investment	−0.0923***	−0.094***	−0.074***	−0.046***	−0.036***	−0.041***
	(−16.33)	(−4.841)	(−13.99)	(−12.23)	(−7.025)	(−8.599)
Low beta	−0.173***	−0.280***	−0.131***	−0.067***	−0.026***	−0.046***
	(−18.51)	(−12.65)	(−15.33)	(−9.053)	(−2.745)	(−4.777)
High payout	−0.259***	−0.168***	−0.229***	−0.116***	−0.120***	−0.086***
	(−33.51)	(−6.810)	(−31.18)	(−16.63)	(−12.91)	(−9.287)
Fixed effect	Date	Date	Date	Firm/Date	Firm/Date	Firm/Date
Cluster	Firm/Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date
Weight	Analysts	Market Cap	None	Analysts	Analysts	Analysts
Sample	Full	Full	Full	Full	Early	Late
Observations	582,580	582,580	582,580	582,488	267,544	314,914
R^2	0.467	0.406	0.321	0.740	0.810	0.707

Continued

Table I
Continued

Panel D: Firm-Level Regressions of Survey Expected Growth Rates on Different Characteristics—International Evidence

	Dependent Variable: Analyst Expected Growth Rates (LTG)					
Non-U.S.	(1)	(2)	(3)	(4)	(5)	(6)
High value	−0.166***	−0.191***	−0.151***	−0.132***	−0.146***	−0.161***
	(−16.92)	(−9.280)	(−17.15)	(−10.93)	(−6.197)	(−9.475)
High profit	−0.090***	−0.112***	−0.076***	−0.157***	−0.055**	−0.270***
	(−8.964)	(−5.087)	(−8.768)	(−12.71)	(−2.129)	(−15.15)
Low investment	−0.025***	−0.007	−0.023***	0.019***	−0.021**	0.036***
	(−3.613)	(−0.525)	(−3.778)	(−3.40)	(−2.173)	(−5.492)
Low beta	−0.055***	−0.115***	−0.052***	0.007	0.021	0.04***
	(−5.770)	(−7.124)	(−5.990)	(−0.765)	(−1.179)	(−2.8210)
High payout	−0.152***	−0.135***	−0.138***	−0.062***	−0.045**	−0.049***
	(−17.53)	(−8.381)	(−17.65)	(−7.075)	(−2.547)	(−4.053)
Fixed effect	Date	Date	Date	Firm/Date	Firm/Date	Firm/Date
Cluster	Firm/Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date
Weight	Analysts	Market Cap	None	Analysts	Analysts	Analysts
Sample	Full	Full	Full	Full	Early	Late
Observations	366,867	366,867	366,867	366,795	104,264	262,498
R^2	0.06	0.09	0.04	0.32	0.49	0.35

B. Expected Growth Rates

To get more precise results and increase statistical power, we next consider the contemporaneous relation between characteristics and ex ante expected growth rates from IBES. These expectations are known to embed their own biases, as we discuss 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 firms' growth rates on average.

Panel B of Table I 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 a 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 of firm j at time t, and $X_{j,t}$ is a vector containing the firm-j characteristics at time t, again both transformed into cross-sectional percentiles. The firm fixed effects Γ_j are included only in a subset of the regressions.[16] Our baseline analysis uses the number of analysts by firm as regression weights, though we consider alternative specifications as well.

Panel C of Table I shows the U.S. results. The LTG expectations load negatively on all the characteristics. In our baseline results (columns (1) to (3)), we exclude firm fixed effects, meaning that right-hand-side variation is driven by both permanent and transitory differences in characteristics. With firm-level fixed effects (columns (4) to (6)), the results are again highly significant and negative but quantitatively smaller in magnitude. The result holds across sample splits and using different regression weights. The R^2 is high in all specifications. Thus, the characteristics all predict low expected growth rates, even multivariately, and they jointly explain expected growth rates well.

We obtain similar results in our international (non-U.S.) sample, as shown in Panel D of Table I. In our baseline regressions, weighted by the 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 entirely robust to removing weights or splitting the sample in the international case.

Panel A of Figure 2 shows the estimated loadings of expected growth rates on characteristics for each individual country in our sample.[17] The clear majority, more than 85%, of the parameter estimates are negative. Panel B zooms in on

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

[17] See Figure IA.1 of the Internet Appendix for the same results split out by individual characteristics, which shows more clearly which characteristics have varying loadings across countries.

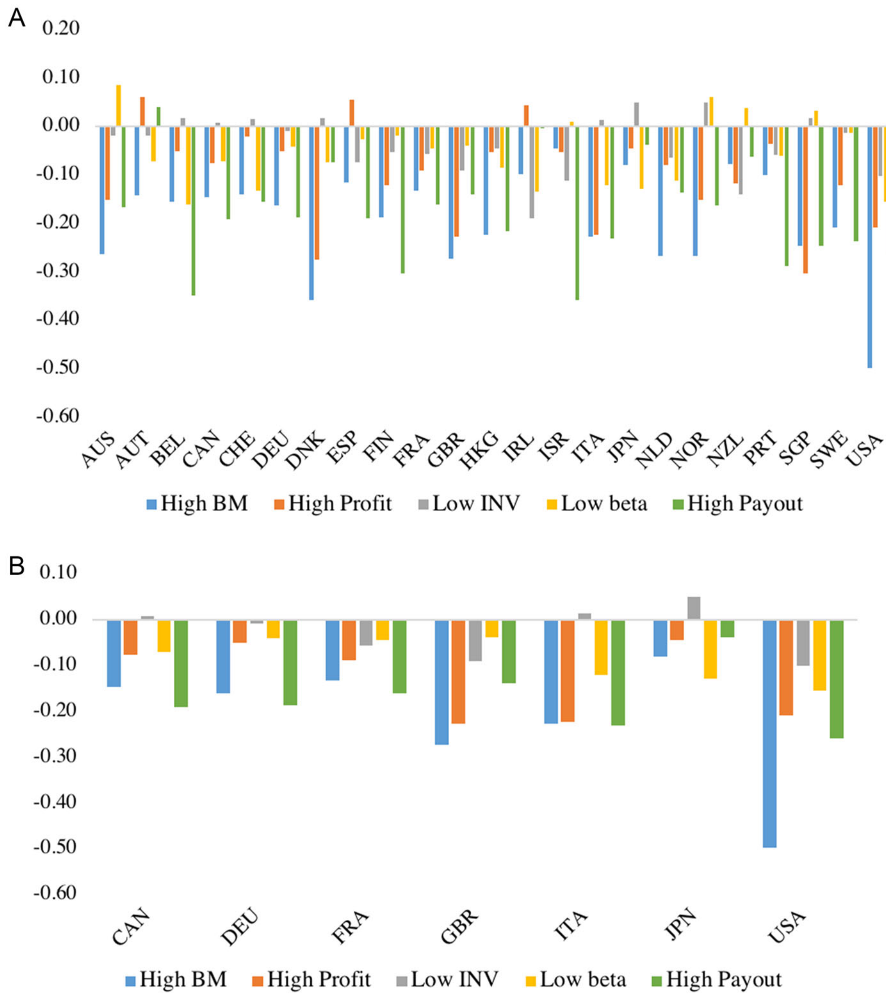

Figure 2. Loadings of expected growth rates on characteristics that predict returns: global evidence. This figure shows the loading of expected growth rates on characteristics that predict returns. In each country, we regress the expected growth rates on the below characteristics in multivariate panel regressions. In almost all cases, the characteristics that predict high also returns predict low expected growth.

the G7 countries. Again, almost all estimates are negative, with the exception of the investment characteristic, which is slightly positive in a few countries.

C. Comments and Relation to Previous Research

The LTG rates are ideal because we directly link firm 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 products (at least in part) of data mining. On the one hand, the IBES expectations 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 LTG rates suffer from overreaction. However, as documented in the next section, these expectations are not pure noise. Firms with high expected LTG do have higher realized ex post growth rates than firms with low LTG expectations.[18] This latter property is sufficient for our purposes in this section, as we measure expectations in cross-sectional percentiles and 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 realized growth rates of value and growth firms. Chen (2017) finds that value firms have lower growth rates than growth firms in his modern sample period (post-1963), but higher growth rates in the early sample (1926 to 1962) and in the full sample. Two points of relation between Chen's results and ours merit comment. First, in this analysis, we also study the modern sample period (post-1952, or post-1981 when IBES data are needed), and our results are thus consistent within this period. Second, and more importantly, the results in the early sample are driven by microcap 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 Internet Appendix Table IA.I.[19,20]

In conclusion, the major risk factors share a common feature, namely, their long legs invest in firms with low growth rates relative to their short legs. In the following sections, we address the asset pricing implications of this new stylized fact.

III. Factor Regressions

The previous section emphasizes that the firms in the major risk factors are similar along a key economic characteristic, namely, the timing, or growth rate, of their cash flows. In this section, we combine the major risk factors into a single low-growth factor to study the similarity of the risk factors in return

[18] The earlier literature also contested the claim that these expectations had any predictive power for realized growth. We do not find support for this finding in the updated data, but we do find evidence that the expectations tend to be upwardly biased on average, consistent with Chan, Karceski, and Lakonishok (2003).

[19] Microcap 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 a relatively large number of microcap firms.

[20] 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, in fact, refers to portfolios that 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).

space. We find that the premia on the major risk factors to a large extent can be summarized by this combined factor.

A. Factor Characteristic

To explore the similarity of the major risk factors, we first combine the characteristics underlying the major risk factors into a single low-growth characteristic. Since the major characteristics are all associated with a low growth rate, one approach would be to equal-weight the characteristics into a single low-growth characteristic, something we explore in the Internet Appendix. In the main specification, however, we instead exploit that some characteristics appear more strongly related to the growth rates than others. In particular, we construct the combined characteristic as the weighted average of the profit, investment, beta, and payout characteristics, where the weights are given by the factor loadings in regression (5) of Table I, Panel C. We exclude book-to-market from our combined characteristic because sorting on book-to-market ratios involves sorting on prices, which is ultimately the variable we seek to explain.[21]

Given this construction, the low-growth characteristic measures the expected growth rate of the firm, conditional on the firm's book-to-market ratio.[22] Empirically, the characteristic is associated with both a low growth rate and a high expected return, as documented below. Both of these contribute to a shorter cash-flow duration (see Section I.E), and we therefore refer to the combined characteristic as a duration characteristic, but we emphasize again that the characteristic omits variation in duration coming from the book-to-market ratio.

B. Properties of the Duration Portfolios and Factor

Table II studies returns on 10 portfolios sorted on our duration characteristic, from short to long duration. 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 nonmonotonic 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 −0.79% per month, with a *t*-statistic of −4.94. As discussed

[21] In the Internet Appendix, we provide robustness analysis on two alternative methods for computing this characteristic. The first, as above, uses the equal-weighted average of the characteristics instead of the weighted average; the second includes the book-to-market characteristic as well. Our main results in this section are unchanged when using the equal-weighted average and differ only slightly when also including the book-to-market characteristic (see Table IA.IX).

[22] For two firms with the same book-to-market ratio, the characteristic captures the difference in expected growth. Empirically, the characteristic is close to uncorrelated with book-to-market ratios, so sorting portfolios on this characteristic is conceptually similar to considering double-sorted portfolios that are sorted first on book-to-market and then on expected growth rates.

Table II

Risk and Return for Portfolios Sorted on Duration

This table reports the risk and return characteristics for 10 long-only portfolios sorted on duration and a long-short portfolio. We sort stocks into 10 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 parentheses under parameter estimates and statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Sharpe ratios and information ratios are annualized. Excess returns 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. The sample is U.S. firms from 1929 to 2019.

	Portfolios Sorted on Duration										
	1	2	3	4	5	6	7	8	9	10	Long/Short 10 minus 1
Excess return	0.67***	0.68***	0.68***	0.69***	0.73***	0.83***	0.71***	0.71***	0.7***	0.55*	−0.13
	(5.87)	(5.22)	(4.57)	(4.28)	(4.09)	(4.35)	(3.34)	(3.16)	(2.70)	(1.80)	(−0.53)
CAPM alpha	0.30***	0.23***	0.15***	0.11**	0.09	0.14**	−0.05	−0.10	−0.22**	−0.49***	−0.79***
	(5.18)	(4.38)	(3.08)	(2.33)	(1.69)	(2.58)	(−0.82)	(−1.38)	(−2.43)	(−3.79)	(−4.94)
CAPM beta	0.61***	0.73***	0.86***	0.95***	1.06***	1.13***	1.25***	1.33***	1.51***	1.69***	1.08***
	(56.68)	(74.66)	(93.59)	(108.21)	(109.33)	(109.59)	(105.90)	(103.92)	(91.62)	(71.32)	(36.73)
Sharpe ratio	0.62	0.55	0.48	0.45	0.43	0.46	0.35	0.33	0.28	0.19	−0.06
Information ratio	0.55	0.46	0.33	0.25	0.18	0.27	−0.09	−0.15	−0.26	−0.40	−0.52
Adjusted-R^2	0.75	0.84	0.89	0.91	0.92	0.92	0.91	0.91	0.89	0.82	0.55
# of observations	1091	1091	1091	1091	1091	1091	1091	1091	1091	1091	1091
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	

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 II also reports the realized and expected cash-flow growth rates of the portfolios. The expected cash-flow growth rate is based on the LTG expectations in the subsample for which we have expectations data. Expected cash-flow growth, as measured by the LTG rates from IBES, increases monotonically as portfolio duration increases. More importantly, the realized growth rates also increase monotonically. The realized growth rates are for the full sample, so they do not directly compare to the expected growth rates from the 1981 to 2019 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 average market return for all stocks. As shown at the bottom of Table II, 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.

Table III analyzes returns on our duration factor, which is constructed using the Fama and French (1993) method.[23] The factor goes long the short-duration firms and short long-duration firms. The U.S. results in Panel A are largely similar to the results in Table II: the factor has only marginally significant expected returns but a highly significant CAPM alpha of 0.50% per month (t-statistic of 5.64). The large alpha is driven neither by the small cap firms nor by the short leg of the portfolio alone. The result is robust across subperiods, as can be seen in Figure 3, which plots the cumulative alpha and return.

The two last rows of Table III, Panel A, 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 realized growth rates are from the full sample, whereas the expected growth rates are from the 1981 to 2019 sample. Figure 4 further 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

[23] 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 United States, portfolio breakpoints are unconditional and based on NYSE firms. In the international sample, breakpoints are conditional and based on the largest 20% of firms. (We follow standard practice in using conditional breakpoints for the international data given small-sample issues; see, e.g., Asness, Frazzini, and Pedersen (2019).) Portfolios are value-weighted and rebalanced at the end of each calendar month.

Table III

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 percentiles 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 cents in the two short-duration portfolios and short 50 cents in each of the two long-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 is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Sharpe ratios and information ratios are annualized. Excess return and alphas are in monthly percent. Returns in the U.S. sample are from 1963 to 2019, realized growth is from 1929 to 2020, and expected growth is from 1981 to 2019. The global sample is from 1990 to 2019.

Panel A: United States

	Long Duration		Short Duration		
	Large Cap	Small Cap	Large Cap	Small Cap	Duration Factor
Excess return	0.43**	0.63**	0.58***	0.94***	0.23*
	(1.99)	(2.33)	(4.10)	(5.66)	(1.91)
CAPM alpha	−0.24***	−0.13	0.15***	0.48***	0.50***
	(−4.38)	(−0.93)	(3.08)	(5.63)	(5.64)
CAPM beta	1.24***	1.40***	0.79***	0.85***	−0.50***
	(99.19)	(45.72)	(69.39)	(43.91)	(−24.69)
Sharpe ratio	0.26	0.31	0.55	0.75	0.25
Information ratio	−0.59	−0.12	0.41	0.76	0.76
Adjusted−R^2	0.94	0.76	0.88	0.74	0.47
# of observations	678	678	678	678	678
Analyst expected growth	14.0%	15.9%	8.1%	8.9%	
Realized dividend growth	4.6%	6.0%	1.3%	1.5%	

Panel B: Global

	Long Duration		Short Duration		
	Large Cap	Small Cap	Large Cap	Small Cap	Duration Factor
Excess return	0.37	0.36	0.54***	0.69***	0.25**
	(1.32)	(1.19)	(2.74)	(3.31)	(1.97)
CAPM alpha	−0.22***	−0.24*	0.13**	0.28***	0.44***
	(−3.80)	(−1.88)	(2.33)	(3.18)	(4.82)
CAPM beta	1.22***	1.24***	0.84***	0.83***	−0.39***
	(89.00)	(41.83)	(62.29)	(39.80)	(−18.34)
Sharpe ratio	0.24	0.22	0.50	0.61	0.36
Information ratio	−0.70	−0.35	0.43	0.59	0.89
Adjusted-R^2	0.96	0.83	0.92	0.82	0.49
# of observations	354	354	354	354	354
Analyst expected growth	11.4%	14.4%	7.2%	8.3%	

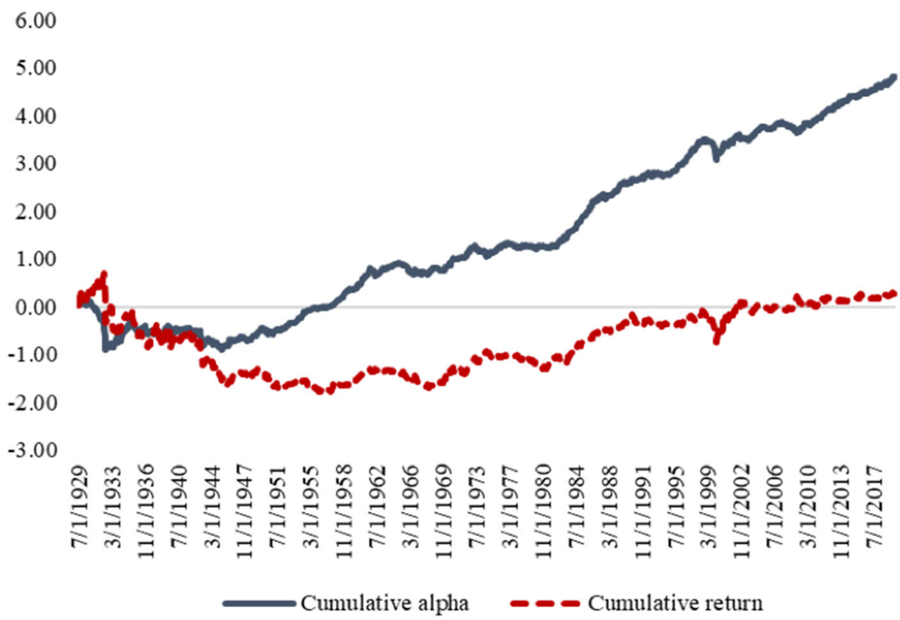

Figure 3. Cumulative return and CAPM alpha to the duration factor. This figure shows the cumulative excess return and CAPM alpha to the duration factor. The duration factor is constructed as follows. We sort stocks into six portfolios based on ex ante size and duration. The breakpoints are the median market capitalization and the 30^{th} and 70^{th} percentiles 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 cents in the two short-duration portfolios and short 50 cents in each of the two long-duration portfolios. The alpha is the return to the duration factor minus the product of the duration factor's market beta and the excess return on the market portfolio. (Color figure can be viewed at wileyonlinelibrary.com)

results verify that our measure of ex ante duration does indeed predict ex post differences in growth rates (and thus duration).

Panel B of Table III reports the performance of the duration factor in the global sample. The factor has a positive and statistically significant CAPM alpha of 0.44% per month. Similarly, Figure 5 shows that the factor has positive alpha in 20 out of 23 countries in our sample, and that it is statistically significant in the majority of them as well, despite the sample being quite short in many exchanges. Given that the characteristics and loadings that underlie our duration factor are all based on our analysis in the U.S. data, this international evidence mitigates data-mining concerns.

C. Spanning Regressions

We use three-factor regressions to study the extent to which our duration factor summarizes the five major equity risk factors studied in Section II. For each factor, we regress the returns on the market, a small-minus-big portfolio,

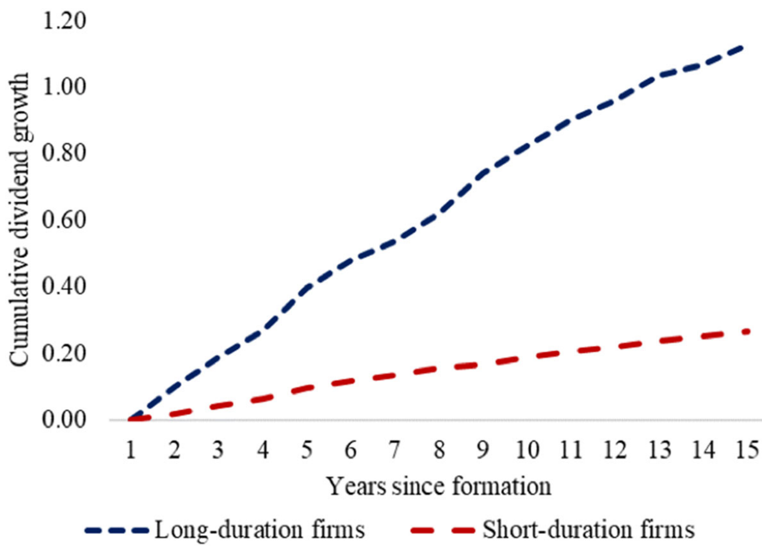

Figure 4. Realized dividend growth rates for long- and short-duration firms. This figure shows the realized dividend growth rates for the long and short legs of our duration factor. We sort stocks into six portfolios based on ex ante size and duration. The breakpoints are the median market capitalization 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 figure shows the average cumulative growth rate of the two high-duration portfolios per year after the formation period and the average cumulative real growth rate of the two low-duration portfolios. The results are based on the 1929 to 2019 U.S. sample. (Color figure can be viewed at wileyonlinelibrary.com)

and the duration factor in the following regression:

$$r^i_{t+1} = \alpha^i_{\mathrm{DUR}} + \beta^i_{\mathrm{Mkt}}\left(r^{Mkt}_{t+1} - r^f_t\right) + \beta^i_{\mathrm{smb}} r^{Smb}_{t+1} + \beta^i_{\mathrm{Dur}} r^{Dur}_{t+1} + \epsilon_{t+1}, \tag{6}$$

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 that are used to construct the duration factor. The size factor 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 that 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 IV presents results of our factor regressions in the United States. The first three columns report the results from the CAPM regressions

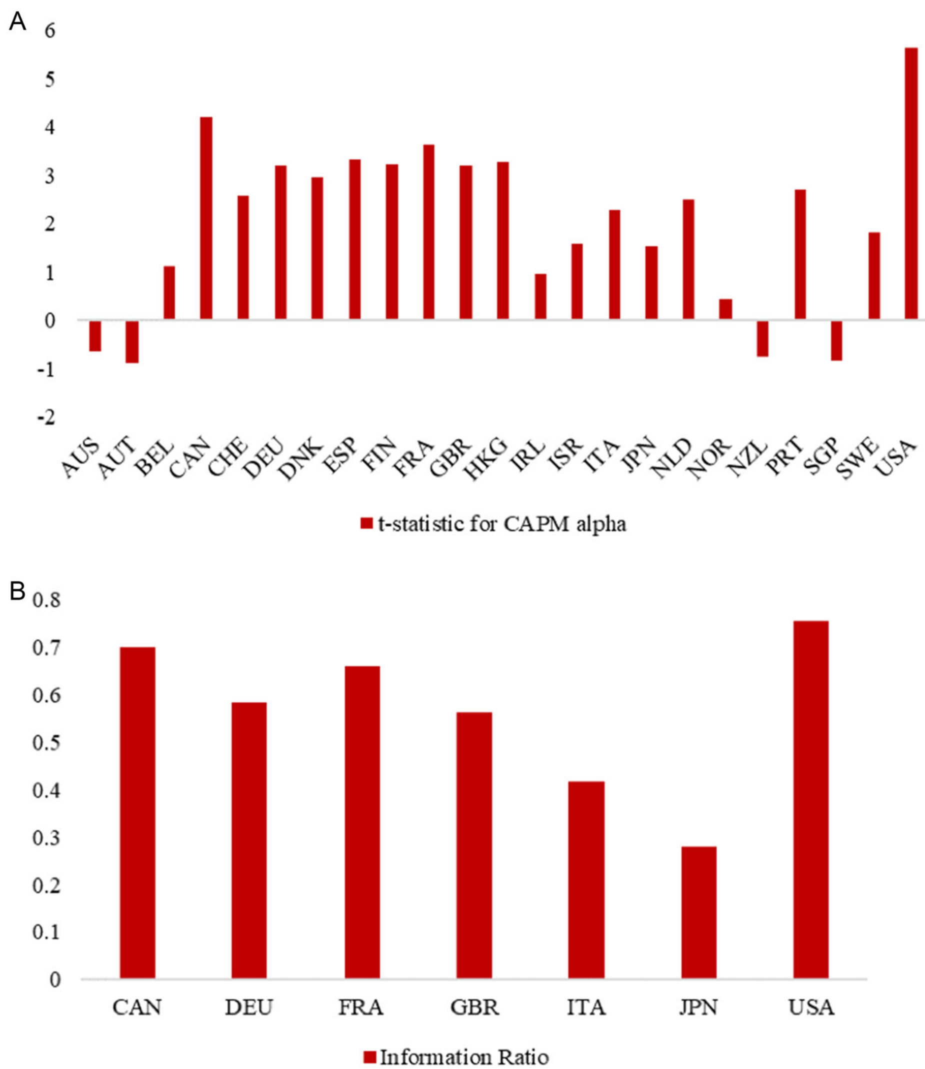

Figure 5. Risk-adjusted returns to the duration factor around the world. This figure shows the *t*-statistic for the CAPM alpha to the duration factor in different countries. The duration factor is constructed as follows. We sort stocks into six portfolios based on ex ante size and duration. The breakpoints are the median market capitalization and the 30$^{\text{th}}$ and 70$^{\text{th}}$ percentiles 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 cents in the two short-duration portfolios and short 50 cents in each of the two long-duration portfolios. The alpha is the intercept in a regression of excess returns to the duration factor on the excess return to the market portfolio. (Color figure can be viewed at wileyonlinelibrary.com)

Table IV

Summarizing the Major Risk Factors with the Duration Factor

This table reports the results of factor regressions in the U.S. 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 percentiles 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 cents in the two high-characteristic portfolios and short 50 cents 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 is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The U.S. sample is from 1963 to 2019 and the global sample is from 1990 to 2019.

Panel A: United States

	CAPM Model			Three-Factor Model						
Factor	α_{CAPM}	β_{CAPM}	R^2	α_{Dur}	β_{Mkt}	β_{Smb}	β_{Dur}	R^2	*LTG*	*# obs*
HML	0.39***	−0.16***	0.06	−0.02	0.13***	0.37***	0.66***	0.32	−9.5%	678
	(3.75)	(−6.73)		(−0.26)	(4.62)	(10.65)	(15.49)			
RMW	0.32***	−0.11***	0.05	0.09	0.14***	−0.07***	0.48***	0.35	−5.1%	678
	(3.87)	(−5.93)		(1.31)	(6.34)	(−2.67)	(15.03)			
CMA	0.37***	−0.18***	0.15	0.09	0.02	0.25***	0.44***	0.38	−6.7%	678
	(5.19)	(−10.87)		(1.38)	(1.15)	(10.56)	(15.48)			
BETA	0.49***	−0.73***	0.53	−0.04	−0.20***	−0.02	1.05***	0.85	−7.9%	678
	(4.22)	(−27.87)		(−0.52)	(−9.63)	(−0.80)	(33.59)			
PAYOUT	0.26***	−0.30***	0.37	−0.03	−0.02	0.04**	0.57***	0.70	−7.2%	678
	(3.86)	(−19.89)		(−0.72)	(−1.67)	(2.32)	(25.83)			

Panel B: Global

	CAPM Model			Three-Factor Model						
Factor	α_{CAPM}	β_{CAPM}	R^2	α_{Three}	β_{Mkt}	β_{Smb}	β_{Dur}	R^2	*LTG*	*# obs*
HML	0.29**	−0.09***	0.03	−0.02	0.17***	0.24***	0.66***	0.24	−7.1%	354
	(2.40)	(−3.18)		(−0.15)	(4.62)	(4.12)	(9.93)			
RMW	0.42***	−0.14***	0.18	0.22***	0.04**	−0.12***	0.47***	0.56	−5.1%	354
	(6.02)	(−8.74)		(4.25)	(2.39)	(−4.42)	(15.27)			
CMA	0.29***	−0.17***	0.18	0.05	0.03	0.20***	0.51***	0.35	−5.7%	354
	(3.17)	(−7.95)		(0.56)	(1.20)	(4.56)	(10.54)			
BETA	0.42***	−0.65***	0.59	−0.10	−0.19***	0.10***	1.18***	0.89	−6.6%	354
	(3.47)	(−22.79)		(−1.58)	(−9.01)	(3.06)	(30.87)			
PAYOUT	0.28***	−0.19***	0.26	0.03	0.03*	0.03	0.56***	0.62	−6.9%	354
	(3.92)	(−11.26)		(0.64)	(1.66)	(1.04)	(17.66)			

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. The remaining alphas for the factors are all insignificant in the three-factor model.[24] Panel B reports similar results in the global sample: the major risk factors all load on our duration factor, and the remaining alpha is insignificant, except for the profit factor.

We provide additional analysis in the Internet Appendix. Table A2 finds that the duration factor generally has positive alpha in the five-factor model of Fama and French (2015). Internet Appendix D then shows, using the "factor zoo" test developed by Feng, Giglio, and Xiu (2020), that our risk factor provides a significant contribution in pricing the cross-section relative to a high-dimensional set of existing factors.

D. Multihorizon Returns Test

We next test the duration factor's ability to price returns at multiple horizons using the multihorizon returns (MHR) misspecification test proposed by Chernov, Lochstoer, and Lundeby (CLL, 2022). CLL construct a moment condition for use in a generalized method of moments (GMMs) overidentification test based on the fact that a correctly specified model must price not only one-period returns but also cumulated MHRs. They test a given model's ability to price its *own* factors' returns at multiple horizons, which "allows for testing most, if not all, aspects of conditional model misspecification" (p. 1311). In order to compare models on common ground, they also consider a common set of test assets, namely, the MHRs for the Fama and French (2015) five (FF5) factors. We consider both versions of the MHR test in Table V.[25]

The first entry in the first row of Table V shows that the GMM J-statistic for our three-factor model has a p-value of roughly 0.06 when tested to match its own factors' returns at multiple horizons (1, 3, 6, 12, 24, and 48 months, as in CLL). It is thus not rejected at the 5% level, though it would be rejected at the 10% level. This performance is nonetheless on par with or stronger than all leading recent factor models considered by CLL, including the Carhart (1997) four-factor model ($p = 0.07$), a $Mkt + BAB$ model ($p = 0.06$), the Hou, Xue, and Zhang (2015) q-factor model ($p = 0.02$), and the FF5 model ($p = 0.02$); see their Table I.[26] Our model's outperformance in capturing conditional factor dynamics, and thus, in pricing MHRs, is even more strongly apparent in the second column: its p-value when tested against the multihorizon FF5 returns is roughly 0.62, whereas all leading models they consider—including FF5 itself—are rejected at the 5% level in this test conducted on common ground ($p = 0.00$ for the Carhart model, $p = 0.00$ for $Mkt + BAB$ and for the CAPM,

[24] While the table reports results from the three-factor model including a small-minus-big factor, the duration factor, in fact, provides the bulk of the explanatory power and reduction in alpha. The average R^2 in analogous two-factor regressions, including only the market and the duration factor, is 0.48 (compared to 0.52 in the three-factor results in the table); similarly, the average alpha in these two-factor regressions is 0.07% per month (compared to 0.02% per month in the three-factor case).

[25] We thank the authors for helpful discussions.

[26] The only model they consider that is not rejected at the 10% level is the CAPM ($p = 0.191$), as the market appears to capture its own conditional dynamics reasonably well.

Table V

Multihorizon Returns Tests for the Duration Factor

This table reports results from the Chernov, Lochstoer, and Lundeby (CLL, 2022) multihorizon return (MHR) tests for our three-factor model with the excess return on the market, the duration factor, and the duration-and-size-based *smb* factor. The first row gives the p-value of the GMM J-test provided in CLL (Section 2), which estimates the three-factor model to fit one-period (monthly) returns and then tests the model's ability to price the test assets' longer-horizon returns at 3, 6, 12, 24, and 48 months. The test assets for the first column are *Mkt*, *Dur*, and *SMB* at those horizons, while for the second column, the FF5 factors at those horizons are used. Mean absolute pricing errors, Sharpe ratios, and information ratios in the remaining rows are with respect to the multihorizon test asset returns. The sample is 1963 to 2019.

Test Assets:	Own Model's Factors	FF5 Factors
p-value (GMM)	0.060	0.619
Mean absolute price error (annualized)	0.042	0.036
Max. Sharpe ratio	1.133	1.133
Max. information ratio (annualized)	0.776	0.779

$p = 0.04$ for the q-factor model, and $p = 0.02$ for FF5, as in their Table A5).[27] The three-factor model thus performs relatively well in explaining returns at longer horizons. As discussed by CLL, this ability to price MHR suggests that the duration factor model provides a parsimonious but accurate summary of conditional factor dynamics for the major risk factors.[28]

E. Summary

Sections II and III show that the major equity risk factors invest in short-duration stocks and can largely be summarized by a duration factor that invests in firms with short cash-flow duration. However, it is unclear whether the premium on the duration factor arises as a product of the short cash-flow duration of the firms in the factor or if it arises from other characteristics associated with these firms. In the next section, we address this issue by leveraging a novel data set of single-stock dividend futures that allows us to identify the effect of cash-flow duration on expected returns.

IV. Identification from Dividend Strips

In this section, we identify the effect of cash-flow duration on stock returns using a novel data set of single-stock dividend futures. The starting point for

[27] The remaining rows of Table V, compared against the results provided in CLL (2022), show that our model also performs well on mean absolute pricing errors and on the maximal information ratio for MHRs, with a maximal Sharpe ratio that is comparable to those of other leading models.

[28] A nonrejection in the MHR test requires that the ratio of the expected factor return to its second moment is roughly constant over horizons. One possible explanation for these results therefore is that by combining many characteristics into one, our factor essentially extracts the more stable component of the premia associated with these factors, thereby allowing it to price long-horizon returns more robustly.

this analysis is the following identity from the law of one price that links the CAPM alphas on individual firms to CAPM alphas on individual cash flows:

$$\alpha_t^i = \sum_{m=1}^{\infty} w_t^{i,m} \alpha_t^{i,m}, \tag{7}$$

where α_t^i is the CAPM alpha on firm i, $\alpha_t^{i,m}$ is the CAPM alpha on the $t+m$ cash flow of firm i, and $w_t^{i,m}$ is the cash flow's relative present value.

Equation (7) shows that firm-level differences in CAPM alphas can arise from two sources: alphas on individual cash flows may vary with the maturity of the cash flows (m) for a given firm, they may vary across firms (i) for all maturities (or both). Our hypothesis is that CAPM alphas decrease with the maturity m of the cash flows. Such a pattern would generate relatively high CAPM alphas for short-duration firms because they have relatively large weights on near-future cash flows. Under this hypothesis, we say that the timing of cash flows affects firm-level alphas: the decomposition in (7) implies that changing the weights on the individual cash flows, while holding fixed the alphas on individual cash flows, would lead to a change in the firm-level alpha whenever cash-flow-level alphas decrease in maturity.[29]

The alternative hypothesis is that CAPM alphas on individual cash flows do not vary with maturity but instead vary across firms. For instance, the characteristics underlying our duration sorts could proxy for firm-level differences in riskiness that cause CAPM alphas on all individual cash flows to vary across firms. In this case, cash-flow duration might be correlated with firm-level CAPM alpha, but changing the weight on the individual cash flows, holding fixed the individual alphas, would not affect firm-level alpha.

We can thus identify the effect of cash-flow duration on firm-level alpha by studying the CAPM alphas on individual cash flows for individual firms. To do so, we turn to a novel data set on single-stock dividend futures. We first describe the data. We then describe our estimation strategy. Finally, we present and discuss our empirical results.

A. 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

[29] Holding fixed the alphas on the individual cash flows amounts to holding fixed the riskiness of the individual cash flows. One could imagine, for example, a change to the expected growth rate of a firm's cash flows while keeping their riskiness (i.e., stochastic discount factor covariances) constant. By contrast, counterfactuals in which one changes cash-flow timing while also changing the riskiness of the individual cash flows would not necessarily change firm-level alphas. Consider, for example, a case in which a firm starts allowing customers to make delayed payments (with interest), with all accounts settled and dividends paid out only in even years. This affects cash-flow weights and thus duration, but the riskiness of the individual cash flows would also change, and our hypothesis would not in general predict a change in alpha from such an accounting-induced change in duration. We thank a referee for suggesting this example.

buyer the right to the dividends paid by Nestlé during the 2021 calendar year. As such, these assets allow us to study the prices and returns on individual dividends for individual firms.

The single-stock dividend futures have traded as dividend swaps in an over-the-counter market since the early 2000s (Manley and Mueller-Glissmann (2008)). Starting in 2010, single-stock dividend futures have traded as a standardized product on the Eurex Exchange. Eurex initially offered dividend futures on 50 firms but as of 2020 offers futures on more than 200 firms. The availability of maturities varies across firms, with the most liquid firms having maturities as far as seven years.

The single-stock dividend futures are similar in nature to the index dividend futures that have become commonly used in asset pricing.[30] The index dividend futures are claims to the dividends on an underlying index, such as the S&P 500 or Euro Stoxx 50. The market for single-stock dividend strips is roughly of the same order of magnitude as the market for Euro Stoxx 50 dividend strips, which also trade on the Eurex Exchange.[31]

Despite being an exchange traded product, the market for single-stock dividend strips continues to exhibit some of the features of over-the-counter markets. Indeed, most of trading in the single-stock futures market are over-the-counter trades that are subsequently brought onto the order book through the Eurex OTC trading facilities for risk-clearing purposes. As such, prices can be stale, as discussed shortly, and bid-ask quotes from the order book are unlikely to be a good measure of actual prices. Throughout the analysis, we keep these features of the market in mind.

As explained in Section I.B, we obtain daily data from Eurex through Deutsche Borse. The data reflect volume from the OTC trading facilities as well as the usual on-the-book trades. We observe daily 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 based either 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 only update prices on days when we see volume in the market.

To give a sense of the data, Figure 6 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 futures trade fairly frequently and do not exhibit any dramatic swings over the sample. We also note that there is no sign of a bid-ask bounce.[32] The

[30] See Binsbergen et al. (2013) for an introduction to index dividend futures.

[31] Euro Stoxx 50 dividend futures had a notional outstanding of around € 12 billion as of mid-2018 (Gormsen and Koijen (2020)). By comparison, we observe a total notional in the single-stock market of around € 4 billion at this point. 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.

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

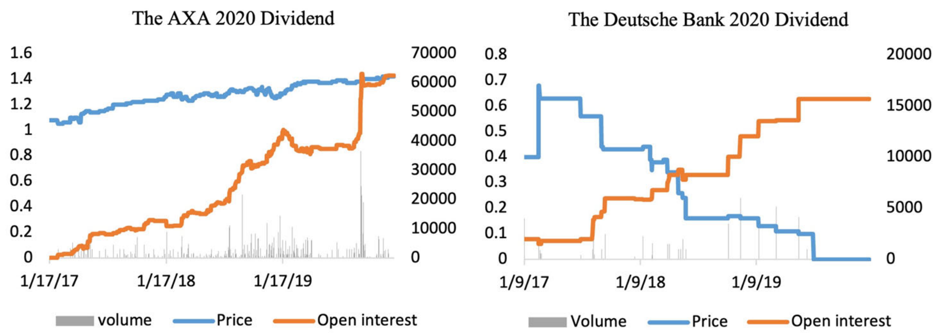

Figure 6. Single-stock dividend futures: two examples. This figure shows the price, open interest, and volume for single-stock dividend futures. The left figure shows the future for the 2020 dividend of AXA. Prices are measured in thousands of Euros on the left y-axis, and open interest is measured in number of contracts on the right y-axis. Volume, shown in bar charts, is standardized for ease of reading. The figure to the right shows similar statistics for the future on the 2020 dividend of Deutsche Bank. (Color figure can be viewed at wileyonlinelibrary.com)

open interest increases over time, reflecting the growing nature of the market. As shown in the right side of the figure, the Deutsche Bank futures trade 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 least liquid strips.

B. Summary Statistics and Representativeness

Table VI 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 mature at the end of December) as explained in Appendix B (Section C). The average raw returns are around 5%, and average log returns are around 3.4%. These are futures returns, which means that they are in excess of the risk-free rate. The average annual volume is 11,864 contracts and the average open interest is 5,444 contracts. A contract is a claim to the dividends paid out on 1,000 shares and trades on average at around € 2,000. The average notional outstanding is around € 4 million. The total value of all the notional outstanding is around € 4 billion at the end of the sample.

Panel B presents summary statistics as they relate to maturity and CAPM betas. The average maturity is two years. The average CAPM beta for an individual strip is 0.51. We estimate CAPM betas in regressions of monthly returns on the monthly returns of the market portfolio in the country of incorporation

Table VI

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 reports summary statistics 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 Appendix B. 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	1,474	0.049	0.21	−1	1.32
Annual returns (using settlement prices)	1,474	0.050	0.21	−1	1.32
Annual log-returns	1,465	0.034	0.22	−2.33	0.84
Annual volume	1,711	11,864	41,701	0	1.07e+06
Open interest	1,711	5,444	15,438	1	341,816
Price of contract	1,711	2,149	3,943	0	69,000
Notional (in thousands)	1,711	4,075	7,011	0	71,781
Panel B: Maturity and Betas					
One-year dummy	1,711	0.36	0.48	0	1
Two-year dummy	1,711	0.33	0.47	0	1
Three-year dummy	1,711	0.22	0.42	0	1
Four-year dummy	1,711	0.090	0.29	0	1
Maturity (in years)	1,711	2.04	0.97	1	5
CAPM beta of strip	1,711	0.51	0.85	−1	1.50
# Obs for CAPM beta	1,711	36.4	27.5	2	101
Panel C: Sample Representativeness					
Duration	1,711	33.1	28.7	0.078	100
Book-to-market	1,696	52.8	27.0	0.26	100
Market cap	1,711	97.2	3.24	74.1	100
Operating profit	1,689	62.4	22.7	4.47	99.9
Investment	1,699	48.8	21.9	2.55	99.5
Beta	1,700	74.5	18.0	7.45	100
Payout	1,669	67.3	21.3	0.51	100

of the underlying firm, accounting for stale prices; see Appendix B (Section D) for details. We trim the betas to be between −1 and 1.5.[33]

[33] For robustness, Tables IA.X–IA.XII show results using betas that are instead winsorized by maturity at the 5% level.

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 in which the firm is traded, meaning that the degree of nonrepresentativeness can be roughly measured using the difference of the average value of each characteristic from 50. 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 representative is market size, as the sample generally contains only the largest firms in the universe of firms.

Finally, Figure IA.2 in the Internet Appendix shows a histogram of monthly returns. The figures excludes all observations in which returns are equal to zero. Returns look fairly symmetric but have negative skewness and exhibit excess kurtosis.

C. Expected Returns and CAPM Alphas

We begin our analysis of the dividend strips by analyzing the expected returns 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 returns and alphas as:

$$E_t\left[r^{i,m}_{t+m}\right] = \left(\frac{E_t\left[D^i_{t+m}\right]}{f^{i,m}_t}\right)^{1/m} - 1, \tag{8}$$

where D^i_{t+m} is analysts' time-t expectations of the dividends paid out on firm i at time $t+m$ and $f^{i,m}_t$ is the price of the m-maturity strip on firm i at time t. See Appendix B (Section C) for details. We note that a cleaner way to map the results on the dividend futures to the cross-section of stock returns would be to look at expected one-period returns instead of the expected yield-to-maturity. When looking at expectations, the data do not allow us to study one-period returns as we do not observe next-period expected prices. However, in the next section, we study realized returns, which do allow us to study one-period returns.

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%:

$$\alpha^{i,m}_t = E_t\left[r^{i,m}_{t+m}\right] - \beta^{i,m}_{maturity} \times 5\%, \tag{9}$$

where $\beta^{i,m}_{maturity}$ is the beta-to-maturity. The estimation of the strip-level betas is outlined in Appendix B (Section D).

As a first look at the data, Table VII reports the average CAPM alphas for dividend strips on long- and short-maturity firms. The first row shows the average CAPM alphas of the strips on the short-duration firms. The alpha starts

Table VII

Expected CAPM Alpha for Single-Stock Dividend Futures

This table reports the expected average CAPM alpha for portfolios of dividend strips on different firms. At the end of December, we assign all dividend strips to a long- or short-duration portfolio based on the cash-flow duration of the underlying firm. Firms are categorized as having long (short) duration if the cash-flow duration is above (below) the median of all firms on the exchange in which the firm is listed. We then calculate a pooled average CAPM alpha for all strips of a given maturity in a given portfolio. Standard errors reported below the estimates are clustered by firm and date. See Appendix B for details on how we calculate CAPM alphas. The data are from 2010 to 2019.

	Maturity of Strip				
	One Year	Two Years	Three Years	Four Years	Average
Short-duration firms	0.078	0.068	0.056	0.038	0.066
	(0.0046)	(0.0061)	(0.0070)	(0.0057)	(0.0045)
Long-duration firms	0.092	0.077	0.064	0.035	0.077
	(0.011)	(0.011)	(0.0071)	(0.0070)	(0.0090)
Average across firms	0.085	0.073	0.060	0.037	
	(0.0066)	(0.0077)	(0.0057)	(0.0054)	

at 8% per year for the one-year claim and decreases steadily to around 4% for the four-year claim. The row below shows the alphas of the strips on the long-duration firms. Here, the alpha starts at around 9% for the one-year claim and decreases to around 3.5% for the four-year claim. The alphas are thus decreasing in the maturity of cash flows even when keeping the underlying firms constant. In addition, the alphas on the cash flows do not appear higher for short-duration firms than for long-duration firms.

The analysis in Table VII is a powerful way of separating between our duration-driven hypothesis and other potential drivers of the premium on short-duration firms. Indeed, when going from left to right in Table VII, we are keeping all of the firm-level characteristics fixed and varying only the maturity, or duration, of the cash flows. Similarly, when going from top to bottom, we are varying all of the firm-level characteristics but keeping the duration of the cash flows constant. This analysis reveals that duration, and not other firm-level characteristics, drives returns.

We do a more rigorous analysis of dividend strips in Table VIII. The table reports the results of the following end-of-year panel regressions:

$$y^{i,m}_{t,t+m} = b_2 D^m_2 + b_3 D^m_3 + b_4 D^m_4 + B'_1 X^{i,m}_t + B'_2 X^i_t + e^{i,m}_t, \tag{10}$$

where $y^{i,m}_{t,t+m} = E_t[r^{i,m}_{t,t+m}]$ or $y^{i,m}_{t,t+m} = \alpha^{i,m}_{t,t+m}$, D_2 to D_4 are maturity dummies for the claims, $X^{i,m}_t$ is a vector of time t strip-level characteristics, and X^i_t is a vector of time t firm-level characteristics. Time t is the end of December of a given year. One of the right-hand side characteristics is duration, which we scale by its cross-sectional standard deviation for ease of interpretation.

Table VIII

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 B for details on how we calculate expected return and betas. The cash-flow duration characteristic is standardized by the cross-sectional standard deviation. In the equations below, t, i, and m denote the time, firm, and maturity of the strip at time t (measured in years). The data are from 2010 to 2019. Standard errors reported in parentheses are two-way clustered as specified in the table. Statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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

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

Dependent variable	Expected ret	Expected ret	Expected ret	CAPM alpha	CAPM alpha	CAPM beta
Two-year dummy		−0.000	−0.004	−0.013*	−0.012*	0.427***
		(0.005)	(0.006)	(0.006)	(0.006)	(0.119)
Three-year dummy		−0.002	−0.009*	−0.027***	−0.025***	0.816***
		(0.003)	(0.004)	(0.005)	(0.005)	(0.111)
Four-year dummy		−0.017***	−0.022***	−0.045***	−0.044***	0.805***
		(0.004)	(0.004)	(0.007)	(0.007)	(0.137)
CAPM beta of strip ($\beta^{i,m}$)	0.011***		0.014***			
	(0.003)		(0.004)			
CAPM beta of firm (β^{i})	0.044**		0.044**			0.599**
	(0.016)		(0.016)			(0.195)
Cash-flow duration of firm	−0.004		−0.003	−0.001	−0.002	
(higher = shorter duration)	(0.004)		(0.004)	(0.004)	(0.004)	
Observations	1,226	1,236	1,226	1,236	1,236	1,699
R^2	0.13	0.10	0.14	0.10	0.12	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

The leftmost regression in the table has expected returns on the left-hand side, and on the right-hand side, it has 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 suggests that betas are priced in the dividend strips and that there is a link between the 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.[34] We cluster standard errors by date and firm.

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 loadings on the dummies are negative, and increasingly so, for the three- and four-year claim. The effect is significant for the four-year claim. Column (3) augments the regression with the CAPM betas. Doing so intensifies the negative relation between returns and maturity, such that the effect is significant for both the two-year and three-year claims. This result reflects the notion that CAPM betas increase in maturity, as shown in the rightmost columns of the table.

The fourth and fifth columns of Table VIII have 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 using notional outstanding as weight, which ensures that the results are not driven by the less liquid strips. In Internet Appendix Table IA.III, we further study the effects of liquidity by including liquidity measures such as volume and open interest on the right-hand side of our regressions. Doing so has no impact on the results, further suggesting that the results are not driven by liquidity issues related to the dividend strips.

The final column has CAPM betas on the left-hand side, finding that betas indeed increase in maturity and that the beta of the individual strip is related to the beta of the underlying firm on the stock exchange. The fact that the CAPM beta of the underlying firm is significantly related to the beta and expected return on the firm's dividend strips is important because it alleviates concerns about potential segmentation between the two markets.

The analysis in Tables VII and VIII essentially decomposes the alpha of the dividend strips into the part that can be explained by maturity and the part that can be explained by duration characteristics. However, alphas could vary across firms even after controlling for duration. Table IA.IV in the Internet Appendix addresses this concern by including firm fixed effects in the regressions. The fixed effects indeed increase the R^2, suggesting that there could be firm-level effects on the strips. Importantly, however, there do not appear to be firm-level differences along the duration characteristic, and controlling for

[34] The contracts are traded in the currency in which the dividends are paid out.

these differences with fixed effects does not influence the results on the maturity dimension.

D. Realized Returns and Alphas

Looking at expected as opposed to realized returns brings 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 in which the firm is incorporated. See Appendix B (Section C) for details.

We start by projecting the realized returns onto the ex ante expected returns. Table IX, Panel A, reports the results. Without regression weights, the slope coefficients are between 0.68 and 0.80, depending on the choice of fixed effects and type of return. We generally cannot reject that the slope coefficients are equal to 1 in the equal-weighted regressions.

We next project the realized returns onto the maturity dummies from the panel regression above. These regressions include firm fixed effects as we have no firm-level characteristics on the right-hand side. The first two regressions in Panel B have 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 coefficients are larger than those 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 replaces the firm fixed effects with the cash-flow maturity of the underlying firm on the right-hand side. The results reveal a positive relation between realized alphas and duration characteristics, which mean that longer cash-flow duration of the underlying firm corresponds to lower returns. The effect is marginally significant in one specification. These results contrast to the results on expected returns, where there we find 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 suggest that overoptimistic expectations about growth rates

Table IX

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 return 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). The cash-flow duration characteristic is standardized by the cross-sectional standard deviation. In the equations below, t, i, and m denote the time, firm, and maturity of the strip at time t (measured in years). The data are from 2010 to 2019. Standard errors reported in parentheses are two-way clustered as specified in the table. Statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Panel A: Realized versus Expected Returns

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

Realized returns: $r^{i,m}_{t+1} = f^{i,m+1}_{t+1} / f^{i,m}_t$

Dependent variable	Realized Return	Realized Returns	Realized Log-Return	Realized Log-Return	Realized Return	Realized Log-Return
Expected return	0.68***	0.76***			0.58***	
	(0.17)	(0.17)			(0.17)	
Expected log-return			0.71***	0.80***		0.71***
			(0.14)	(0.14)		(0.12)
Observations	1,059	1,059	1,054	1,054	1,059	1,054
R^2	0.203	0.251	0.171	0.218	0.187	0.194
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

Continued

Table IX
Continued

Panel B: Realized Returns and Alphas

Realized returns: $r_{t+1}^{i,m} = f_{t+1}^{i,m+1} / f_t^{i,m}$
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
Two-year dummy	0.0021	0.00066	−0.035	−0.035	−0.037	−0.037*
	(0.018)	(0.016)	(0.026)	(0.023)	(0.023)	(0.019)
Three-year dummy	0.011	0.0018	−0.062	−0.062	−0.071	−0.071*
	(0.031)	(0.028)	(0.041)	(0.041)	(0.038)	(0.038)
Four-year dummy	−0.020	−0.035	−0.084*	−0.084*	−0.100**	−0.100**
	(0.034)	(0.032)	(0.042)	(0.042)	(0.042)	(0.041)
Observations	1,466	1,457	1,466	1,466	1,457	1,457
R^2	0.187	0.156	0.227	0.227	0.205	0.205
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

Continued

Table IX

Continued

Panel D: Expectations Errors

Dependent Variable	Realized Returns – Expected Returns		Realized Log-Returns – Expected Log-Returns	
Two-year maturity dummy	0.0061	0.0050	−0.0012	−0.0032
	(0.016)	(0.016)	(0.012)	(0.014)
Three-year maturity dummy	0.015	0.011	−0.0041	−0.0059
	(0.031)	(0.029)	(0.029)	(0.028)
Four-year maturity dummy	−0.0020	−0.0029	−0.023	−0.023
	(0.031)	(0.029)	(0.034)	(0.032)
Cash-flow duration of firm	0.017	0.017	0.017	0.018
(higher = shorter duration)	(0.012)	(0.012)	(0.010)	(0.010)
Observations	1,065	1,065	1,060	1,060
R^2	0.078	0.074	0.074	0.070
Fixed effect	Date/currency	Date/currency	Date/currency	Date/currency
Cluster	Date/Firm	Date/Firm	Date/Firm	Date/Firm
Weight	None	Notional	None	Notional

of long-duration firms could play a role in explaining the returns on the duration factor. We explore this explanation more in Section V. We note, however, that an overreaction explanation cannot easily account for the negative relation between cash-flow maturity and both realized and expected alphas.

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

E. Alpha Accounting

The analysis above identifies a relation between cash-flow duration and stock returns. We next explore whether cash-flow duration can quantitatively explain the return on the duration factor. To asses the quantitative effects, we need the full term structure of CAPM alphas for dividend strips. As we only observe prices of dividend strips for the first few years, we specify a functional form for the term structure and calibrate it such that it is consistent with the dividend strips we observe and such that the market has a CAPM alpha of zero. We then analyze whether such a term structure can generate a meaningful difference in the expected returns between long- and short-duration firms.

We specify that CAPM alphas on dividend strips of maturity m follow

$$\widehat{\alpha}^m = \kappa_0 - \kappa_1 \ln(m) \tag{11}$$

and set $\kappa_0 = 9\%$. We choose κ_1 such that the market portfolio has a CAPM alpha of zero. To do so, we must take a stand on how the weights on future cash flows develop for the market portfolio. We assume that the weight on the mth period cash flow is

$$w^m = \left(\frac{1+g}{1+r}\right)^m = (0.97)^m, \tag{12}$$

which results in a cash-flow duration of 33.33 years.[35] We then choose κ_1 such that

$$\sum_{m=1}^{\infty} \left(0.97^m \times (\kappa_0 - \kappa_1 \ln(m))\right) = 0. \tag{13}$$

Figure 7 plots the resulting term structure of CAPM alphas for the first 100 years. The term structure starts at 9% by assumption and reaches −5.5% for the 100-year claim.

We next study the CAPM alphas to a long- and a short-duration firm. For the short-duration firm, we assume that the ratio of growth rates to discount

[35] In calculating duration, we approximate the weights ω^m by the weights w^m. As explained in Section I.E, these two weights are slightly different because the weights for duration, ω^m, are based on present values calculated based on the yields, whereas w^m are weights based on the actual present values.

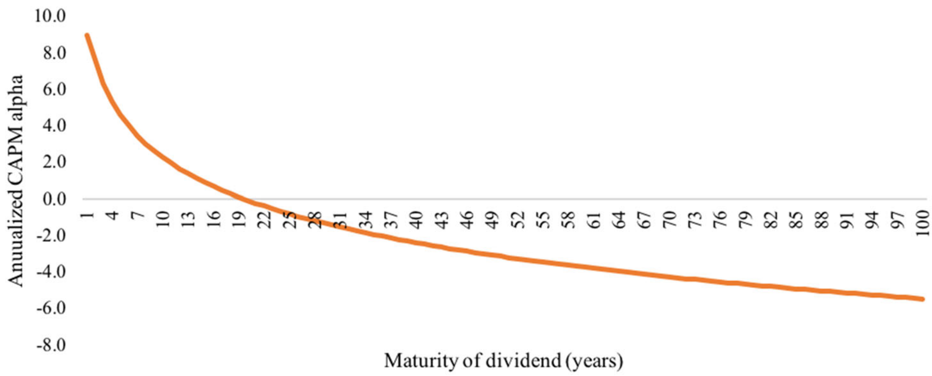

Figure 7. A term structure of implied CAPM alphas. This figure shows an implied term structure of CAPM alpha for the first 100 dividend strips. We specify the following functional form for CAPM alphas: $\hat{\alpha}^m = k_0 - k_1 \ln m$, and choose YZ and YG such that the alphas are consistent with the evidence from dividend strips and such that the alpha on the market portfolio is equal to zero. The latter is based on assumptions about the weights on future cash flow for the market; see the text for details. (Color figure can be viewed at wileyonlinelibrary.com)

rates is 0.94, which results in a duration of approximately 16 years. For the long-duration firm, we assume a ratio of 0.985, which results in a duration of approximately 66 years.

Table X shows the average CAPM alphas and weights for different parts of the term structure in this exercise. The first row shows that the average CAPM alpha for the 1- to 20-year claims is around 2.8% per year. From there, it decreases as shown in Figure 7. The table also reports the average weights that the market portfolio puts on different parts of the term structure. More importantly, it shows the average weights that long- and short-duration firms put on different parts of the term structure and the resulting CAPM alphas.

The CAPM alpha on short-duration firms is 2.11% per year and the CAPM alpha on long-duration firms is −2.27% per year. These results compare well to the results on the large-cap firm portfolios in Table III. The large-cap short-duration portfolio has an annual alpha of around 2% and the long-duration portfolio has a CAPM alpha of around −2.9%. As such, the effect of cash-flow duration is quantitatively large enough to explain most of the CAPM alpha of large-cap firms in this example (we cannot easily evaluate the CAPM alpha of small-cap firms as these firms do not have dividend futures traded on them).

The above is a reduced-form approach meant to illustrate the quantitative effects of cash-flow duration. A more rigorous approach would be to specify a flexible functional form for the data-generating process and the pricing kernel, to estimate these, and to calculate implied prices of dividend strips as in Hansen, Heaton, and Li (2008). In this context, one can discipline the model by forcing it to price the dividend futures we observe. We consider this approach an interesting avenue for future research.

Table X
Alpha Accounting

This table reports an implied term structure of CAPM alpha and the implied CAPM alpha on long- and short-duration firms. We specify a functional form for the term structure of CAPM alphas and calibrate it such that it is consistent with the pricing of near-future dividends and such that the market has a CAPM alpha of zero. The table reports the average CAPM alpha for different parts of the term structure. It also reports the average weights of the market portfolios along these parts, calculated based on the assumption that discount rates are two percentage points higher than growth rates in perpetuity. The table also shows the weights and aggregate CAPM alphas for a hypothetical short-duration firm and a hypothetical long-duration firm. See the text for more details.

	Maturity of Claims (Years)						
	1 to 20	21 to 40	41 to 60	61 to 80	81 to 100	100+	Total
Average CAPM alpha	2.8	−1.40	−3.14	−4.27	−5.11	−7.27	
Market portfolio:							
Total weight	0.46	0.25	0.14	0.07	0.04	0.05	1
Duration ($\sum \omega^m m$)							33.33
CAPM alpha: ($\sum w^m \alpha^m$)							0.00
Short-duration firm:							
Total weight	0.71	0.21	0.06	0.02	0.01	0.00	1
Duration ($\sum \omega^m m$)							16.7
CAPM alpha: ($\sum w^m \alpha^m$)							2.11
Long-duration firm:							
Total weight	0.28	0.21	0.16	0.11	0.08	0.22	1
Duration ($\sum \omega^m m$)							66.67
CAPM alpha: ($\sum w^m \alpha^m$)							−2.27

F. Relation to the Results on Index-Level Dividends

Binsbergen and Koijen (2017) study the pricing of index-level dividends and find a negative relation between maturity of dividends and risk-adjusted returns. These results are consistent with ours but it is important to emphasize that the negative relation between maturity and CAPM alphas on index-level dividends *does not* necessarily imply a similar effect at the firm level. The reason is that the composition of the index varies with maturity. By construction, the near-future index has a relatively large weight on short-duration firms, while the distant-future dividends have a relatively large weight on long-duration firms.[36] Accordingly, when comparing near- and distant-future dividends on the market portfolio, one is effectively comparing cash flows on long- and short-duration firms. As discussed above, these cash flows may have

[36] This effect can be large. In the example in Section IV.E, long-duration firms have twice as large a weight in the market portfolio as in the near-future dividends.

different returns because of cash-flow duration or because of other differences in the characteristics of long- and short-duration firms, something we cannot distinguish between without the single-stock dividend futures. In addition, the index-level dividends naturally cannot speak to whether or not there are firm-level differences in the alpha on the individual cash flows.

G. Robustness Analysis from Corporate Bonds

We perform a similar exercise using the corporate bonds described in Section I.C. 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 XI reports 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. In addition, the alpha does not vary across the duration characteristic. These results again suggest that the maturity of the cash flows, not firm-level characteristics, is the main driver of risk-adjusted returns. We find similar results for the other characteristics. Figure IA.3 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.

V. Economic Mechanisms

In the previous section, we identify an effect of cash-flow timing on equity returns. We show that part of the alpha on our duration factor must come from the fact that near-future cash flows have high CAPM alphas. In Section V.A below, we analyze potential economic drivers of such a premium on near-future cash flows. In Section V.B, we address alternative economic drivers of the duration factors that are unrelated to the timing of cash flows. Finally, in Section V.C, we relate our results to the investment CAPM.

A. Duration-Driven Returns through Consumption Risk

The results on dividend futures, and the duration factor in general, are conceptually consistent with a simple framework that features a consumption,

Table XI

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 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 parentheses and statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Alphas are annualized. The sorting is such that the 2-year portfolio, for instance, contains all bonds with maturity between one and two years. The sample is U.S. 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	

or cash flow, risk factor, and a discount-rate risk factor, where the former has a high premium and the latter has a low premium, as in Campbell and Vuolteenaho (2004).

To see how, consider the extreme case in which only consumption risk is priced. If consumption risk is constant over the term structure, all claims will have largely similar expected returns, as we indeed find in Tables III, VII, and VIII. If, at the same time, discount rate risk increases in horizon, betas will increase in maturity, as is observed empirically. However, if this discount-rate risk is unpriced, it will not increase expected returns and CAPM alphas will therefore decrease in maturity. In Internet Appendix C, we study a model with some of these dynamics based on Lettau and Wachter (2007), which shows that the major risk factors are indeed priced in such a setting.

The key for the above dynamics is that there is more consumption risk per unit of beta in the near-future claims than in the distant-future claims. We test whether this is the case by studying consumption risk in the 10 duration-sorted portfolios in Table II.

Figure 8, Panel A, plots the covariance between future consumption and quarterly returns net of the market exposure of the given portfolio. We consider two-year consumption as opposed to quarterly consumption to allow for lags in the consumption response to bad news.[37] The figure shows a higher exposure to consumption risk for short-duration portfolios than for long-duration portfolios. More precisely, when short-duration firms underperform relative to their market exposure, consumption tends to decrease over the next two years and vice versa for long-duration firms. The negative consumption beta for the long-short portfolio is statistically significant. The economic significance is more difficult to evaluate without a structural model, but we note that the covariances are modest. If we consider covariance with dividends instead of consumption, the covariances are more than 10 times as large, suggesting larger economic significance.

Panel B shows that consumption risk of raw returns on duration-sorted portfolios is more or less constant across duration. This finding is consistent with the fact that we find very limited variation in expected returns across duration-sorted portfolios. Panel C shows the relation between realized returns and future two-year returns on the market portfolio. With some simplification, this relation captures how exposed a given portfolio is to changes in expected returns and thus to discount rate risk; a more negative loading suggests a higher exposure to discount-rate risk. As expected, long-duration firms appear more exposed to changes in expected returns, though the effect is imprecisely estimated. This discount-rate risk may partly explain why long-duration firms have high CAPM betas, as realized market returns mostly reflect discount-rate risk (Cochrane, 2011).

In conclusion, the evidence in Figure 8 is consistent with consumption risk and discount rate risk playing a role in the alpha on our duration factor and

[37] In addition, contemporaneous consumption is essentially uncorrelated with returns in this exercise.

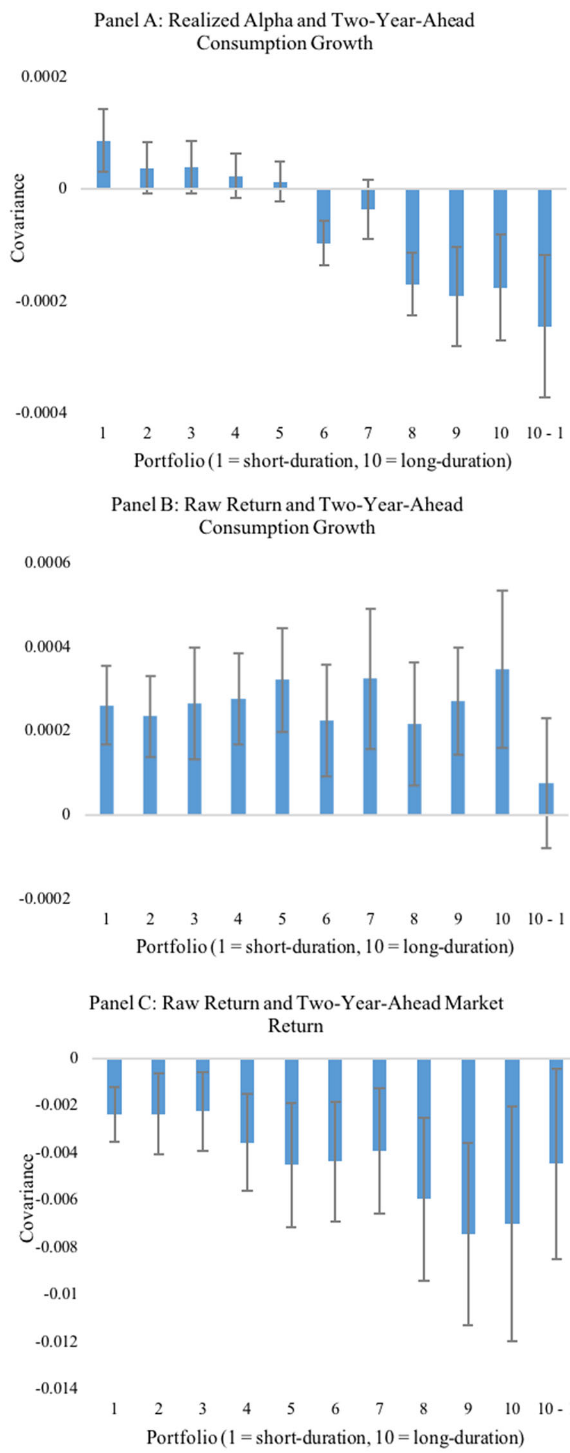
Panel A: Realized Alpha and Two-Year-Ahead Consumption Growth
0.0002
0
-0.0002
-0.0004
Covariance
1
2
3
4
5
6
7
8
9
10
10 - 1
Portfolio (1 = short-duration, 10 = long-duration)
Panel B: Raw Return and Two-Year-Ahead Consumption Growth
0.0006
0.0004
0.0002
0
-0.0002
1
2
3
4
5
6
7
8
9
10
10 - 1
Portfolio (1 = short-duration, 10 = long-duration)
Panel C: Raw Return and Two-Year-Ahead Market Return
0
-0.002
-0.004
-0.006
-0.008
-0.01
-0.012
-0.014
Covariance
1
2
3
4
5
6
7
8
9
10
10 - 1
Portfolio (1 = short-duration, 10 = long-duration)

Figure 8. Consumption and discount rate risk for duration-sorted portfolios. This figure shows covariances between the returns on the duration-sorted portfolios considered in Table II and two-year-ahead cumulative realized consumption growth and market returns. Panel A shows the covariances between each portfolio's realized alpha in quarter t, measured as $\alpha_t^i - r_t^i - \hat{\beta}^i \times r^{m}kt_t$ and log real consumption growth (PCE on nondurable goods and services, deflated by the CPI) summed $t + 1$ through $t + 8$. Panel B shows covariances between each portfolio's raw return in quarter t and the same consumption measure. Panel C shows covariances between each portfolio's raw return in quarter t and cumulative $t + 1$ through $t + 8$ market returns. Heteroskedasticity- and autocorrelation-robust standard errors (bars ± 1 SE) are calculated using the quadratic spectral kernel with 13 lags, following the lag selection rule in Lazarus et al. (2018, eq. (22)). The samples are 1947 to 2019 for Panels A and B, and 1929 to 2019 for Panel C. (Color figure can be viewed at wileyonlinelibrary.com)

on the dividend strips more generally. We note, however, that other forces such as horizon-dependent risk aversion (Eisenbach and Schmalz (2016), Lazarus (2022)) or institutional features (Belo, Collin-Dufresne, and Goldstein (2015)) may also play a role.

B. Alternative Drivers of the Duration Factor

The returns on our duration factor are driven at least in part by the premium on near-future future cash flows, and above we discuss how that premium can arise. However, as discussed earlier, the duration factor can, in principle, also arise from firm-level differences in returns. One option is that there are firm-level differences in expected returns on individual cash flows, but the evidence in Table VII suggests that this is unlikely. The expected CAPM alpha is almost the same for long- and short-duration firms, and if anything, long-duration firms have higher expected CAPM alphas than short-duration firms. These findings suggest that rational explanations of the duration factor have to revolve around a premium on near-future cash flows.

However, another possibility is that there are differences in unexpected returns across dividend strips, as implied by certain behavioral theories. In particular, La Porta (1996) and Bordalo et al. (2019) argue that high-growth firms have low realized returns because investors overestimate the expected growth rates. This theory predicts that there are no firm-level differences in expected alpha on dividend strips, as is the case empirically. However, the theory also predicts that, going forward, high-growth firms have lower realized growth than expected, leading to low realized returns on these firms. As reported in Table IX, Panel C, we indeed find that long-duration firms have lower realized returns than short-duration firms, suggesting that this theory has some validity. The statistical significance is very marginal, with p-values going below 10% in only one specification where we weight by notional and consider log-alphas. In this sense, our data do not allow us to say that diagnostic expectations influence returns with very high levels of confidence. At the same time, we cannot rule out that overreaction plays a role for the duration factor.

It is important to emphasize that the behavioral explanation from La Porta (1996) and Bordalo et al. (2019) cannot explain the finding that alphas decrease in the maturity of the cash flows. This would require a theory of maturity-rather firm-dependent expectations errors, such as that proposed by Cassella et al. (2021). As shown in Table IX, Panel D, we do not find significant evidence that investors make horizon-dependent forecast errors in this sample.

C. The Link to Production-Based Asset Pricing

Our duration-based framework is related to the production-based model (Cochrane (1991, 1996)) and the investment CAPM (Zhang (2005), Hou, Xue, and Zhang (2015), Hou et al. (2020)). These papers study stock returns from the perspective of corporations, building on the idea that corporate investment responds to discount rates from financial markets. In particular, the first principle of investment implies that firms with higher profit and lower investment must have higher discount rates to prevent them from investing more, a prediction that is strongly supported by the data. This is essentially a supply-side approach, focusing on how the supply of capital, or cash flows, ensures that the law of one price holds.

Our approach instead takes the supply of cash flows as given and focuses on the demand side, namely, how investors price these cash flows. In our framework, the 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. One advantage of this approach is that it is more easily mapped to pricing dynamics in traditional exchange economies (Lucas, 1978). However, it is also somewhat more restrictive, as it only focuses on discount rate variation coming from one dimension, whereas the production CAPM can reflect discount rate variation coming from many different dimensions at once. The fact that both approaches produce similar fundamental predictions is reassuring and suggests that the two may be able to be combined into a common framework.

VI. 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, 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. We refer to our new factor as a duration factor, because the firms in the long leg of the factor have not only low growth rates but also a short cash-flow duration.

We document that cash-flow duration is an important determinant of the premium on short-duration firms. Using a new data set of single-stock dividend strips, we find that expected and realized CAPM alphas decrease in the maturity of cash flows for individual firms, implying a direct link between duration and CAPM alphas. At the same time, the firm-level duration characteristic does not explain the expected CAPM alphas on the individual strips, suggesting that the duration characteristic only predicts expected CAPM alphas because it predicts the duration of cash flows.

Our results thus bring identification to a large literature on the role of cash-flow duration in stock returns. Lettau and Wachter (2007), for example, suggest a model in which value firms have high returns because they load more on near-future cash flows, which have a high alpha. But it is not ex ante obvious that it is the timing of cash flows—rather than other firm-level characteristics—which generates the premium on value firms. Our data allow 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.

Having identified an effect of duration on returns, the next question that arises is whether the effect is strong enough to fully explain the premium on the duration factor. We observe dividend strips only for a subset of the future dividends, meaning that we cannot provide a model-free answer to this question. That said, we show that under reasonable assumptions about the term structure of CAPM alphas and the duration of cash flows, the effect of duration is indeed large enough to explain the premium on the duration factor.

We also provide suggestive evidence on why near-future cash flows have high CAPM alphas. A large literature discusses this question (see Binsbergen and Koijen, 2017, for review). A 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). Consistent with such theories, we indeed find that our duration factor is exposed to consumption risk in that low abnormal returns on our factor are associated with lower consumption over the subsequent two years.

However, we cannot reject the possibility that irrational expectations also play a role for the returns to our duration factor. While there are no differences across firms in expected return and CAPM alpha by cash-flow maturity, 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. The statistical significance for this finding, however, is very marginal. In addition, this behavioral explanation cannot account for the maturity dimension of CAPM alphas, which exists in both expected and realized returns.

Going forward, we hope that our data set 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 for our continued understanding of the cross-section.

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Appendix A: Detail on Data and Estimation

A. 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 returns, 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:

$$V_{t+s}^{t} = V_{t+s-1}^{t}\left(1 + retx_{t+s}^{t}\right), \tag{A1}$$

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

$$D_{t+s}^{t} = V_{t+s-1}^{t}\left(ret_{t+s}^{t} - retx_{t+s}^{t}\right), \tag{A2}$$

where ret_{t+s}^{t} is the cum dividend return between periods $t+s-1$ 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.

For earnings growth, we again use the methodology developed in Chen (2017). To mitigate the fact that earnings are volatile, we average earnings over three years before calculating growth rates. In particular, to calculate 15-year growth rates, we compare the average earnings in years 13, 14, and 15 after formation to the average earnings in the year after formation, the year of formation, and the year prior to formation.

B. 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.

C. Sample Periods

We work with three different sample periods in the United States depending on data availability. Whenever we need IBES data, the sample starts in 1981. When we conduct cross-sectional factor analysis, the sample starts in 1963 because that is when the Fama and French five-factor model 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).

Appendix B: Details on Single-Stock Dividend Strips

A. Matching and Cleaning

We obtain data on single-stock dividend futures directly from the Eurex Exchange. The strips are organized by product ID. Each product ID is associated with an underlying ISIN, which is the asset that keeps track of the dividend points for the given firm. Each product ID is also associated with a firm ISIN, which is the firm that the underlying ISIN is associated with. Finally, each contract is also associated with a currency, a contract size,[38] and a minimum price change. At each point in time, a firm can be associated with multiple product IDs.

We first match the firm underlying each product ID to a GVKEY in Compustat using ISIN. In the case that product ID is associated with multiple GVKEYS, we use the first issuance number in Compustat. We then aggregate contracts across GVKEYS such that at each point in time t, we have only one firm $(i) \times$ maturity (m) observation. We aggregate notional outstanding and volume across contracts. Only in three cases do we observe a firm that has multiple dividend claims of a given maturity traded at different prices. In two of the cases, this occurs because the underlying index (the asset that keeps track of the dividends) is different. The dividend indexes are apparently different because of spin-offs.[39] In all three cases, the prices are fairly close, so we simply value-weight across the claims. Regarding currencies, the Vodafone claim has both a euro and a pound version, but since the euro version has no open interest, we simply discard it from our data set. We also discard all observations without any open interest, which is a substantial number of observations. The resulting data set comprises 599,125 unique day$\times$firm$\times$maturity observations.

[38] Almost all contracts are for 1,000 contracts of the underlying, that is, 1,000 shares, but this can vary for some of the contracts.

[39] We conjecture that one of the indexes includes the dividends associated with the company subject to the spin-off.

B. Prices

We observe the daily end-of-day settlement prices on Eurex Exchange. These are the prices that the outstanding contracts are settled against in the risk management systems. These reflect a combination of traded prices, quotes, and proprietary models. The settlement prices are sometimes updated without there being any trading. We complement these settlement prices with a time series of traded prices that we construct ourselves. For each claim, we create a traded price that we keep track of in calendar time and update to the new settlement price only on days where we observe traded volume for the particular claim.

Our main returns are based on our traded prices, but we note that in some cases, settlement prices are likely more useful. For instance, Deutsche Bank announced a dividend ban in July 2019. Naturally, there was no trading in the 2020 claim following the ban, as the contracts were worthless, which means that traded prices stay at the preban level. Settlement prices, however, were adjusted by Eurex to 0.

C. Calculating Returns

C.1. Realized Returns and Alphas

We calculate realized annual returns by looking at the one-year change in prices. At the end of each December, we calculate the realized returns over the next year as

$$r_{t+1}^{i,m} = \frac{f_{t+1}^{i,m-1}}{f_t^{i,m}} - 1. \tag{B1}$$

We use traded prices as the time t prices. We also use traded prices as the time $t+1$ prices unless the contract matures at $t+1$, in which case we use settlement prices. Note that these are futures returns, meaning that they are measured in excess of the risk-free rate.

We also calculate a time series of realized monthly returns that we use to calculate CAPM betas (see Section D of this appendix). The monthly realized returns are based on settlement prices to minimize the impact of market microstructure issues.

Finally, we calculate realized alphas by looking at the realized market returns,

$$\tilde{\alpha}_t^{i,m} = r_{t+1}^{i,m} - \beta^{i,m} r_{t+1}^{i,MKT}. \tag{B2}$$

Here, the market return is the excess return on the stock market in the country in which the firm is listed. Betas are calculated as explained in Section D of this appendix.

C.2. Expected Returns and Alphas

We match the data to expected dividends from IBES. For each claim at time t, we match the observation to the most recent IBES expectations for the same firm, matched by GVKEY, for the period ending at the expiration of the claim. We use annual expected dividends per share.

Using these expectations, we calculate expected yield-to-maturity as:

$$E_t\left[r_{t,t+m}^{i,m}\right] = \left(\frac{E_t\left[D_{t+m}^{i,m}\right]}{f_t^{i,m}}\right)^{1/m} - 1, \tag{B3}$$

where $E_t[r_{t,t+m}^{i,m}]$ is the expected return between periods 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 time t expected value of the dividend.

There is a risk that the dividends expectations in IBES refer to a different traded version of the firm than the dividend strip refers to. We therefore discard any observation for which the expected annualized return is above 30% or below -10%.

We calculate expected yield-to-maturity alphas as:

$$\alpha_{t,t+m}^{i,m} = E_t\left[r_{t,t+m}^{i,m}\right] - \beta_{Maturity}^{i,m}\lambda_{t,t+m}^{Mkt}, \tag{B4}$$

where $\alpha_{t,t+m}^{i,m}$ is the annualized alpha between periods 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%. Finally, $\beta_{Maturity}^{i,m}$ is the beta-to-maturity, calculated as explained in the next section.

D. Calculating CAPM Betas

We estimate CAPM betas in regressions of monthly returns on the strip on 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 and run the following regression:

$$r_{t,t+1}^{i,m} = \beta_0^{i,m} + \beta_1^{i,m} r_{t+1}^{M,e} + \beta_2^{i,m} r_t^{M,e} + \beta_3^{i,m}\left(r_{t-1}^{M,e} + r_{t-2}^{M,e} + r_{t-3}^{M,e}\right) + \varepsilon_{t,t+1}^{i,m}, \tag{B5}$$

where $r_{t+1}^{M,e}$ is the excess return on the market between periods t and $t+1$. The market is again the return on the market portfolio in the country in which the main trading vehicle of the underlying firm is located. We calculate $\beta^{i,m} = \beta_1^{i,m} + \beta_2^{i,m} + \beta_3^{i,m}$. 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 is often noninteger, that is, a claim has a maturity of n when $12 \times (n-1) <$ maturity in months $\leq 12 \times n$.

When calculating the expected alpha-to-maturity, we use yield-to-maturity betas. We calculate these as the average betas over the remaining life of a given strip:

$$\beta^{i,m}_{Maturity} = \frac{1}{m}\sum_{j=1}^{m}\beta^{i,j}. \tag{B6}$$

For instance, the yield-to-maturity beta of a 3-year claim is the average beta on the 1-year, 2-year, and 3-year strips on the given firm.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.