Do Growth Expectations Help Explain Characteristic-Sorted Portfolio Returns?

Gregg Fisher[a*], Ronnie Shah[b*], Sheridan Titman[c*]

Abstract

We find that accounting ratios (asset and sales growth, profitability, and equity dilution) that predict stock returns are associated with errors in analyst long-term growth forecasts. Specifically, accounting information that is associated with favorable long-term growth forecasts tends to predict negative analyst forecast errors and negative future excess returns. This and other evidence we present is consistent with the idea that biased long-term growth forecasts generate the observed return premia of popular characteristic-sorted portfolios.

[a*] Portfolio Manager and Head of Research at Gerstein Fisher, 565 Fifth Avenue, 27th Floor, New York, NY 10017, United States. Phone: 212-968-0707 ext. 111. E-mail: gfisher@gersteinfisher.com.

[b*] Head of US Quantitative Research at Deutsche Bank and Adjunct Professor in Finance at the University of Texas at Austin, 60 Wall St, 17th Floor, New York, NY 10005, United States. Phone: 212-250-1173. E-mail: ronnie.shah@db.com.

[c*] University of Texas at Austin, Department of Finance, McCombs School of Business, Walter W. McAllister Centennial Chair in Financial Services, Austin, TX 78712, United States. Phone: 512-232-2787. E-mail: sheridan.titman@mccombs.utexas.edu.

Introduction

There is now substantial evidence that links various accounting ratios to expected rates of stock returns.[1] For example, measures of firm profitability are shown to be positively correlated with stock returns while growth measures are shown to be negatively correlated with stock returns. There are two potential explanations for these observations. The first is that these accounting ratios are associated with systematic sources of risk and that characteristic-sorted portfolios formed with these ratios require return premia that compensate investors for bearing this risk. The second is that these accounting ratios are associated with mispricing that arises from systematically biased investor expectations.

This paper, which explores the second possibility, examines the biases of long-term earnings forecasts of sell-side analysts.[2] Specifically, we decompose the biased forecasts into what we call a hard component, which can be explained by accounting variables that predict returns, and a soft component, which is the residual.[3] The hard component is our measure that captures the analyst forecast bias that is related to accounting ratios that capture current profitability and growth. We specifically examine the Novy-Marx (2013) profitability measure; the Lakonishok, Shleifer and Vishny (1994) sales growth

---

1 The culmination of past academic research has identified what Cochrane (2011) has coined as the “factor zoo” of different firm characteristics that explain the cross-section of stock returns. Maclean and Pontiff (2016) examine 82 different characteristics and find evidence post-publication that return premia associated with these characteristics are much lower than experienced in-sample. Harvey, Liu and Zhu (2016) survey 313 articles and find 316 characteristics that have been previously shown to explain differences in average stock returns. In one of the largest studies to date, Hou, Xue and Zhang (2017) find 447 distinct return anomaly variables sourced from different academic papers.

2 Analysts periodically provide forecasts of the current, one-, and two-year forward EPS and a longer-term growth rate (LTG) that reflect expected annual percentage changes in EPS after the two-year EPS forecast. The exact forecast period for LTG is subjective and can vary by analyst. Da and Warachka (2011) explain that LTG reflects an analyst’s perception of EPS growth over the three-year period starting two years from now.

3 Our measure of soft information is a residual which reflects estimation errors in the hard component of the growth forecasts as well as the actual soft information analysts uncover in their discussions with various managers. These estimation errors make it difficult to say much about the precision and bias of this soft component, which is why most of our focus is on the hard component of long-term forecasts.

measure; a net equity issuance measure from Daniel and Titman (2006) and Bradshaw, Richardson and Sloan (2006); and the asset growth measure of Cooper, Gulen and Schill (2008).

Our evidence indicates that while the soft component of growth is positively related to actual earnings growth, the relation between the hard accounting-based component of forecasted earnings growth and actual earnings growth is perverse or negative. For example, the forecasts are consistent with analysts believing that profits are mean reverting – but profitability actually tends to be fairly persistent. The evidence is also consistent with the hypothesis that analysts believe that high past sales growth is a good predictor of future earnings growth. However, high sales growth is actually weakly negatively associated with future earnings growth. Managerial choices that reflect expected growth, such as the rate of asset growth and the use of external financing, are associated with higher earnings growth forecasts – but the relationship between these choices and realized earnings growth is actually negative. Analyst forecast revisions provide additional evidence of the bias in the initial forecasts. Specifically, the hard component of forecasted earnings growth is strongly negatively related to revisions in long-term earnings forecasts.

Having established that the bias in long-term growth forecasts, we next ask whether the perverse component of the forecast is in fact reflected in stock prices. Are market prices influenced by these biases? Our evidence indicates that they are – we find that stock prices reflect both components – that stocks have higher prices relative to forward earnings when the hard component as well as the soft component indicate greater expected earnings growth.[4] Thus, investors set prices and growth

[4] There is a large literature that links analyst long-term growth forecasts to stock prices. Copeland, Dolgoff, and Moel (2004) examine this directly, and Easton, Taylor, Shroff and Sougiannis (2001), Bradshaw (2004), Gebhardt, Lee and Swaminathan (1998), Nekrasov and Ogneva (2011), Mohanram and Gode (2013) and Kang and Sadka (2015) use analyst long-term growth as an input for a residual income valuation model to estimate the cost of capital. Bandyopadhyay, Brown and Richardson (1995) examine 128 Canadian firms and find that 60% of the variation in analyst stock-price recommendations can be explained by long-term earnings growth forecasts. There are also several papers, including Stickel (1995), Womack (1996), Barber, Lehavy and Trueman (2001, 2006, 2010), Cowen, Groysberg and Healy (2006), that examine whether levels and

expectations too high for stocks with low profitability, high sales and asset growth, and high use of external financing.

Finally, to close the analysis we show that the soft component of earnings growth does not predict future returns – the evidence suggests that this information is efficiently captured by market prices – but that high realizations of the hard component predict that excess returns are likely to be negative in the future. This last result is not really surprising given that the hard component contains information that is shown in previous research to predict returns. Indeed, we also find that investors eventually revise their biased growth expectations downward for stocks with high realizations of the hard component.

Our paper extends the existing literature relating investor biases to the value effect. Previous research by Dechow and Sloan (1997); Chan, Karceski and Lakonishok (2003); La Porta (1996), and Skinner and Sloan (2002) finds evidence that overly optimistic long-term growth forecasts contribute to the value premium and that growth stocks underperform when high expectations are not met. The evidence in these papers suggest that when stock prices are high relative to a measure of fundamentals (such as the book value of equity), growth expectations tend to be overly optimistic. We take this analysis one step further and consider the firm characteristics that tend to be associated with these biases. Specifically, our evidence suggests that investors are pessimistic about highly profitable firms, potentially because they think profits are more mean-reverting than they actually are, and that they are optimistic when firms take actions that promote growth, possibly because they fail to account for managers making choices that are either overly optimistic or have "empire building" tendencies.

---

changes in analyst buy-sell recommendations forecast stock returns. For a broader review of the literature that relates analyst long-term growth forecasts to stock returns, please see Ramnath, Rock and Shane (2008), Richardson, Tuna and Wysocki (2010) and Kothari, So and Verdi (2016).

The paper closest to our research design is Jegadeesh, Kim, Krische and Lee (2004), who find that analysts tend to give buy ratings to “glamour” firms that tend to have positive momentum, high growth, high volume, and high price ratios, and among glamour firms, higher consensus recommendations are a negative predictor of future returns. The focus of this paper is on the buy-sell recommendations. Jegadeesh et al (2004) use analyst long-term growth as a proxy for growth expectations. Our paper, instead, seeks to use biases in long-term forecasts to explain why different accounting ratios explain differences in average stock returns.

The rest of this paper is organized as follows. The first section describes the data used in our analysis and the characteristics of high- and low-forecasted growth firms. The second section presents the decomposition of analyst long-term growth forecasts and examines the persistence of long-term growth forecasts and different accounting and valuation ratios. The third section presents the main analysis, exploring how various measures of expected growth are related to valuation ratios and realized earnings growth. The fourth section analyzes how different components of long-term growth forecasts predict future stock returns. The fifth section concludes.

1. Data

Our main variable of interest, consensus analyst long-term growth (LTG), is taken from Institutional Brokers Estimate System (I/B/E/S) and reflects the mean analyst estimate of annualized earnings growth.[5] There are a few challenges associated with using this measure as an estimate of projected growth. First, each individual analyst long-term growth estimate is updated periodically at the discretion of the analyst, which creates the possibility of stale data. However, as we show, consensus

[5] Our empirical results are economically similar using the median instead of the mean consensus forecast.

analyst growth forecasts are very persistent through time, suggesting that the individual analyst forecasts change very slowly. Second, analysts do not always report long-term growth estimates.[6]

The starting sample for this study includes all NYSE, AMEX, and NASDAQ stocks listed on both the Center for Research in Security Prices (CRSP) return files and the Compustat annual industrial files from 1982 through 2014. Information on stock returns, market capitalizations, and stock prices are from the CRSP database. Balance-sheet and income-statement information, shares outstanding, and GICS industry codes are from the Compustat database. Analyst long-term consensus growth forecasts (LTG), stock prices at the time of the analyst estimate, next year's consensus EPS, and actual five-year annual EPS growth rates are from the I/B/E/S Summary file. I/B/E/S compiles these forecasts on the third Thursday of each month.

We exclude stocks that have negative or missing book equity, missing industry codes or LTG estimates, or missing accounting data required to construct the different variables used in this study. Two of our measures require non-zero information on sales and assets in year *t-2*, which mitigates backfilling biases. While we include financial companies, excluding those securities has very little impact on the results reported in the paper. Our final sample has an average of 2,213 firms in each year.

Variable definitions are as follows. Realized EPS growth (REAL EPS) is from I/B/E/S and reflects the past five-year EPS annualized growth rate. Equity dilution (EQDIL) is measured as the percentage growth in split-adjusted shares outstanding. Sales growth (ΔSALES) is constructed as the year-over-year percentage growth in revenues per share adjusted for share splits. Asset growth (ΔASSETS) is the year-over-year percentage growth in assets per share adjusted for share splits. Profitability (ROA) is defined as operating income before depreciation scaled by assets. SIZE is the logarithm of company market

---

6 Jung, Shane and Yang (2012) explore the motivation for reporting LTG forecasts. They argue that by reporting long- term forecasts, analysts signal that they are likely to be long-term players, and in fact analysts that make these forecasts are less likely to leave the industry or move to a smaller brokerage house.

capitalization measured at the end of June.[7] P/E_{t+1} is the logarithm of the forward price-to-earnings calculated as the analyst consensus EPS for the next year divided by the price per share. Change in analyst long-term earnings forecasts (ΔLTG) is the year-over-year change in analyst consensus long-term earnings forecasts. Each year, variables are cross-sectionally winsorized to reduce the effect of outliers by setting values greater than the 99th percentile and less than the 1st percentile to the 99th and 1st percentile breakpoint values, respectively. Our variable definitions are largely consistent with previous studies.

Following Fama and French (1992), we form all of our variables at the end of June in year *t*, using fiscal year *t-1* accounting information and analyst estimates from June of year *t*. For EPS valuation ratios based on analyst estimates and measures of company size, we use market equity from June of year *t* to measure the information in the numerator and the denominator at the same point in time. Stock returns are adjusted for stock delisting to avoid survivorship bias, following Shumway (1997). Portfolios used in various asset-pricing tests are formed once a year on the last day in June, allowing for a minimum of a six-month lag between the end of the financial reporting period and portfolio formation.

Figure 1 reports the average and median annual consensus analyst long-term growth forecast (LTG) from 1982 to 2014 and the five-year realized EPS annualized growth rate from 1982 to 2009. The mean estimated growth rate over this period is remarkably stable, increasing from 15.4% in 1982 to 19.7% in 2001, and then decreasing to 14.0% in 2014. The actual five-year growth rate (1982 reflects the

[7] To calculate book equity, we use the following logic, which is largely consistent with the tiered definitions used by Fama and French (1992). Book equity is equal to stockholders' equity plus deferred taxes less preferred stock. If stockholders' equity is missing, we substitute common equity. If common equity and shareholders' equity are both missing, the difference between assets and liabilities less minority interest is selected. Deferred taxes are deferred taxes and/or investment tax credits. Preferred stock is redemption value if available; otherwise, carry value of preferred stock is used. We set to zero the following balance sheet items, if missing: preferred stock, minority interest, and deferred taxes.

five-year growth rate between years 1982 and 1987) fluctuates from slightly higher than 0% to 17.8%. The median cross-sectional forecast and realized earnings growth rates follow a similar pattern. Realized growth tends to be high following recessions (1991, 2001, and 2008) and much lower in periods that include recessions in the five-year window.

At the end of June of each year, *t* stocks are allocated into quintiles based on LTG. Table 1 reports formation period (using accounting information from year *t-1*) value-weighted summary statistics for various accounting ratios, price-ratio variables, and market capitalizations for each of the five quintile portfolios. The first quintile portfolio contains the firms with the lowest expected growth; the fifth quintile portfolio contains the firms with the highest expected growth. Over our sample period, analysts expect the lowest-growth firms to average 7% annualized growth in earnings per share, while the top group has average projected EPS growth rates that are four times as large. The distribution of LTG is right-skewed: the middle group (3rd quintile) has close to a 14% lower growth rate than the highest growth group, but only a 7% higher growth rate than the lowest growth group.

Although the following comparison is plagued by clear survival bias, it is useful to compare the long-term growth forecasts with realized EPS growth. Realized EPS growth does line up with projected growth – increasing monotonically from a low of 3.0% for the quintile portfolio with the lowest LTG to a high of 13.6% for the highest LTG. The average forecast error, defined as the difference between the forecast and actual growth, also increases monotonically moving from left to right, rising from 3.9% for the lowest LTG growth to 14.4% for the highest LTG group. Even the lowest expected- growth firms based on LTG miss their long-term earnings projections, although the misses are relatively small. In contrast, the highest expected-growth firms have average realized growth that is more than 50% less than their ex-ante forecasts.

The second section of Table 1 Panel B shows that many of the accounting variables used in our study have a meaningful relation with long-term growth forecasts. High expected-growth firms tend to have greater equity dilution (EQDIL) and higher past sales (ΔSALES) and asset growth (ΔASSETS). We also observe the same asymmetry associated with expected growth rates – the highest growth group has equity dilution ratios, sales and asset growth rates that are twice as large as the 4^{th} quintile, while the difference between the 3^{rd} and 4^{th} quintile is not as large. Our last non-price variable, profitability (ROA), does not appear to be related to consensus long-term analyst growth.

The third section of Table 1 Panel B examines how price-related variables are related to growth expectations. The results show that low growth-rate firms tend to be larger than high growth-rate firms. High-growth firms also tend to have much higher valuation ratios – the highest growth group has a market capitalization that is on average 39x next-period expected earnings, while the lowest growth group has a market capitalization that is only 14x next-period expected earnings. This is consistent with the idea that greater growth prospects are reflected in higher valuation ratios.

2. Decomposing Growth Expectations

Table 2 presents regressions that document the relation between hard information variables and long-term growth forecasts. The first four rows of Table 2 display univariate panel regressions of LTG on different firm characteristics using annual data from 1982 to 2014. Errors are clustered by firm and year. Long-term growth is measured as of June of year *t*, while the independent variables use accounting information from fiscal year *t-1*. Similar to Table 1, equity dilution (EQDIL), sales growth (ΔSALES), and asset growth (ΔASSETS) are all positively related to LTG. The fourth variable, profitability (ROA), is negatively related to long-term growth, but is not reliably different from zero (t-stat=1.65). Past sales growth has the highest explanatory power, explaining 10% of the variation in long-term growth.

Rows 5 through 8 report our estimates for multivariate cross-sectional regressions of LTG on the four non-price accounting variables. The regressions are run both with and without fixed effects that capture variation in long-term growth forecasts by industry and year. In most regressions, the coefficients of both the accounting variables and the industry and firm fixed effects are statistically significant, indicating that analyst long-term growth forecasts are significantly related to our measures of hard information.

The positive coefficients on sales growth are consistent with the idea that analysts believe that past sales growth will persist into the future, and that this will in turn lead to future EPS growth. The positive coefficient on asset growth may reflect the belief that growing firms are making positive NPV investments that will generate future earnings. Equity issuances can also indicate the presence of growth opportunities due to a need for additional capital, while share repurchases may indicate the lack of growth opportunities. The negative coefficient on profitability may reflect expected mean reversion in profits; i.e., low-profit firms are expected to experience the highest growth in EPS.

In the tests that follow, we decompose analyst long-term growth forecasts into two parts. The first component, which we call *Hard Growth*, is the fitted values from the linear regression reported in the last row of Table 2 and reported in Equation 1.[8]

Equation 1.

$$\textit{Hard Growth} = 0.04 + 0.08\ \text{EQDIL} + 0.05\ \Delta\text{SALES} + 0.04\ \Delta\text{ASSETS} - 0.12\ \text{ROA}$$

The second component, denoted *Soft Growth*, is the difference between LTG and Hard Growth. Soft Growth reflects analyst private views or information content in LTG that is unexplained by observable accounting variables. For our measure of Hard Growth, we use the coefficients of the

[8] There is a potential forward-looking bias associated with using the entire sample period to estimate Hard Growth, which assumes that the relation between LTG and different accounting ratios are known at the beginning of the sample period. In robustness tests (not reported), we find that our results are largely unchanged if Hard Growth is estimated using an expanding window or by estimating the regression of LTG on accounting ratios each year using contemporaneous information only. The reason why there is not much difference is the stability of the relation between the accounting ratios and LTG as reported in Figure 4 and discussed later in the paper.

independent variables from the equation reported above, but we do not include the coefficients on industry or time dummies to avoid any forward-looking bias.[9]

To better understand how growth expectations are incorporated into market prices, Table 3 estimates the relation between the components of long-term growth and the natural log of the forward price-to-earnings (P/E_{t+1}).[10] As we show, the sign of the coefficients on the positive indicators of growth (EQDIL, ΔASSETS, ΔSALES) and the negative indicator of growth (ROA) is consistent with their correlations with long-term growth expectations reported in Table 2. We do, however, find that the coefficients for ΔSALES are not significantly different from zero.

The last row in Table 3 uses Hard Growth (the fitted values from the last regression reported in Table 2) and Soft Growth (the difference between LTG and Hard Growth, or the residual of the same regression) as independent variables. We find that Soft Growth has a positive and highly significant correlation with valuation ratios. The coefficient on Hard Growth is also positive and significant, but the relation is not as strong. Indeed, all of the regressions are consistent with market prices incorporating both the hard and soft information contained in analyst forecasts.

3. Do Growth Estimates Predict Future Earnings Growth?

We next examine whether the soft and hard components of forecasted earnings growth actually predict realized earnings growth (REAL EPS). I/B/E/S and Dechow and Sloan (1997) estimate realized earnings growth over the past five years using an AR(1) regression of log (EPS) using six annual observations between years *t* and *t+5*, where year *t* is the reference year that LTG is measured. Hence, one can estimate the extent to which long-term growth forecasts and the various components of expected growth predict actual growth.

---

9 This assumption is not material – when we use only same-period information to form hard and soft growth measures, the results presented in later sections are not materially different.

10 For robustness, we also examined using price-to-book ratio as a valuation ratio and found economically similar results to those presented in Table 3, with the exception of weaker results for our ROA measure.

Unfortunately, sample-selection bias creates a major problem for this analysis. Estimating realized earnings growth requires future realizations of non-negative EPS values, but a number of firms in the sample experience negative earnings and a number of other firms drop out of our sample. Specifically, in our sample from 1982 to 2009, we have five-year earnings growth rates for only two-thirds of the original sample (41,957 out of 63,842 firm-years). For those stocks with five-year earnings growth data (REAL EPS), 97.4% have a full 60 months of stock returns, and the average compound return is 14.4% per year for this sample. In comparison, only 22.5% of stocks with missing REAL EPS data have 60 months of stock returns – those firms with 60 months of data, but missing REAL EPS data, have stock returns that averaged only 5.37% per year.

Clearly, firms with missing data performed worse on average than those that stayed in our database. However, firms leave the sample for a variety of reasons, such as mergers, acquisition by private equity firms, as well as bankruptcy and negative expected future earnings. Hence, in addition to losing firms that do very poorly, we lose some firms that did very well – as a result, the bias should affect both low and high expected-growth firms. Indeed, we find that 42% of the high expected-growth firms (top quintile based on LTG each year) and 27% of low expected-growth firms (lowest quintile) have missing five-year earnings growth information.

Heckman's (1979) two-stage selection model provides a potential solution for this sample selection problem. However, this approach requires an instrument that is correlated with whether or not REAL EPS is missing but which is uncorrelated with actual EPS growth. Unfortunately, we have not been able to come up with a suitable instrument. Instead, we come up with proxies for the missing EPS data. Specifically, we calculate the five-year market-adjusted return $R_{i,MAR(t,t+5)}$ as the difference between the compound annual five-year stock return $R_{i(t,t+5)}$ measured from July of year *t* to June of year *t+5* less the compound annual market return $R_{Mkt(t,t+5)}$ measured over the same period.[11]

Equation 2.

$$R_{i,MAR(t,t+5)} = R_{i(t,t+5)} - R_{Mkt(t,t+5)}$$

Figure 2 reports value-weighted, market-adjusted returns $R_{MAR(t,t+5)}$ for decile portfolios formed by ranking stocks on the I/B/E/S five-year realized EPS growth rate (REAL EPS). We include all stocks that have non-missing EPS data. Moving from left-to-right, the average five-year market-adjusted return rises from -19.0% to 8.6%. The monotonic relation between the EPS growth and stock returns is consistent with Ball and Brown (1968), Ball, Kothari and Watts (1993), Daniel and Titman (2006) and suggests that return information is a good proxy for EPS growth.

The approach we take fills in missing earnings data with estimates based on observed stock returns. Specifically, our matching process, which we need to use on the one-third of our sample with missing EPS data, involves calculating the percentile rank of $R_{MAR(t,t+5)}$ for a given year using all firms (including those with missing REAL EPS), defined as the percentage of firms with a lower $R_{MAR(t,t+5)}$, and takes values between 0 and 100. We then repeat the same exercise calculating the percentile rank of REAL EPS using the sample of non-missing firms from Figure 2.

For each missing REAL EPS observation, we then assign the average five-year EPS growth rate estimated in the same year for the REAL EPS percentile rank that corresponds to the same percentile rank of $R_{MAR(t,t+5)}$. Our procedure matches a distressed firm with poor stock returns and a missing EPS growth rate (potentially due to negative earnings or a bankruptcy) to a low EPS growth rate. Similarly,

[11] When a firm has less than 60 months of data, we use the available return data to estimate compound annual market-adjusted returns.

the procedure matches a firm that has high stock returns and a missing five-year EPS growth rate, possibly due to a corporate action such as a merger, with a high EPS growth rate.

Figure 3 displays a histogram of $R_{MAR(t,t+5)}$ for those firms with missing REAL EPS data. This figure provides a sense of the distribution of market-adjusted stock returns for the sample with missing data and whether firms are matched to low or high realized EPS growth rates. The matched firms often have very low or very high market-adjusted returns – 22% of the missing sample in which $R_{MAR(t,t+5)}$ was in the bottom decile of future average returns, while 19% were in the top decile. In contrast, only 11% of the missing sample had future five-year returns that were either in the fifth or sixth deciles.

We examine why firms have missing REAL EPS. For those firms in the highest decile of market-adjusted returns, 93% were delisted because of a merger or acquisition. Among those in the firms with the lowest decile of market-adjusted returns, almost all were either delisted over the next five years due to bankruptcy or had negative earnings over the five-year period.

Table 4 reports panel regression results of 5-year realized EPS growth (REAL EPS) on our measures of hard and soft information. When REAL EPS is missing, we assign a future EPS growth rate as described above. Errors are clustered by industry and firm, which help correct for the overlapping nature of estimating realized EPS growth over five years. The first two rows display results without inclusion of LTG; the third and fourth rows include LTG. In our fourth specification reported on the fourth row, we find equity dilution (t-stat=7.40), sales growth (t-stat=2.66), and asset growth (t-stat=2.12) are all significantly negatively related to actual growth, despite being positively related to forecasted growth. Profitability is also reliably positively related to actual growth (t-stat=5.06), even though profitability loads negatively on forecasted growth. We also find a negative relation between the LN (P/B) ratio (t-stat=3.11) and realized growth, suggesting that growth stocks have lower earnings growth when compared to value stocks. After including industry and year dummies, the coefficient on analyst long-term growth (t-stat=0.99) is no longer significant, indicating that analyst long-term estimates are relatively poor predictors of actual earnings growth after controlling for hard information and industry and year fixed effects.

The last two rows of Table 4 report regression results of hard and soft growth on realized five-year earnings growth. In the specification in row 5, we find a negative and significant relation between hard growth (t-stat=4.39) and realized earnings growth. We also find a significant positive relation between soft growth (t-stat=2.58) and realized earnings growth. After including industry and year dummies reported in the last row of Table 4, the coefficient on soft growth declines from 0.11 to 0.02 and is no longer significantly different from zero (t-stat=0.63). A straightforward extension of our analysis (which, for the sake of brevity, we do not report) is that hard accounting information also explains analyst forecast errors; i.e., the difference between the realized 5-year earnings growth and the analyst long-term consensus growth forecast.

To understand the importance of these results, recall that Table 2 shows that sales and asset growth and equity dilution variables are positively related to analyst long-term growth expectations, while profitability is negatively related. Table 4 illustrates the opposite: Profitability is positively related to actual earnings growth, but sales and asset growth and equity dilution are negatively related. These results are consistent with a bias in how analysts and markets perceive hard information when making earnings growth forecasts and setting prices.

Analysts, and by extension financial markets, may make mistakes due to the way they interpret the persistence of certain accounting variables. Increasing sales and high profitability are generally associated with greater earnings growth. Similarly, endogenous variables such as asset growth and equity dilution may indicate future investment or the presence of growth opportunities. In Figure 4, we report Spearman rank correlations for each variable and their future values to examine the persistence of different variables that are related to growth expectations. The x-axis reflects the number of years between the current and future variable values. Correlations for each measure decline as more time elapses.

Our results suggest that analysts make mistakes when interpreting the persistence of accounting information while setting growth expectations. As we show in Figure 4, the “level” variables based on ratios of balance-sheet information or market prices (ROA, P/E_{t+1}) tend to have high persistence, initially ranging from 0.69 to 0.84 for a one-year lag (t+1) and falling to 0.43 to 0.60 for a five-year lag (t+5). Value companies tend to stay value companies, and profitable firms tend to stay profitable. In contrast, the “change” variables, or those variables based on differences in balance-sheet quantities (EQDIL, ΔASSETS, ΔSALES), exhibit far less persistence: One-year lag correlations are between 0.27 to 0.41 and decline to 0.11 to 0.20 for a five-year lag. Analyst long-term growth (LTG) is also very persistent, with serial correlations that decline from 0.84 (one-year) to 0.61 (five-year).

The correlations reported in Table 2 and Equation 1 show how analysts expect certain accounting quantities to affect future earnings growth. For example, profitability has a negative loading on LTG, indicating that analysts believe that low-profit firms today will have higher earnings growth and hence high future profits. In reality, profitability is fairly persistent and low-profit firms do not have higher earnings growth when compared to high-profit firms. Sales growth also has a positive correlation with analyst long-term earnings growth forecasts, indicating that analysts expect sales growth to persist in the future, even though it is actually not very persistent and is a negative (weak) indicator of actual earnings growth. Similarly, endogenous variables such as asset growth and equity dilution, which should reflect growth opportunities, load positively on LTG. However, these indicators of growth are also not very persistent and are actually negatively related to actual earnings growth.

As we show, there is a tendency for these mistakes to at least partially correct over the following year. Table 5 reports regressions of year-over-year changes in analyst consensus long-term growth (LTG) on accounting and manager-choice variables. The first four rows show that change variables (equity dilution, asset and sales growth) are associated with strong negative revisions in LTG. The coefficient on the fourth variable, ROA, does not predict changes in LTG. Our composite variable, Hard Growth, also predicts when LTG forecasts will be revised downwards.

4. Do Errors in Growth Forecasts Lead to Return Predictability?

Table 6 examines how the different components of long-term growth forecasts explain differences in average stock returns. Each month, we sort stocks into 10 groups according to LTG, Hard Growth, and Soft Growth measures. Panel A of Table 6 reports average value-weighted returns for those firms with available LTG and accounting data. Consistent with Jung, Shane and Yang (2012), we find that analysts' consensus long-term growth expectations are unrelated to future stock returns. Our measure of Hard Growth, however, is strongly negatively related to average returns. Average returns for value-weighted portfolios formed on Hard Growth reported in the 2nd row of Table 6 Panel A decline from 1.19 for Decile 1 (lowest growth) to 1.04 for Decile 9. The last decile, which includes the firms with the highest Hard Growth indicators (low profitability, high external financing, high asset and sales growth), has monthly returns that are 55 basis points lower than the previous decile; the difference between the top and bottom decile is -0.60% per month (t-stat=2.66). Our results are not very surprising, given the extensive literature on growth and profitability return anomalies. In contrast, the last row of Table 6 Panel A shows that Soft Growth, which reflects analysts' views that are unrelated to accounting information, is also unrelated to stock returns.

Panels B and C of the table report these same portfolio returns for smaller firms and for a larger sample that also includes firms that do not have LTG data. Panel B, which reports returns on the smallest half of the firms (based on market capitalization), shows stronger results – the average return of the top decile is 0.86% less per month (t-stat=3.88) when compared to the average return of the bottom decile. Panel C examines an expanded dataset on firms with information available to measure Hard Growth, but also includes firms that do not have LTG forecasts. Not requiring LTG estimates doubles the sample size to an average of 4,045 firms per month. As we show, with this larger sample that more closely reflects the samples used in earlier studies of these return anomalies, we find a very strong relation between our estimate of hard growth and stock returns – the average return of a portfolio that is long the highest decile of hard growth firms and short the lowest decile of hard growth firms is -0.79% (t-stat = 3.38).

5. Conclusion

There is now substantial evidence linking various characteristic-based insights that derive information from income statement and balance sheet items to future excess stock returns. While it is possible that these excess returns are associated with systematic sources of risk that investors wish to avoid, the magnitudes of the observed abnormal returns and the Sharpe ratios that can be obtained by exploiting the strategies are simply too large to be consistent with equilibrium risk premia. In other words, during our sample period, the evidence suggests that the consensus views of investors were incorrect along some meaningful dimensions.

To explore this hypothesis, we use the consensus analyst long-term earnings growth forecast as a proxy for growth expectations and examine how these expectations are influenced by various accounting variables. Our focus is on two variables that are under the direct control of a firm's management – the extent to which the firm issued or repurchased its shares and the extent to which it grew its assets, along with two variables that management can only indirectly control – the sales growth and profitability of the firm. As we show, these variables explain the consensus long-term growth forecasts of analysts and, as such, they also influence stock prices. However, the sign of the correlation between these variables and realized earnings growth is inconsistent with the correlation between these variables and both analyst long-term earnings growth forecasts and firm valuations. Thus, high market prices reflect faulty growth expectations and sorting stocks on these accounting variables produces meaningful differences in average returns.

Although we do not identify new quantitative strategies per se, our analysis helps to understand what causes the mispricing. In particular, hard information signals that are not good predictors of future earnings do in fact explain long-term earnings forecasts as well as forward earnings-to-price ratios. Our interpretation is that these signals are thus associated with mispricing. Our analysis of the links between firm characteristics, long-term growth forecasts, valuation ratios, and future returns is potentially useful as a forward-looking indicator of market efficiency. Specifically, our analysis suggests that the future return predictability of various firm characteristics is dependent on whether these characteristics continue to be associated with what appears to be biases in analyst long-term growth forecasts.

Acknowledgment

The views expressed here are those of the authors and not necessarily those of any affiliated institution. Sheridan Titman is an advisor to Gerstein Fisher, which employs quantitative investment strategies that use the accounting ratios considered in this study. We thank members of the Gerstein Fisher Investment Strategy Group for their research assistance. This research has benefited from discussion with Michael Clement, S.P. Kothari, Yong Yu and Sunny Yang.

References

Abarbanell, J., and Lehavy, R. (2003). Biased Forecasts or Biased Earnings? The Role of Reported Earnings in Explaining Apparent Bias and Over/Underreaction in Analysts’ Earnings Forecasts, Journal of Accounting and Economics, 36(1-3), 105-146.

Ackert, L. F., and Athanassakos, G. (2003). A Simultaneous Equations Analysis of Analysts’ Forecast Bias, Analyst Following, and Institutional Ownership. Journal of Business Finance and Accounting, 30(7-8), 1017-1042.

Ball, R., and Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. Journal of Accounting Research, 159-178.

Ball, R., Kothari, S. P., and Watts, R. L. (1993). Economic Determinants of the Relation between Earnings Changes and Stock Returns. Accounting Review, 622-638.

Bandyopadhyay, S. P., Brown, L. D., and Richardson, G. D. (1995). Analysts' Use of Earnings Forecasts in Predicting Stock Returns: Forecast Horizon Effects. International Journal of Forecasting, 11(3), 429-445.

Barber, B., Lehavy, R., McNichols, M., and Trueman, B. (2001). Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns. The Journal of Finance, 56(2), 531-563.

Barber, B. M., Lehavy, R., McNichols, M., and Trueman, B. (2006). Buys, Holds, and Sells: The Distribution of Investment Banks' Stock Ratings and the Implications for the Profitability of Analysts' Recommendations. Journal of Accounting and Economics, 41(1-2), 87-117.

Barber, B. M., Lehavy, R., & Trueman, B. (2010). Ratings Changes, Ratings Levels, and the Predictive Value of Analysts' Recommendations. Financial Management, 39(2), 533-553.

Bradshaw, M. T. (2004). How do Analysts use their Earnings Forecasts in Generating Stock Recommendations?. The Accounting Review, 79(1), 25-50.

Bradshaw, M. T., Richardson, S. A., and Sloan, R. G. (2006). The Relation between Corporate Financing Activities, Analysts' Forecasts and Stock Returns. Journal of Accounting and Economics, 42(1-2), 53-85.

Chan, L. K., Karceski, J., and Lakonishok, J. (2003). The Level and Persistence of Growth Rates. The Journal of Finance, 58(2), 643-684.

Chan, L. K., Karceski, J., and Lakonishok, J. (2007). Analysts' Conflicts of Interest and Biases in Earnings Forecasts. Journal of Financial and Quantitative Analysis, 42(4), 893-913.

Clement, M. B. (1999). Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter?. Journal of Accounting and Economics, 27(3), 285-303.

Cochrane, J. H. (2011). Presidential address: Discount rates. The Journal of Finance, 66(4), 1047-1108.

Cooper, M. J., Gulen, H., and Schill, M. J. (2008). Asset Growth and the Cross-section of Stock Returns. The Journal of Finance, 63(4), 1609-1651.

Copeland, T., Dolgoff, A., & Moel, A. (2004). The Role of Expectations in Explaining the Cross-section of Stock Returns. Review of Accounting Studies, 9(2-3), 149-188.

Cowen, A., Groysberg, B., and Healy, P. (2006). Which Types of Analyst Firms are More Optimistic?. Journal of Accounting and Economics, 41(1-2), 119-146.

Da, Z., and Warachka, M. (2011). The disparity between Long-term and Short-term Forecasted Earnings Growth. Journal of Financial Economics, 100(2), 424-442.

Daniel, K., and Titman, S. Market Reactions to Tangible and Intangible Information. The Journal of Finance, vol. 61, 2006, pp. 1605-1643.

Das, S., Levine, C. B., and Sivaramakrishnan, K. (1998). Earnings Predictability and Bias in Analysts' Earnings Forecasts. Accounting Review, 277-294.

Dechow, P. M., and Sloan, R. G. (1997). Returns to Contrarian Investment Strategies: Tests of Naive Expectations Hypotheses. Journal of Financial Economics, 43(1), 3-27.

Duru, A., and Reeb, D. M. (2002). International Diversification and Analysts' Forecast Accuracy and Bias. The Accounting Review, 77(2), 415-433.

Easterwood, J. C., and Nutt, S. R. (1999). Inefficiency in Analysts' Earnings Forecasts: Systematic Misreaction or Systematic Optimism?. The Journal of Finance, 54(5), 1777-1797.

Easton, P., Taylor, G., Shroff, P., and Sougiannis, T. (2002). Using Forecasts of Earnings to Simultaneously Estimate Growth and the Rate of Return on Equity Investment. Journal of Accounting Research, 40(3), 657-676.

Fama, E. F., and French, K. R. (1992). The Cross-section of Expected Stock Returns. The Journal of Finance, 47(2), 427-465.

Gebhardt, W. R., Lee, C. M., and Swaminathan, B. (2001). Toward an Implied Cost of Capital. Journal of Accounting Research, 39(1), 135-176.

Gu, Z., and Wu, J. S. (2003). Earnings Skewness and Analyst Forecast Bias. Journal of Accounting and Economics, 35(1), 5-29.

Harvey, C. R., Liu, Y. and Zhu, H. (2016). … and the Cross-section of Expected Returns. The Review of Financial Studies, 29(1), 5-68.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. Econometrica: Journal of the Econometric Society, 153-161.

Hilary, G., and Hsu, C. (2013). Analyst Forecast Consistency. The Journal of Finance, 68(1), 271-297.

Hou, K., Xue, C., and Zhang, L. (2017). Replicating Anomalies (No. w23394). National Bureau of Economic Research.

Hong, H., and Kubik, J. D. (2003). Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. The Journal of Finance, 58(1), 313-351.

Jegadeesh, N., Kim, J., Krische, S. D., and Lee, C. M. (2004). Analyzing the Analysts: When do Recommendations Add Value?. The Journal of Finance, 59(3), 1083-1124.

Jung, B., Shane, P. B., and Yang, Y. S. (2012). Do Financial Analysts' Long-term Growth Forecasts Matter? Evidence from Stock Recommendations and Career Outcomes. Journal of Accounting and Economics, 53(1-2), 55-76.

Kang, N., Ozik, G., and Sadka, R. (2015). Fund Structure, Investor Protection, and the Long-Run Performance of Activism. Investor Protection, and the Long-Run Performance of Activism (November 1, 2015).

Kothari, S. P. (2000). Discussion of the Relation between Analysts' Forecasts of Long-term Earnings Growth and Stock Price Performance Following Equity Offerings. Contemporary Accounting Research, 17(1), 33.

Kothari, S. P., Sabino, J. S., and Zach, T. (2005). Implications of Survival and Data Trimming for Tests of Market Efficiency. Journal of Accounting and Economics, 39(1), 129-161.

Kothari, S. P., So, E. and Verdi, R. (2016). Analysts' Forecasts and Asset Pricing: A Survey. Annual Review of Financial Economics 8: 197-219.

Kwag, S. W. A., and Small, K. (2007). The Impact of Regulation Fair Disclosure on Earnings Management and Analyst Forecast Bias. Journal of Economics and Finance, 31(1), 87-98.

Lakonishok, J., Shleifer, A., and Vishny, R. W. (1994). Contrarian Investment, Extrapolation, and Risk. The Journal of Finance, 49(5), 1541-1578.

La Porta, R. (1996). Expectations and the Cross-section of Stock Returns. The Journal of Finance, 51(5), 1715-1742.

Lim, T. (2001). Rationality and Analysts' Forecast Bias. The Journal of Finance, 56(1), 369-385.

Lin, H. W., and McNichols, M. F. (1998). Underwriting Relationships, Analysts' Earnings Forecasts and Investment Recommendations. Journal of Accounting and Economics, 25(1), 101-127.

McLean, R. D., and Pontiff, J. (2016). Does Academic Research Destroy Stock Return Predictability?. The Journal of Finance, 71(1), 5-32.

Mikhail, M. B., Walther, B. R., and Willis, R. H. (1999). Does Forecast Accuracy Matter to Security Analysts?. The Accounting Review, 74(2), 185-200.

Mohanram, P., and Gode, D. (2013). Removing Predictable Analyst Forecast Errors to Improve Implied Cost of Equity Estimates. Review of Accounting Studies, 18(2), 443-478.

Nekrasov, A., and Ogneva,M. (2011) Using Earnings Forecasts to Simultaneously Estimate Firm-Specific Cost of Equity and Long-Term Growth. Review of Accounting Studies, 16 (3), 414-457.

Novy-Marx, R. (2013). The Other Side of Value: The Gross Profitability Premium. Journal of Financial Economics, 108(1), 1-28.

Pontiff, J., and Woodgate, A. (2008). Share Issuance and Cross-sectional Returns. The Journal of Finance, 63(2), 921-945.

Ramnath, S., Rock, S., and Shane, P. (2008). The Financial Analyst Forecasting Literature: A Taxonomy with Suggestions for Further Research. International Journal of Forecasting, 24(1), 34-75.

Richardson, S., Tuna, I., and Wysocki, P. (2010). Accounting Anomalies and Fundamental Analysis: A Review of Recent Research Advances. Journal of Accounting and Economics, 50(2-3), 410-454.

Skinner, D. J., and Sloan, R. G. (2002). Earnings surprises, Growth Expectations, and Stock Returns or don't let an Earnings Torpedo Sink your Portfolio. Review of Accounting Studies, 7(2-3), 289-312.

Stickel, S. E. (1995). The Anatomy of the Performance of Buy and Sell Recommendations. Financial Analysts Journal, 51(5), 25-39.

Shumway, T. (1997). The Delisting Bias in CRSP Data. The Journal of Finance, 52(1), 327-340.

Titman, S., Wei, K. J., and Xie, F. (2004). Capital Investments and Stock Returns. Journal of Financial and Quantitative Analysis, 39(4), 677-700.

Womack, K. L. (1996). Do Brokerage Analysts' Recommendations have Investment Value?. The Journal of Finance, 51(1), 137-167.

Zhang, X. F. (2006). Information Uncertainty and Analyst Forecast Behavior. Contemporary Accounting Research, 23(2), 565-590.

Table 1. Sample Summary Statistics from 1982-2014.

This table presents summary statistics for firms that meet the restrictions described in the data section. The first panel describes the distribution of analyst long-term growth forecasts, LTG. At the end of June of each year *t*, stocks are ranked on LTG and then allocated to five groups, each with an equal number of stocks. The second panel reports value-weighted averages for LTG, 5-year realized earnings growth, accounting ratios, valuation ratios, and market capitalization for each quintile portfolio using information available at the portfolio formation date. Variable definitions are as follows: LTG measures the mean estimate of all analysts' expectations of the future EPS annual growth rate measured in the 3rd week of June of year *t*. REAL EPS is the five-year average annualized future EPS growth rate between year *t* and year *t+5*. FORECAST ERROR is the difference between LTG and REAL EPS. EqDil (equity dilution) is the percentage change in split-adjusted shares outstanding from year *t-2* to year *t-1*. ΔSales (sales growth) is the percentage change in revenues per split-adjusted share from year *t-2* to year *t-1*. ΔAssets (asset growth) is the percentage change in assets per split-adjusted share from *t-2* to *t-1*. ROA (profitability) is operating income in year *t-1* divided by assets for year *t-1*. SIZE x 10^9 is market capitalization (in millions) as of June of year *t*. P/B (price/book ratio) is market capitalization as of December of year t-1, divided by book equity in year *t-1*. P/E_{t+1} (price/forward earnings ratio) is price per share, divided by fiscal year 1 analyst consensus earnings per share measured in the 3rd week of June of year *t*. The sample has an average of 2,213 firms per year.

Panel A. Average Analyst Long-Term Growth Statistics					
	p1	Median	Mean	p99	σ
LTG	0.010	0.142	0.158	0.484	0.084

Panel B. Average Firm Characteristics by Analyst Long-Term Growth Quintile					
	1	2	3	4	5
Growth Variables					
LTG	0.070	0.111	0.141	0.181	0.280
REAL EPS	0.030	0.057	0.070	0.087	0.136
FORECAST ERROR	-0.043	-0.057	-0.074	-0.097	-0.144
Non-Price Variables					
EQDIL	0.024	0.018	0.015	0.037	0.076
ΔSALES	0.048	0.070	0.098	0.155	0.311
ΔASSETS	0.059	0.091	0.122	0.181	0.335
ROA	0.140	0.145	0.170	0.188	0.171
Price Variables					
SIZE x 10^9	30.91	32.93	26.55	23.34	19.80
P/E_{t+1}	14.31	16.15	19.04	23.60	39.00

Table 2. Panel Regression Explaining Long-Term Growth from 1982-2014.

This table reports results from panel regressions of analyst long-term growth (LTG) on past accounting growth measures. LTG is the mean estimate of all analysts' expectations of the EPS annual growth rate between year *t+2* to year *t+5* measured in the 3rd week of June of year *t*. EQDIL (equity dilution) is the percentage change in split-adjusted shares outstanding from fiscal year-end in *t-2* to *t-1*. ΔSALES (sales growth) is the percentage change in revenues per split-adjusted share from *t-2* to *t-1*. ΔASSETS (asset growth) is the percentage change in assets per split-adjusted share from year *t-2* to year *t-1*. ROA (profitability) is operating income in year *t-1* divided by assets in year *t-1*. N is the average number of stocks each year. Certain regressions use industry (Based on GICS sector definitions) and year fixed effects. T-statistics are reported in parentheses based on robust standard errors that are clustered by firm and industry. The number of firm-year observations is 74,130.

	Intercept	EQDIL	ΔSALES	ΔASSETS	ROA	R^2	Industry Fixed Effect?	Year Fixed Effect?
Coefficient	0.16	0.12				0.04	No	No
t-stat	(11.75)	(4.02)						
Coefficient	0.15		0.08			0.10	No	No
t-stat	(11.35)		(13.56)					
Coefficient	0.15			0.08		0.07	No	No
t-stat	(10.62)			(12.68)				
Coefficient	0.17				-0.11	0.02	No	No
t-stat	(8.23)				(1.65)			
Coefficient	0.15	0.10	0.06	0.05	-0.11	0.17	No	No
t-stat	(8.23)	(9.36)	(13.99)	(8.12)	(1.87)			
Coefficient	0.07	0.09	0.05	0.04	-0.12	0.34	Yes	No
t-stat	(20.92)	(7.50)	(10.46)	(13.40)	(4.54)			
Coefficient	0.14	0.09	0.06	0.05	-0.10	0.20	No	Yes
t-stat	(10.77)	(11.18)	(15.13)	(7.68)	(1.85)			
Coefficient	0.04	0.08	0.05	0.04	-0.12	0.37	Yes	Yes
t-stat	(7.56)	(8.43)	(10.52)	(14.23)	(4.64)			

Table 3. Panel Regression Explaining Price-to-Forward Earnings Valuation Ratios from 1982-2014.

The dependent variable for the regression is the natural log of the P/E_{t+1} ratio. P/E_{t+1} (price/forward earnings ratio) is market capitalization as of December of year t-1, divided by book equity in year *t-1*. EqDil (equity dilution) is the percentage change in split-adjusted shares outstanding from fiscal year-end in *t-2* to *t-1*. ΔSales (sales growth) is the percentage change in revenues per split-adjusted share from *t-2* to *t-1*. ΔAssets (asset growth) is the percentage change in assets per split-adjusted share from *t-2* to *t-1*. ROA (profitability) is operating income in *t-1* divided by assets for *t-1*. Hard Growth is the fitted value from the last regression listed in Table 2, and Soft Growth is equal to LTG minus Hard Growth. The independent variables are constructed using financial statement data from the fiscal period ending in year t-1. N is the average number of firms each year. For brevity, the intercept is not reported. Robust standard errors are clustered by firm and industry.

	EqDil	**ΔSales**	**ΔAssets**	**ROA**	**Hard Growth**	**Soft Growth**	**R^2**	**Industry Dummy**	**Year Dummy**	**N**
Coefficient	0.21	0.06	0.14	-0.62			0.02	No	No	2,213
t-stat	(5.31)	(0.90)	(3.15)	(0.86)						
Coefficient	0.21	0.06	0.14	-0.43			0.13	No	Yes	2,213
t-stat	(4.91)	(0.84)	(3.87)	(0.61)						
Coefficient	0.14	0.01	0.09	-1.25			0.14	Yes	No	2,213
t-stat	(3.37)	(0.16)	(2.71)	(3.70)						
Coefficient	0.14	0.01	0.10	-1.10			0.23	Yes	Yes	2,213
t-stat	(3.03)	(0.12)	(3.40)	(3.53)						
Coefficient					2.10	2.32	0.28	Yes	Yes	2,213
t-stat					(4.24)	(8.36)				

Table 4. Panel Regression Explaining Realized Earnings Growth from 1982-2014.

The dependent variable for the regression is realized earnings growth (REAL EPS), which is the five-year annualized EPS growth rate. EQDIL is equity dilution measured as the percentage change in adjusted shares outstanding over the previous year. ΔSALES is the percentage change in split-adjusted revenues over the previous year. ΔASSETS is the percentage change in split-adjusted assets over the previous year. ROA is profitability, measured as operating income before depreciation divided by assets. LTG is measured as of the 3rd week in June of year t, while the independent variables are constructed using financial statement data from the fiscal period ending in year t-1. T-statistics, reported in parentheses, are based on robust standard errors that are clustered by firm and industry. For brevity, the intercept is not reported.

	LTG	EQDIL	ΔSALES	ΔASSETS	ROA	Hard Growth	Soft Growth	LN(P/B)	R^2	Ind & Year Fixed Effect?	N
Coefficient		-0.09	-0.02	-0.03	0.05			0.00	<.01	No	2,280
t-stat		(6.33)	(1.67)	(2.44)	(1.83)			(0.79)			
Coefficient		-0.10	-0.02	-0.03	0.12			-0.01	0.05	Yes	2,280
t-stat		(7.37)	(2.19)	(2.12)	(5.13)			(2.79)			
Coefficient	0.11	-0.10	-0.02	-0.03	0.07			-0.01	0.02	No	2,280
t-stat	(2.60)	(6.78)	(2.61)	(2.62)	(3.21)			(1.91)			
Coefficient	0.03	-0.10	-0.02	-0.03	0.13			-0.02	0.05	Yes	2,280
t-stat	(0.99)	(7.40)	(2.66)	(2.12)	(5.06)			(3.11)			
Coefficient						-0.52	0.11	-0.01	<.01	No	2,280
t-stat						(4.39)	(2.58)	(1.84)			
Coefficient						-0.61	0.02	-0.01	0.05	Yes	2,280
t-stat						(6.09)	(0.63)	(2.24)			

Table 5. Panel Regression Explaining Changes in Long-Term Growth Estimates from 1982-2013.

The dependent variable for the regression is the year-over-year change in analyst long-term growth forecasts ($LTG_{t+1} - LTG_t$) measured in the 3rd week of June of year *t*. EqDil (equity dilution) is the percentage change in split-adjusted shares outstanding from fiscal year-end in *t-2* to *t-1*. ΔSales (sales growth) is the percentage change in revenues per split-adjusted share from *t-2* to *t-1*. ΔAssets (asset growth) is the percentage change in assets per split-adjusted share from *t-2* to *t-1*. ROA (profitability) is operating income in *t-1* divided by assets for *t-1*. Hard Growth is the fitted value from the last regression listed in Table 2. The independent variables are constructed using financial statement data from the fiscal period ending in year t-1. There is an average of 1,929 firms in the sample each year. For brevity, the intercept is not reported. Robust standard errors are clustered by firm and industry.

	EQDIL	**ΔSALES**	**ΔASSETS**	**ROA**	**Hard Growth**	**R^2**	**Industry Effect?**	**Year Effect?**
Coefficient	-0.02	-0.02	-0.01	0.00		0.03	No	No
t-stat	(7.81)	(5.91)	(8.21)	(0.31)				
Coefficient	-0.02	-0.02	-0.01	0.00		0.05	No	Yes
t-stat	(8.44)	(6.13)	(7.85)	(0.11)				
Coefficient	-0.02	-0.02	-0.01	0.00		0.03	Yes	No
t-stat	(7.62)	(5.74)	(7.82)	(0.41)				
Coefficient	-0.02	-0.02	-0.01	0.00		0.05	Yes	Yes
t-stat	(8.31)	(5.91)	(7.32)	(0.25)				
Coefficient					-0.24	0.02	No	No
t-stat					(5.40)			
Coefficient					-0.23	0.05	Yes	Yes
t-stat					(6.30)			

Table 6. Value-weighted Monthly Returns for Portfolios Formed on Long-Term Growth Measures from July 1982-December 2014.

At the end of June of year *t*, stocks are allocated to 10 portfolios based on the decile breakpoints for LTG (analyst long-term growth estimate), Hard Growth (fitted values from the last regression in Table 2), and Soft Growth (LTG minus Explained Growth). Panel A presents results for the original sample of firms with non-missing LTG. Panel B presents results for the bottom half of firms in the original sample based on market capitalization at the end of June of each year. Panel C reports results for all firms listed in CRSP/Compustat (including those with missing LTG data) that have valid data to construct EQDIL, ΔSALES, ΔASSETS, ROA and positive book equity. T-statistics are reported in parentheses to the right of each estimate. Monthly returns are reported in percentages.

Panel A. Original Sample

	1	2	3	4	5	6	7	8	9	10	10-1	*t-stat*	n
LTG	1.14%	1.10%	1.15%	1.12%	1.03%	1.08%	1.13%	1.25%	0.89%	1.15%	0.01%	(0.02)	2,153
Hard Growth	1.19%	1.18%	1.07%	1.22%	1.08%	1.23%	0.95%	1.05%	1.04%	0.59%	-0.60%	(2.66)	2,153
Soft Growth	0.98%	1.06%	1.15%	1.06%	1.22%	0.96%	1.06%	1.21%	1.02%	1.31%	0.33%	(0.96)	2,153

Panel B. Small Firms Only

	1	2	3	4	5	6	7	8	9	10	10-1	*t-stat*	n
LTG	1.24%	1.29%	1.23%	1.30%	1.29%	1.39%	1.28%	1.10%	1.17%	1.06%	-0.18%	(0.54)	1,077
Hard Growth	1.41%	1.44%	1.49%	1.27%	1.28%	1.37%	1.13%	1.36%	1.12%	0.55%	-0.86%	(3.88)	1,077
Soft Growth	1.18%	1.18%	1.14%	1.24%	1.25%	1.28%	1.32%	1.32%	1.23%	1.22%	0.05%	(0.15)	1,077

Panel C. All Firms (Includes Missing LTG Data Firms)

	1	2	3	4	5	6	7	8	9	10	10-1	*t-stat*	n
Hard Growth	1.16%	1.18%	1.11%	1.12%	1.11%	1.20%	1.02%	0.99%	0.98%	0.37%	-0.79%	(3.38)	4,045

Figure 1. Average Consensus Analyst Long-term Growth Estimates and Realized 5-year EPS Growth Rate from 1982-2014.

The figure plots cross-sectional mean and median estimates for LTG and REAL EPS by year. LTG is the mean estimate of all analysts' expectations of the future EPS annual growth rate measured in the 3rd week of June of year *t*. REAL EPS is the five-year average annualized realized EPS growth rate between year *t* and year *t+5*.

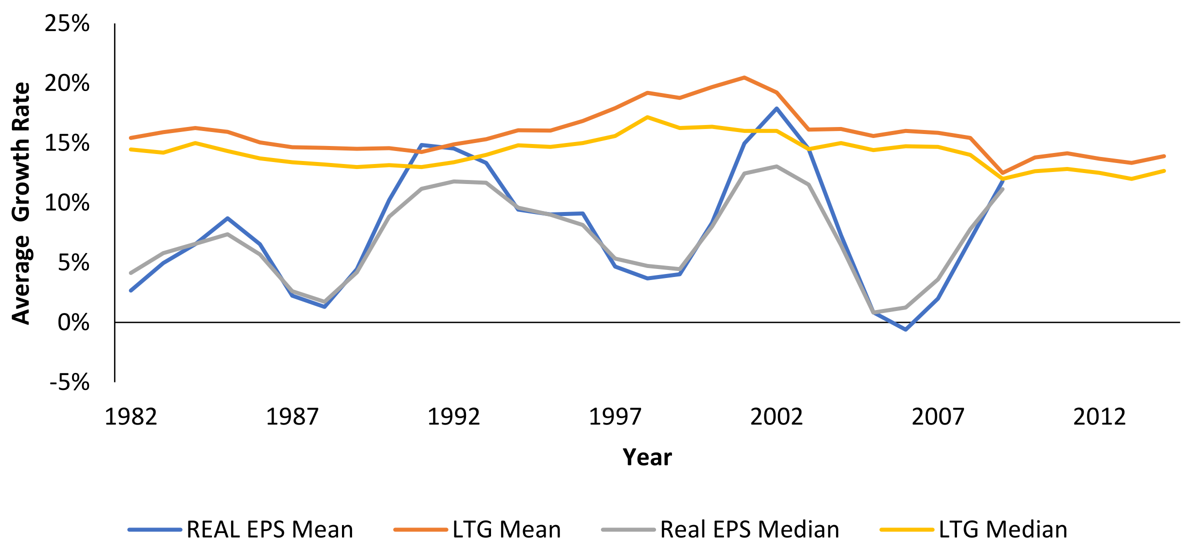


Figure 2. Value-weighted Average Market-Adjusted Return for Portfolios Formed on Realized EPS Growth Rate from 1982-2009.

At the end of June of year *t*, stocks are allocated to 10 portfolios according to the realized EPS growth rate (REAL EPS). The figure reports the average value-weighted (using market capitalization as of the end of June in year *t*), market-adjusted five-year return measured over the 60 months starting in July of year *t*. There is an average of 1,498 firms per year with non-missing five-year EPS growth rates.

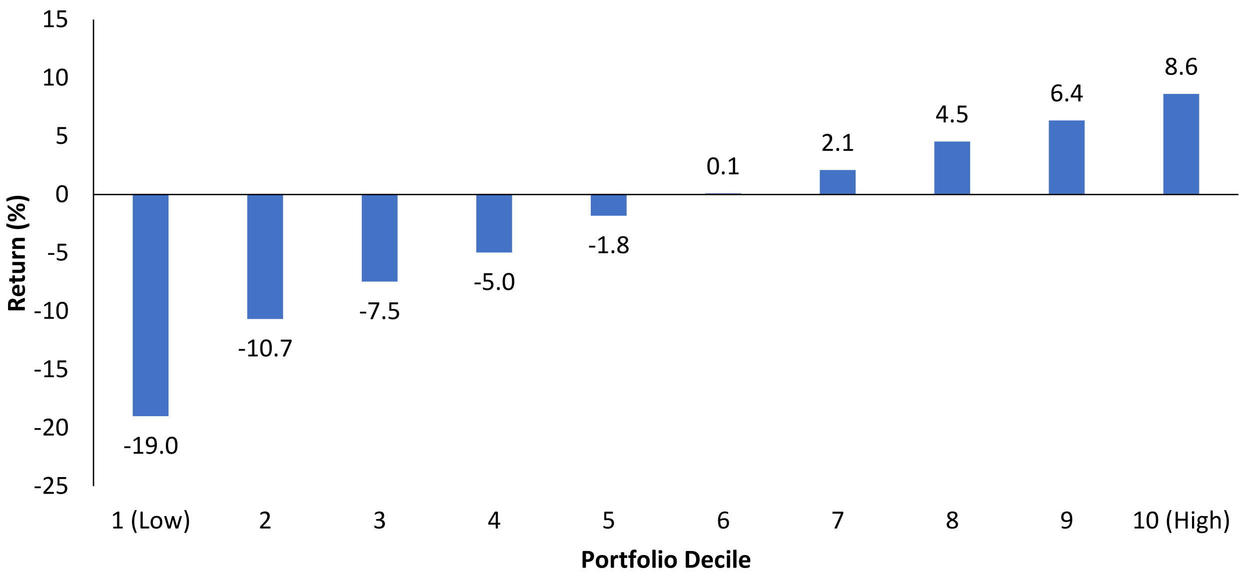


Figure 3. Histogram of Five-year Market-adjusted Returns with Missing EPS Five-year Growth Rates from 1982-2009.

This figure reports the percentage of firm-years with missing realized earnings (REAL EPS) information by market-adjusted return decile. There are 21,885 firm-years with future stock returns that have missing five-year EPS growth rates that were assigned EPS growth rates using our matching technique.

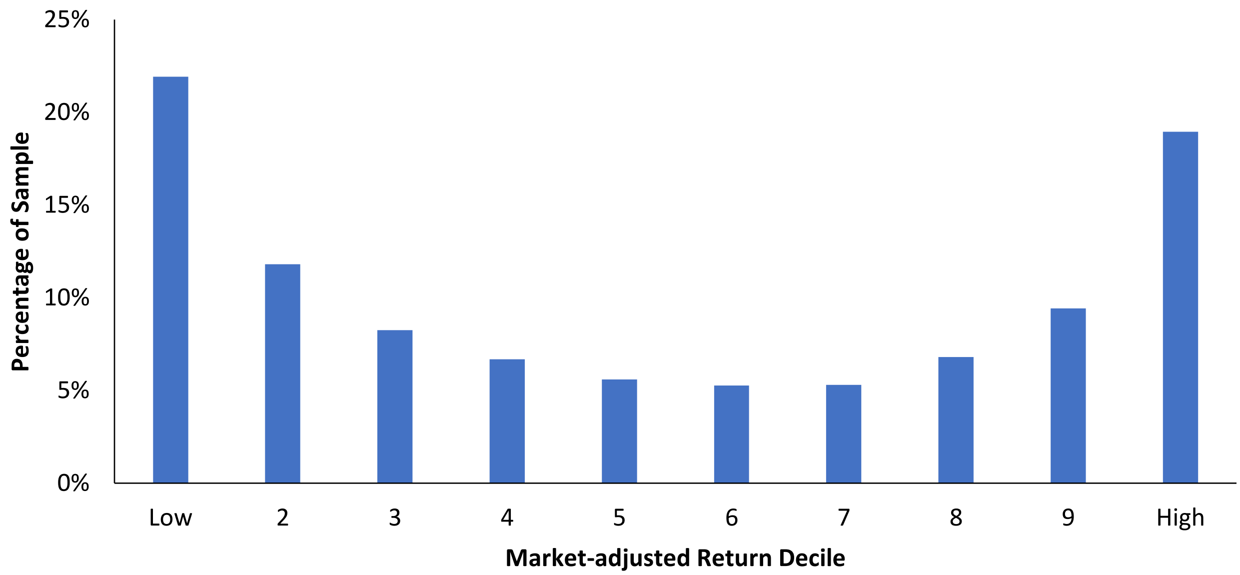
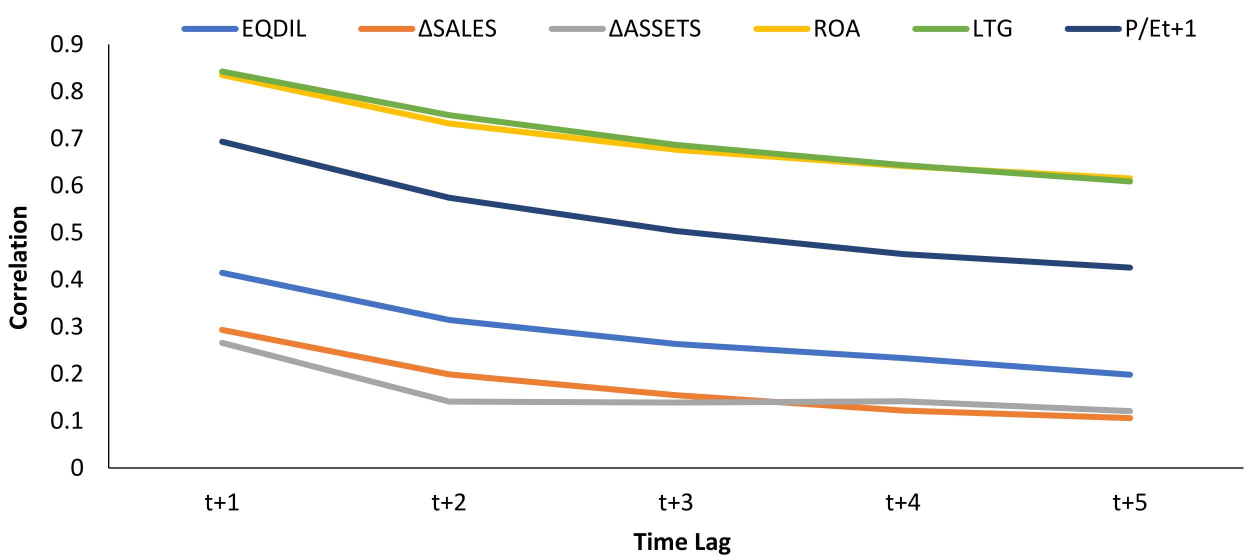


Figure 4. Persistence of Variables that Explain Growth from 1982-2009.

This figure plots the average time-series Spearman correlation for different variables and their 1-, 2-, 3-, 4- and 5-year lag values using annual data. LTG measures the mean estimate of all analysts' expectations of the EPS annual growth rate between year *t+2* to year *t+5* measured in the 3rd week of June of year *t*. EQDIL (equity dilution) is the percentage change in split-adjusted shares outstanding from fiscal year-end in *t-2* to *t-1*. ΔSALES (sales growth) is the percentage change in revenues per split-adjusted share from *t-2* to *t-1*. ΔASSETS (asset growth) is the percentage change in assets per split-adjusted share from *t-2* to *t-1*. ROA (profitability) is operating income in *t-1* divided by assets for *t-1*. P/E_{t+1} is the price per share in June *t*, divided by analyst EPS estimate for the next year *t+1*.



Investment Products & Services

- Not insured by FDIC or any Federal Government Agency
- May Lose Value
- Not a Deposit or Guaranteed by a Bank or any Bank Affiliate

Gerstein Fisher is a division of People's United Advisors, Inc., a registered investment advisor and a wholly-owned subsidiary of People's United Bank, N.A.

This is a publication of Gerstein Fisher, a division of People's United Advisors, Inc., ("Gerstein Fisher").

Economic and market views and forecasts reflect Gerstein Fisher's judgment as of the date of this presentation and are subject to change without notice. Views and forecasts are estimated based on assumptions, and may change materially as economic and market conditions change. Gerstein Fisher has no obligation to provide updates or changes to these views and forecasts. Certain information contained herein has been obtained from third parties. While such information is believed to be reliable for the purpose used herein, Gerstein Fisher assumes no responsibility for the accuracy, completeness or fairness of such information.

Past performance is not an assurance of future returns.

Gerstein Fisher is not soliciting any action based on this material. It is for general informational purposes only. It does not constitute a personal recommendation or take into account the particular investment objectives, financial situations, or needs of individual investors.

Information pertaining to Gerstein Fisher's advisory operations, services, and fees is set forth in Gerstein Fisher's current ADV Part II, a copy of which is available from Gerstein Fisher upon request or through our website as outlined below.

Annual ADV Part II Offering: Federal and State securities laws require we maintain and make available current copies of our Registered Investment Advisor Disclosure Statement, also known as ADV Part II. You can obtain a current copy of our ADV Part II by logging onto our site: www.GersteinFisher.com or you can contact our office and request a copy. Annual Privacy Notice Offering: Pursuant to Regulation S-P, the Gerstein Fisher Privacy Notice can be found by logging onto our site: www.GersteinFisher.com or you can contact our office and request a copy.