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Valuation and Long-Term Growth Expectations

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Abstract

Long-term growth expectations are central to investment analysis and corporate valuation. Despite a dominant effect on firm value, the academic literature and practitioner conventions provide little guidance on determining this long-term growth rate. This article takes a step in addressing this gap: we estimate the relationship between long-term growth and an extensive selection of firm, industry, and market characteristics. Market prices do not seem to fully capture long-term growth information. Cross sectional tests yield substantial positive abnormal returns for firms with high expected long-term growth.

I. Introduction

The standard discounted cash flow (DCF) corporate valuation consists of 3 steps: i) estimate cash flows over a short-term "projection period", ii) estimate an appropriate discount rate for these cash flows, and iii) estimate a terminal value for the years beyond the projection period, where the terminal value is typically found either by assuming some future growth process or by applying some valuation multiple.[1] However, while there is voluminous practical guidance and large research literature for the first 2 steps, there is very little guidance, both in research

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[1]The EV/EBITDA multiple is perhaps the most common valuation ratio in practice (see, e.g., Eaton, Guo, Liu, and Officer (2021)), and is often preferred over multiples based on sales or net income because EBITDA is less subject to accounting distortions (see, e.g., Demiroglu and James (2010) and

and in practice, for the third step. Thus, the same finance textbooks that devote multiple chapters to short-term pro forma projections and discount rate estimation often have only a few paragraphs discussing how one might predict a long-term corporate growth rate. Similarly, there are huge research literatures on the pricing of risk and short-run pro forma projections of earnings and cash flows, yet the literature on estimating and predicting long-term corporate growth rates is very scarce.

This inattention to long-term corporate growth rates is all the more striking given the sensitivity of corporate valuation to this variable. In many valuations, this is the most important input, that is, results are more sensitive to changes in long-term growth than any other parameter in the valuation. For example, the market value of many start-ups and other rapidly growing firms will often derive primarily or exclusively from long-term cash flows, which in turn will be entirely dependent on the long-term operating growth of these companies. Small changes in the magnitude or duration of high growth can have a dramatic effect on the valuation. The reason for this inattention to long-term growth rates may be informational: we know very little about how long-term growth rates evolve, and estimating long-term growth well for a given company is difficult. Instead, a common practice in industry is to assume an ad-hoc long-term growth rate (often taken to be the overall growth rate of the economy) and then perform sensitivity analysis on this rate. This, however, seems to be more an acknowledgment of the absence of a good estimate, than a sensible strategy to estimate a long-term growth rate.

A primary goal of this article is to address this inattention and advance what is known about predicting long-term corporate growth rates. This article presents an exploratory analysis of how firms' long-term growth is related to various firm and industry characteristics. Here, we are searching for correlations—what firm, industry, and market characteristics predict long-term growth rates—without attempting to demonstrate causation. While we at times provide potential interpretations for the correlations we find, it should be understood that these interpretations are speculative and our results are predictive and not causal. While we expect our predictive ability of long-term growth rates to be fairly modest—that is, such growth is hard to predict and we will only explain a relatively small fraction of the variation, we argue that such estimation is of sufficient importance in valuation, and so little is known on the question, that even a relatively small advance can be of first-order importance to the theory and practice of corporate valuations.

To be clear, when we speak of a long-term growth rate, we mean something different than the infinite-horizon growth rate that this term is sometimes taken to represent. Instead, we have in mind the intermediate to long-term growth rate, beyond the cash flow projection period. While we agree with the general notion that in the *very* long run one would expect corporate growth to match economic growth, there is little reason to think this provides a meaningful estimate for a company's growth rate 10, 20, or even 30 years into the future. It is growth over this range, rather than at infinity, which will typically be most relevant for valuation. Indeed, this study is motivated by this distinction. Our starting point is the notion

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Purnanandam and Swaminathan (2004)). Projections about future long-term growth play a fundamental role in determining cross-sectional variation in EV/EBITDA.

that one should be able to do better estimating growth over this range than the common practice of defaulting to an economy-wide growth rate and that this distinction will have a large impact on valuation. Hence, when we speak of long-run growth throughout this article, it is to be understood that we have in mind the intermediate- to long-term range that is relevant for valuation, and not the growth rate at an infinite horizon.[2]

We find a number of industry and firm variables that predict a firm's long-term growth. Overall, our empirical models explain up to 22% of the variation in long-term growth rates. This contrasts with existing literature, which generally concludes that there is very little predictability of long-term growth rates.[3] While we view our primary contribution here as predictive, there are some interesting qualitative insights from predictors of long-run growth, including the following:

First, we find a positive relation between barriers to entry, a variable representing firms' competitive positioning, and subsequent long-term growth rates. We also find that the propensity of firms exiting an industry is correlated with lower future long-term growth rates of remaining firms in that industry.[4]

Second, we find that companies with more leverage are associated with lower long-term growth. One potential explanation is that increased usage of debt financing is indicative of higher bankruptcy likelihood and costs, which lead to lower future growth.

Third, we document negative firm size and age effects, indicating that as firms grow larger and older they grow at lower rates.

Fourth, we document that a prominent measure of market expectations, equity analysts' long-term earnings forecasts, is positively related to long-term growth. We also find a positive relation between the number of analysts following a company and subsequent growth rates, evidence consistent with securities analysts providing oversight and disciplining management through their role in providing information to the capital markets.

Finally, we find a positive relation between variables representing current investment opportunities, such as capital expenditures, and subsequent long-term growth rates.

[2]To illustrate this point numerically, consider a highly stylized example of a firm whose cash flows grow at an 8% rate for years 1–5, at a 5% rate from years 6–30, and at a 2% rate in perpetuity after that, with a discount rate of 12%. Then, about 90% of the overall firm value comes from cash flows from the first 30 years, and if one were to incorrectly use a perpetual growth rate of 5% beyond year 5, one would misestimate value by only 4.7%. In contrast, if one were to use the infinite horizon 2% growth rate in perpetuity beyond year 5, one would misestimate value by 24.7%. If we apply a lower discount rate in this example we arrive at an even higher misestimation.

[3]Chan, Karceski, and Lakonishok (2003), for example, conclude that only about 3% of the variation in 5-year growth rates is explained by their model. Variables that proxy for the expectations of the market do not perform better either. In Table IA1 in the Supplementary Material we show that a market implied long-term growth rate derived from a constant growth dividend discount model explains only up to 3% of the variation in corporate long-term growth rates.

[4]These findings relate our study to a body of literature that examines the impact of competition, persistence of profitability, and accounting rates of return (see, e.g., Fama and French (2000), (2006), Penman (1991)). While the focus of that literature is primarily on profitability and accounting rates of return, we are interested in predicting growth for the purpose of valuation. We contribute to this literature by incorporating predictors that capture competition and profitability and provide evidence that competitive forces do shape corporate long-term growth.

While many of these relations are not surprising, our analysis provides a quantitative prediction of firms' long-run growth rates that appear to be an improvement over current practice. We provide specific support for this in the second part of the article, where we test whether the long-term growth estimates are a better predictor of expected growth than those estimates that are implicit when investors calculate prices. If this is indeed that case, then we would expect to find a positive association between long-term growth expectations and future stock returns. Alternatively, if the expected long-term growth rates are already fully reflected in prices, then we would not expect to find an association between long-term growth expectations and future returns.

As a natural test of our hypothesis, we estimate cross sectional (Fama and MacBeth (1973)) regressions with future returns as a dependent variable and expected long-term growth as the main explanatory variable. We find a positive and significant association between expectations for long-term growth and subsequent stock returns. The association persists even after controlling for major known return predictors. Since the long-term growth expectations are of main interest here, we perform an analysis of the out-of-sample performance for several different predictive frameworks. We find that the least absolute shrinkage and selection operator (LASSO) provides the best out-of-sample long-term growth predictions.

As noted above, the literature that deals directly with estimating long-term corporate growth rates for valuation purposes is rather limited. Most closely related to our contribution is the article by Chan, Karceski, and Lakonishok (2003).[5] In particular, they analyze sales and earnings growth and conclude that traditional valuation ratios, for example, earnings yield, book-to-market, and sales-to-price, have little explanatory power, and IBES long-term growth estimates also add little value to predicting long-term growth. However, their focus is on firm growth rather than on valuation, they primarily consider growth of only up to 5 years, and they look at a much narrower range of explanatory variables than we do. Kryzanowski and Mohsni (2013) and (2014) document that some firm and industry-level variables have predictive power for subsequent 5-year growth rates in earnings. In particular, they show that industry-level variables have predictive power for 5-year growth in aggregated industry-level earnings, and market expectations variables have predictive power for 5-year firm-level earnings growth.[6]

We differ from these articles in several important manners. First, we consider longer-term growth and extend the definition of "long term" to periods beyond 5 years. Second, we predict growth using a much wider set of potential long-term

[5]We note that researchers have adopted different conventions for calculating growth rates. In our paper, we are analyzing long-term growth for the purposes of valuation from the perspective of the individual investor, who buys and holds stock over some horizon and reinvests dividends (see, e.g., Chan et al. (2003)). In contrast, other papers take the perspective of the overall firm and track overall firm growth. For example, Lakonishok, Shleifer, and Vishny (1994) argue that investors tend to favor companies with strong overall past growth performance, with strong management, and in a glamorous line of business.

[6]Our study is also related to papers that examine how analysts form their growth expectations. For example, Jylha and Ungeheuer (2021) provide evidence that there is an association between beta and growth overestimation and suggest that analysts adjust growth expectations to offset the valuation effects resulting from time-varying beta estimates. Gao and Wu (2014) focus on creating an earnings growth model that performs better than analysts' long-term growth estimates from IBES.

growth predictors, looking at more than 30 different predictors and spanning more than 50 years of data. Third, we develop a predictive framework, test its out-of-sample performance, and relate the resulting growth predictions to market valuations. We demonstrate that simple cross sectional asset pricing tests based on long-term growth expectations yield significant abnormal returns.

There is also a related literature analyzing expected dividends implied by market prices. Some contributions to this literature focus on dividend derivatives to back out the present value of expected future dividends at various time horizons.[7] More recent articles, such as Giglio, Kelly, and Kozak (2021), exploit equilibrium relations between stock price dynamics and the implied dynamics of dividend yields, without relying on dividend futures.[8] All these articles take market prices as given and derive the implied dividend expectations. We essentially take the opposite approach: we estimate cash flow growth to derive the resulting fair valuations. Thus, our approach does not rely on market prices that correctly reflect cash flow growth, and consequently, we can provide firm valuations, ask questions about misvaluation, and value private firms.

The remainder of this article is organized as follows: Section II describes variable construction, the underlying data, and the predictive model specification. An analysis of the corresponding results is presented in Section III. Section IV outlines our model selection procedures for the construction of long-term growth expectations and evaluates the corresponding results. Section V relates the long-term growth expectations to the cross section of firm values. Additional robustness is presented in Section VI. Section VII concludes this article.

II. Empirical Approach

A. Measuring Long-Term Growth

As discussed in the introduction, a company's long-term growth rate is a crucial input for valuation and investment decisions. To make progress in our understanding of the determinants of long-term growth rates, one first needs to define an appropriate measure for corporate growth. From a theoretical valuation perspective, free cash flows to the firm (FCFF) or free cash flows to equity (FCFE) are the most appropriate measures since they are immediate inputs when calculating net present values. While this direct link to valuation is crucial, a major drawback of these measures is that, on average, about 53% of the FCFF observations and about 48% of the FCFE observations in our sample are negative or missing so that growth rates cannot be calculated in a consistent way. This, in turn, can introduce a substantial sample selection bias. Alternative definitions of corporate growth can be derived from the company's income statement. EBITDA is a widely used historical cash flow measure and an important input for valuation multiples such as the EV/EBITDA or EBITDA/Price (see, e.g., Liu, Nissim, and Thomas (2002)). Furthermore, EBIT or Net Income are important components of free cash flows and

[7]See, for example, Van Binsbergen, Brandt, and Koijen (2012), Van Binsbergen, Hueskes, Koijen, and Vrugt (2013), and Van Binsbergen and Koijen (2017).

[8]Other important contributions to this strand of literature include Bansal, Miller, Song, and Yaron (2021) and Gormsen, Koijen, and Martin (2020).

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are natural candidates for alternative growth measures. Compared to free cash flows, data availability on all these items is improved, and fewer observations are negative. For example, on average, only 14% of observations are missing or negative for EBITDA, 19% for EBIT, and 24% for Net Income. Alternatively, one can move further up the income statement and focus on sales. Sales are less closely related to cash flows than, say, EBITDA, but data availability is virtually 100%, and there is no problem with negative observations. Based on these tradeoffs, we choose long-term growth in EBITDA as our primary measure in the analyses below.[9] In addition, we also consider long-term growth in sales as a second measure in the first part of the article.[10]

Finally, to make these definitions of long-term growth operational, we need to decide how to define the long term. The feasible definition of long-term growth is constrained by sample length. For example, in Compustat comprehensive data only exist since 1962. Thus, the tradeoff is to define growth over a sufficiently long term such that a significant portion of the overall firm value is captured versus ensuring a sufficiently large sample of long-term growth observations. In our analyses, we therefore use two alternative definitions of long term: 5 years and 10 years.

B. Predicting Long-Term Growth: Variables

Many different factors contribute to the long-term growth of a firm. Our econometric specifications are guided by different strands of the finance and economics literature, as well as conventional practitioner beliefs, whch imply

[9]Using the discounted cash flow (DCF) approach Kaplan and Ruback (1995) study the valuation properties of highly leveraged transactions. While they determine that DCF valuations approximate transacted values reasonably well, they conclude that simple EBITDA multiples result in similar valuation accuracy. Indeed EBITDA is a metric that investors and company management closely monitor. For example, equity analysts often assume that in the last period, when free cash flow is modelled, fixed capital investments are equal to depreciation and amortization (i.e., maintenance CapEx) and net working capital investments are equal to 0, which makes long-term free cash flow measures very similar to EBITDA. Sometimes, exit multiples, such as EV/EBITDA are applied. Therefore, EBITDA growth is more relevant for firm valuation, than, say, Sales or Net Income, as it is directly related to free cash flows. To asses if EBITDA growth rates are a suitable proxy for FCF growth rates, in additional tests (untabulated) we regressed realized FCF growth rates on realized EBITDA growth rates and examined the slope coefficients. We hypothesize that if EBITDA growth rates are a good proxy for FCF growth rates we would expect that the slope coefficient be significantly different from 0, and insignificantly different from 1. While this is not the case for 5-year growth rates, we find that, for our sample, the coefficient estimates from the regression estimations of the 10-year FCF growth rates on 10-year EBITDA growth rates are significantly different from 0 and also insignificantly different from 1 for the more recent period, 1981–2018. We interpret these results as evidence that the bias in our data is not too large and that 10-year EBITDA growth rates are a suitable proxy for 10-year FCF growth rates.

[10]As explained in the text we focus on EBITDA and Sales because annual earnings, and annual free cash flows are remarkably volatile and frequently negative for a typical company. This, in turn, prevents the reliable estimation of long-term growth rates for a big proportion of the firm-year observations. Although Sales are less closely related to free cash flows than EBITDA, Sales are also a key input in DCF corporate valuation. For example, the components of FCF are often modelled as ratios of Sales (e.g., CoGS divided by Sales, SGA divided by Sales, Depreciation and Amortization divided by Sales, Capex divided by Sales, etc.). To arrive at a terminal FCF figure these components are then combined with a terminal Sales figure. A long-term Sales growth is then applied as a proxy for the growth rate in perpetuity (see, e.g., Allee, Erickson, Esplin, and Yohn (2020), who provide evidence that valuation specialists often use future growth estimates based on a historical sales growth rate).

correlations between different market and firm characteristics and future firm performance. In particular, the finance literature has linked future growth of corporations to market expectations implicit in dividend-to-price ratios or book-to-market ratios, to their ownership and capital structure, dividend policy, corporate governance, and managerial characteristics. In addition, the IO literature has identified industry characteristics such as barriers to entry as a determinant of future corporate growth. In the following, we discuss empirical proxies for these long-term growth drivers.

1. Market Expectations

The most obvious starting point for identifying predictors of long-term growth is information contained in market valuations. Prices can be expressed by free cash flow, EBITDA, or dividends, divided by the difference between the discount rate and the growth rate. Thus, in a traditional Gordon growth valuation framework (see Gordon (1959)), dividend-to-price ratios, earnings-to-price ratios, or book-to-market ratios can be expressed as linear functions of future growth rates. We therefore rely on these measures as predictors of long-term growth rates. Specifically, we use dividend yield (*Dividend Yield*), earnings-to-price ratio (*E/P*), and book-to-market ratio (*B/M*) as predictive variables in the analysis below.

We construct these ratios in accordance with the existing literature. The *Dividend Yield* is the ratio of dividends per share divided by the current price per share, *E/P* is the ratio of income before extraordinary items available to common equity relative to equity market value, and *B/M* is the ratio of book value of common equity plus deferred taxes divided by the market value of common equity. Since valuation models imply that higher expected long-term growth increases a company's current market value, and thus, the denominators of all three ratios, we expect a negative relation between these ratios and future long-term growth rates of a company.

An alternative proxy for growth expectations is security analysts' predictions. We therefore include the mean analyst forecast for long-term growth in earnings (*ALTGF Earnings*) in the predictive regression.

In Section VI.B, we estimate our predictive regressions and construct our long-term growth expectations for the purpose of corporate valuation by excluding all variables based on market information. The reason we perform these additional estimations is twofold: we want to alleviate concerns about the potential circularity of using market-based information as an ingredient in the valuation exercise, plus we want to provide long-term growth expectations for the valuation of private companies.[11]

2. Firms' Investment Decisions

Given the criterion of positive net present value for evaluating investment projects, going back to Fisher (1907) or Von Böhm-Bawerk (1899), capital investments should be related to the trajectory of future cash flows. We therefore consider

[11]For example, stock analysts often adjust their long-term earnings growth forecasts to justify the current stock price. This so-called model calibration may be a reasonable practice, but it does amount to admitting that the analyst is unable to predict long-term growth rates independently and thus relies on the very same stock price s/he is supposed to evaluate.

the capex ratio (*CAPEX*), measured as capital expenditures in the current period divided by property, plant, and equipment in the previous period, and the R&D intensity ratio, defined as the ratio of research and development expenditures to sales (*R&D Intensity*), to capture future growth related to investments in tangible and intangible assets.

We also include the amount of external financing a company obtains in any given period, constructed as the change in total assets minus the change in retained earnings all scaled by total assets (*External Financing*). Additionally, we consider the dividend payout ratio, defined as common dividends divided by earnings before extraordinary items (*Payout Ratio*).

3. Firms' Riskiness

Riskier firms are likely to be subject to higher probabilities of distress or even liquidation, due to their inability to meet operating expenses or debt obligations. Even if they are subsequently restructured, this is not costless and generates legal expenses or losses from liquidating assets (as analyzed, for example, in Bernanke (1981), Fischer, Heinkel, and Zechner (1989), or Goldstein, Ju, and Leland (2001)). These costs impact firms' long-term growth trajectories. Furthermore, firms' growth options may be related to measures of systematic risk, such as their betas. Since beta at least partly reflects a firm's cash-flow sensitivity to the state of the economy (see, e.g., Campbell, Polk, and Vuolteenaho (2010)), high beta-firms may be hit particularly hard by disasters or economic crises and exhibit less robust long-term cash-flow growth. We therefore include a company's systematic risk (*Beta*). *Beta* is calculated by estimating a regression over the past 60 months of a stock's excess returns against the market's excess returns with the requirement that at least 24 months of data are available (for the relation between systematic risk and growth options, see also Carlson, Fisher, and Giammarino (2006)).

As discussed, default risk may adversely influence future growth via negative consequences of financial distress or bankruptcy. An increase in the probability of financial distress is related to companies being more prone to, among other things, losing customers, business opportunities, and favorable credit terms, all of which will negatively impact companies' future operating growth. To this end, we include the modified *Altman's Z* score as a proxy for a company's probability of bankruptcy (see Graham and Leary (2011)).

There are a number of manners in which firm leverage might be related to long-term growth. The widespread explanations of leverage (taxes, signaling, agency, strategic interactions, etc.) yield multiple potential implications for long-run growth. Thus we include the leverage ratio defined as total debt scaled by book assets (*Leverage*).

4. Firms' Competitive Positioning

Industry structure is likely to play a significant role in company growth (see, for example, Bain (1956), Stigler et al. (1983), and Dixit and Norman (1979)). We therefore include a set of variables related to companies' competitive positioning.

First, we include the industry Herfindahl index based on sales as a standard measure of industry competition (*HHI sales*).

Second, we also construct two variables that capture the change in the industries' competitive environment. Specifically, we calculate the change in the number of companies in a particular industry based on *Industry Entries* and *Industry Exits*. These variables are constructed as the number of company entries or exits for a particular industry-year pair divided by the total number of companies in the same industry and year. As an industry definition, we use the Fama–French (FF) 48 industry classification.

In addition, we include a measure that captures the level of barriers to entry. We use the plant, property, and equipment-to-total assets ratio (*Barriers to Entry*). This ratio captures how capital-intensive firms are. We construct this ratio at the industry level by computing the mean ratio of property, plant, and equipment to total assets for a particular industry-year pair, using the FF 48 industry classification.

We also consider proxies for product differentiation (see, e.g., Hotelling (1929) and Salop (1979)). If a firm with a differentiated product earns above-normal operating profits, it may grow faster in the future. We use two variables to proxy for this: the ratio of depreciation, depletion, and amortization expense to net sales (*Capital Intensity*) and the ratio of advertising expense to net sales (*Advertising Intensity*) (see Cheng (2005)). An additional measure for competitive advantage is the number of patents on the company's books. Bloom and Van Reenen (2002) showed that patents have economically and statistically positive significant impact on firm-level productivity and market value. Having a large number of patents on the balance sheet implies that a company has heavily invested into intangible assets, which have materialized and lead to above average profit margins. Consequently, we would expect that such a company would achieve higher growth in the future. To this end, we include the number of patents a company has, defined as the natural logarithm of total number of patents (*Number of Patents*).

5. Firms' Corporate Governance

Firms' corporate governance may also potentially influence its long-term growth in a number of different ways. Governance may impact project choice, efficiency, empire-building tendencies of management, competitive advantages, and cost of capital, thereby affecting long-term growth (see Berle and Means (1932), Jensen and Meckling (1976), Grossman and Hart (1982), and Jensen (1986)). Thus, we will consider a number of variables related to governance.

Large outside shareholders may play an important role in corporate governance (see, e.g., Shleifer and Vishny (1986), Admati, Pfleiderer, and Zechner (1994), and Gillan (2006)). A large shareholder has the incentive to gather information, monitor the management, and also put pressure on the management through sizeable voting control (see, e.g., Harris and Raviv (1988), Grossman and Hart (1988), and Shleifer and Vishny (1997)). To capture the potential monitoring by large shareholders and its effect on the firm's future growth, we construct a measure of institutional ownership concentration (*Inst. Ownership HHI*). In addition, we also use the percentage of total institutional ownership to total equity ownership in the company (*Inst. Ownership*) (see Hartzell and Starks (2003)). Finally, security analysts may provide oversight as well, through their role in providing information to the market (see Gillan (2006)). Therefore, we include the number of analysts issuing a forecast for a company's long-term growth (*Number Analysts*).

6. Additional Variables

We also include several additional variables, which do not directly relate to the categories discussed above.

First, we include a company's sustainable growth rate as explanatory variable, given by the product of its return on equity and the retention ratio. This is the sustainable growth rate if a company's profitability and payout policy remain constant. We construct the sustainable growth (*G*), where the return on equity is measured as a company's earnings before extraordinary items divided by book equity and the retention ratio is 1 minus the payout ratio, measured as a common dividend divided by earnings before extraordinary items (see Chan et al. (2003)).

Second, we include last year's growth in sales (*Growth Sales 1Y*) or growth in EBITDA (*Growth EBITDA 1Y*) in the respective predictive regression specifications to capture information obtained from past performance.

Third, a company's size might also be related to future long-term growth rates. Large firms may require organizational and operational structures that make it more difficult to realize growth opportunities, as formalized, for example, by Arrow (1974), Holmstrom (1989), and Manso (2011). We therefore construct a variable for the size of the company by taking the natural logarithm of total assets (*Size*).

Fourth, we also include a proxy for the age of the company. As discussed by Loderer, Stulz, and Waelchli (2016), corporate aging could reflect an increase in organizational rigidities over time or diffusion of rent-seeking behavior in the firm. Consistent with the existing literature, we measure the age of the company (*Firm Age*) as the natural log of years since IPO or years of information on Compustat if the IPO year is missing.

Finally, we include a set of macroeconomic variables, which have been regarded as factors influencing the overall business environment a company operates in and consequently its long-term growth. The variables that we consider are the change in the logarithm over 10 years of the real GDP (*GDP Growth 10Y*), the change in the logarithm of the U.S. Consumer Price Index (*Inflation Rate*) and also the 10Y treasury rate (*RFR*). Prior literature shows that these variables are related to both expected earnings growth and expected returns (see, e.g., Sharpe (2002)). We also include industry dummies (based on FF 48 industries) to capture that companies operating in different industries might differ in the average long-term growth rate.

A detailed description of the construction of each variable is contained in the Appendix. To be eligible for inclusion in the predictive regressions at a given horizon, a company must have a positive base-year value for the corresponding growth variable, that is, sales or EBITDA, so as to calculate a growth rate. In addition, the company must not have any missing values for any of the predictors.

C. Data

Our sample is obtained from several data sources. Our primary data source for accounting information is Compustat. Compustat provides comprehensive data starting in 1962 and contains relevant accounting variables as well as data for the operating performance measures. Macroeconomic data, such as data on the U.S. Consumer Price Index (CPI), real GDP, and the risk-free rate, are obtained from the Federal Reserve Bank of St. Louis (FRED) database. Price data are from CRSP. Data on the Fama–French factors are taken from Kenneth French's data webpage. We obtain firm-level data on patents from Noah Stoffman's website (see Kogan, Papanikolaou, Seru, and Stoffman (2017)). The institutional ownership data are derived from Thomson Reuters Institutional (13f) Holdings. Data on the number of analysts following a company and analysts' forecasts for long-term growth rates are retrieved from IBES.

To make use of all available company and time-series information, we take into account that the different data sets provide data availability for different sets of companies and different time periods. We therefore construct two data sets, covering different periods and containing different numbers of variables. First, we merge the Compustat data file with the Macroeconomic data file and the CRSP data file to cover the largest number of companies and the longest time period. In performing our predictive estimations, we utilize independent variables that require accounting information lagged by 1 year.[12] Therefore, the longest period we cover in our estimations is from 1963 to 2018. Second, we complement this data set with information about patents, institutional ownership, and analysts' forecasts. The resulting data set covers the period from 1981 to 2018.

We focus on U.S. companies traded on AMEX, NASDAQ, and NYSE. We remove utilities (SIC 4900–4949) and financial companies (SIC 6000–6999). We also remove firms with negative or missing asset and equity values, or gross plant, property, and equipment larger than assets. We perform our estimations on a yearly basis since most of the data that we use are available only on yearly frequency. Firms are selected at the end of each fiscal year. To control for the effect of outliers in the subsequent estimations the variables are winsorized at the 1% level in both tails of the distribution. We winsorize the variables year by year to avoid a look-ahead bias. The two final data sets that we use in our tests are as follows: i) the data set for the period 1963–2018 contains 105,007 firm-year observations for 8505 unique firms, and ii) the data set for the period 1981–2018 contains 53,469 firm-year observations for 6,283 unique firms. Due to missing data on a variety of data items, we often employ a smaller sample in the analyses.

Panels A and B in Table 1 provide summary statistics for the periods 1963–2018 and 1981–2018, respectively. The median firm growth rates in Sales and EBITDA are in line with the growth rates in the sample of Chan et al. (2003). Figure 1 displays the empirical histograms of the 5- and 10-year growth rates in Sales and EBITDA. The histograms show that there is wide dispersion in growth rates and that the dispersion widens as we move from 5- to 10-year growth rates.

[12]For example, we construct the predictor variable *CAPEX* defined as capital expenditures in year t divided by property, plant, and equipment in year $t-1$. Another example is the variable *External Financing* defined as the change in total assets (from year $t-1$ to year t) minus change in retained earnings (from year $t-1$ to year t) divided by total assets. Both examples show that we lose the first year of the sample period when constructing these variables for the purpose of our predictive regression estimations.

TABLE 1

Descriptive Statistics

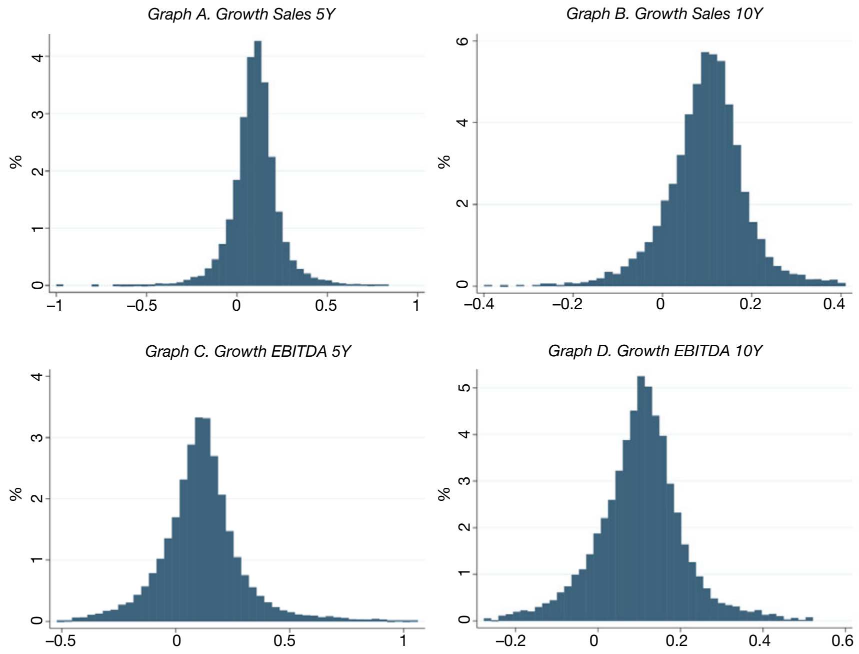
Table 1 presents descriptive statistics for the variables used in the analyses for the sample period 1963 to 2018 (in Panel A) and the sample period 1981–2018 (in Panel B). To control for the effect of outliers in the subsequent estimations the variables are winsorized at the 1% level in both tails of the distribution.

	Obs.	Mean	Standard Deviation	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Panel A (1963–2018)								
Advertising Intensity$_t$	105,007	0.01	0.03	0	0	0	0.01	0.16
Altman's Z$_t$	101,612	1.72	2.73	−10.28	1.21	2.21	3	5.55
B/M$_t$	99,199	0.73	0.65	0.05	0.31	0.54	0.93	3.22
Barriers to Entry$_t$	105,005	0.43	0.15	0.15	0.3	0.43	0.53	0.76
Beta$_t$	89,981	1.24	0.71	−0.14	0.79	1.16	1.6	3.51
Capex$_t$	92,949	0.21	0.27	0.01	0.07	0.13	0.23	1.45
Capital Intensity$_t$	103,441	0.06	0.14	0	0.02	0.03	0.05	0.59
Dividend Yield$_t$	102,955	0.01	0.02	0	0	0	0.02	0.09
E/P$_t$	103,029	0	0.26	−0.93	0	0.05	0.08	0.28
External Financing$_t$	93,797	0.09	0.2	−0.31	−0.01	0.05	0.14	0.87
Firm Age$_t$	103,739	2.11	1.01	0	1.39	2.3	2.89	3.89
G$_t$	104,703	−0.03	0.51	−2.32	−0.01	0.07	0.13	0.49
GDP Growth 10Y$_t$	104,753	0.03	0.01	0.01	0.03	0.03	0.03	0.05
Growth EBITDA 1Y$_t$	81,915	0.18	1	−2.72	−0.09	0.12	0.34	4.4
Growth EBITDA 5Y$_t$	53,174	0.11	0.18	−0.34	0.02	0.11	0.19	0.69
Growth EBITDA 10Y$_t$	34,104	0.1	0.11	−0.19	0.05	0.11	0.16	0.4
Growth Sales 1Y$_t$	93,645	0.18	0.46	−0.53	0.01	0.11	0.24	2.28
Growth Sales 5Y$_t$	62,567	0.1	0.13	−0.27	0.04	0.1	0.17	0.5
Growth Sales 10Y$_t$	39,353	0.1	0.09	−0.15	0.05	0.1	0.15	0.33
HHI Sales$_t$	105,007	0.13	0.1	0.03	0.07	0.1	0.15	0.57
Industry Entries$_t$	105,007	0.08	0.07	0	0.02	0.06	0.11	0.3
Industry Exits$_t$	105,007	0.08	0.13	0	0.03	0.06	0.09	0.92
Inflation Rate$_t$	104,753	0.04	0.03	0	0.02	0.03	0.04	0.14
Leverage$_t$	104,596	0.2	0.18	0	0.03	0.17	0.32	0.68
Payout Ratio$_t$	104,705	0.16	0.39	−0.42	0	0	0.25	1.98
R&D Intensity$_t$	105,007	0.28	2.77	0	0	0	0.06	5.9
RFR$_t$	105,007	0.06	0.03	0.02	0.04	0.06	0.08	0.14
Size$_t$	105,007	5.24	1.98	1.35	3.8	5.05	6.53	10.26
Panel B (1981–2018)								
Advertising Intensity$_t$	53,469	0.01	0.03	0	0	0	0.01	0.17
Altman's Z$_t$	51,381	1.87	1.82	−5.77	1.24	2.08	2.84	5.27
B/M$_t$	50,261	0.57	0.47	0.05	0.28	0.46	0.73	2.18
Barriers to Entry$_t$	53,468	0.41	0.15	0.19	0.28	0.4	0.52	0.77
Beta$_t$	47,251	1.27	0.72	−0.06	0.81	1.16	1.61	3.65
Capex$_t$	43,683	0.2	0.24	0.02	0.08	0.13	0.23	1.26
Capital Intensity$_t$	53,131	0.05	0.08	0	0.02	0.04	0.06	0.33
Dividend Yield$_t$	53,079	0.01	0.02	0	0	0	0.02	0.08
E/P$_t$	53,171	0	0.25	−0.81	0.01	0.04	0.07	0.18
External Financing$_t$	43,778	0.08	0.17	−0.27	−0.02	0.04	0.13	0.69
Firm Age$_t$	52,998	1.91	0.98	0	1.1	2.08	2.71	3.56
G$_t$	53,324	0.01	0.39	−1.7	0	0.08	0.14	0.52
GDP Growth 10Y$_t$	53,305	0.03	0.01	0.01	0.03	0.03	0.03	0.04
Growth EBITDA 1Y$_t$	40,358	0.16	0.79	−2.09	−0.07	0.11	0.31	3.35
Growth EBITDA 5Y$_t$	20,833	0.11	0.16	−0.3	0.03	0.1	0.18	0.61
Growth EBITDA 10Y$_t$	10,892	0.11	0.1	−0.14	0.06	0.1	0.15	0.38
Growth Sales 1Y$_t$	44,156	0.16	0.33	−0.39	0.01	0.1	0.23	1.44
Growth Sales 5Y$_t$	22,677	0.1	0.1	−0.15	0.05	0.1	0.15	0.41
Growth Sales 10Y$_t$	11,525	0.1	0.07	−0.07	0.06	0.1	0.14	0.32
HHI Sales$_t$	53,469	0.14	0.11	0.05	0.08	0.1	0.16	0.61
Industry Entries$_t$	53,469	0.12	0.13	0	0.04	0.09	0.16	0.89
Industry Exits$_t$	53,469	0.12	0.14	0	0.05	0.1	0.14	0.91
Inflation Rate$_t$	53,305	0.03	0.02	0	0.02	0.03	0.03	0.1
Leverage$_t$	53,211	0.19	0.18	0	0.02	0.17	0.31	0.67
Payout Ratio$_t$	53,325	0.17	0.47	−0.56	0	0	0.23	2.18
R&D Intensity$_t$	53,469	0.09	0.32	0	0	0.01	0.08	1.62
RFR$_t$	53,469	0.06	0.03	0.02	0.04	0.06	0.07	0.14
Size$_t$	53,469	6.18	1.81	2.81	4.82	5.99	7.41	10.75
ALTGF Earnings$_t$	53,469	18.51	11.13	0.4	12	15.75	22.5	56
Inst. Ownership$_t$	51,768	0.52	0.26	0.03	0.3	0.52	0.73	0.98
Inst. Ownership HHI$_t$	51,825	0.11	0.11	0.02	0.04	0.07	0.13	0.59
Number Analysts$_t$	53,469	0.92	0.82	0	0	0.69	1.61	2.83
Number Patents$_t$	39,763	0.81	1.4	0	0	0	1.39	5.56

FIGURE 1

Distribution of Long-Term Growth Rates in Sales and EBITDA

Figure 1 displays the empirical histograms of 5-year and 10-year growth rates in sales and EBITDA in our sample period 1963–2018.



It is important to note that the 5-year and 10-year growth rates can only be estimated for firms that survive 5 and 10 years, respectively. This, in turn, restricts the first stage of our predictive estimations to firms for which 5- and 10-year growth rates are available, which may introduce a survivorship bias.[13] In the Supplementary Material, we therefore analyze and compare the behavior of nonsurviving firms to that of surviving firms, to provide evidence on potential biases.[14] In addition, in the second stage of our predictive regression framework, we construct long-term growth expectations for all firms with available predictors in a given sample year (and not only the firms with available 5- and 10-year growth estimates). Thus, any survivorship bias in the first stage in the predictive regression framework would

[13]This corresponds to the measurement convention in the literature (see, e.g., Chan et al. (2003)).

[14]To gauge the potential impact of survivorship on our results at every fiscal year-end over the sample period we select two sets of firms: firms that survive the following 10 years (survivors), and firms that survive over the following 5 years but not until year 10 (non-survivors). In the Supplementary Material in Table IA2 we show that the mean (median) annualized growth rates are slightly higher for survivors compared to non-survivors. Importantly, in Tables IA3 and IA4 we replicate our predictive regression tests for non-survivors and find very similar results for the long-term growth predictors of non-survivors compared to those of survivors. We conclude that survivorship does not have a pronounced impact on our results.

work against finding predictive power for the growth estimates in the second stage.[15] Next, we discuss our estimation framework and results.

D. Model Specification

In this section, we outline our methodology. For long-term growth, we consider annualized geometric growth rates as the dependent variable. We adjust these growth rates for stock splits and dividends, as well as reinvestment of cash dividends,[16] that is,

$$(1) \qquad G_{i,j,t\rightarrow t+n} = \left(\frac{V_{i,j,t+n}}{V_{i,j,t}} \times \prod_{m=1}^{n} \left(1 + Div_{i,j,t+m}\right) \right)^{\frac{1}{n}} - 1,$$

where $G_{i,j,t\rightarrow t+n}$ is the annualized geometric growth rate in Sales or EBITDA from t to $t+n$, and $n=5$ or $n=10$. $V_{i,j,t+n}$ is the end of period value of the cash flow measure, and $V_{i,j,t}$ is the start of period value of the cash flow measure. These cash flow measures are adjusted for stock splits and dividends. $Div_{i,j,t}$ is the cash dividend in the stock each year, $i=1,\ldots,N$ is a firm index, $j=1,\ldots,48$ is an industry index based on the FF 48 industry classification, and $t=1,\ldots,T$ is a year index.

We predict the long-term growth rates in the above-mentioned cash flow variables using a 2-stage procedure. Specifically, in the first stage, we estimate the following model:

$$(2) \qquad G_{i,j,t\rightarrow t+n} = \alpha_j + \sum_{f=1}^{m} \beta_{f,t+n} X_{i,j,t} + \varepsilon_{i,j,t+n},$$

where $G_{i,j,t\rightarrow t+n}$ is the annualized geometric growth rate per share in Sales or EBITDA with dividends reinvested over the years from t to $t+n$, where $n=5$ or $n=10$. m denotes the number of predictors. The independent variables $X_{i,j,t}$ are measured at the beginning of 5 and 10 years, respectively. The model is estimated with industry dummies (α_j). Statistical inference is based on double-clustered standard errors. In particular, to account for both cross sectional and time-series serial correlation, we report t-statistics that are based on standard errors clustered by firm and year.[17]

[15]To shed more light on the robustness of our results, we perform the first stage predictive regressions over different sample periods, different forecasting horizons (5 and 10 years), and different dependent variables (Sales and EBITDA).

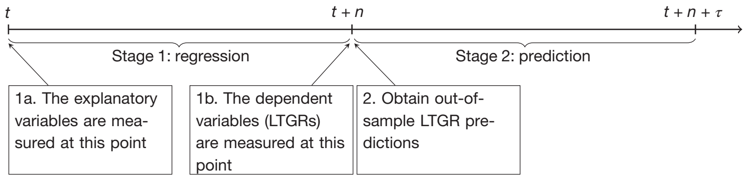
[16]Estimating long-term growth as an annualized geometric average growth adjusted for stock splits and dividends, as well as reinvestment of cash dividends is in line with extant literature (see, e.g., Chan et al. (2003)). In robustness estimations we also estimate realized long-term growth as the average of one-year growth rates over the long run (5 and 10 years). The results are quantitatively and qualitatively very similar (untabulated). This, in turn, alleviates concerns that the geometric growth formula only uses the data points at the start and the end of the growth window.

[17]To take into account serial correlation we explore a number of standard error correction methodologies with different lag structures. We find that double clustering by firm and year is the most conservative approach. Therefore, we report our results based on this approach. See Petersen (2009) for a study on standard error estimation in panel data sets.

FIGURE 2

Model Estimation Timeline

Figure 2 illustrates a timeline for the estimation of model (2) as well as the construction of the LTGR expectations. In period $t+n$, we measure the LTGRs and regress them on the set of explanatory variables X_i measured in period t, that is, at the beginning of the growth rate measurement period. This estimation generates coefficients $\widehat{\alpha}_j$ and $\widehat{\beta}_{1,t+n}, \widehat{\beta}_{2,t+n}, \ldots, \widehat{\beta}_{m,t+n}$, which we then combine with the same explanatory variables X_i, that we use in the estimation of the model but measured in period $t+n$ to obtain predictions for the LTGRs over the next τ years, that is, from period $t+n$ to period $t+n+\tau$ (see model (3)).



In the second stage, we take the point of view of an investor, who uses only the past information available and updates information each year as time passes. Specifically, we perform an expanding window estimation[18] of model (2) and perform out-of-sample forecasting. In other words, in the second stage, the estimated parameters, $\widehat{\alpha}_j$ and $\widehat{\beta}_{1,t+n}, \widehat{\beta}_{2,t+n}, \ldots, \widehat{\beta}_{m,t+n}$, which are re-estimated each year, are combined with the independent variables (X_i) in the same year ($t+n$), to generate predicted growth rates over the next $\tau = 5$ and 10 years ($\widehat{G}_{i,j,t+n \to t+n+\tau}$), as outlined below in model (3). The predicted growth rates are generated for all companies in our sample that have available information for the independent variables (X_i) and not only for the companies with available 5- or 10-year growth information. This, in turn, reduces the potential impact of survivorship bias in the second-stage estimation.

$$(3) \qquad \widehat{G}_{i,j,t+n \to t+n+\tau} = \widehat{\alpha}_j + \sum_{f=1}^{m} \widehat{\beta}_{f,t+n} X_{i,j,t+n}$$

Figure 2 outlines the timeline of the estimation procedure.

III. Predicting Long-Term Growth: Analysis and Results

In this section, we present and evaluate the results of the predictive regressions of companies' long-term growth rates in Sales and EBITDA. While we view our primary contribution as predictive, there are some interesting qualitative insights from predictors of long-run growth which we discuss below. Tables 2 and 3 summarize the results from regressions with different sample periods (i.e., starting 1963 or 1981), different forecasting horizons (5 and 10 years), and different dependent variables (Sales and EBITDA growth). In general, the estimated results for a particular predictor have predominately the same coefficient signs, similar magnitudes, and similar statistical significance. However, in some of the estimations, frequently in the shorter periods, statistical significance weakens although the

[18]The model is re-estimated each year including the information from the new period and all past available information.

coefficient sign and magnitude remain.[19] We concentrate our attention on variables that have statistically significant results and have the same coefficient sign in at least 75% of the estimations for either Sales or EBITDA growth. To infer relative economic importance, we multiply the coefficient estimate of each predictive variable by its standard deviation. We then normalize these products by the sample average for the respective dependent variable. This procedure allows for relative comparisons, that is, by how many percent does the long-term growth measure change if an independent variable changes by 1 standard deviation. For brevity, we take the average across the different data set periods and also long-term growth periods for Sales and EBITDA.

A. Market Expectations

We start the discussion of our results with the variables that capture the expectations of the market. The variable *B/M* exhibits a negative and statistically significant relation to future long-term growth in Sales. This finding is in line with the predictions from a simple Gordon growth model and is indicative of future growth being at least partially reflected in current stock prices, that is, higher expected long-term growth increases a company's current stock price, which, in turn, results in an increase of the denominator of this ratio. On average a 1-standard-deviation increase in *B/M* is associated with a 12.5% decrease in long-term Sales growth.[20]

The next prominent measure for market expectations is security analysts' long-term growth earnings forecasts *ALTGF Earnings* (see, e.g., Dechow and Sloan (1997) and Chan et al. (2003)). We find a positive and statistically significant relation with long-term growth in Sales, which indicates that analysts' long-term forecasts are informative for future realizations of long-term growth. A 1-standard-deviation increase in *ALTGF Earnings* is associated with an 11.1% increase in long-term Sales growth.

B. Firms' Investment Decisions

Tables 2 and 3 reveal that the level of a company's *External Financing* has a positive and statistically significant coefficient in all long-term growth in Sales estimations. This finding confirms that in a well-functioning capital market, firms with growth potential look for external funds to finance investment opportunities. A 1-standard-deviation increase in *External Financing* is associated with a 4.1% increase in long-term Sales growth.

[19]For example, the results for the Industry Exits variable indicate negative and statistically significant association in 3 out of 4 estimations for future long-term Sales growth, and in 3 out of 4 estimations for future long-term EBITDA growth. In the period 1981–2018, when looking at 10-year Sales and 10-year EBITDA growth, statistical significance disappears, although the coefficient sign remains negative. This is likely due to the decrease in sample size. Still, we proceed by providing economic interpretations for the association between Industry Exits and subsequent long-term growth in Sales and EBITDA because statistically significant association is present in 3 out of 4 estimations.

[20]The variable *B/M* exhibits a positive and significant relation to future long-term growth in EBITDA during the period 1963–2018. However, when we include additional growth predictors, such as *ALTGF Earnings* and *Number Analysts*, the coefficient estimate becomes negative and statistically significant. We therefore refrain from providing an interpretation for the association between *B/M* and future long-term growth in EBITDA.

TABLE 2

Predicting Long-Term Growth Rates in Sales

Table 2 reports the results from the long-term growth predictive regression estimation described in Section II 2.4. The dependent variables are 5- and 10-year annualized geometric growth rates in Sales (5 YS and 10 YS). The data sets consist of U.S. exchange-listed companies for two different periods: i) 1963 to 2018 and ii) 1981 to 2018. To account for both cross sectional and time-series serial correlation we report *t*-statistics in parentheses that are based on standard errors clustered by firm and year (see Petersen (2009)). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	5YS 1963–2018	10YS 1963–2018	5YS 1981–2018	10YS 1981–2018
	1	2	3	4
Advertising Intensity$_t$	0.0918*	0.0202	0.0559	0.0272
	(1.787)	(0.429)	(0.898)	(0.468)
Altman's Z$_t$	0.0033**	0.0027**	−0.0036*	−0.0041*
	(2.273)	(2.632)	(−1.936)	(−1.955)
B/M$_t$	−0.0169***	−0.0155***	−0.0340***	−0.0279***
	(−4.387)	(−6.095)	(−7.761)	(−4.497)
Barriers to Entry$_t$	0.2285***	0.1823***	0.1726***	0.0805**
	(6.341)	(6.719)	(3.732)	(2.128)
Beta$_t$	−0.0031	−0.0027	−0.0074**	−0.0083***
	(−1.565)	(−1.475)	(−2.605)	(−2.872)
Capex$_t$	0.0293***	0.0234***	0.0256**	0.0209*
	(4.010)	(4.534)	(2.384)	(1.968)
Capital Intensity$_t$	0.1716**	0.1437***	0.0739	0.0222
	(2.656)	(2.910)	(1.510)	(0.404)
Dividend Yield$_t$	0.3330***	0.2117***	0.1255	−0.0367
	(4.046)	(3.388)	(1.027)	(−0.239)
E/P$_t$	0.0277*	0.0224**	−0.0174	0.0034
	(1.894)	(2.129)	(−1.157)	(0.169)
External Financing$_t$	0.0388***	0.0138***	0.0220**	0.0126*
	(4.529)	(2.703)	(2.683)	(1.766)
Firm Age$_t$	−0.0154***	−0.0140***	−0.0059*	−0.0034
	(−6.428)	(−7.419)	(−1.832)	(−0.885)
G$_t$	0.0317***	0.0265***	0.0540***	0.0373***
	(5.561)	(4.724)	(5.090)	(3.172)
GDP Growth 10Y$_t$	0.7645	1.7632***	−0.2890	0.4019
	(1.520)	(3.531)	(−0.674)	(1.115)
Growth Sales 1Y$_t$	−0.0025	−0.0038	0.0022	−0.0005
	(−0.509)	(−1.113)	(0.237)	(−0.057)
HHI Sales$_t$	−0.0133	0.0169	0.0286	0.0449
	(−0.738)	(0.847)	(1.026)	(1.697)
Industry Entries$_t$	−0.0139	0.0007	−0.0391	−0.0298**
	(−0.319)	(0.032)	(−1.559)	(−2.407)
Industry Exits$_t$	−0.1680***	−0.0944***	−0.1062**	−0.0111
	(−3.728)	(−3.385)	(−2.729)	(−0.542)
Inflation Rate$_t$	0.1208	0.1964*	−0.4294*	0.2230
	(0.527)	(1.813)	(−1.719)	(1.411)
Leverage$_t$	−0.0601***	−0.0514***	−0.0588***	−0.0504***
	(−6.848)	(−6.634)	(−4.697)	(−3.287)
Payout Ratio$_t$	0.0006	0.0042**	0.0018	−0.0005
	(0.252)	(2.195)	(0.659)	(−0.180)
R&D Intensity$_t$	−0.0057	−0.0054	0.0414	0.0154
	(−1.384)	(−1.172)	(1.683)	(0.556)
RFR$_t$	0.0553	0.1136	0.1416	−0.0363
	(0.351)	(0.977)	(1.021)	(−0.303)
Size$_t$	−0.0016	−0.0006	−0.0069***	−0.0094***
	(−1.604)	(−0.646)	(−3.182)	(−4.798)
ALTGF Earnings$_t$			0.0009***	0.0011***
			(2.796)	(3.278)
Inst. Ownership$_t$			−0.0027	−0.0100
			(−0.309)	(−1.011)
Inst. Ownership HHI$_t$			−0.0306	0.0263
			(−1.350)	(1.022)

(continued on next page)

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TABLE 2 (continued)

Predicting Long-Term Growth Rates in Sales

	5YS 1963–2018	10YS 1963–2018	5YS 1981–2018	10YS 1981–2018
	1	2	3	4
Number Analysts$_t$			0.0036*	0.0070***
			(1.711)	(3.446)
Number Patents$_t$			−0.0009	0.0003
			(−0.732)	(0.255)
Observations	48,373	30,362	12,059	6386
Adjusted R^2	0.112	0.163	0.147	0.222
Industry dummies	FF48	FF48	FF48	FF48

Furthermore, we find that *Capex* has a positive and statistically significant relation to future long-term growth rates in sales. Thus, investments in tangible capital are indicative of future growth opportunities, which lead to higher future growth. A 1-standard-deviation increase in *Capex* is associated with a 6.3% increase in long-term Sales growth.

C. Firms' Riskiness

We document a negative relation between *Altman's Z*, a measure of a firm's riskiness, and subsequent long-term growth rates in EBITDA. Higher values of the variable are associated with lower probability of financial distress in the short-run, so the negative relation indicates that companies with higher short-run probability of financial distress enjoy higher long-term growth in the future. One economic interpretation is that firms might need to undertake riskier ventures to achieve higher growth in the future. Thus, "low Altman's Z" companies are more likely to go bankrupt, but those that survive generate substantially higher long-term growth. A 1-standard-deviation increase in *Altman's Z* is associated with a 24.3% decrease in long-term EBITDA growth.

Furthermore, we find that *Leverage* has negative and statistically significant relation to future long-term growth rates. One potential explanation is that increased usage of debt financing is indicative of higher bankruptcy likelihood and costs, which lead to lower future growth. A 1-standard-deviation increase in *Leverage* is associated with a 9.9% decrease in long-term sales growth and 13.3% decrease in long-term EBITDA growth.

D. Firms' Competitive Positioning

We also find a positive and statistically significant association between the *Barriers to Entry* variable and future long-term growth rates. This finding confirms the intuition that companies in more capital-intensive industries enjoy higher barriers to entry and tend to grow at higher future rates. A 1-standard-deviation increase in *Barriers to Entry* is associated with a 24.9% increase in long-term sales growth and a 21.3% increase in long-term EBITDA growth. Furthermore, *Industry Exits* predicts lower long-term growth rates for those companies that remain in the industry. A 1-standard-deviation increase in *Industry Exits* is associated with a

TABLE 3

Predicting Long-Term Growth Rates in EBITDA

Table 3 reports the results from the long-term growth predictive regression estimation described in Section II.D. The dependent variables are 5- and 10-year annualized geometric growth rates in EBITDA (5 YE and 10 YE). The data sets consist of U.S. exchange-listed companies for two different periods: i) 1963 to 2018 and ii) 1981 to 2018. To account for both cross sectional and time-series serial correlation we report *t*-statistics in parentheses that are based on standard errors clustered by firm and year (see Petersen (2009)). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	5YE 1963–2018	10YE 1963–2018	5YE 1981–2018	10YE 1981–2018
	1	2	3	4
Advertising Intensity$_t$	0.0737	0.0640	0.1411	0.1205
	(0.999)	(0.983)	(1.650)	(1.623)
Altman's Z$_t$	−0.0135***	−0.0047**	−0.0200***	−0.0108***
	(−5.232)	(−2.394)	(−5.763)	(−3.168)
B/M$_t$	0.0118***	0.0016	−0.0196**	−0.0151*
	(3.149)	(0.478)	(−2.548)	(−1.863)
Barriers to Entry$_t$	0.2220***	0.1046***	0.2064***	0.0817
	(5.134)	(3.656)	(2.962)	(1.535)
Beta$_t$	−0.0058*	−0.0010	−0.0044	−0.0090*
	(−1.789)	(−0.384)	(−0.882)	(−1.976)
Capex$_t$	0.0084	0.0177***	−0.0085	0.0317**
	(0.839)	(3.209)	(−0.491)	(2.183)
Capital Intensity$_t$	0.0226	0.0208	−0.1489	−0.1668
	(0.473)	(0.445)	(−1.402)	(−1.469)
Dividend Yield$_t$	−0.0551	0.1107	−0.0254	−0.0827
	(−0.476)	(1.403)	(−0.141)	(−0.398)
E/P$_t$	−0.0430	−0.0801***	−0.0243	−0.1743***
	(−0.898)	(−3.006)	(−0.574)	(−3.516)
External Financing$_t$	0.0150	−0.0074	0.0148	0.0021
	(1.352)	(−1.071)	(0.863)	(0.210)
Firm Age$_t$	−0.0063**	−0.0082***	−0.0010	−0.0023
	(−2.175)	(−3.883)	(−0.207)	(−0.474)
G$_t$	−0.0382***	−0.0140	−0.0470***	−0.0145
	(−3.559)	(−1.194)	(−3.063)	(−0.739)
GDP Growth 10Y$_t$	0.3101	1.8187***	−0.4669	0.7210
	(0.517)	(4.087)	(−0.615)	(1.443)
Growth EBITDA 1Y$_t$	−0.0184***	−0.0086***	−0.0217***	−0.0034
	(−8.732)	(−5.840)	(−4.036)	(−0.658)
HHI Sales$_t$	−0.0069	0.0239	0.0656	0.0494
	(−0.271)	(1.079)	(1.429)	(1.433)
Industry Entries$_t$	0.0100	−0.0211	−0.0469	−0.0451***
	(0.185)	(−1.009)	(−1.327)	(−2.782)
Industry Exits$_t$	−0.2628***	−0.1067***	−0.1672***	−0.0272
	(−4.634)	(−3.128)	(−2.873)	(−0.717)
Inflation Rate$_t$	0.0340	0.1274	−0.1498	0.6226***
	(0.132)	(1.335)	(−0.385)	(2.860)
Leverage$_t$	−0.0885***	−0.0573***	−0.1056***	−0.0684***
	(−7.177)	(−5.815)	(−5.025)	(−3.589)
Payout Ratio$_t$	0.0036	0.0059**	0.0025	0.0022
	(0.917)	(2.182)	(0.827)	(0.843)
R&D Intensity$_t$	0.2011***	0.0635	0.1464*	0.0117
	(4.505)	(1.529)	(1.843)	(0.177)
RFR$_t$	0.0622	0.1713	−0.0520	−0.1758
	(0.364)	(1.435)	(−0.263)	(−1.135)
Size$_t$	−0.0065***	−0.0031***	−0.0077**	−0.0110***
	(−5.302)	(−2.994)	(−2.688)	(−4.202)
ALTGF Earnings$_t$			0.0018***	0.0005
			(2.936)	(0.960)
Inst. Ownership$_t$			−0.0209	−0.0169
			(−1.555)	(−1.251)
Inst. Ownership HHI$_t$			0.0227	0.0431
			(0.622)	(1.122)

(continued on next page)

TABLE 3 (continued)

Predicting Long-Term Growth Rates in EBITDA

	5YE 1963–2018	10YE 1963–2018	5YE 1981–2018	10YE 1981–2018
	1	2	3	4
Number Analysts$_t$			0.0020	0.0089***
			(0.623)	(3.694)
Number Patents$_t$			0.0030	0.0038**
			(1.576)	(2.230)
Observations	40,550	25,951	11,085	6046
Adjusted R^2	0.058	0.080	0.072	0.112
Industry dummies	FF48	FF48	FF48	FF48

12.6% decrease in long-term sales growth and 17.4% decrease in long-term EBITDA growth.

E. Additional Variables

We also find that the coefficient of the sustainable growth rate *G* is positive and statistically significant in the long-term Sales growth regressions. This finding suggests that companies, which sustain high profitability and high profit retention, that is, have higher *G*, enjoy higher long-term Sales growth rates in the future. A 1-standard-deviation increase in *G* is associated with a 16.3% increase in long-term Sales growth.

We also document a negative and statistically significant relation between *Firm Age* and subsequent long-term growth in Sales. This evidence supplements earlier findings that as firms grow older, their profitability and capital expenditures decline (see, e.g., Loderer et al. (2016)). A 1-standard-deviation increase in *Firm Age* is associated with a 9.7% decrease in long-term Sales growth.

Furthermore, we find a positive and statistically significant relation between *Number Analysts* and subsequent long-term growth in Sales. This evidence is in line with securities analysts providing oversight and disciplining management through their role in providing information to the capital markets, which is associated with higher growth rates. A 1-standard-deviation increase in *Number Analysts* is associated with a 4.3% increase in long-term Sales growth.

Moreover, the coefficient of the *Size* variable is negative and statistically significant across all long-term growth in EBITDA specifications. This is in line with the economic intuition that there exist dis-economies of scale so that bigger firms grow more slowly. A 1-standard-deviation increase in *Size* is associated with a 12.2% decrease in long-term EBITDA growth.

We finally document that the *Growth EBITDA 1Y* variable is negatively associated with subsequent long-term growth in EBITDA. This is indicative of reversals in the growth rates. A 1-standard-deviation increase in *Growth EBITDA 1Y* is associated with a 10.8% decrease in long-term EBITDA growth.

IV. Model Selection for Long-Term Growth Expectations

In this part of the article, we explore whether long-term corporate growth expectations are reflected in the cross section of stock returns. We hypothesize that if our long-term growth predictions are more informative than the ones used by investors when determining market prices, we would find a positive association between long-term growth expectations and future stock returns. Since long-term growth predictions are of main interest here, we first analyze which predictive model delivers the best out-of-sample results. We then analyze whether the resulting long-term growth expectations are related to the cross section of firm values. To this end a natural testing framework is a cross sectional regression (see Fama and MacBeth (1973)). We therefore regress monthly returns on predicted long-term growth rates, controlling for other return predictors.

A. Model Selection

In this section, we take the viewpoint of an investor who is interested in obtaining an investment signal rather than having a causal explanation of the effects of a particular explanatory variable on long-term growth. Cox and Snell (1974) argued that it is more important to apply predictions from a model that result in smaller mean squared error than obtaining unbiased estimates when the main emphasis lies on prediction and not on the economic explanation of the effects of the right-hand side variables on the left-hand side variable. We therefore apply in addition to the full model specification presented in the previous section two additional dynamic procedures for variables selection: i) backward elimination and ii) the least absolute shrinkage and selection operator (LASSO) of Tibshirani (1996). Our goal here is to select the model that delivers the best out-of-sample performance. We do this by determining which model produces predictions with the smallest error. We apply two popular measures for prediction evaluation: the root mean squared error (RMSE) and the mean absolute error (MAE).[21]

B. Backward Elimination

The backward elimination procedure starts with the full model, that is, with the model containing all explanatory variables. In a second step, the variable with the least significant coefficient is removed from the model. We apply a threshold of a p-value greater than 0.10, which is a widely applied drop-out rule in empirical research. The model is then re-fitted and step 2 is repeated until no further explanatory variables can be dropped.[22]

C. Least Absolute Shrinkage and Selection Operator

Standard subset selection procedures, such as backward elimination may produce highly sample-dependent results due to their discrete selection process

[21] We do not use the mean absolute percentage error (MAPE) criterion since the MAPE is likely to be quite unstable and less reliable due to very small or negative values in the denominator.

[22] Mantel (1970) shows that the backward elimination procedure has an advantage over other related model selection procedures (e.g., forward selection) when the dependent variable is highly correlated with some linear combination of a group of explanatory variables, but only shows a low correlation with single explanatory variables. The backward elimination procedure tends to leave such groups in the model, while they will usually not enter the model when using forward selection. We therefore apply the backward elimination procedure.

TABLE 4

Model Selection for Long-Term Growth Expectations

Table 4 reports root mean squared errors (RMSEs) and mean absolute errors (MAEs) for out-of-sample predictions with different horizon specifications. RMSE is defined as $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$, and MAE is defined as $\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i|$, where y_i is the actual value and $\hat{y}_i$ is the predicted value. Full, BE and LASSO correspond to i) the full model containing all predictors, ii) a model based on the backward elimination (BE) procedure, and iii) a model based on the LASSO procedure, respectively. The *t*-statistics are based on HAC standard errors and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	RMSE (Full)	RMSE (BE)	RMSE (LASSO)	MAE (Full)	MAE (BE)	MAE (LASSO)
1963–2018						
Exp LTGR5 Sales	0.181***	0.160***	0.128***	0.144***	0.123***	0.093***
	(5.508)	(7.126)	(20.002)	(4.397)	(5.198)	(16.066)
Exp LTGR5 EBITDA	0.273***	0.230***	0.174***	0.218***	0.184***	0.128***
	(4.306)	(4.687)	(38.610)	(3.687)	(3.655)	(27.526)
Exp LTGR10 Sales	0.161***	0.116***	0.093***	0.134***	0.091***	0.069***
	(3.688)	(9.886)	(17.744)	(3.039)	(6.412)	(13.624)
Exp LTGR10 EBITDA	0.192***	0.114***	0.106***	0.165**	0.087***	0.078***
	(2.787)	(17.173)	(40.395)	(2.376)	(12.790)	(32.995)
1981–2018						
Exp LTGR5 Sales	0.107***	0.099***	0.096***	0.081***	0.074***	0.071***
	(15.454)	(20.099)	(19.973)	(15.535)	(24.547)	(20.497)
Exp LTGR5 EBITDA	0.179***	0.156***	0.149***	0.132***	0.114***	0.106***
	(8.898)	(40.014)	(25.358)	(8.863)	(39.899)	(21.645)
Exp LTGR10 Sales	0.156*	0.068***	0.065***	0.095**	0.050***	0.048***
	(1.819)	(12.173)	(14.944)	(2.158)	(10.989)	(12.905)
Exp LTGR10 EBITDA	0.206**	0.102***	0.096***	0.131**	0.075***	0.069***
	(1.998)	(18.131)	(18.582)	(2.355)	(14.599)	(14.155)

(see Tibshirani (1996) and Friedman, Hastie, and Tibshirani (2010)). Shrinkage procedures may be preferred in this case since they produce models which are more stable. Therefore, we apply also the LASSO.

D. Results

Table 4 reports the results from the out-of-sample tests. In general, the RMSE and the MAE deliver similar results. In particular, compared to both the full model and the backward elimination model, the LASSO model has the lowest RMSE and MAE during all periods.[23] For the following analyses, we therefore use the expectations estimated according to the LASSO model. We also examine how much of the cross sectional variation in realized growth rates is captured by the expected (out-of-sample) growth rates from our LASSO model. We find that the average R^2 in all estimations is positive, and that the expected growth rates explain between 1.5% (5-year EBITDA, 1981–2018) and 12.5% (10-year Sales, 1981–2018) of the variation in realized growth rates out of sample.[24] As discussed in Section II compared to EBITDA, Sales are less closely related to shareholders' free

[23]In Table IA5 in the Supplementary Material, as a robustness check, we also compare the out-of-sample performance of the LASSO model to a naïve forecast using the most recently realized growth rate and an alternative forecast using the analysts' long-term growth estimates. We find that the LASSO model has the lowest RMSE and MAE during all periods.

[24]In particular, in additional estimations reported in Table IA6 in the Supplementary Material we regress the realized growth rates on the out-of-sample growth rate forecasts every year and examine the

cash flows. Therefore, we concentrate on long-term growth in EBITDA in the remainder of the article. Furthermore, we are interested in utilizing a growth proxy that better captures the true long-term growth rate. We therefore perform our cross sectional firm-value tests using 10-year EBITDA expectations (*Exp LTGR10 EBITDA LASSO*).[25]

LASSO minimizes the sum of squared residuals subject to the constraint that the sum of absolute coefficient values is equal or less than a given constant λ. We utilize the extended Bayesian information criterion (EBIC) to determine λ every period (see Schwarz (1978) and Chen and Chen (2008)).[26] Specifically, every year in our sample LASSO estimates the model for a range of different λ parameters and computes the corresponding EBIC information criteria. Next, the model with λ corresponding to the minimum EBIC information criterion is selected (this corresponds to "Stage 1: regression" in Figure 2). The first cross section of 10-year EBITDA expectations (*Exp LTGR10 EBITDA LASSO*) is obtained 10 years later, that is, starting 1973 and 1991 for the data sets beginning in 1963 and 1981, respectively. This corresponds to $t+n$ in "Stage 2: prediction" in Figure 2. Figure 3 graphically shows, over the periods 1973–2018 and 1991–2018, which characteristics from the universe of all characteristics are selected by the LASSO procedure to generate predictions.[27]

Figure 4 plots the time-series evolution of the annual average realized and expected 10Y EBITDA LTGRs. We observe some time-series variation and that the 2 time series move closely together. Table 5 presents the corresponding summary statistics. We observe that the empirical distributions of the two variables are comparable and that *Exp LTGR10 EBITDA LASSO* has a slightly higher mean and median values.[28] Overall, we conclude that the LASSO procedure performs well out of sample, producing economically sensible growth rate expectations.

average R^2 from these estimations across all years. In the spirit of Campbell and Thompson (2008) and Clark and West (2006), if the realized growth rate series is truly unpredictable, then in a finite sample the predictive regression will on average have a higher mean squared prediction error. Therefore, the expected R^2 under the null of unpredictability is negative, and a 0 or positive R^2 can be interpreted as evidence of predictability. We interpret our results as evidence that long-term growth expectations from our LASSO model have predictive power for actual long-term growth realizations out-of-sample (see also Engelberg, McLean, Pontiff, and Ringgenberg (2023) for a helpful discussion about in-sample and out-of-sample predictability).

[25]In the Supplementary Material we provide evidence using 5-year EBITDA expectations. The results are qualitatively and quantitatively very similar.

[26]As mentioned LASSO relies on λ, a tuning parameter that controls the degree and type of penalization. We examined the out-of-sample performance of several different approaches for selecting λ in arriving at our choice (see Ahrens, Hansen, and Schaffer (2020)). In general, for the construction of the *Exp LTGR EBITDA LASSO*, EBIC performs best out-of-sample during the 1963–2018 period (untabulated). We note that it is standard practice for predictors to be "standardized" and we incorporate this standardization into the penalty loadings when performing the LASSO estimations. We thank Christian Hansen and an anonymous referee for feedback on this point.

[27]In the Supplementary Material in Figure IA1 we present the corresponding plots for *Exp LTGR5 EBITDA LASSO.*

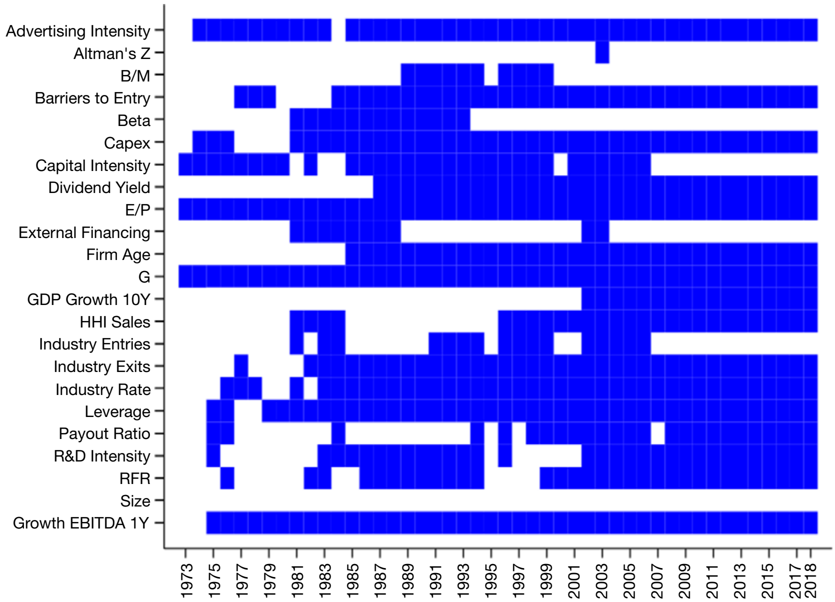
[28]In the Supplementary Material in Figure IA2 and Table IA7 we present the corresponding figure and summary statistics for *Exp LTGR5 EBITDA LASSO.* In general, we observe more time-series variation in both the realized and expected LTGR5 EBITDA. We also observe that the empirical distributions of the two variables are very similar.

FIGURE 3

LASSO-Selected Characteristics for 10Y EBITDA Expectations

Figure 3 graphically shows which characteristics, from the universe of all characteristics for the respective period, are selected by the LASSO procedure to construct EBITDA Expectations. Blue indicates that the characteristic is selected. Variables that are selected for the construction of the Exp LTGR10 EBITDA LASSO for the period 1973–2018 and the Exp LTGR10 EBITDA LASSO for the period 1991–2018 are depicted in Graphs A and B, respectively.

Graph A. 1973–2018



Graph B. 1991–2018

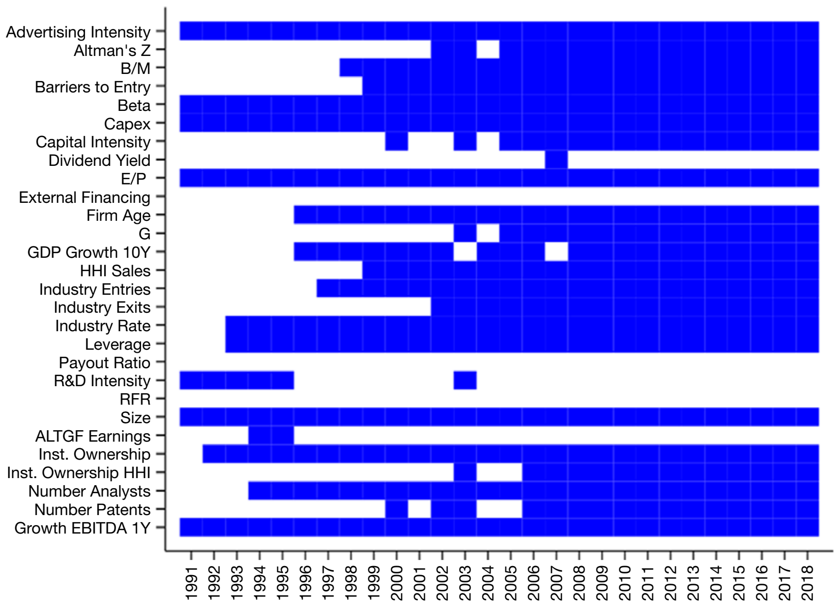


FIGURE 4

Realized Versus Expected Average 10Y EBITDA LTGRs

Figure 4 plots the evolution of annual average realized and expected 10Y EBITDA long-term growth rates (LTGRs) for the period 1973–2018. The gray-shaded periods denote NBER recessions.

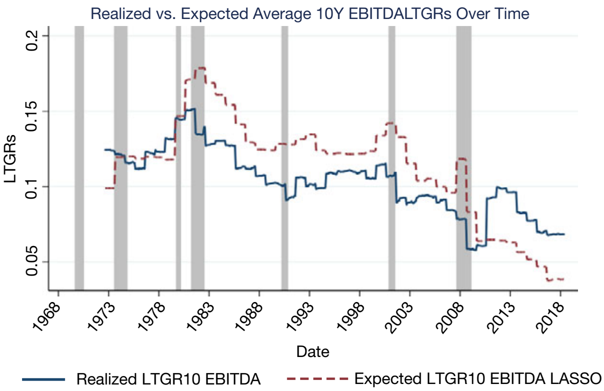


TABLE 5

Descriptive Statistics for Realized and Expected Average 10Y EBITDA LTGRs

Table 5 presents descriptive statistics for the realized LTGR10 EBITDA and expected LTGR10 EBITDA LASSO. The time-series evolution of the annual averages of these variables is depicted in Figure 4.

	Obs.	Mean	Standard Deviation	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Realized LTGR10 EBITDA	34,104	0.10	0.11	−0.19	0.05	0.11	0.16	0.40
Exp LTGR10 EBITDA LASSO	69,818	0.11	0.06	−0.03	0.09	0.12	0.14	0.28

We proceed with testing whether *Exp LTGR10 EBITDA LASSO* are reflected in the cross section of future equity values.

V. Long-Term Growth Expectations and Stock Returns

A. Fama–MacBeth Regressions: Methodology

To explore the relation between long-term growth expectations and firm value realizations we conduct cross sectional tests based on individual stocks. The use of tests based on individual stocks is motivated by recent literature that argues that using individual stocks permits more efficient tests of whether firm characteristics predict returns (see, e.g., Ang, Liu, and Schwarz (2020)).[29] We therefore perform

[29]In robustness estimations we confirm that our results hold when using a portfolio sorting approach. Although, portfolio sorting has become the standard to explore cross-sectional variation in expected returns this approach has some limitations, as pointed out, for example, by Ang et al. (2020). In particular, Ang et al. (2020) argue that using portfolios creates the potential for data-mining biases. They also argue that portfolios destroy information by shrinking the dispersion of betas, leading to larger standard errors. Still, we confirm that our findings are robust to applying this approach and report the results for ease of comparability to other existing papers.

Fama and MacBeth (1973) tests where we predict firm-level returns. In particular, each month we estimate a cross sectional OLS regression as follows:

$$R_{i,t+1} = \alpha + \beta_t \widehat{G}_{i,t} + \gamma_t X_{i,t} + \varepsilon_{i,t+1}, \tag{4}$$

where $R_{i,t+1}$ is the stock return (in decimal) for company i in month $t+1$, $\widehat{G}_{i,t}$ is the long-term growth expectation for EBITDA. As discussed in section IV.D, we obtain these expectations from the LASSO model. X_i contains a set of firm characteristics documented to explain the cross section of expected stock returns.[30] We estimate multiple specifications which differ in the control variables they include (see, e.g., Wang (2019) and Wahal (2019)). All independent variables are winsorized month by month at the 1% level in both tails.

B. Fama–MacBeth Regressions: Results

Table 6 presents the results for the periods starting 1973 and 1991 in Panels A and B, respectively. In column 1 of each panel, we only include *Exp LTGR10 EBITDA LASSO*. In column 2 we include *Beta*, *Size*, and the *Book/Market*. *Beta* is computed from a rolling-window regression of the excess return of a company on the excess return of the market over the past 5 years of monthly data, with the requirement that at least 24 months of data are available. *Size* is computed as the log of market capitalization, and *Book/Market* is computed as the log of book-to-market. In column 3 we add *Profitability*, computed as $(sales_{t-1} - cogs_{t-1})/assets_{t-1}$, and *Investment*, computed $(assets_{t-1} - assets_{t-2})/assets_{t-2}$. In column 4, we add *Momentum*, computed as the cumulative return from month $t-12$ to month $t-2$, and *Reversal*, computed as the return from month $t-1$ to month t. In column 5 we add *External Financing* and *Altman's Z*, as previously defined in Section II.B.[31] In column 6, we add *Operating Leverage*, computed as $(cogs_t + xsga_t)/assets_t$, and standardized unexpected earnings (*SUE*) computed as $(ibcom_t - ibcom_{t-1})/sd(ibcom)$, where $sd(ibcom)$ is the standard deviation of *ibcom* over the prior 6 years (2 years minimum). In column 7, we add *Asset Turnover* computed as $revt_t/assets_t$, and *Accruals* computed as $((act_t - act_{t-1}) - (che_t - che_{t-1}) - ((lct_t - lct_{t-1}) - (dlc_t - dlc_{t-1}) - (txp_t - txp_{t-1})) - dp_t)/assets_t$. The results in both panels indicate that *Exp LTGR10 EBITDA LASSO* has positive and significant association with subsequent stock returns. *Exp LTGR10 EBITDA LASSO* retains significant predictive power even

[30]The following papers, among others, also apply a similar estimation: Novy-Marx (2013), Ball, Gerakos, Linnainmaa, and Nikolaev (2015), Ball, Gerakos, Linnainmaa, and Nikolaev (2016), Wang (2019).

[31]We include *Altman's Z* to take into account the potential effect of financial distress on future returns of surviving firms. Specifically, one might be skeptical that survivorship bias will induce a bias in the estimate for any variable that captures the probability of financial distress. In particular, firms that have high distress probabilities at the beginning of the prediction period but still survived in the end may exhibit special growth patterns that may be correlated with return patterns. In line with prior literature we find that firms with lower probability of financial distress have higher expected returns (see, e.g., Campbell, Hilscher, and Szilagyi (2008)). Importantly, the results show that controlling for *Altman's Z* and the additional return predictors has very little effect on the positive association between *Exp LTGR10 EBITDA LASSO* and future stock returns.

TABLE 6

Fama–MacBeth Regressions of Monthly Returns

Table 6 reports the average slopes from Fama and MacBeth (1973) regressions of monthly returns (in decimal) on expected long-term EBITDA growth rates from the LASSO model for 10 years (Exp LTGR10 EBITDA LASSO). The estimation procedure and variable constructions are described in Section V. All independent variables are lagged and winsorized month by month at the 1% level in both tails. We report *t*-statistics based on standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991) in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7
Panel A. 1973–2018							
Exp LTGR10 EBITDA LASSO	0.0637**	0.0775**	0.0744***	0.0798***	0.1001***	0.1240***	0.1128***
	(2.334)	(2.568)	(2.653)	(2.919)	(3.625)	(4.207)	(3.953)
Beta		0.0009	0.0012	0.0010	0.0016	0.0020*	0.0020*
		(0.706)	(0.983)	(0.879)	(1.458)	(1.754)	(1.794)
Size		−0.0015***	−0.0013***	−0.0012***	−0.0012***	−0.0015***	−0.0016***
		(−4.195)	(−3.555)	(−3.442)	(−3.466)	(−4.283)	(−4.705)
Book/Market		0.0025***	0.0029***	0.0045***	0.0045***	0.0059***	0.0060***
		(2.980)	(3.228)	(6.027)	(5.880)	(7.354)	(7.465)
Profitability			0.0067***	0.0075***	0.0025*	0.0051***	0.0037**
			(4.580)	(5.408)	(1.739)	(3.321)	(2.275)
Investment			−0.0041***	−0.0035***	0.0012	−0.0045***	−0.0034**
			(−4.665)	(−4.135)	(0.756)	(−2.714)	(−1.979)
Momentum				0.0060***	0.0050***	0.0043***	0.0039***
				(4.475)	(3.764)	(3.224)	(2.918)
Reversal				0.0001	−0.0010	−0.0012	−0.0021
				(0.049)	(−0.334)	(−0.409)	(−0.704)
External Financing					−0.0083	0.0038	0.0089***
					(−0.897)	(1.358)	(3.096)
Altman's Z					0.0021***	0.0053***	0.0056***
					(6.180)	(9.207)	(9.448)
Operating Leverage						−0.0059***	−0.0098***
						(−9.601)	(−8.030)
SUE						0.0009***	0.0009***
						(4.542)	(4.485)
Asset Turnover							0.0038***
							(3.384)
Accruals							−0.0278***
							(−8.205)
Constant	0.0089**	0.0245***	0.0199***	0.0170***	0.0107*	0.0094	0.0107*
	(2.250)	(4.285)	(3.503)	(3.043)	(1.800)	(1.542)	(1.772)
Observations	752,286	722,362	718,607	715,266	697,394	667,637	658,911
Average R^2	0.006	0.039	0.044	0.052	0.056	0.061	0.065
Panel B. 1991–2018							
Exp LTGR10 EBITDA LASSO	0.0405**	0.0879**	0.0720**	0.0711**	0.0936**	0.1109**	0.1198***
	(1.983)	(2.102)	(2.133)	(2.208)	(2.148)	(2.544)	(2.774)
Beta		0.0024	0.0027	0.0021	0.0033*	0.0036*	0.0038**
		(1.184)	(1.346)	(1.099)	(1.777)	(1.965)	(2.101)
Size		−0.0007	−0.0004	−0.0005	−0.0004	−0.0007	−0.0007
		(−1.551)	(−0.923)	(−1.112)	(−0.918)	(−1.386)	(−1.486)
Book/Market		0.0026**	0.0034***	0.0042***	0.0043***	0.0052***	0.0056***
		(2.335)	(2.697)	(4.150)	(4.042)	(4.622)	(4.856)
Profitability			0.0084***	0.0091***	0.0055*	0.0082***	0.0044
			(3.195)	(3.568)	(1.911)	(2.779)	(1.414)
Investment			−0.0032**	−0.0032**	−0.0053**	−0.0100***	−0.0092***
			(−2.308)	(−2.178)	(−2.471)	(−4.341)	(−4.053)
Momentum				0.0021	0.0016	0.0013	0.0010
				(1.002)	(0.774)	(0.629)	(0.511)
Reversal				−0.0015	−0.0012	−0.0009	−0.0010
				(−0.272)	(−0.204)	(−0.155)	(−0.173)
External Financing					0.0039	0.0135***	0.0187***
					(1.112)	(3.550)	(4.998)
Altman's Z					0.0017***	0.0035***	0.0037***

(continued on next page)

TABLE 6 (continued)

Fama–MacBeth Regressions of Monthly Returns

Panel B. 1991–2018 (continued)

					(3.654)	(4.895)	(5.117)
Operating Leverage						−0.0046***	−0.0130***
						(−5.339)	(−5.719)
SUE						0.0007**	0.0008**
						(2.386)	(2.548)
Asset Turnover							0.0091***
							(4.410)
Accruals							−0.0287***
							(−4.349)
Constant	0.0081	0.0118	0.0070	0.0079	0.0010	0.0026	0.0001
	(1.547)	(1.272)	(0.748)	(0.840)	(0.109)	(0.270)	(0.012)
Observations	274,380	258,360	254,593	254,448	244,383	232,671	228,524
Average R^2	0.008	0.052	0.061	0.072	0.079	0.086	0.093

after we include additional known return predictors.[32] The coefficient estimates are 0.1128 and 0.1198 for the most restrictive estimations for the periods starting 1973 and 1991, respectively. The coefficients on the control variables are similar to those documented in the literature.

Overall, the evidence confirms that *Exp LTGR10 EBITDA LASSO* expectations constructed from our predictive LASSO model are useful in explaining cross sectional differences in firm value. The evidence supports the hypothesis that the long-term growth estimates are a better predictor of expected growth compared to the estimates investors are actually using when determining prices. The association with stock returns is not explained by firm characteristics known to be associated with stock returns. Next, we proceed with a battery of robustness tests.

VI. Robustness

A. Firm Size and the Effect of Exp LTGR EBITDA LASSO

In this subsection, we investigate whether the predictive power of long-term growth EBITDA expectations derived from our LASSO model is different for different firm size subsamples. Specifically, we split our samples into microcaps and all-but-microcaps subsamples. Applying NYSE breakpoints, we assign stocks smaller than the 20th percentile of the market equity into the microcaps subsample and all remaining stocks into the all-but-microcaps subsample.

For brevity, we report the results in the Supplementary Material. Specifically, Tables IA8 and IA9 summarize the results for the data sets with *Exp LTGR10 EBITDA LASSO* starting in 1973 and 1991, respectively. The results in both tables indicate that *Exp LTGR10 EBITDA LASSO* has a positive and significant association with subsequent stock returns, even after controlling for known predictors of returns such as variables that capture external financing or investments. We also find that the predictive power of *Exp LTGR10 EBITDA LASSO* is concentrated in the microcaps subsample. These results indicate that the return performance is

[32]The results are somewhat stronger after we control for the additional known return predictors. This is consistent with the literature (see, e.g., Wang (2019)).

concentrated in smaller companies with high growth potential.[33] We report further robustness results using 5-year EBITDA expectations in the Supplementary Material in Tables IA10 and IA11. We find a positive and significant association between *Exp LTGR5 EBITDA LASSO* and stock returns in the microcaps subsample 1968–2018. During the shorter period, 1986–2018, we find that the positive and significant association between *Exp LTGR5 EBITDA LASSO* and stock returns is concentrated in the all-but-microcaps subsample, indicating that *Exp LTGR5 EBITDA LASSO* constructed based on a wider set of predictors has explanatory power for the valuation of large firms. Furthermore, in Table IA12 in the Supplementary Material, we report pairwise correlation coefficients between the long-term growth EBITDA expectations derived from our LASSO model and the known predictors of returns. In general, the correlation coefficients between the *Exp LTGR10 EBITDA LASSO*, *Exp LTGR5 EBITDA LASSO*, and the established return predictors are very low, indicating that the long-term growth expectations derived from the LASSO model contain firm value information that is somewhat orthogonal to these well-known predictors.[34]

While these results suggest that utilizing *Exp LTGR EBITDA LASSO* expectations in a trading strategy within a sample of microcaps might have a limited scope due to the limited investment capacity and high transaction costs of microcaps we note that microcaps are nevertheless important to study because they constitute a sizable proportion of the population of firms and play an important role in the real economy. In particular, in our longest sample microcaps account for about 50% of the number of companies. This is in line with Fama and French (2008), who report that microcaps account for about 60% of the total number of stocks. Moreover, microcaps have contributed more than large caps to aggregate employment growth (Birch (1987) and Moscarini and Postel-Vinay (2012)) and account for a large proportion of aggregate employment (Luttmer (2010)) and total economic growth more generally (Evans (1987) and Hou, Xue, and Zhang (2020)).

The stronger results for small companies can be readily interpreted with our notion of imprecise growth estimates. Arguably, simple rules of thumb that practitioners use for growth rates are better estimates for large firms than small firms, as large mature companies may have more reliable and consistent growth. Similarly, behavioral explanations such as rational inattention could give rise to stronger results for small firms.[35] However, in the spirit of Kozak, Nagel, and Santosh

[33]The *t*-statistics in the estimations where we control for the largest number of additional known predictors of returns exceed 3, as advocated by Harvey, Liu, and Zhu (2016).

[34]In Table IA13 in the Supplementary Material we also assess if there is an interaction effect between analysts' growth forecasts and *Exp LTGR10 EBITDA LASSO*. We find that controlling for analysts' long-term growth forecasts has little impact on the positive association between *Exp LTGR10 EBITDA LASSO* and stock returns in the microcaps sub-sample. For the all-but-microcaps sub-sample we find a positive and statistically significant interaction effect between analyst long-term growth forecasts and *Exp LTGR10 EBITDA LASSO*. While research has shown that analysts overreact to certain stocks and stocks that receive optimistic analyst long-term growth forecasts exhibit poor subsequent stock market performance (see, e.g., Bordalo, Gennaioli, La Porta, and Shleifer (2019)), the results indicate that among these stocks growth predictions from our LASSO model are able to differentiate between stocks that indeed underperform and stocks that perform well going forward.

[35]More broadly, our findings are also related to a body of literature that examines psychology-based models of asset prices (see Barberis (2018) for a survey of the topic). A general prediction of the

(2018), we note that it is challenging to differentiate between "risk-based" and "behavioral" explanations in our framework.

The overall evidence indicates that capital markets appear to price growth expectations more efficiently for large stocks, whereas long-term growth expectations for small stocks contain valuable information when predicting their future stock returns. A deeper investigation of the driving forces behind the positive association with returns is outside of the scope of this article and constitutes, we believe, a fruitful avenue for further research.

B. Excluding Growth Predictors Based on Market Information

In this subsection, we estimate our predictive regressions and construct our long-term growth expectations by excluding all variables based on market information. Specifically, we exclude the variables *E/P*, *B/M*, *Dividend Yield*, and *Beta.* Furthermore, we perform the estimations with data for the period 1963–2018, which provides a longer history and does not include information about analyst expectations. The primary motivation to perform these additional robustness estimations is to provide predicted long-term growth rates for private companies, which, in contrast to their publicly traded counterparts, do not have market information readily available.[36] As a result, determining appropriate inputs for the long-term value becomes even more challenging. A secondary motivation for these robustness estimations is to alleviate concerns about the potential circularity of using market-based variables as ingredients in the valuation exercise.

We start with estimating model (2) by excluding market-based predictors, that is, using only information that would be available for private companies. For brevity, we present the results in the Supplementary Material in Table IA14. The results are quantitatively and qualitatively very similar to the ones presented in Section III. Thus, we relegate the discussion of the results to the Supplementary Material.

Next, we concentrate on the model selection for long-term growth expectations without market-based variables. In particular, we follow the methodology outlined in Section IV and apply in addition to the full model specification the backward elimination and the LASSO procedures. The results are presented in

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theoretical literature on the topic is that information processing biases, such as extrapolation of past information, can generate return predictability (see, e.g., Barberis, Shleifer, and Vishny (1998), Fuster, Laibson, and Mendel (2010), Alti and Tetlock (2014), Hirshleifer, Li, and Yu (2015), Choi and Mertens (2019), and Bordalo, Gennaioli, Ma, and Shleifer (2020), among others). Empirically, the evidence on the topic is mixed. While Lakonishok, Shleifer, and Vishny (1994) suggest that individual investors might extrapolate past growth, even when such growth is highly unlikely to persist in the future, Daniel and Titman (2006) argue that past growth in a firm's fundamentals is not related to the subsequent return of the firm's stock. Bordalo, Gennaioli, La Porta, and Shleifer (2019) show that the returns on stocks with the most optimistic analyst long-term earnings growth forecasts are lower than those on stocks with the most pessimistic forecasts. Huang, Zhang, Zhou, and Zhu (2023) show that a strategy based on extrapolating firms' fundamental information earns positive and significant returns. We contribute by showing that taking into account a wide range of information sources significantly improves long-term growth predictability and firm value estimates. In particular, the market does not fully incorporate information contained in long-term growth expectations derived from our predictive model.

[36]Private companies are a large, important part of the U.S. economy. They generate a big portion of the U.S. GDP and represent a substantial portion of all firms in the U.S.

Table IA15. The table shows that the LASSO model delivers the lowest RMSE and MAE during all periods, which is consistent with the results presented in Section IV.

Finally, we examine the interaction between long-term growth expectations without market-based variables and stock returns. Specifically, to test the predictive power of *Exp LTGR10 EBITDA LASSO* constructed without predictors based on market information, that is, information available only for private companies, similarly to Section V, we perform Fama and MacBeth (1973) regression tests.[37] Table IA16 presents the results. The results in the table indicate that *Exp LTGR10 EBITDA LASSO* has a positive association with subsequent stock returns. Similar to before, these results are statistically significant in the microcaps subsample. *Exp LTGR10 EBITDA LASSO* retains significant predictive power even after we include the major known predictors of returns.

Overall, the results are in line with the main results presented in Section V. Assuming that private firms are similar to public firms in the dimensions examined in the paper our model also provides useful input for the valuation of private firms, for which market-based variables are not available.

C. Additional Corporate Governance Growth Predictors

As further robustness we include additional corporate governance predictors related to characteristics about firms' CEOs. In particular, we consider the variables *CEO Stock Ownership*, *CEO Stk.&Opt. Compensation*, *CEO Age*, *CEO Tenure*, and *CEO Duality.* To construct these variables we utilize data from ExecuComp which provides coverage for a much shorter time span, namely from 1992 to 2018, and a smaller number of companies. The variable definitions and summary statistics are provided in the Supplementary Material in Table IA18 and the results are presented in Tables IA19 and IA20. Overall, the results indicate that CEO characteristics do not consistently have statistically significant predictive power for subsequent long-term growth realizations and therefore do not appear to represent fundamental determinants of corporate long-term growth.

D. Portfolio Sorts

As another robustness test to the estimations in Section V, we conduct portfolio-sort tests as follows: We allocate firms into deciles according to their long-term growth forecasts for EBITDA. We then calculate the returns of these portfolios for a 1-year holding period. For the 1-year holding period, the portfolios are rebalanced once a year. We ensure that we use information that was publicly available on each rebalancing date in accordance with previous literature (see, e.g., Lakonishok et al. (1994) and Dechow and Sloan (1997)).

For brevity, we present a detailed discussion and the corresponding results in the Supplementary Material. Tables IA21 and IA22 report the average monthly

[37]In the Supplementary Material we present evidence from portfolio sorts in Table IA23. The long-short portfolio produces positive and highly statistically significant abnormal returns. These results are positive and robust throughout the alternative estimations and highly statistically significant in the 5-f and 6-f alpha estimations.

excess returns as well as monthly abnormal returns for the stock portfolios.[38] The long-short portfolios produce positive and statistically significant abnormal returns. Given the magnitude of these returns, they are likely to survive even when accounting for transaction costs, etc.[39] In this context, it is important to recall that the analyzed trading strategy only requires portfolio rebalancing once per year. Overall, these results accord well with the findings in Section V.

E. Subsamples

As a further robustness test, it is a common practice to perform sample splits for periods characterized by very significant differences in the underlying economic conditions. The financial crisis of 2008–2009 constitutes such a period. In unreported tests we therefore perform our estimations by excluding the period of the 2008–2009 financial crisis. These alternative estimations deliver results generally very similar to the results presented in the article.

VII. Conclusion

Expectations about long-term growth are crucial in investment analysis and corporate valuation. Despite its often dominating effect on overall firm value, the academic literature provides very little guidance on the determinants of long-term corporate operating growth. In any MBA Corporate Finance textbook, there are multiple chapters detailing cash flow forecasting, translating accounting numbers and forecasts into cash flows, and choosing the right discount factor for the valuation. However, the literature on the long-term growth determinants is scarce and inconclusive.

This article presents an exploratory analysis of how firms' long-term growth is related to various firm and industry characteristics. We apply an extensive selection of predictors spanning more than 50 years of data. While extant literature only finds low predictability for long-term growth measures (see, e.g., Chan et al. (2003)), we find a much greater degree of predictability in a firm's long-term growth. In particular, we are able to explain up to 22% of the long-term growth rate variation. We document a negative relation between long-term growth rates and industry exits, leverage, as well as firm size and age. We also find a positive relation between variables representing firms' competitive positioning, such as barriers to entry, analysts' long-term earnings forecasts and the number of analysts following a firm, and variables representing firms' investment decisions, such as capital expenditures and external financing, and subsequent long-term growth rates. Our growth estimates could be used by practitioners to value companies more accurately.

In the second part of the article, we show the relevance of our estimates by developing trading strategies based on them. To this end, we first determine the

[38]We concentrate on equally-weighted (1/N) portfolio returns to eliminate any bias toward large-cap, possibly mature and/or overvalued stocks. We have also computed value-weighted portfolio returns and found weaker excess and abnormal return results (untabulated). These results indicate that the stock performance is concentrated in smaller companies with high growth potential.

[39]For a valuable discussion on anomalies, trading costs, and cost mitigation techniques see Novy-Marx and Velikov (2015).

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empirical model that delivers the best out-of-sample predictions for EBITDA long-term growth. Also, we examine the out-of-sample predictive performance of this LASSO model by regressing realized growth rates on growth forecasts and document a positive R^2. Finally, we test whether long-term growth expectations from this LASSO model are reflected in the cross section of future stock returns. Using our long-term growth predictions in cross sectional asset pricing tests, we find significant positive abnormal returns.

Appendix. Variable Definitions

Advertising intensity: Advertising expense divided by sales $(\frac{XAD_t}{SALE_t})$

ALTGF earnings: Mean of individual analysts' forecasts for long-term earnings growth

Altman's Z: 3.3*(operating income/assets) + 1.4*(retained earnings/assets) + (sales/assets) + 1.2*((current assets - current liabilities)/assets) $(Z_t = 3.3 \times \frac{OIADP_t}{AT_t} + 1.4 \times \frac{RE_t}{AT_t} + \frac{SALE_t}{AT_t} + 1.2 \times \frac{ACT_t - LCT_t}{AT_t})$

B/M: The ratio of book value of common equity plus deferred taxes to the market value of common equity $(\frac{CEQ_t + TXDB_t}{PRCC\_F_t \times CSHO_t})$

Barriers to entry: The mean ratio of property, plant and equipment to total assets $(\frac{PPEGT_t}{AT_t})$ for a particular industry-year pair (FF48 industries used)

Beta: Historical stock beta is calculated by estimating a regression (over 60 months) of a stock excess returns against the market excess returns with the requirement that at least 24 months of data are available

CAPEX: Capital expenditures in year t divided by property, plant, and equipment in year $t-1$ $(\frac{CAPX_t}{PPEGT_{t-1}})$

Capital intensity: Depreciation, depletion, and amortization expense divided by sales $(\frac{DP_t}{SALE_t})$

Dividend yield: Common dividends per share divided by price per share $(\frac{DVC_t}{CSHO_t \times PRCC\_F_t})$

E/P: Income before extraordinary items divided by market value $(\frac{IBCOM_t}{PRCC\_F_t \times CSHO_t})$

External financing: Change in total assets minus change in retained earnings divided by total assets $(\frac{(AT_t - AT_{t-1}) - (RE_t - RE_{t-1})}{AT_t})$

Firm age: The natural log of years since IPO or years of information on Compustat if IPO year is missing

G: The sustainable growth rate is the product of return on equity and plowback ratio $(\frac{IBCOM_t}{CEQ_t} \times \left(1 - \frac{DVC_t}{IBCOM_t}\right))$

GDP growth 10Y: The GDP growth is the percentage change over 10 years in the Real GDP

Growth EBITDA 1Y: 1-year growth in EBITDA $(\frac{EBITDA_t - EBITDA_{t-1}}{EBITDA_{t-1}})$

Growth EBITDA 5Y: 5-year annualized per-share growth in EBITDA with reinvestment of cash dividends and other special distributions

$$\left(\frac{EBITDA_{t+5}/CSHPRI_{t+5} \times AJEX_{t+5}}{EBITDA_t/CSHPRI_t \times AJEX_t} \times \prod_{n=1}^{5}\left(1 + \frac{DVC_{t+n}/CSHPRI_{t+n}}{PRCC\_F_{t+n}}\right)\right)^{\frac{1}{5}} - 1$$

Growth EBITDA 10Y: 10-year annualized per-share growth in EBITDA with reinvestment of cash dividends and other special distributions.
$\left(\frac{EBITDA_{t+10}/CSHPRI_{t+10} \times AJEX_{t+10}}{EBITDA_t/CSHPRI_t \times AJEX_t} \times \prod_{n=1}^{10}\left(1+\frac{DVC_{t+n}/CSHPRI_{t+n}}{PRCC\_F_{t+n}}\right)\right)^{\frac{1}{10}} - 1$

Growth sales 1Y: 1-year growth in sales $(\frac{SALE_t - SALE_{t-1}}{SALE_{t-1}})$

Growth sales 5Y: 5-year annualized per-share growth in sales with reinvestment of cash dividends and other special distributions
$\left(\frac{SALE_{t+5}/CSHPRI_{t+5} \times AJEX_{t+5}}{} \times \prod_{n=1}^{5}\left(1+\frac{DVC_{t+n}/CSHPRI_{t+n}}{PRCC\_F_{t+n}}\right)\right)^{\frac{1}{5}} - 1$

Growth sales 10Y: Ten-year annualized per-share growth in sales with reinvestment of cash dividends and other special distributions
$\left(\frac{SALE_{t+10}/CSHPRI_{t+10} \times AJEX_{t+10}}{} \times \prod_{n=1}^{10}\left(1+\frac{DVC_{t+n}/CSHPRI_{t+n}}{PRCC\_F_{t+n}}\right)\right)^{\frac{1}{10}} - 1$

HHI sales: Herfindahl index based on company sales (*SALE*) (FF48 industries used)

Industry dummies: Dummies based on the Fama and French 48-industry classification using 4-digit SIC codes

Industry Entries: Number of company entries for a particular industry-year pair divided by the total number of companies in the same industry and year (FF48 industries used)

Industry Exits: Number of company exits for a particular industry-year pair divided by the total number of companies in the same industry and year (FF48 industries used)

Inflation rate: The inflation rate is the 1-year percentage change in the U.S. Consumer Price Index (CPI)

Inst. ownership: The shares held by all 13-f institutional investors divided by the total number of shares outstanding

Inst. ownership HHI: Herfindahl index of institutional ownership concentration

Leverage: Total debt divided by total assets $(\frac{DLC_t + DLTT_t}{AT_t})$

Number analysts: Natural logarithm of the number of analysts issuing a forecast for long-term growth in EPS

Number of patents: Natural logarithm of the total number of patents

Payout ratio: Common dividends divided by income before extraordinary items $(\frac{DVC_t}{IBCOM_t})$

R&D intensity: The ratio of research and development expenditures to sales $(\frac{XRD_t}{SALE_t})$

Risk-free rate (RFR): 10Y Treasury Rate

Size: Natural logarithm of total assets $(ln(AT_t))$

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109024000425.

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