THE JOURNAL OF FINANCE • VOL. LI, NO. 5 • DECEMBER 1996

Expectations and the Cross-Section of Stock Returns

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ABSTRACT

Previous research has shown that stocks with low prices relative to book value, cash flow, earnings, or dividends (that is, value stocks) earn high returns. Value stocks may earn high returns because they are more risky. Alternatively, systematic errors in expectations may explain the high returns earned by value stocks. I test for the existence of systematic errors using survey data on forecasts by stock market analysts. I show that investment strategies that seek to exploit errors in analysts' forecasts earn superior returns because expectations about future growth in earnings are *too extreme*.

IT IS BECOMING INCREASINGLY accepted that stock returns have a predictable component. Fama and French (FF, 1992) find that size (the market value of a stock's equity) and the ratio of the book value of a firm's common equity to its market value (BM), but not β (the slope coefficient in the regression of a security's return on the market's return), capture much of the cross-section of average stock returns.[1] FF argue that size and BM are proxies for unobservable common risk factors, and that their findings are consistent with rational asset pricing.

An alternative interpretation, argue Lakonishok, Shleifer, and Vishny (LSV, 1994), is that financial ratios have predictive power because they capture systematic errors in the way that investors form expectations about future returns, and because the stock market is not fully efficient. Strategies that call for the purchase of stocks with low prices relative to dividends, earnings, and

* Harvard University. I thank Alberto Ades, Judith Chevalier, Kenneth Froot, Edward Glaeser, Gikas Hardouvelis, Steven Kaplan, Florencio López-de-Silanes, Patricia O'Brien, two anonymous referees, René Stulz, Thierry Wizman, and participants of the Chicago Finance Seminar for their helpful comments. I am deeply grateful to Andrei Shleifer for guidance and support and to Robert Vishny for many useful discussions. I gratefully acknowledge the contribution of I/B/E/S International Inc. for providing earnings forecast data, available through the Institutional Brokers Estimate System. This data has been provided as part of a broad academic program to encourage earnings expectations research. I thank Patricia Martin for editorial assistance.

[1] FF are not the first to find evidence against the CAPM. Banz (1981) shows that controlling for β risk, average returns are too high for small stocks and too low for big stocks. Bhandari (1988) shows that financial leverage helps explain the cross-section of average stock returns even after controlling for β and size. Furthermore, Stattman (1980) and Rosenberg, Reid, and Lanstein (1985) find that average stock returns are positively related to BM. Basu (1983) and Jaffe, Keim, and Westerfield (1989) find that earnings-to-price ratios (EP) help explain the cross-section of stock returns in regressions that include β and size. Finally, Keim (1985) shows that a similar result obtains for dividend yields (DP).

book value have been popular with *"value"* investors at least since Graham and Dodd (1934). LSV postulate that value strategies work because they are *contrary* to the strategies followed by *naïve* investors who make systematic errors in their expectations about the future.

Naïve investors may make two types of systematic errors that can account for the superior performance of value stocks: errors about risk and errors about growth in earnings. Naïve investors may perceive value stocks to be more risky than their ex post performance would merit because they fail to distinguish properly between systematic and idiosyncratic risk. Alternatively, as a result of a series of bad news about earnings, naïve investors could become excessively pessimistic about the future growth in earnings of value stocks. If arbitrage is incomplete, then the out-of-favor value stocks that naïve investors eschew may become underpriced, resulting in a low price relative to book value. Similarly, the *"glamour"* stocks that naïve investors favor may become overpriced. This would be reflected, for example, in a high price relative to book value. According to LSV, the predictive power of financial ratios merely reflects the unraveling of past errors made by naïve investors.

In a nutshell, the key question is whether returns on value stocks are high to compensate for high fundamental risk, or whether they are high because investors systematically misperceive their future performance. This article seeks to answer the question of *why* stock returns are predictable by using *survey data* on the expectations of stock market analysts; I examine whether investors make the type of systematic mistakes that are consistent with the errors-in-expectations hypothesis when they forecast growth in earnings. My focus is on errors in expected growth rates, not because they are a priori more plausible than failures to properly evaluate risk, but because they are more tractable and have been at the center of the debate in the finance literature.

The benefit of using survey data on the expectations of stock market analysts is straightforward: analysts' forecasts for the five-year growth rate in earnings provide a relatively clean proxy for investors' expected growth rates. Survey data make it possible to explicitly test the hypothesis that the predictability of returns is driven by expectational errors. Most of the previous literature has concentrated on testing particular parametrizations of risk, such as the Capital Asset Pricing Model (CAPM). Clearly, rejecting a specific risk model does not validate the errors-in-expectations hypothesis per se, as it is still possible that the data are consistent with a different risk model. For this reason, it is important to provide direct evidence on whether the forecasting errors that investors make are consistent with the behavior of stock returns.

As with all proxies, however, there are problems with using survey data in lieu of market expectations. First, survey data on expected growth rates are only available for a subsample of firms and only have been collected systematically since 1981. Second, and perhaps more troublesome, analysts' forecasts may be noisy proxies for the expectations of market participants. It is possible that some of the recorded forecasts are outdated and that others are motivated by the desire to sell securities, or the need to protect investment banking relationships (Cragg and Malkiel (1982)). While there is no immediate way to deal with the loss of sample size, the evidence on stock returns suggests that measurement problems associated with the use of analysts' expectations are not too severe. Specifically, the testable implication of the measurement error hypothesis that there should be no relationship between survey data and stock returns is not supported by the data.

To examine the hypothesis that expectations are *too extreme*, I construct portfolios on the basis of the expected growth in earnings. I find that the one-year postformation raw return for stocks with low expected growth rates is 20 percent higher on average than the return for stocks with high expected growth rates. Furthermore, in the year following formation, analysts revise their expectations sharply for both high and low expected growth stocks in the direction and magnitude predicted by the errors-in-expectations hypothesis. In addition, the behavior of excess returns around quarterly earnings announcement dates strongly supports the errors-in-expectations hypothesis. For high expected growth stocks, the cumulative one-year event return over a three-day earnings' announcement window is a large −1.6 percent. The fact that event returns for high expected growth stocks are *negative* makes the risk hypothesis less plausible unless one believes that these stocks are a hedge against risk. Finally, contrary to the risk hypothesis, there is no evidence that low expected growth stocks carry more risk than stocks with high expected growth.

This article is organized into five sections. The first section describes the methodology and introduces the data. Section II presents the results of forming contrarian portfolios on the basis of analysts' expectations. Section III analyzes the role of extrapolation as a source of systematic errors in expectations. Section IV examines the risk characteristics of contrarian portfolios, and Section V concludes.

I. Data and Methodology

Returns are drawn from the Center for Research on Securities Prices (CRSP) monthly New York Stock Exchange/American Stock Exchange (NYSE/AMEX) tape.[2] Annual portfolio returns are constructed by compounding monthly returns.[3] To insure that the accounting variables are known to the market before the returns that they are used to explain, I match the accounting data for all fiscal years ending in calendar year $t - 1$ with returns for the period from July of year t to June of year $t + 1$.[4]

[2] The margin by which value outperforms glamour for investment strategies based on analysts' expectations is larger for Nasdaq stocks than for NYSE/AMEX stocks. However, the results presented in the article are not affected significantly by the Nasdaq exclusion because very few Nasdaq stocks meet the article's data requirements.

[3] When a company has more than one issue of common stock outstanding, I use the value-weighted return on all classes of common.

[4] Firms are required by the SEC to file a 10-K within 90 days of their fiscal year end. Alford, Jones, and Zmijewski (1992) find that 40 percent of the December fiscal year-end firms that comply with the 90-day rule file on March 31, and that their reports are not made public until

I use a firm's market equity at the end of December of year $t - 1$ to compute its book-to-market, earnings-to-price, and cash-flow-to-price ratios. Thus, to be included in the returns tests for July of year t, a firm must have a CRSP stock price for December of year $t - 1$ and for June of year t. The firm also must have data in COMPUSTAT on book value and on sales, earnings, cash flow, and operating profit for the statistical year ending in calendar $t - 1$. To compute growth rates, I exclude firms that fail to meet any of the CRSP/COMPUSTAT requirements in the five years preceding formation ($t - 6$, $t - 1$).

As previously discussed, I define the return on each portfolio as the equally-weighted return for the period from July of year t to June of year $t + 1$. If a stock is delisted, CRSP makes an effort to establish its price after delisting. Whenever a postdelisting price exists, I use it in the computations. When CRSP is not able to determine the value of a stock after delisting, I follow the standard practice of assuming that the investor was able to trade at the last quoted price. As in LSV, after a stock has disappeared from the sample, I replace its return until the end of the following June with the return of the corresponding size decile. I present size-adjusted returns for most of my results. All stocks that meet CRSP/COMPUSTAT requirements are sorted into size decile portfolios on the basis of the June market value of equity, and then equally-weighted returns for each size-control portfolio are computed. After a stock has disappeared from a size-control portfolio, its return is replaced with the return on CRSP's equally-weighted index until the end of the following June.

For descriptive purposes, I present growth rates and multiples of accounting measures such as sales, earnings, and cash flow for the various portfolios. All such accounting information is drawn from COMPUSTAT.[5] The measures used, and their COMPUSTAT item numbers given in parentheses, are: Book value (60 + 74), includes balance sheet deferred taxes. Earnings (18 + 50 − 19) is defined as income before extraordinary items plus deferred taxes minus preferred dividends. Cash flow is the sum of earnings and depreciation (14). Sales (12) are net sales.

Accounting ratios, such as earnings-to-price and cash-flow-to-price, are computed per dollar invested in each stock in the portfolio. This procedure is attractive, since returns are equally-weighted. Similarly, the growth rate in sales is computed for portfolios of stocks. To estimate the portfolio's growth rate of sales in year $t - 5$ relative to the year of formation, I consider investing one dollar in each stock in that portfolio in period $t - 5$ and then obtain the total value of the sales that would have been generated by such an investment in years $t - 5$ and $t - 4$. The growth rate of sales in period $t - 5$ is defined as the percent change in the total value of sales measured in this way, between

April. Therefore, using June as the formation month makes it very likely that accounting data for calendar year $t-1$ is known to the market.

[5] To limit the weight of outliers, for each accounting ratio and for each period, the smallest and largest 0.5 percent of the observations are set equal to next largest or smallest values of the ratios (the 0.005 and 0.995 fractiles). Expected growth rates and expected earnings-to-price ratios are treated the same way.

years $t - 4$ and $t - 5$. The same procedure is used to compute the growth rate for every period between period $t - 5$ and the year of formation. The growth rate in sales presented in the article is the geometric average of the compounded annual growth rates.

Analysts' earnings forecasts and expected earnings growth rates are taken from the Institutional-Brokers-Estimates-System (IBES) produced by Lynch, Jones, and Ryan. Stock analysts contribute their earnings forecasts for the current and next fiscal year, as well as forecasts of the expected long-run earnings growth rate (E$\{g\}$). Both forecasts refer to earnings per share before extraordinary items. The forecast of the earnings growth rate covers the five-year period that starts on the first day of the current fiscal year. The measures of expected earnings and earnings growth used in this article are drawn from the Monthly IBES History Tape. Every stock in my sample has both a five-year (i.e. "long-run") earnings growth rate forecast, and an earnings estimate available in December of year $t - 1$ ($t = 1982$ to 1990). The stock price that is used to compute the expected earnings-to-price ratio (E$\{e\}$) is drawn from IBES and corresponds to the last day of the month. Unless otherwise stated, the results that I report are for stocks that meet both the article's IBES and CRSP/COMPUSTAT requirements noted earlier in this section.

A. IBES Sample Selection Issues

Securities analysts periodically contribute their forecasts to IBES. There is no way of knowing to what extent these forecasts are representative of the expectations of stock market investors. Since the investment research included in the IBES tape is bought primarily by institutional investors, it is reasonable to assume that the IBES sample is representative of their expectations. Analysts' forecasts also may embody the expectations of other investors to the extent that they use similar techniques to forecast earnings.

Table I shows that the performance of stocks in the IBES sample is almost identical to those in CRSP. Stocks in the IBES sample are size-adjusted returns of -0.1 percent (t-stat $= -0.25$). Size-adjusted returns are not statistically different from zero for any one decile. Perhaps the most salient feature of the sample of stocks in the intersection of CRSP, COMPUSTAT, and IBES is that it is very heavily biased towards big stocks (see Fig. 1). For example, 74 percent of the stocks in IBES are above the median size in CRSP, and only 2 percent of the stocks in the smallest size decile in CRSP are present in IBES. The number of stocks in the sample averages 900 per year and ranges from a low of 814 in 1989 to a high of 1,029 in 1983.

In my sample, only one firm is delisted during the first postformation year as a result of bankruptcy.[6] This suggests that financially distressed firms may

[6] A table describing the various reasons stocks in the sample were delisted from the exchanges is available from the author upon request.

Table I

Size-Adjusted Returns for Stocks on CRSP, CRSP/IBES and CRSP/IBES/COMPUSTAT: July 1982–June 1991

Size-adjusted portfolios are constructed using all NYSE/AMEX stocks. Firms in the intersection of CRSP and COMPUSTAT are required to have five years of history in both data sets. Standard errors are shown in parentheses.

			In IBES				
	Not in IBES		CRSP/ IBES/COMPUSTAT		CRSP/IBES		All
Size Decile	Size-Adj. Return	Number Observ.	Size-Adj. Return	Number Observ.	Size-Adj. Return	Number Observ.	Number Observ.
Smallest	0.008	1,678	0.061	36	−0.071	145	1,823
	(0.019)		(0.170)		(0.063)		
2	0.011	1,444	−0.044	165	−0.038	386	1,830
	(0.018)		(0.036)		(0.028)		
3	−0.014	1,119	0.079	368	0.022	712	1,831
	(0.016)		(0.030)		(0.021)		
4	0.006	736	0.022	679	−0.004	1,093	1,829
	(0.021)		(0.018)		(0.014)		
5	−0.012	514	0.011	873	0.006	1,316	1,830
	((0.022)		(0.014)		(0.011)		
6	0.026	355	0.012	1,020	−0.004	1,476	1,831
	(0.029)		(0.015)		(0.012)		
7	0.053	261	−0.012	1,177	−0.008	1,569	1,830
	(0.032)		(0.010)		(0.009)		
8	−0.028	238	0.002	1,176	0.005	1,592	1,830
	(0.026)		(0.008)		(0.008)		
9	−0.026	94	0.008	1,282	0.001	1,737	1,831
	(0.041)		(0.009)		(0.007)		
Biggest	−0.020	72	0.009	1,394	0.001	1,754	1,826
	(0.040)		(0.007)		(0.006)		
All	0.004	6,511	0.009	8,170	−0.001	11,780	18,291
	(0.008)		(0.004)		(0.004)		

be under represented in my sample, as analysts may drop coverage of companies before they face serious bankruptcy risk. However, it is unclear what additional biases may be at work. Analysts' investment advice has a well-known bias toward "buy" recommendations, but forecasts for all firms that were followed by the analysts surveyed are included in the IBES sample. Hence, it cannot be the case that the forecasts in the IBES sample were formed to support "buy" recommendations. While it may be argued that companies that would not merit a "buy" recommendation may simply not be covered by analysts, most investment firms tend to provide forecasts for all the large-capitalization companies in which there is substantial investment interest. In this regard, given the large size of the firms that meet the article's data requirements, it may well be the case that analysts have little choice but to cover them.

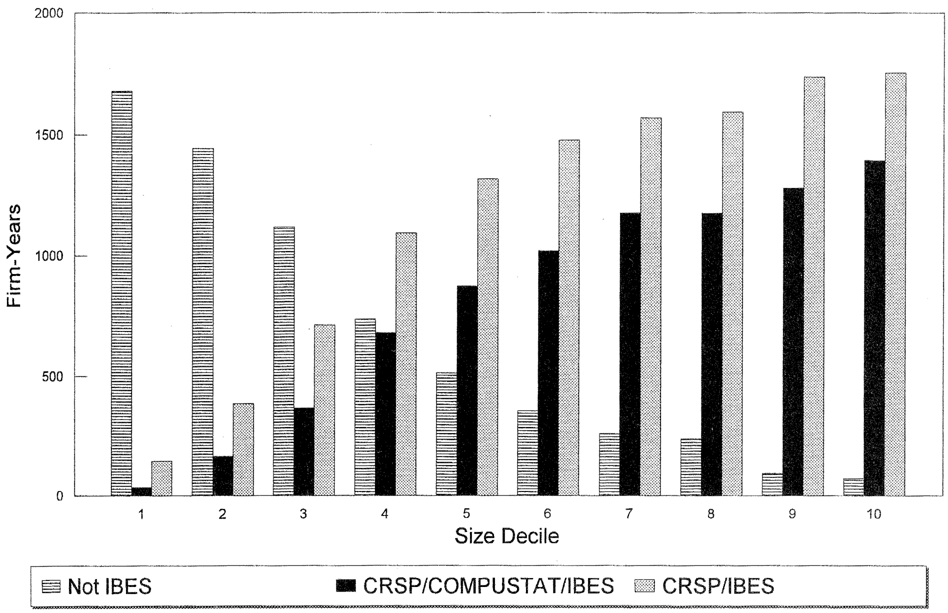

Figure 1. Firm-Year Observations in CRSP, CRSP/IBES, and CRSP/IBES/COMPUSTAT by Size Decile. In June of each year between 1982 and 1990, stocks are sorted into decile portfolios on the basis of market value of common equity in December of year $t - 1$ (1 is the smallest decile). The figure shows the total number of firm-year observations in each size decile that meet the article's CRSP, CRSP/IBES, and CRSP/IBES/COMPUSTAT data requirements.

Kothari, Shanken, and Sloan (KSS, 1995) claim that value strategies appear to work because of the inherent survivorship bias in the COMPUSTAT sample. KSS point out that in 1978, COMPUSTAT launched a major database expansion project that increased the number of companies in the sample from about 2,700 NYSE/AMEX and large Nasdaq firms to about 6,000. Five years of annual data, going back to 1973, were added for most of these firms. KSS argue that the survivorship bias introduced by adding firms to the sample with five years of history helps to explain the predictive power of BM in the work of FF.

The sample selection issues raised by KSS are driven by the rapid increase in the number of *small* stocks in the COMPUSTAT sample in the late 1970s. Readers who share the KSS concern about possible selection biases in COMPUSTAT should bear in mind that the survivorship bias for stocks in the intersection of COMPUSTAT and IBES is minimal on four accounts. First, KSS correctly point out that the COMPUSTAT sample suffers from survivorship bias because firms typically were incorporated into the sample with a maximum of five years of financial history. This bias can be minimized by requiring that a firm be included in COMPUSTAT for at least five years before being part of the sample used for testing investment strategies.[7] Second, there

[7] The five-year history requirement ensures that the investment strategies described in the article do not rely on back-filled data.

are very few small stocks in the intersection of IBES and CRSP. Third, the COMPUSTAT expansion project was completed prior to 1982, the first year in my sample. Finally, an Appendix available upon request shows that the results reported in the next section for stocks in the intersection of CRSP, COMPUSTAT, and IBES are very similar to the results for stocks in the intersection of CRSP and IBES alone.

II. The Performance of Contrarian Strategies

A. Are Expectations too Extreme?

The essence of the errors-in-expectations hypothesis is that growth expectations are *too extreme*. Naïve investors may become excessively pessimistic about future earnings growth after a series of bad earnings or other negative news (De Bondt and Thaler (1985)). In subsequent periods, the price of out-of-favor stocks rise as naïve investors are surprised positively by the earnings' growth of those stocks and consequently revise the expectations for their future growth upwards. To provide evidence on the role of forecast errors in driving the predictability of stock returns, I use survey data on stock market analysts' forecasts as proxies for the expected earnings' growth rates of naïve investors.

To test the hypothesis that growth expectations are too extreme, I first sort stocks on the basis of their expected five-year earnings growth rate (E{g}) in December of year $t - 1$ (where t ranges from 1982 to 1990). If expectations are too extreme, then stocks with high E{g} are likely to be overpriced and should earn low returns in subsequent periods. Conversely, stocks with low E{g} should earn high postformation returns because they are likely to be underpriced.

Alternatively, two hypotheses are consistent with a finding that analysts' expectations do not explain the cross-section of stock returns: the risk hypothesis and the measurement error hypothesis. The defining feature of the risk hypothesis is the notion that forecasts are rational. If expected growth rates are uncorrelated with risk factors, the risk hypothesis predicts that analysts' forecasts have no power to explain the cross-section of stock returns.[8] According to the measurement error hypothesis, analysts' forecasts are bad proxies for the expectations of market participants and have low power in explaining stock returns, even when investors make systematic errors in forecasting future growth in earnings. The two most likely sources of measurement error are recording errors (for example, stale forecasts) and analysts' incentives to avoid offending management by posting forecasts of poor growth in earnings. If forecasts are not measured accurately, then ranking stocks on the basis of expected growth rates is likely to yield extreme measurement error for the first and last deciles. Stated differently, measurement error should be at its max-

[8] Perhaps a more plausible assumption is that risk and E{g} are positively correlated. In this case, the risk hypothesis predicts that returns and E{g} should be positively correlated, which is opposite of what I find. Section IV examines the risk characteristics of portfolios formed on the basis of E{g}.

Table II

Portfolios Formed on Analysts' Expected Earnings Growth: July 1982–June 1991

At the end of June of each year t, 10 decile portfolios are formed on the basis of ranked analysts' expected growth in earnings in December of year $t - 1$. R is the raw return in the year after formation. R-Size is the size-adjusted return. Prior-R is the average market-adjusted excess return over the previous five years ($t - 65$, $t - 6$). E{g} is the analysts' expected growth rate. E{e} is the ratio of expected earnings in the current fiscal year to stock price. Both, E{g} and E{e} are measured in December of year $t - 1$. Size is the total market value of common stock, in millions, in June of year t. BP, EP, defined below use market equity corresponding to the end of December of year $t - 1$ and preformation year accounting. BP is the ratio of the book value of common plus balance sheet deferred taxes to market equity. EP is the ratio of earnings (income before extraordinary items plus income statement deferred taxes minus preferred dividends) to market equity. Earn(+) is the fraction of firms with positive earnings. GS5 is the portfolio preformation five-year-average-growth rate in sales.

Panel A: Properties of Returns

E{g}	"Low" 1	2	3	4	5	6	7	8	9	"High" 10	All
R	0.295	0.280	0.256	0.221	0.217	0.216	0.178	0.170	0.156	0.086	0.208
R-Size	0.088	0.075	0.048	0.017	0.013	0.007	−0.027	−0.038	−0.048	−0.113	0.002
Prior-R	0.002	−0.003	−0.010	−0.026	−0.037	−0.038	−0.036	−0.031	−0.021	−0.012	−0.021
E{g}	2.298	4.189	5.663	7.092	8.596	10.191	11.843	13.650	16.058	26.130	10.571
E{e}	0.090	0.096	0.077	0.062	0.060	0.063	0.077	0.071	0.058	0.050	0.070
Size	$2,143	$2,361	$2,424	$1,700	$1,467	$1,682	$1,277	$1,174	$1,169	$945	$1,634
BP	1.071	0.947	0.861	0.847	0.864	0.888	0.879	0.816	0.729	0.699	0.860
EP	0.088	0.098	0.070	0.046	0.025	0.039	0.067	0.053	0.035	−0.001	0.052
Earn(+)	0.930	0.939	0.910	0.889	0.853	0.855	0.890	0.881	0.853	0.798	0.880
GS5	0.048	0.065	0.069	0.058	0.064	0.074	0.079	0.080	0.082	0.062	0.068

Panel B: Time-Series of Size-Adjusted Returns

At the end of June of each year t, 10 decile portfolios are formed on the basis of analysts' expected earnings' growth rates in December of year $t - 1$. The results presented in the panel are size-adjusted returns for each formation period between 1982 and 1990.

Yr/E{g}	"Low" 1	2	3	4	5	6	7	8	9	"High" 10	All
82	0.052	0.061	−0.009	−0.079	0.090	0.183	−0.135	−0.071	−0.138	−0.247	−0.029
83	0.105	0.068	0.052	0.053	0.002	−0.012	0.013	−0.046	−0.048	−0.154	0.003
84	0.164	0.193	0.072	0.044	0.001	−0.065	−0.012	−0.085	−0.010	−0.161	0.008
85	0.331	0.090	0.083	0.101	−0.001	−0.114	−0.126	−0.030	−0.064	−0.171	0.010
86	−0.038	−0.016	0.038	0.022	0.038	0.067	0.074	−0.066	−0.054	−0.045	0.002
87	0.047	0.048	0.030	0.018	0.005	0.048	−0.027	−0.034	−0.053	−0.102	−0.002
88	0.057	0.060	0.051	0.009	0.060	0.060	0.011	−0.033	−0.070	−0.108	0.010
89	0.025	0.064	0.083	0.021	−0.062	−0.066	−0.041	0.009	0.015	0.002	0.005
90	0.049	0.107	0.031	−0.037	−0.014	−0.038	−0.003	0.011	0.052	−0.035	0.012
All	0.091	0.076	0.049	0.020	0.013	0.004	−0.026	−0.040	−0.049	−0.115	0.000

imum, and the link between expectations and returns weakest, for the two extreme decile portfolios.

The results of sorting stocks according to E{g} are presented in Panel A of Table II. By construction, using analysts' expectations to sort stocks produces a wide range for E{g}. The earnings of low E{g} stocks are expected to grow at a modest 2.3 percent per year over the next five years, whereas the earnings of high E{g}

stocks are expected to grow at 26 percent over the same period.[9] The stocks in the different portfolios have remarkably similar five-year preformation rates of both return and growth in sales. As expected, both BM and the earnings-to-price ratio generally decline as E{g} increases.[10] Note that a large fraction of the firms in the high E{g} portfolio have negative earnings. This suggests that some of the stocks in the high E{g} portfolio may have experienced poor earnings performance during the preformation period. I revisit this issue later in the article when I examine whether investors extrapolate. Consistent with the extreme expectations hypothesis, the average raw return of low E{g} stocks is 20.9 percentage points higher than that of high E{g} stocks (that is, 29.5 percent versus 8.6 percent) during the sample period. Since measurement error may play an important role in extreme portfolios, it is worth noting that the strong explanatory power of E{g} is not confined to extreme decile portfolios, and that raw returns decline uniformly with expected growth rates.

Size cannot account for the superior performance of the low E{g} portfolio. Low E{g} stocks earn an 8.8 percent size-adjusted return, while high E{g} stocks decline by 11.3 percent in size-adjusted terms. The irrelevance of size is not surprising since the average market capitalization of low E{g} stocks, \$2.1 billion, is approximately twice that of high E{g} stocks.[11] Furthermore, regression results presented in the next section show that the explanatory power of E{g} is robust to controlling for both size and book-to-market.

The superior performance of low E{g} stocks does not seem to be driven by a particular time period. Panel B of Table II shows that low E{g} stocks exhibited higher returns than high E{g} stocks in each of the nine formation periods. For eight of the nine formation periods, size-adjusted returns are positive for low E{g} stocks and negative for high E{g} stocks.

As a check for robustness, it is important to examine whether the difference in returns is driven by a small number of industries. F-tests (not reported) cannot reject the null hypothesis that the average size-adjusted rate of return of each of the two extreme E{g} portfolios are equal across industries aggregated at the two-digit Standard Industrial Classification (SIC) level. Figure 2 provides a more intuitive way of examining differences in returns across industries. It plots the average rate of return for high E{g} stocks for industries defined at the four-digit SIC level of aggregation. The diameter of each circle in the plot is proportional to the number of high E{g} firm-years in that SIC code. Firms that do not have an SIC number are assigned arbitrarily one with a value of zero. Figure 2 shows that the majority of industries in the high

[9] The median expected growth rate is 2.6 percent for low E{g} stocks and 20.9 percent for high E{g} stocks.

[10] Correlations between expected growth rates and accounting ratios are negative and fairly weak. The absolute value of the correlation coefficient with E{g} is highest for the earnings-to-price ratio (-0.12) and lowest for the book-to-market ratio (-0.07).

[11] Results from Fama-MacBeth univariate regressions (not reported) suggest that role of size in my sample period is weaker than in the period 1968–91. For the sample of stocks that meet CRSP and COMPUSTAT data requirements, the estimated coefficient on size falls from -0.009 in the 1968–1991 period to -0.002 in my sample period.

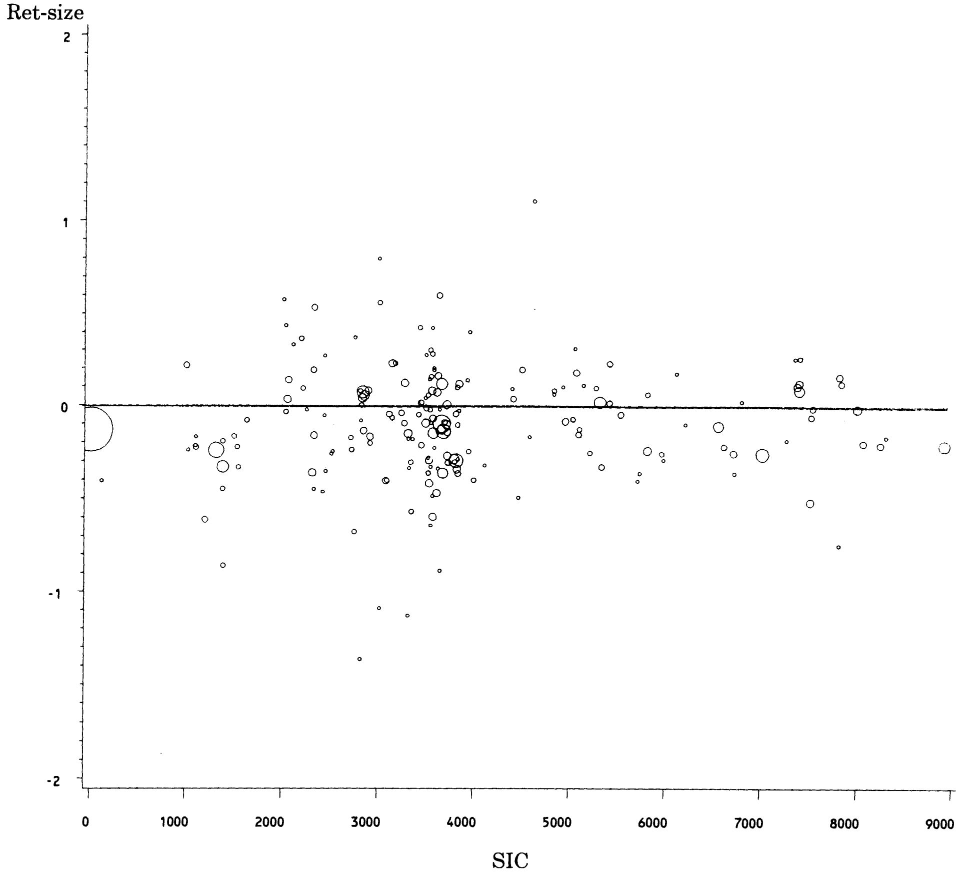

Figure 2. Average Size-Adjusted Return by SIC Code for Stocks with High Expected Growth in Earnings. At the end of June of each year between 1982 and 1990, ten decile portfolios are formed on the basis of the expected growth rate of earnings in December of year $t - 1$. Returns presented in Figure 2 are one-year postformation size-adjusted returns for stocks in the decile portfolio with the highest expected growth in earnings. The diameter of each circle in the figure is proportional to the total number of observations in the corresponding SIC code.

E{*g*} portfolio exhibit negative size-adjusted returns and that there is no evidence that the disappointing performance of the high E{*g*} portfolio is the result of the bad performance of a small number of large industries. Figure 3 repeats the analysis for low E{*g*} stocks. Most industries in the low E{*g*} portfolio have positive size-adjusted returns; once again, there is no evidence that a few large industries are responsible for the superior performance of low E{*g*} stocks.[12]

[12] Regression results presented in the next section show that the negative relationship between E{*g*} and returns still holds after controlling for the average expected growth rate of the industry to which the firm belongs.

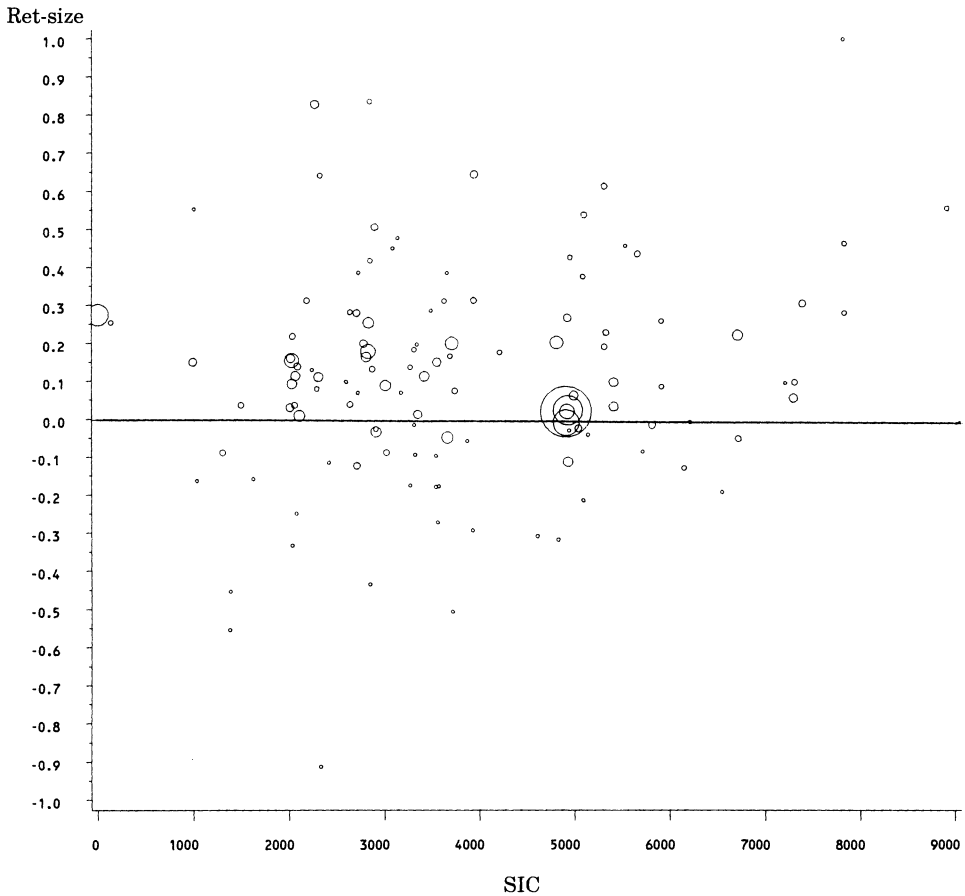

Figure 3. Average Size-Adjusted Return by SIC Code for Stocks with Low Expected Growth in Earnings. At the end of June of each year between 1982 and 1990, ten decile portfolios are formed on the basis of the expected growth rate of earnings in December of year $t - 1$. Returns presented in Figure 3 are one-year postformation size-adjusted returns for stocks in the decile portfolio with the lowest expected growth in earnings. The diameter of each circle in the figure is proportional to the total number of observations in the corresponding SIC code.

It would be interesting to study the behavior of returns over longer horizons to make sure that we are not capturing a "momentum" phenomenon (Jagadeesh and Titman (1993)). The difference in raw returns between low $E\{g\}$ and high $E\{g\}$ stocks is highly persistent in my sample. The margin by which the raw returns of low $E\{g\}$ stocks exceed those of high $E\{g\}$ stocks in years one through five is 20.9 percent, 19 percent, 18.1 percent, 12.9 percent, and 6.4 percent, respectively. To fully address the persistence of stock returns for portfolios formed on the basis of analysts' forecasts, we would need a longer sample; that is left for future research.[13]

[13] To verify that my results were not dependent on using expectations measured in the month of December, I also analyzed portfolios formed every month on the basis of expectations for the

Table III

Cross-Section Regression of Raw Returns on Characteristics of all Firms: July 1982–June 1991

For each year in the sample, a cross-section regression is run with the one year raw return as the dependent variable. The independent variables are: 1) WGS, the preformation 5-year weighted average rank of sales growth; 2) BM(+) equal to BM, the ratio of end of previous year's book value of equity to market value of equity, if BM is positive and to zero if BM is negative; 3) Size, the end of June natural logarithm of market value of equity (in millions); 4) EP(+), equal to EP, the ratio of previous year's earnings to end of June market equity, if EP is positive and to zero if EP is negative; 5) CP(+), equal to CP, the ratio of previous-year's cash flow to end of June market equity, if CP is positive and to zero if CP is negative; 6) E{*e*(+)}, equal to E{*e*}, the ratio of analysts' expected earnings to the stock price at the end of December of the previous year, if E{*e*} is positive and to zero if E{*e*} is negative; 7) E{*g*}, equal to the natural logarithm of the analysts' expected long-run growth of earnings at the end of December of the previous year.

	WGS	BM(+)	Size	EP(+)	CP(+)	E{*e*(+)}	E{*g*}
Mean	−0.0359						
t-stat	−0.8148						
Mean		0.0106					
t-stat		0.3716					
Mean			−0.0004				
t-stat			−0.0242				
Mean				0.1658			
t-stat				0.5709			
Mean					0.0945		
t-stat					0.7165		
Mean						0.3488	
t-stat						0.9565	
Mean							−0.0882
t-stat							−4.9012
Mean		−0.0077	−0.0111				−0.0872
t-stat		−0.2957	−0.5458				−3.9928
Mean		−0.0197	−0.0114		0.0120		−0.0895
t-stat		−0.8462	−0.5858		0.1498		−4.1902

B. Regression Results

This section assesses the role of analysts' expectations in explaining the cross-section of stock returns in a multivariate setting. Following the procedure in Fama and MacBeth (1973), I run a separate cross-section regression for each postformation period in which the dependent variable is the return on stock j and the independent variables are various characteristics of stock j. The reported coefficients are the time-series average of the coefficients obtained for each postformation period. Similarly, the t-statistics are computed using the standard error of the estimates for each year.

Table III presents the results of regressions of one year postformation raw returns on accounting ratios and measures of analysts' expectations. All esti-

prior month. The results did not change significantly. I do not report them here because of space considerations.

mated coefficients for the CRSP/COMPUSTAT/IBES sample have the expected sign. However, the only variable with explanatory power is the log of E{g}. The estimated slope of E{g} indicates that the average raw return of a stock is 1 percent lower for every 12 percent increase in the average expected growth rate. The estimated slope is highly significant, with a t-statistic of -4.9. Furthermore, E{g} remains the only significant variable in multivariate regressions when it is combined with size, book-to-market and cash-flow-to-price.[14] The regression results confirm the role of the expected rate of earnings growth in explaining stock returns. Of course, regression results cannot tell us whether E{g} acts as a proxy for risk or whether it captures errors in expectations. The goal of the rest of this article will be to discern the role of E{g}.

The estimates of the coefficients on accounting variables are also interesting because they show that the explanatory power of financial ratios in my sample is low when compared with that reported by previous researchers, such as FF. Although I do not report these results here, the value of the estimated coefficients in regressions of the one year postformation return on *accounting ratios* is always lower during 1982–1991 period than during the 1968–1991 period. Given that value strategies perform particularly well when the stock market falls (LSV), the lower value of the estimated coefficients during 1982–1991 likely reflects the fact that stock prices rose during the sample period. The value of the estimated coefficients drops even further for stocks in the intersection of CRSP, COMPUSTAT, and IBES, possibly because stocks in that sample are larger. To illustrate, consider the case of BM. The estimated coefficient for stocks that meet the paper's CRSP/COMPUSTAT data requirement is 0.032 for 1968–1991 but drops to 0.020 for 1982–1991. The estimated slope coefficient drops even further, to 0.011, for stocks that also meet IBES data requirements.[15]

[14] An interesting question relates to whether the explanatory power of E{g} is coming from an industry or firm-specific component. Fama-MacBeth regressions using both industry and idiosyncratic growth rates (i.e., the ratio of the firm's expected growth rate to the expected growth rate of its industry) show that although both variables are statistically significant, most of the explanatory power of E{g} is coming from the idiosyncratic component. While the t-statistic for the idiosyncratic component is 5.32, the corresponding value for the industry component is 2.21. The estimated coefficients suggest that a firm that is expected to grow twice as fast as the industry in which it operates will have an average return that is 7.6 percentage points lower than the typical firm in that industry. In contrast, the return for a firm will be on average 10.4 percentage points lower if it belongs to an industry that is expected to grow twice as fast as the IBES/COMPUSTAT population.

[15] An alternative way of making the same point is to examine the performance of portfolios formed on the basis of accounting ratios. The margin by which value stocks outperform glamour stocks for stocks sorted on the basis of book-to-market, cash-flow-to-price, earnings-to-price, and five-year preformation growth in sales is always lower for stocks in the CRSP/IBES/COMPUSTAT sample than for stocks that meet CRSP/COMPUSTAT data requirements during the 1968–91 period. Once again, consider the case of portfolios formed on the basis of book-to-market. The high book-to-market decile portfolio earns raw returns that are 9.2 percent higher than those of the low book-to-market decile portfolio for the sample of stocks that meet the article's CRSP/COMPUSTAT data requirements over the period 1968–91. The margin by which high book-to-market stocks

C. Errors and Revisions in Analysts' Expectations

This section seeks to provide direct evidence linking the performance of portfolios formed on the basis of E{g} with errors in analysts' expectations. Panel A of Table IV presents the evolution of actual earnings in periods t through $t + 5$.[16] Surprisingly, the earnings of high E{g} stocks remain largely stagnant between periods t and $t + 5$. In contrast, the earnings of low E{g} stocks grow at an average annual rate of 7.5 percent, increasing from 0.105 to 0.144 over the first five postformation years. The results on the long-run growth in earnings are consistent with the evidence on returns presented in the previous section. However, they should be interpreted with great caution, given the small number of independent five-year formation periods that are available. There are at least three additional caveats that make it hard to interpret the postformation behavior of earnings as evidence of forecasting errors. First, analysts base their long-run growth forecasts on "normalized" earnings, making it very difficult to determine the expected *level* of earnings in period $t + 5$. For example, companies that are experiencing negative earnings typically have positive growth forecasts. Second, accounting changes, spinoffs, and other corporate changes give rise to very large measurement problems in the computation of errors in five-year earnings' forecasts. Finally, a large number of firms disappear from the sample in the course of five years.

The errors-in-expectations hypothesis predicts that in subsequent periods analysts revise the expectations for extreme E{g} stocks towards the mean. Panel A of Table IV presents revisions in the expected growth rate in earnings (E{g}) between April of years t and $t + 1$.[17] I also calculate a measure of the change in the stock price ($\%\ p$) that would result from changes in E{g} between years t and $t + 1$ if the discount rate were 10 percent and the market expected E{g} to prevail for five years.[18] Consistent with the errors-in- expectations hypothesis, the expected rate of growth for low E{g} stocks rises from

outperform low book-to-market stocks drops to 8.2 percent for the CRSP/COMPUSTAT sample over the 1982–91 period and to 3.1 percent when the additional IBES requirements are imposed.

[16] The last year for which actual earnings were available is 1992.

[17] Computing revisions in analysts' expectations introduces survivorship bias, since firms that are not part of IBES in April of year $t + 1$ are dropped from the sample. However, as noted in Section I, bankruptcy delistings are a relatively rare event in my sample and are not likely to affect the results significantly. It may be true, however, that broker coverage of stocks is influenced by past performance. If companies that do not perform well are dropped from IBES, the observed revisions for E{g} would be biased upwards. As an empirical matter, introducing the additional requirement that stocks be included in the IBES sample in April of year $t + 1$ does not significantly alter the relative performance of portfolios formed on the basis of expected growth in earnings. Results, available upon request, show that size-adjusted returns for the sub-sample of stocks that are also present in the IBES sample in April of year $t + 1$ are very close to those of the original IBES sample for all E{g} portfolios. Thus, the selection bias introduced by requiring that the firm be included in the IBES sample in April of year $t + 1$ does not seem to be large.

[18] To minimize the risk that some of the IBES forecasts may be stale, in this section I restrict the sample to companies with December fiscal year and analyze forecasts made in April, when most analysts post fresh forecasts.

3.1 percent to 4.1 percent, while growth expectations for high E{g} stocks fall sharply, from 21.7 percent to 18.4 percent. Given the assumptions used to compute % p, these revisions would justify returns for low E{g} stocks that are 11.6 percentage points higher than those for high E{g} stocks (2.9 percent versus −8.7 percent), and would explain approximately half of the observed difference in returns.

It could be argued that it is not surprising to find mean reversion in forecasts for long-run growth in earnings, given that earnings' growth follows a mean reverting process (Brooks and Buckmaster (1976)). Fortunately, there is a way

Table IV

Evidence on Expectational Errors for Portfolios Formed on the Basis of Growth Forecasts: July 1982–June 1991

At the end of June of each year t, stocks are independently sorted into deciles by ranked analysts' expected earnings growth (E{g}) in December of year $t - 1$. AE(j) is the actual value of earnings associated with an investment of one dollar into each company in the portfolio in period t with nonmissing earnings in COMPUSTAT in period j. E{$g|t + 0$} and E{$g|t + 1$} are analysts' expected earnings growth in April of years t and $t + 1$, respectively. Revision(g) is the change in E{g} between April of years $t + 1$ and t for those stocks that are present in IBES in both periods. %p is the percentage change in the stock price that would result from Revision(g), assuming that expected earnings are unchanged, that the discount rate is 10% and that the growth rate expected to prevail starting in year $t + 6$ is unchanged. E{e(fy 1)|t} is the ratio of the April of year t forecast for the level of earnings in the next fiscal year, to the stock price in April of year t. E{e(fy 0)|$t + 1$} is the ratio of the April of year $t + 1$ forecast for the level of earnings in fiscal year $t + 1$, to the stock price in April of year t. Revision(e) is the difference between E{e(fy 1)|t} and E{e(fy 0)|$t + 1$}. Error(t) and Error($t + 1$) are the errors associated with the earnings' forecasts for the current and next fiscal year, respectively. They are computed for a hypothetical investment of one dollar into each stock in the portfolio that has nonmissing earnings of COMPUSTAT for the relevant period. The standard errors presented in the table are based on the time-series of the means of the appropriate variables.

Panel A: Revisions and Errors in Analysts' Expectations

E{g}	"Low" 1	2	3	4	5	6	7	8	9	"High" 10
AE($t + 0$)	0.105	0.100	0.088	0.079	0.066	0.065	0.067	0.061	0.057	0.039
AE($t + 1$)	0.113	0.107	0.092	0.081	0.072	0.064	0.063	0.064	0.054	0.035
AE($t + 2$)	0.119	0.112	0.101	0.086	0.073	0.066	0.068	0.063	0.054	0.034
AE($t + 3$)	0.127	0.117	0.111	0.091	0.072	0.070	0.064	0.063	0.048	0.032
AE($t + 4$)	0.137	0.127	0.118	0.102	0.083	0.077	0.073	0.063	0.054	0.031
AE($t + 5$)	0.144	0.142	0.116	0.115	0.088	0.086	0.074	0.070	0.060	0.045
E{g|A. $t + 0$}	3.099	4.936	6.292	7.708	8.965	10.391	11.793	13.590	15.442	21.698
E{g|A. $t + 1$}	4.063	6.035	7.444	8.650	9.781	10.588	11.666	13.088	14.737	18.408
Revision(g)	0.964	1.099	1.152	0.942	0.816	0.197	−0.127	−0.502	−0.705	−3.290
Std. Error	0.169	0.168	0.189	0.208	0.301	0.312	0.251	0.182	0.309	0.664
%p	0.029	0.033	0.034	0.028	0.024	0.006	−0.003	−0.014	−0.020	−0.087
Std. Error	0.005	0.005	0.006	0.006	0.009	0.008	0.007	0.005	0.009	0.016
E{e(fy 1)|A. $t + 0$}	0.120	0.114	0.111	0.109	0.108	0.110	0.110	0.108	0.101	0.099
E{e(fy 0)|A. $t + 1$}	0.114	0.108	0.100	0.094	0.082	0.085	0.084	0.078	0.070	0.059
Revision(e)	−0.006	−0.006	−0.011	−0.015	−0.026	−0.025	−0.026	−0.030	−0.031	−0.040
Std. Error	0.003	0.003	0.006	0.007	0.003	0.005	0.006	0.007	0.008	0.011
Error(t)	−0.005	0.001	−0.007	−0.009	−0.021	−0.022	−0.021	−0.023	−0.020	−0.031
Std. Error	0.004	0.004	0.008	0.008	0.004	0.009	0.005	0.008	0.010	0.005
Error($t + 1$)	−0.001	−0.001	−0.008	−0.013	−0.010	−0.022	−0.021	−0.014	−0.016	−0.025
Std. Error	0.005	0.005	0.008	0.008	0.008	0.011	0.010	0.009	0.014	0.012

Table IV—*Continued*

Panel B: Regression Results

For each year in the sample, four cross-sectional regressions are run with E{g} and the book-to-market ratio (BM) as independent variables. The dependent variables are: 1) Revision(g); 2) Revision(e); 3) Error(t); 4) Error(t + 1). See Panel A for a description of the variables. The table reports mean coefficients and t-statistics based on the time-series of the year-by-year estimates.

Dependent Variable	E{g}	BM
1) Revision(g)	−0.225	−0.830
	−9.959	−4.481
2) Revision(e)	−0.002	−0.010
	−15.907	−4.074
3) Error(t)	−0.002	−0.017
	−9.590	−2.530
4) Error(t + 1)	−0.004	−0.002
	−6.669	−3.052

Panel C: Excess Return Around Earnings' Announcement Dates

At the end of June of each year t, 10 decile portfolios are formed on the basis of ranked analysts' expected earnings' growth (E{g}) in December of year $t - 1$; For each of the resulting decile portfolios, I compute the three-day excess return and the one-month excess return for all quarterly earnings' announcement dates in the twelve months following formation. The three-day-excess-return is defined as the raw return on the portfolio minus the return on CRSP's equally-weighted index on the announcement date and the two preceding days ($t - 2$, t). Similarly, the one-month-excess-return is defined as the raw return on the portfolio minus the return on CRSPs equally-weighted index on the month of the announcement ($t - 30$, t).

E{g}	"Low" 1	2	3	4	5	6	7	8	9	"High" 10
3 Day	0.003	0.002	0.003	0.000	0.001	0.000	−0.001	−0.001	−0.002	−0.004
Std. Error	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
1 Month	0.013	0.011	0.009	0.004	0.002	0.003	0.000	0.001	0.000	−0.010
Std. Error	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002

of examining revisions in analysts' expectations that avoids the difficulties created by anticipated changes. We can study changes in the forecast for the *level* of earnings in fiscal year $t + 1$ that occur between calendar years t and $t + 1$; hence, we can compare the two-year earnings forecast made in calendar year t with the one-year earnings forecast made in calendar year $t + 1$. Panel A of Table IV shows that earnings forecasts for high E{g} stocks decline by roughly 40%, with their expected earnings-to-price ratio dropping from 0.099 in April of year t to 0.059 in April of year $t + 1$. Earnings expectations for low E{g} stocks remain essentially unchanged over this period. Thus, high E{g} stocks suffer a double blow: a sharp reduction in both the expected rate of long-run growth in earnings and the level of expected earnings. This may explain why their size-adjusted returns is −10 percent.

Panel A of Table IV also provides evidence on the accuracy of analysts' earnings forecasts for the current fiscal year and the following one. Note that the realized value of earnings in periods t and $t + 1$ is lower than their expected value for all portfolios. This result is consistent with previous work that has showed that analysts are on average too optimistic when forecasting earnings' levels (see for example, De Bondt and Thaler (1990)). However, whereas earnings for low E{g} stocks are very close to their expected value, earnings for the high E{g} portfolio are sharply lower than expected. Specifically, the error associated with the earnings' forecast for the current fiscal year is $-\$0.031$ for high E{g} stocks and only $-\$0.005$ for the low E{g} portfolio. Similarly, the error associated with the earnings' forecast for fiscal year $t + 1$ is $-\$0.025$ for high E{g} stocks and only $-\$0.001$ for the low E{g} portfolio.

Panel B of Table IV explores the relationship between BM and analysts' errors and revisions. It presents the results of four regressions in which the dependent variables are revisions in E{g}; changes in the forecasted level of earnings for fiscal year $t + 1$; the error associated with forecasts for the current fiscal year; and the error associated with forecasts for the next fiscal year. In all four cases, the independent variables, E{g} and BM, are strongly significant. To illustrate, consider the case of errors in the forecast of the level of earnings in the current fiscal year. The t-statistic for E{g} is -9.59, while the t-statistic for BM is -2.53. These results suggest that part of the reason why BM explains stock returns in my sample is that it is correlated with errors in expectations.

For portfolios formed on the basis of E{g}, the errors-in-expectations hypothesis is consistent with the errors associated with E{e} and revisions in both E{e} and E{g}. The finding that analysts' errors are systematic is inconsistent with the risk hypothesis, but compatible with the measurement error hypothesis. However, only the errors-in-expectations hypothesis can account for *both* the pattern of errors in analysts' expectations and the power of E{g} to explain the cross-section of stock returns documented in the previous section.

D. Returns Around Earnings Announcement Dates

This section looks at returns around earnings announcements for evidence that errors in expectations explain the superior performance of low E{g} stocks. The errors-in-expectations hypothesis predicts that prices for low E{g} (or high E{g}) stocks should rise (or fall) when the market learns the actual earnings figures. Returns around earnings announcements also provide indirect evidence on the extent to which analysts' expectations reflect the expectations of the market. Confidence in survey data as a proxy for market expectations will increase if the evidence on analysts' errors and revisions lines up with event returns.

I drew from COMPUSTAT the dates on which the *Wall Street Journal* published earnings' releases for the stocks in my sample during the first post-formation year (Chopra, Lakonishok, and Ritter (1992)), use a similar methodology). There are 25,573 such events for the stocks in my sample. Panel C of Table IV shows how each portfolio performed relative to the market in both the thirty days leading to the event ($t - 30$, t) and the three days preceding the event ($t - 2$, t). I find that excess returns decrease as E{g} increases in a fairly uniform way. For example, low E{g} stocks earn three-day excess returns of 0.3 percent (t-stat = 3) while high E{g} stocks *decline* by 0.4 percent (t-stat = −4). In annualized terms, these twelve information days account for 2.8 percentage points of the 20.9 percent spread between low E{g} and high E{g} stocks during the first year after formation. Similarly, in the month that precedes the event, low E{g} stocks rise relative to the market by 1.3 percent (t-stat = 6.5), while high E{g} stocks decline relative to the market by 1 percent (t-stat = 5).[19]

The risk hypothesis posits that the market correctly anticipates the future growth in earnings of the different portfolios. Risk potentially can account for the excess return of low E{g} stocks if we assume that much of the risk of holding a portfolio is earnings' risk, and that a significant amount of uncertainty is resolved around quarterly announcement dates. In other words, if low E{g} stocks have very high earnings risk, then their high event returns may be consistent with the risk hypothesis. However, it is very difficult for the risk hypothesis to explain the *negative raw* return of high E{g} stocks unless one believes that high E{g} stocks offer insurance against earnings' risk.

In contrast to the results in this section, the measurement error hypothesis predicts that there should be no relationship between event returns and E{g}. Therefore, although the evidence on analysts' revisions is compatible with the measurement error hypothesis, neither the yearly nor the event return evidence supports it.

III. Do Investors Extrapolate?

The previous section showed that IBES growth expectations are too extreme. But where do these extreme expectations come from? Experiments have found that individual's beliefs are not Bayesian. Rather, individuals consistently tend to overweigh recent information (Kahneman and Tversky (1973, 1982)). Thus, extreme expectations may be the result of investor overreaction to either good or bad news. In this section, I examine a special case of overreaction: extrapolation. The essence of the extrapolation hypothesis is that it takes time for investors to become aware of new trends, but once they do, they often latch onto these perceived trends for too long.

Extrapolation implies that the future is expected to be similar to the past. If extrapolation of the past is prevalent, then overpriced *glamour stocks* likely will be those that performed well in the past *and* are expected to perform well in the future. A testable implication of the extrapolation hypothesis is that the return on glamour stocks will be lower than the return on stocks that also are expected to perform well in the future but have performed poorly in the past (*temporary losers*). Similarly, if naïve investors extrapolate the past, then out-of-favor *value*

[19] In cross-sectional regressions, where the two-day return around earnings announcement dates is run on expected growth rates and various characteristics of the firm like size and book to market, the only significant variable is expected growth.

Table V

Portfolios Formed on the Basis of Analysts' Expected Growth and Five-Year Preformation Growth in Sales: July 1982–June 1991

At the end of June of each year t, stocks are independently sorted on the basis of analysts' expected earnings growth (E{g}) and ranked five year preformation weighed growth in sales (WGS). Three equal-size portfolios are formed for both E{g} and WGS. All numbers presented in the table are time-series averages of all formation periods for the nine resulting portfolios.

Panel A: Properties of Returns

R is the raw return in the year after formation. R-Size is the size-adjusted return. Prior-R is the average market-adjusted excess return over the previous five years ($t - 65$, $t - 6$). E{g} is the analysts' expected growth rate. E{e} is the ratio of expected earnings in the current fiscal year to stock price. Both, E{g} and E{e} are measured in December of year $t - 1$. Size, is the total market value of common stock, in millions, in June of year t. BP and EP, defined below use market equity corresponding to the end-of-December of year $t - 1$ and preformation-year-accounting. BP is the ratio of the book value of common plus balance sheet deferred taxes to market-equity. EP is the ratio of earnings (income before extraordinary items plus income statement deferred taxes minus preferred dividends) to market equity. Earn(+) is the fraction of firms with positive earnings. GS5 is the portfolio preformation five year average growth rate in sales.

	"Value"		"Temp. Winner"				"Temp. Loser"		"Glamour"	
E{g}	1	1	1	2	2	2	3	3	3	
WGS	1	2	3	1	2	3	1	2	3	All
R	0.269	0.260	0.302	0.191	0.209	0.214	0.175	0.159	0.110	0.210
R-Size	0.060	0.055	0.096	−0.017	0.003	0.014	−0.027	−0.049	−0.093	0.005
Prior-R	−0.045	−0.006	0.043	−0.102	−0.032	0.041	−0.115	−0.044	0.052	−0.023
E{g}	4.067	4.331	4.801	9.370	9.441	9.423	18.711	17.223	18.121	10.610
E{e}	0.060	0.100	0.097	0.029	0.082	0.082	0.032	0.067	0.075	0.069
Size	$2,318	$2,467	$2,141	$1,255	$1,471	$1,770	$756	$1,021	$1,374	$1,619
BP	1.067	0.949	0.780	0.991	0.844	0.754	0.918	0.771	0.629	0.856
EP	0.038	0.107	0.110	−0.019	0.065	0.082	−0.031	0.036	0.068	0.051
Earn(+)	0.860	0.952	0.965	0.751	0.914	0.950	0.716	0.852	0.928	0.877
GS5	0.001	0.083	0.161	−0.004	0.084	0.170	−0.021	0.065	0.192	0.081

stocks likely will be those that performed poorly in the past *and* are expected to continue to perform poorly in the future. Hence, the average return on value stocks should be higher than the return on stocks that also are expected to perform poorly in the future but performed well in the past (*temporary winners*).

To test for extrapolation, we need to answer two questions. First, what variable do investors extrapolate? Second, over what time period do they do this? Following LSV, I assume that naïve investors form their expectations on the basis of the ranked five-year preformation growth in sales (WGS). Admittedly, naïve investors are more likely to extrapolate past growth in earnings than in sales. However, the advantage of using WGS is that it avoids the problems created by negative numbers that would arise with using a measure of profitability.[20]

[20] I also sorted stocks on the basis of the five-year preformation rate of return. The results were qualitatively similar and are available upon request.

Table V—*Continued*

Panel B: Revisions and Errors in Analysts' Expectations

AE($t + j$) is the actual value of earnings associated with an investment of one dollar into each company in the portfolio in period t with nonmissing earnings in COMPUSTAT in period $t + j$. $E\{g|t + 0\}$ and $E\{g|t + 1\}$ are analysts' expected earnings growth in April of years t and $t + 1$, respectively. Revision(g) is the change in E{g} between April of years $t + 1$ and t for those stocks that are present in IBES in both periods. %p is the percentage change in stock price that would result from Revision(g), assuming that expected earnings are unchanged, the discount rate is 10% and that the growth rate expected to prevail starting in year $t + 6$ is unchanged. E{e(fy 1)|t} is the ratio of the April of year t forecast for the level of earnings in fiscal year $t + 1$, to the stock price in April of year t. E{e(fy 0)|$t + 1$} is the ratio of the April of year $t + 1$ forecast for the level of earnings in fiscal year $t + 1$, to the stock price in April of year t. Revision(e) is the difference between E{e(fy 1)|t} and E{e(fy 0)|$t + 1$}. Error(t) and Error($t + 1$) are the errors associated with the forecasts for the current and next fiscal year earnings, respectively. They are computed for a hypothetical investment of one dollar into each stock in the portfolio that has nonmissing COMPUSTAT earnings for the relevant period. The standard errors presented in the table are based on the time-series of the means of the appropriate variables.

	"Value"		"Temp. Winner"				"Temp. Loser"		"Glamour"
E{g}	1	1	1	2	2	2	3	3	3
WGS	1	2	3	1	2	3	1	2	3
AE(t + 0)	0.084	0.102	0.098	0.053	0.073	0.080	0.039	0.056	0.062
AE(t + 1)	0.094	0.105	0.103	0.059	0.071	0.077	0.047	0.057	0.053
AE(t + 2)	0.102	0.111	0.110	0.066	0.075	0.074	0.052	0.056	0.051
AE(t + 3)	0.109	0.119	0.119	0.068	0.072	0.076	0.048	0.056	0.044
AE(t + 4)	0.124	0.125	0.126	0.088	0.074	0.084	0.060	0.057	0.044
AE(t + 5)	0.137	0.132	0.130	0.094	0.084	0.087	0.062	0.070	0.047
E{g|A. t + 0}	4.519	5.328	5.521	13.405	13.623	14.310	23.704	20.958	21.759
E{g|A. t + 1}	5.619	6.319	8.518	13.429	13.022	13.995	18.162	17.984	19.192
Revision(g)	1.100	0.991	2.997	0.024	−0.601	−0.315	−5.542	−2.974	−2.567
Std. Error	0.212	0.283	0.359	0.361	0.219	0.214	2.064	0.548	0.399
%p	0.030	0.042	0.079	0.000	−0.016	−0.012	−0.121	−0.084	−0.067
Std. Error	0.007	0.009	0.011	0.010	0.006	0.006	0.042	0.014	0.010
E{e(fy 1)|A. t + 0}	0.112	0.114	0.116	0.103	0.108	0.113	0.091	0.101	0.098
E{e(fy 0)|A. t + 1}	0.101	0.108	0.109	0.075	0.083	0.074	0.054	0.060	0.054
Revision(e)	−0.011	−0.006	−0.007	−0.028	−0.025	−0.039	−0.037	−0.041	−0.044
Std. Error	0.004	0.003	0.004	0.009	0.004	0.007	0.007	0.009	0.011
Error(t)	−0.010	0.000	0.008	−0.023	−0.013	−0.011	−0.014	−0.018	−0.012
Std Error	0.006	0.005	0.004	0.013	0.006	0.004	0.014	0.006	0.009
Error(t + 1)	−0.007	−0.003	−0.006	−0.016	−0.012	0.003	−0.007	−0.003	−0.001
Std. Error	0.006	0.003	0.010	0.013	0.008	0.012	0.023	0.014	0.016

Panel C: Excess Return Around Earnings Announcement Dates

For each portfolio, I compute the three-day excess return and the one-month excess return for all quarterly earnings' announcement dates in the twelve months following formation. The three-day-excess-return is defined as the raw return on the portfolio minus the return on CRSP's equally-weighted index on the announcement date and the two preceding days ($t - 2, t$). Similarly the one month excess return is defined as the raw return on the portfolio minus the return on CRSP's equally-weighted index on the month of the announcement ($t - 30, t$).

	"Value"		"Temp. Winner"				"Temp. Loser"		"Glamour"
E{g}	1	1	1	2	2	2	3	3	3
WGS	1	2	3	1	2	3	1	2	3
3 Day	0.0031	0.0026	0.0021	0.0003	0.0003	−0.0008	0.0006	−0.0016	−0.0032
Std. Error	0.0010	0.0012	0.0012	0.0011	0.0010	0.0009	0.0013	0.0013	0.0009
1 Month	0.0130	0.0110	0.0090	0.0040	0.0020	0.0030	0.0000	0.0010	0.0000
Std. Error	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020

Since the number of stocks in the sample make it impractical to rank stocks independently in decile portfolios, I form three equal-size portfolios of stocks for both E{g} and WGS and consider the portfolios in their intersection. Panel A of Table V shows that over the next five years, the earnings of low E{g} stocks are expected to grow 4 to 5 percent. The average market capitalization of this group exceeds \$2 billion. The two-way classification of stocks succeeds in capturing the essence of the distinction between value stocks and temporary winners. Value stocks (those with low WGS) had declined relative to the market by an average 4.5 percent during each of the previous five years. By contrast, temporary winners (those with high WGS) had risen relative to the market by an average 4 percent over each of the previous five years. While the earnings of temporary winners are expected to be slightly lower than in the previous fiscal year, they are expected to recover quickly from depressed levels in the case of the value portfolio.

The earnings of high E{g} stocks are expected to grow 18 percent per year during the next five years. These high E{g} stocks can be broken into two categories: temporary losers (those with low WGS) and glamour stocks (those with high WGS). Roughly one-third of temporary losers had negative earnings in the previous fiscal year and had dropped, relative to the market, by an average of 11 percent during each of the previous five years. In contrast, only 7 percent of the stocks in the glamour portfolio had negative earnings and their prices had risen, relative to the market, an average of 5 percent per year over the previous five years.

Consistent with the extrapolation hypothesis, size-adjusted returns for glamour stocks are more negative than those for temporary losers. In fact, the difference in size-adjusted returns between temporary losers (−2.7 percent) and glamour stocks (−9.3 percent) is a large and statistically significant 6.6 percent.[21] However, the extrapolation hypothesis is not supported for low E{g} stocks. Value stocks earn size-adjusted returns of 6 percent, but temporary winners have size-adjusted returns of 9.6 percent in the year following formation. Yet, I cannot reject the null hypothesis that the average size-adjusted return on value stocks and temporary winners is the same (t-stat = 1.24).

Analysts' revisions and errors line up well with raw returns and are similarly inconsistent with the extrapolation hypothesis. The superior performance of temporary winners over value stocks during the sample period may be linked to larger upward revisions in expected growth rates and smaller downward revisions in forecasts for the level of earnings. Panel B of Table V shows that the growth rate for temporary winners rose 54 percent (from 5.5 percent to 8.5 percent) in the year that followed the formation period, while it rose 24 percent (from 4.5 percent to 5.6 percent) for value stocks. In addition, expected earnings for period $t + 1$ are approximately unchanged for temporary winners, but decline by 10 percent for value stocks. Finally, the errors associated with forecasts of the level of earnings are larger for value stocks than for temporary winners.

[21] The t-statistic for the null hypothesis that both sample means are identical is 2.65.

In contrast, the pattern of returns around earnings announcement dates is consistent with the extrapolation hypothesis. Panel C of Table V shows that around those dates, the market is positively surprised for value stocks and negatively surprised for glamour stocks, and that the excess returns for both value and glamour stocks are statistically different from zero. The average three-day excess return on value stocks is 0.31 percent (t-stat = 3.10) per quarter, but is −0.32 percent (t-stat = −3.55) for glamour stocks. In contrast, neither temporary winners nor temporary losers earn three-day excess returns that are statistically different from zero.

To summarize, the evidence on the extrapolation hypothesis is mixed. All three pieces of evidence, i.e., returns, survey data and earnings announcements, support the prediction that glamour stocks will more likely be overpriced than temporary losers. However, both the return and survey data— but not the earnings announcements—are inconsistent with the prediction that value stocks will more likely be underpriced than temporary winners. The finding that returns earned by value stocks are lower than those of temporary winners suggests that extrapolation is not the whole story behind the superior performance of value stocks. Other behavioral and institutional factors may also play a role. However, one may want to be cautious before passing final judgment on the extrapolation hypothesis since the performance of low E{g} stocks is very sensitive to the behavior of the market portfolio. Using *monthly* observations reveal that value stocks *outperform* temporary winners by 0.6 percent (t-stat = 1.76) when the market declines, but *underperform* them by 0.7 percent (t-stat = −2.5) when the market rises.[22] Given that stock prices rose over the sample period, the failure of the extrapolation hypothesis to explain the superior performance of value stocks could be specific to this period.

IV. Risk Characteristics of Contrarian Portfolios

Section II showed that E{g} plays a large role in explaining the cross-section of stock returns, and explored the role of expectational errors in accounting for that result. The natural competing hypothesis is that E{g} is negatively correlated with a common underlying risk factor. The risk hypothesis says that the low return earned by high E{g} stocks is the result of their low fundamental risk, not of excessive optimism. In Section II, I ruled out size as the underlying common risk factor associated with E{g}. In this section, I examine additional measures of risk, including standard deviations, betas, and performance in up and down markets to further illuminate the relationship between E{g} and risk.

[22] The outperformance of value stocks in declining stock markets is a characteristic of contrarian strategies. To illustrate, consider the case of portfolios formed on the basis of CP and WGS during the 1968–91 period: value stocks outperform temporary winners by 6.8 percent in size-adjusted terms when the market declines, but underperform by 0.8 percent per year in size-adjusted terms when the market portfolio rises.

Table VI

Risk Characteristics of Portfolios Formed on the Basis of Analysts' Expectations: July 1982–June 1991

Using monthly observations for all post-formation periods, I compute the standard deviation and beta for the return on each portfolio. Beta is calculated as the sum of the slopes in the regression of the return on each portfolio on the current and prior return on CRSP's equally-weighted index. Ret > 0 is the average monthly portfolio return when the return on CRSP's equally-weighted index is positive. Similarly, Ret < 0 is the average monthly portfolio return when the return on CRSP's equally-weighted index is negative. Worst (20%) is the average portfolio return in the 21 months with the lowest return on CRSP's equally-weighted index. Best (20%) is the average portfolio return in the 21 months with the highest return on CRSP's equally-weighted index.

At the end of June of each year t, 10 decile portfolios are formed on the basis of ranked analysts' expected growth in earnings (E{g}) in December of year $t - 1$.

Panel A: Properties of Portfolios Sorted by E{g}

E{g}	"Low" 1	2	3	4	5	6	7	8	9	"High" 10	All
Std. Deviation	0.040	0.043	0.050	0.055	0.058	0.058	0.059	0.060	0.061	0.067	0.056
Beta	0.537	0.663	0.800	0.884	0.994	0.987	0.982	0.998	1.046	1.150	0.904
Worst (20%)	−0.027	−0.035	−0.046	−0.055	−0.059	−0.059	−0.060	−0.063	−0.067	−0.077	−0.053
Ret < 0	−0.011	−0.017	−0.024	−0.033	−0.036	−0.036	−0.037	−0.040	−0.042	−0.054	−0.032
Ret > 0	0.040	0.043	0.046	0.048	0.048	0.047	0.046	0.045	0.045	0.044	0.045
Best (20%)	0.060	0.066	0.071	0.077	0.083	0.078	0.082	0.082	0.084	0.086	0.075

Panel B: Properties of Portfolios Sorted by E{g} and WGS

At the end of June of each year t, stocks are independently sorted by ranked analysts' expected earnings growth (E{g}) in December of year $t - 1$ and ranked five-year preformation weighted growth in sales (WGS). Three equal-size portfolios are formed for both E{g} and WGS.

	"Value"		"Temp. Winner"				"Temp. Loser"		"Glamour"	
E{g}	1	1	1	2	2	2	3	3	3	
WGS	1	2	3	1	2	3	1	2	3	All
Std. Deviation	0.043	0.044	0.052	0.057	0.057	0.060	0.060	0.062	0.065	0.056
Beta	0.684	0.644	0.828	0.941	0.968	0.999	1.031	1.050	1.062	0.912
Worst (20%)	−0.036	−0.037	−0.040	−0.057	−0.056	−0.064	−0.060	−0.066	−0.073	−0.053
Ret < 0	−0.018	−0.020	−0.019	−0.057	−0.056	−0.064	−0.060	−0.066	−0.073	−0.053
Ret > 0	0.041	0.042	0.048	0.046	0.046	0.049	0.045	0.046	0.044	0.045
Best (20%)	0.066	0.063	0.073	0.075	0.083	0.084	0.082	0.083	0.084	0.075

Panel A of Table VI presents the crudest measure of risk available: standard deviations. These are computed for each portfolio by pooling the monthly data for all nine postformation years. When stocks are sorted on the basis of E{g}, the standard deviation of low E{g} stocks is approximately 2.7 percentage points *lower* than that of high E{g} stocks, and 1.6 percentage points lower than that of the population of stocks. Therefore, based on standard deviations, the risk inherent in high E{g} stocks is greater than that of low E{g} stocks, not less as predicted by the risk hypothesis.

Given that stock prices generally rose over the sample period, it is conceivable that the low returns earned by high E{g} stocks merely reflect their low beta risk. To examine this hypothesis, I compute betas by adding the slopes in the regression of the portfolio's return on the current and lagged return on

CRSP's equally-weighted portfolio.[23] Estimates of beta for the entire sample are close to 0.9, which is consistent with the bias toward large stocks in my sample. Betas for portfolios formed on the basis of expected growth rates range from 0.54 to 1.15, and increase uniformly with E{g}. Therefore, market risk for the high E{g} portfolio is roughly double that of the low E{g} portfolio, and is the highest beta estimate of all the investment strategies considered in this article. As in the case of adjusting returns for size, adjusting returns for market risk fails to explain the superior performance of contrarian strategies.

Betas may be an inadequate measure of risk if E{g} portfolios behave differently in bull and bear markets. For example, if low E{g} stocks experience poor relative performance when the stock market declines, then the superior returns documented in the previous section may reflect compensation for risk. To test this hypothesis, Panel A of Table VI divides the return on each portfolio into two separate components: the average return for every month in which the market portfolio rose and the average return for every month in which the market portfolio declined. When the stock market falls, high E{g} stocks drop by a steep 5.4 percent, while low E{g} stocks decline by only 1.1 percent. A similar result obtains if we consider only one fifth of stock market months with the worst market portfolio return in the sample. During those months, low E{g} stocks drop by 2.7 percent while high E{g} stocks fall by 7.7 percent. In summary, there is no evidence that the superior returns earned by low E{g} stocks are compensation for poor performance in down markets.

It is also interesting to note that for portfolios formed on the basis of E{g} and WGS, value stocks have lower standard deviations and betas than temporary winners, and they perform better when the stock market declines (see Panel B of Table VI). Conversely, glamour stocks have higher standard deviations and betas than temporary losers, and they perform worse when the stock market declines.

V. Summary and Interpretation of the Results

Contrarian strategies that use analysts' expectations to form portfolios yield high returns. Specifically, when stocks are sorted by the expected growth rate in earnings, low E{g} stocks beat high E{g} stocks by twenty percentage points. In the year following formation, analysts sharply revise their expectations about both the level of earnings and the rate of growth in earnings in the direction predicted by the errors-in-expectations hypothesis. Furthermore, for high E{g} stocks there is evidence of large errors in analysts' forecasts of the *level of earnings* in the next fiscal year. Finally, event study evidence suggests that the market was overly pessimistic about the earnings of the low E{g} portfolio and excessively optimistic about the earnings of the high E{g} portfolio.

[23] Summing the slopes is meant to alleviate the problems created by nonsynchronous trading (Dimson (1979)). Such problems may be more important for portfolios of small stocks and thus, less of an issue for portfolios formed on the basis of analysts' expectations.

There is no evidence that low E{g} stocks are more risky than high E{g} stocks. When portfolios are formed on the basis of the expected growth rate in earnings, low E{g} stocks have significantly lower standard deviations and betas than high E{g} stocks. Not only do low E{g} stocks yield higher average returns than high E{g} stocks in every year, but they also perform significantly better than high E{g} stocks in bear markets. These results are consistent with De Bondt and Thaler (1990), who also find systematic errors in analysts' expectations. The results are also consistent with LSV, who document that a large number of contrarian strategies based on accounting ratios earned superior returns during 1968–1989, although these strategies do not appear to have entailed higher fundamental risk.

How should we interpret these results? One view is that the large returns generated by contrarian strategies are implausible. Although some skepticism is healthy, there are several reasons to believe that these results are not spurious. First, concerns about data mining should be minimal, because the strategies tested here for the IBES sample represent natural extensions of the strategies developed by others who used COMPUSTAT, an alternative database. Second, the results obtain for a sample of large and financially sound firms, a class of firms for which contrarian strategies generally work less well (see Chan and Chen (1991) and Fama and French (1995)). Third, stock prices rose during the sample period, and value strategies typically perform better when the market declines (De Bondt and Thaler (1987)). Finally, the returns obtained by betting against analysts' expectations are consistent with the magnitude of the errors made by analysts in forecasting earnings growth over the sample period.

The securities business is a competitive industry, and one may wonder why investors pay high fees for forecasts that are systematically mistaken. However, the success of analysts is not measured by the accuracy of their long-run growth forecasts, but rather by the timeliness of their stock recommendations. In this regard, the available empirical evidence suggests that an investor can earn excess returns by trading in the direction of changes in analyst advice. Specifically, both Elton, Gruber, and Grossman (1986) and Womack (1995) show that it is profitable to follow an investment strategy that is long on stocks that recently were upgraded to "buy," and short on stocks that were downgraded to "sell" (see also Dimson and Marsh (1984)). These results do not conflict with my findings, given that analysts probably issue buy recommendations when stock prices are low relative to their estimated intrinsic value, and not simply because their E{g} is high. A naïve model that captures this idea equates "buy" ("sell") ratings with a low (high) price-to-E{g} ratio.[24] Consistent with the previous findings on analyst advice, I find that an investment strategy based on buying stocks with a low price-to-E{g} ratio and selling short stocks with a high price-to-E{g} ratio yields excess returns within my

[24] Unfortunately, IBES does not collect data on analysts' advice, and I cannot test the accuracy of this model.

sample.[25] In future work, I intend to examine more closely the link between earnings' expectations and analyst advice.

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[25] The excess returns are of the same order of magnitude as those obtained by Womack. They are available upon request.

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