THE VALUATION OF GROWTH AND INVESTOR SENTIMENT

by

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ABSTRACT

The valuation of growth, measured as the sensitivity of the forward P/E ratio to analyst growth forecasts, fluctuates over time. This study investigates whether these fluctuations can be explained by investor sentiment. The testable prediction is that investor sentiment affects the valuation of growth, both in the cross section and at the aggregate market level. Empirical analyses show that growth is valued high in the cross section when measures for irrational sentiment are high. At the market level, sentiment measures are shown to have conditional effect on the time-series relation between the market P/E ratio and aggregate growth forecasts. Future return patterns based on growth-related characteristics are consistent with the hypothesis that sentiment causes mispricing on stocks whose earnings are expected to grow fast and stocks whose growth is valued too extremely.

For My Beloved Parents

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TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

I. INTRODUCTION

Investors are said to pay for future earnings growth. However, their willingness to do so appears to change over time. Casual observation suggests that expected earnings growth is priced much higher in bull markets than in bear markets. This paper empirically investigates the sensitivity of stock valuation to expected earnings growth; I refer to this sensitivity as the *valuation of growth*. The main objective is to assess the extent to which fluctuations in the valuation of growth over time can be attributed to investor sentiment.

The valuation of growth reflects the underlying process that transforms growth expectations into market price. Hence, the valuation of growth lies at the center of fundamental analysis. Security analysts and financial media routinely refer to earnings growth prospects when interpreting market movements, justifying valuation, and predicting broad market trends or individual stock performances. The changing valuation of growth is of particular interest to investors who want to judge a stock's worth based on valuation attributes (future earnings growth being one of the most important). It is also relevant to management that desires to tailor corporate characteristics to maximize market value. The issue, however, has received little attention in the recent accounting literature.[1]

This paper investigates whether investor sentiment contributes to the fluctuation in the valuation of growth over time. Popular views often hold that some investors behave out of *irrational* sentiment, i.e., optimistic or pessimistic assessment of market conditions,

[1] A few exceptions are Cragg and Malkiel (1982), Zarowin (1990), and Thomas and Zhang (2006), which focus on explaining stock valuation by expected growth. They, however, didn't investigate the changing relation between stock valuation and expected growth.

which is unwarranted by economic fundamentals.[2] Thus it is plausible that shifts in sentiment also influence how investors price growth. Specifically, overly optimistic investors are willing to pay a lofty price for future earnings growth. Pessimistic investors are skeptical to rosy growth stories and only put a modest price on growth. Such differences in investor attitudes show up empirically as the changing valuation of growth.

I test this prediction by examining the time-series relation between measures for the valuation of growth and sentiment. Because the valuation of growth can be operationalized both in the cross section of individual stocks and over the time series of the aggregate market, separate empirical analyses are conducted for both cases, as described below.

The first test focuses on the relative valuation of individual stock growth in the cross section, or the *cross-sectional* valuation of growth. I quantify the construct as the cross-sectional sensitivity of the forward earnings yield to analyst long-term growth forecasts (LTG). The measure, referred to as the *Growth Response Coefficient* (GRC), can be conveniently obtained from cross-sectional regression. GRC possesses desirable properties. Over the period between 1982 and 2005, the estimated GRC remains reliably negative, as required by the basic investment principle: investors trade off between near term (in forms of the earnings yield) and long term (i.e., delivery of future earnings). Moreover, the measure varies considerably and such variations are aligned with major stock market episodes in the sample period.

[2] Refer to Section II for a detailed discussion of the concept of investor sentiment. Section IV discusses empirical measures for investor sentiment in more detail.

Empirical analysis employs two measures for market-wide sentiment, which are suggested in the recent finance literature. One is based on a consumer confidence survey, and is constructed to be unrelated to economic fundamentals (Lemmon and Portniaguina 2006). The other is based on trading patterns, such as closed-end fund discounts, IPO activities, market turnover, aggregate equity issuance, and dividend premium (Baker and Wurgler 2006, 2007). Evidence exists suggesting that these measures relate to stock market mispricing.

I then test whether GRC comoves with the sentiment measures in a time-series regression over the period from 1982 to 2005. Consistent with the prediction, I find that the sentiment measures contribute to the observed fluctuations in GRC, even after controlling for fundamental factors such as real interest rates, market volatility, quality of analyst forecasts, and business cycles. Moreover, GRC relates to the sentiment measures in an economically sensible and significant manner. Specifically, when sentiment increases by one standard deviation, investors give up sixteen basis points (in the form of the earnings yield) for every incremental percentage of expected growth. These results suggest that investors price expected growth differently, depending on prevailing sentiment regimes.

In the second test, I examine whether sentiment influences the valuation of expected growth in aggregate earnings. It is possible that the cross-sectional effect of sentiment documented above disappears at the market level if it is largely idiosyncratic. A market level analysis helps clarify the issue. Operationally, I treat sentiment as a conditional variable in the time-series regression of the market P/E ratio on aggregate growth forecasts. The results confirm the effect of sentiment in a manner consistent with the prediction that aggregate earnings growth is valued higher as sentiment grows increasingly optimistic.

At face value, the results so far suggest that *investor sentiment is relevant to the valuation of growth, and its impact differs under different regimes of sentiment.* Because investor sentiment is commonly regarded as a cause of mispricing, a natural question arises: is growth mispriced? I thus perform a third set of tests, which examine cross-sectional return predictability based on growth-related characteristics. Because high growth stocks are likely to be overpriced (underpriced) during high (low) sentiment periods, I hypothesize that the relative performance between high vs. low growth stocks reverses when sentiment shifts. I perform two-way sorts based on LTG and sentiment measures. When portfolios are formed at high sentiment dates, I find that the highest LTG stocks underperform the lowest LTG stocks by nine percentage points over subsequent six months. In contrast, when portfolios are formed at low sentiment dates, the pattern reverses to the highest LTG stocks outperforming the lowest by two percentage points. Additional sorting based on the PEG ratio and sentiment also provides some evidence that stocks whose growth is valued too extremely are more sensitive to sentiment-induced mispricing.

In summary, I test a behavioral view that allows investor sentiment to affect the relation between stock market value and expected earnings growth. To the best of my knowledge, little empirical research exists examining stock valuation from a behavioral perspective. My findings have a number of implications for valuation research. First, the results verify the validity of the first-cut valuation principle: The forward P/E ratio increases with expected earnings growth, controlling for risk. Second, I confirm a common impression that the relation between stock market value and fundamentals changes over time. This phenomenon is relevant to studies that rely on the value-growth relation. For instance, several recent studies reverse engineer valuation models to estimate the cost of equity (e.g., Clause and Thomas 2001; Gebhardt *et al.* 2001; Easton 2004; Easton and Sommers 2007). The results in my study raise doubt on whether existing static valuation models adequately approximate the real valuation process.

Third, the paper provides evidence that shifts in investor sentiment explain the fluctuation in the valuation of growth. This finding lends validity to colorful accounts in the popular media claiming investors behave "between fear and greed" (Wall Street Journal, July 27, 2007, p. C1). One implication is that one may need to take into account the effect of broad-based sentiment when conducting fundamental analysis on individual stocks as well as broad markets.

The rest of the paper is organized as follows. Section II surveys prior literature. Section III presents a simple model of growth and sentiment. Section IV describes empirical approach and key measures. Section V examines the time-series relation between the cross-sectional valuation of growth and sentiment. Section VI investigates the influence of sentiment on the valuation of aggregate growth. Section VII presents the sorting test for growth-related mispricing. Alternative explanations are discussed in section VIII. Section IX concludes.

II. PRIOR LITERATURE

This study builds on valuation research that aims at understanding how earnings growth is related to equity value. It, however, departs from the efficient market view and is partly motivated by the fast growing field of behavioral finance.

Valuation Research

My study closely relates to empirical and theoretical works in the valuation literature. This line of research attempts to explain stock intrinsic value by a set of fundamentals, namely, growth in future cash flows and risk. The assumption of market efficiency enables market price to be explained in a similar fashion. Theory often summarizes the relation between value/price and fundamentals in the forms of valuation formulas. Empirical works exist to verify these theoretical relations.

Earnings Growth in Analytical Valuation Models

There exists a family of valuation models that explain the P/E ratio by earnings growth and other fundamentals. Earnings growth receives the prominence in valuation for obvious reasons. First, earnings are *the value* created by a firm's operation, and thus are the ultimate source of dividend distribution and the basis for stock value. Second, an earnings-based valuation theory has a wider applicability than a dividend-based theory. Firms may opt not to pay dividends but are more likely to have (core) earnings. Third, earnings as an accounting measure incorporates management's private information about firm performance as well as accountants' professional judgment. It is generally agreed that earnings is preferred to cash flows as a valuation attribute.

Early examples of earnings-based theory include the Gordon (1962) Growth model and those in Cragg and Malkiel (1982). However, the entrance of earnings into these models is quite rudimentary: earnings is simply a fixed proportion of dividends. Explicitly including a dividends payout ratio in the valuation model runs against the dividends irrelevancy proposition of Miller and Modigliani (1961). Moreover, in these models, earnings grow constantly from here to kingdom-com.

Without explicitly referring to the dividends discount model, Litzenberger and Rao (1971) formulate stock price as a non-growth component adjusted by the net present value of future earnings growth. By imposing the CAPM-like structure, the model justifies the presence of earnings volatility in valuation: a surrogate for the systematic risk inherent in future payoffs. However, the growth concept adapted by the model is actually growth in book value of equity[3], inconsistent with the common notion of growth in earnings.

Accounting-based valuation models in Ohlson (1995) and Feltham and Ohlson (1995) place greater emphasis on the driving role of earnings. Growth in these models thus appears more intuitive. Departing from prior models that use book value as a valuation anchor, Ohlson and Jeuttner-Nauroth (2005) proposes a model that explains stock price by expected earnings; in one variant the forward P/E ratio is a function of short- and long-term earnings growth (along with the discount rate). Such formulation is appealing because it conforms to the common belief that both growth and risk are the central attributes in valuation. The empirical model used in Section IV to estimate the Growth Response Coefficient (GRC) can be thought as a linearized version of the OJ model.

Most existing valuation models are based on the rational framework. My work

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[3] This is a balance sheet view of growth, roughly equivalent to the growth through investment.

extends the valuation literature by explicitly considering a non-fundamental factor, investor sentiment, in the otherwise traditional fundamental analysis.

Related Empirical Literature

Empirical evidence pertaining to earnings growth and stock valuation mostly comes from early literature. Two lines of research are examined here: (i) studies that examine the relation between value and earnings growth; (ii) the implied cost-of-capital literature relying on the theorized growth-value relation.

The parsimonious relation between value and fundamentals, as suggested by valuation models, points to straightforward empirical implications. Despite variations in sample construction, measurement of valuation metrics and growth, empirical results generally confirm the central role of expected earnings growth in the cross-sectional stock valuation. Cragg and Malkiel (1982) is the first comprehensive study that examines growth expectations as a valuation attribute. For 175 large NYSE stocks over the period between 1960 and 1969, their study uses consensus analyst forecasts of earnings growth (both short- and long-term) to proxy for stock market expectations on growth, and finds that expected growth measures explain the cross section of P/E ratios. Using the same data, Zarowin (1990) shows that analyst long-term growth forecasts dominate other factors, such as beta, short-term growth forecast, accounting methods, in explaining the cross-sectional valuation.[4] Thomas and Zhang (2006) examine and confirm the positive relation between the forward P/E ratio and analyst long-term growth forecasts.

[4] Early empirical studies find that realized earnings growth weakly explains the cross-sectional variation in the P/E ratio (i.e., Boatsman and Baskin 1981; Alford 1992; Penman 1996). This comes as no surprise because realized growth is likely to be a poor proxy for future growth perceived by investors.

The cross-sectional approach used by the early studies partially motivates the procedure of estimating GRC in this work. My study extends the literature by allowing the growth-value relation to vary over time and further investigating the causes of the variation.

Several recent studies estimate the cost of equity by reverse-engineering valuation formulas (e.g., Claus and Thomas 2001; Gebhardt *et al.* 2001; Easton 2004; Easton and Sommers 2007). These studies rely on static valuation models without accounting for the changing relation between value and growth, which my study confirms. My results suggest that the quality of estimation may improve if one employs a more descriptive growth-value relation.

Stability of the Value-Growth Relation

The literature has long recognized that the relation between stock price and growth (or other fundamentals) vary over time. The relation is termed as the "valuation of growth" in my study. Granger and Morgenstern (1970) note that earnings' coefficients in cross-sectional valuation regression vary over time. Lev and Ohlson (1982) claim "the temporal instability in the relationship between stock prices and earnings" as a major hurdle in developing valuation models. Regressing the P/E ratio on growth forecasts year by year between 1961 to 1968, Cragg and Malkiel (1982) find the slope for growth forecasts ranges from 1.74 in 1968 to 3.91 in 1961.

Little effort has been made to investigate the underlying cause of the fluctuation in the valuation of growth. On the one hand, Lev and Ohlson (1982) believe that the time-series behavior of the valuation coefficients is driven by dynamics of macroeconomic variables. On the other hand, in interpreting the changes in the growth slope, Cragg and

Malkiel (1982) cite the anecdotes that growth stocks were highly in favor at the end of 1961 but fell out of favor in 1962. My study contributes to the literature by systematically investigating the time-series behavior of the valuation of growth, and furthermore, exploring both fundamental and non-fundamental factors as the determinants.

Investor Sentiment and Behavioral Finance

The fast-growing literature of behavioral finance provides both theoretical underpinnings and empirical tools for my study. In this new paradigm, mispricing occurs when systematic sentiment creates uninformed demand shocks, and when market frictions prevent stock prices from returning to their fundamental levels. In what follows, I first discuss the concept of investor sentiment, then review theoretical works, and finally, examine relevant empirical evidence.

The Concept of Investor Sentiment

Investor sentiment remains an elusive concept. Theoretical works in behavioral finance often refer to various forms of investor irrationality as "investor sentiment." For example, Barberis *et al.* (1998) propose a model of sentiment in which investors form biased beliefs due to conservatism and the representative heuristic. In Daniel *et al.* (1998), investors are overconfident and make biased self-attribution.[5] In my study investor sentiment is *investors' optimistic or pessimistic assessment of market conditions, which is unwarranted by economic fundamentals*. This definition is adapted from the two main empirical studies that my work builds on: Lemmon and Portniaguina (2006) and Baker

[5] See Barberis and Thaler (2003) for a comprehensive review of the literature.

and Wurgler (2006).

The existence of investor sentiment, as well as its behavior, is attributed to investors' cognitive biases. To model a particular form of irrationality, researchers often turn to psychology for guidance. A variety of systematic biases in human cognition have been invoked in the literature. For example, *conservatism* is a phenomenon that people sometimes overemphasize their priors relative to new information and thus insufficiently update their beliefs. Barberis *et al.* (1998) argue that this bias causes the market to underreact to public information. One form of *representative heuristics* leads people to exaggerate the similarity between two items they need to make inference, and consequently, draw incorrect inferences from a too small sample (the "Law of Small Numbers"). Barberis *et al.* (1998) contend this phenomenon as the psychological basis for investors' erroneous extrapolation. People are often *overconfident*: they overestimate their abilities and prospects and underestimate the difficulty of a task. Daniel *et al.* (1998) explain market underreaction to public information by assuming investors are overconfident to their private information.

Even though factors such as learning, expertise, and incentives can somehow mitigate these cognitive biases, there has been no evidence that the attenuating factors completely eliminate cognitive biases (e.g., Camerer and Hogarth 1999). Thereby, money managers, financial analysts, and other investment professionals are not immune to sentiment. Agency conflicts may also cause professionals' behaviors to deviate from full rationality.

Sentiment would not cause mispricing in equilibrium as long as rational arbitrageurs[6] actively bet against sentiment-based trading. Thus, behaviorial finance theory further assumes that arbitrageurs have limited desire or ability to correct sentiment-induced mispricing (the "limited arbitrage" assumption). Limited arbitrage has institutional backgrounds. First, arbitrageurs typically have short horizon. Delong *et al.* (1990) argue that arbitrageurs are deterred from fully exploiting mispricing by the concern that the mispricing may temporarily deepen at the time of closing positions. Second, arbitrageurs have limited trading capacities. Shleifer and Vishny (1997) point out that it is especially true when short-term losses trigger margin calls, investors' withdrawal, or lenders' credit cut. Third, the short-sells constraint prevents arbitrageurs from entering into an overpriced stock market (Baker and Stein 2004).

Theoretical Works for Investor Sentiment

Behavioral theory relies on investor sentiment, along with limited arbitrage, to explain a variety of anomalies in asset pricing. To produce testable implications, theories make varied assumptions about investor sentiment, ranging from the minimum, i.e., its existence, to elaborate psychological phenomena. Here I only discuss models with minimum sentiment assumptions; my model falls into this category.

De Long *et al.* (1990) assume existing unpredictable and systematic sentiment. Their central result shows that security prices are depressed by "noise trader risk", the uncertainty that in the short run unpredictable waves of sentiment may drive stock prices further away from true values. The underpricing persists because noise trader risk

[6] Institutions are considered to fall into this category.

discourages arbitrageurs from fully exploiting the mispricing, especially when arbitrageurs have short horizons. The theory suggests an indirect measure for investor sentiment: the closed-end fund discount (e.g., Lee *et al.* 1991; Baker and Wurgler 2006).

Similarly to De Long *et al.* (1990), Baker and Stein (2004) also assume irrational investors (co-existing with rational investors) exhibit unpredictable and systematic sentiment. By further imposing the short-sells constraint, their model shows that the security pricing is dominated by different groups of investors, depending on the state of sentiment. Specifically, when sentiment is high, irrational investors bid prices so high that rational investors don't buy (and they can not sell short due to the short-sells constraint). By contrast, when sentiment is low, rational investors bid prices at a level that is too high for irrational investors to buy. The resulting price coincides with true values. This model features the "one-way" mispricing: high liquidity is a sign of high sentiment and over-pricing but low liquidity leads to the correct price. The theory rationalizes using liquidity/turnover as a proxy for investor sentiment (also see Baker and Wurgler 2006).

Related Empirical Evidence

The literature has documented that mispricing occurs to different types of assets, the aggregate stock market, and stocks with certain characteristics. Collectively, the body of evidence suggests the significance and prevalence of investor sentiment.

Lee *et al.* (1991) contend that small investor sentiment, which represents an undiversified risk, causes the discount in closed-end funds. Their theory is able to explain (or backed up by) empirical regularities such as the co-movement of funds discounts, low discounts around fund startups, and the co-movement between fund discounts and small stock returns.

Evidence shows that IPO activities are under the influence of sentiment. For example, Lowry (2003) finds investor sentiment, proxied by the closed-end fund discount, explains the fluctuation of IPO volumes. In addition, periods of high IPO volume are found to be followed by low market returns, suggesting firms successfully time capital raising to take advantage of investor over-optimism. Cornelli *et al.* (2006) investigate whether the post-IPO prices are driven by small investor sentiment, which is proxied by prices in European grey markets[7]. They find that only high prices in grey markets, but not low prices, predict post-IPO first-day prices and long-run price reversals. The findings are consistent with the hypothesis that IPO-share holders opportunistically trade to take advantage of small investor optimism.

There also exists the evidence of mispricing in broad stock markets (e.g., Neal and Wheatley 1998; Brown and Cliff 2005; Lamont and Stein 2006). Brown and Cliff (2005) document a positive relation between a survey measure of investor sentiment and the pricing error in market indexes[8]. They interpret the relation as that excessive optimism leads to market overvaluation. Lamont and Stein (2006) find that net equity issuance and merger activities are more sensitive to aggregate stock returns than to firm-level returns. To the extent that financing decisions are made to take advantage of market mispricing, the findings are consistent with the proposition that a price movement in broad markets contains a greater proportion of investor sentiment than the same-sized movement in firm-level prices.

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[7] Grey markets are pre-IPO markets in which investors trade yet-issued shares of IPOs on a forward basis.

[8] Refer to their paper for how to estimate the pricing error.

My study adds to this body of evidence by focusing on growth. The mispricing of growth examined here is a special case of the more general phenomenon of mispricing.

There is also evidence suggesting that market-wide sentiment causes differential mispricing on individual stocks in the cross section. Specifically, Baker and Wurgler (2006) examine whether ex ante sentiment predicts cross-sectional return patterns identified by firm characteristics. These characteristics are selected to indicate a stock's proneness to speculation and/or the effectiveness of arbitrage on it. They find that market-wide sentiment causes differential mispricing in stocks that differ in size, age, volatility, among others. Brown and Cliff (2005) show that the predictability of sentiment to long-term returns is most pronounced among large-cap growth stocks. My study finds that sentiment contributes to the fluctuation in GRC, which can be interpreted as the differential impact of sentiment on expected earnings growth in the cross section.

Advances in empirical techniques and greater data availability make it possible to quantify the elusive concept of investor sentiment. This study relies on two measures for investor sentiment, proposed by Lemmon and Portniaguina (2006) and Baker and Wurlger (2006, 2007), respectively. Section IV discusses these measures in more detail.

Erroneous Beliefs on Growth

This study examines the distorted *functional* relation between growth expectations and stock value. Such emphasis differs from prior studies that examine the effects of distorted *expectation* of growth (see Lakonishok *et al.* 1994; La Porta 1996; Dechow *et al.* 2000; Chan *et al.* 2003). Using analyst forecasts as a proxy for market expectations, these studies find strong evidence against rational expectation. However, criticism of their results holds that analyst forecasts may not adequately proxy for market expectation. The proxy issue is less a concern in my study. Under the null hypothesis of rationality, investors recognize the bias in analyst forecasts and discount it properly. In sharp contrast, I report that investors not only take analyst forecasts at face value but exacerbate the distortion through the valuation process.

III. ANALYTICAL MODEL OF GROWTH AND SENTIMENT

This section presents a simple model in which the impact of investor sentiment on the valuation of growth can be sharply seen. The testable implications are drawn upon comparative statics. The model also justifies the procedure of estimating the cross-sectional valuation of growth. The basic modeling technique follows the well-known Noise Trading Model by De Long *et al.* (1990). The simplicity of such a framework makes clear the two tenets of the behavioral perspective of asset pricing: sentiment-induced trading shocks and limited arbitrage.

A Simple Model

Settings

The economy consists of overlapping generations of two-period-lived agents. The population is constant and normalized to one. There are no first-period consumption, no labor supply decision, and no bequest. A generation of agents born at time t receives exogenous endowments l and invests it in financial markets. At time t+1 they sell all holdings to the newly-born generation and consume all proceeds.

Two financial assets are available to agents: a bond and a stock. The bond bears a fixed real risk-free rate r, and is in perfectly elastic supply. The bond is treated as a numeraire so its price is thus normalized to one. The stock is in the fixed supply of one. It generates uncertain earnings X and pays the full amount out as dividends. Thus the stock's total payoff at time t+1 is simply $P_{t+1} + X_{t+1}$.

Each generation consists of two types of agents: noise traders (denoted by n) in measure of μ, and rational investors (denoted by r) in measure of 1-μ. Agents within each type are homogenous; I only consider representative agents thereafter. For a generation born at time t, both types of agents must allocate their endowments between the bond and the stock in the aim of maximizing their expected utility, based on their beliefs about the stock's payoff at time t+1. Both types of agents have an exponential utility

$$-\exp\{-2\rho W_{t+1}\},$$

where ρ is the coefficient of absolute risk aversion. The optimization problem of the representative agent in type $i \in \{n, r\}$ at time t is to choose the number of stock shares λ_t^i to maximize

$$E_t[-\exp\{-2\rho W_{t+1}{}^i\}],$$

subject to the budget constraint

$$W_{t+1}{}^i = \lambda_t^i (P_{t+1} + X_{t+1}{}^i) + R(l - \lambda_t^i P_t), \tag{1}$$

where l is the exogenous labor income received at time t and $R \equiv 1+r$. The superscript highlights the difference in the earnings processes perceived by each type of agents. Specifically, rational investors correctly expect future earnings to grow at a constant rate of θ

$$E_{t+s}[X^r_{t+s+2}] = \theta\, E_{t+s}[X^r_{t+s+1}],\ \text{for } s = 0, 1, \ldots. \tag{2}$$

To keep the price formula derived later meaningful, θ is required not too large to exceed the internal growth rate in the economy (i.e., $0 < \theta < R$). Because rational investors have unbiased belief, the superscript r is omitted in the future.

Noise traders, by contrast, misperceive the earnings growth rate as if it is drawn independently from a normal distribution[9]

[9] I require both θ and θ^* to be strictly less than R so that price is finite.

$$\theta_t \sim^{\text{iid}} N(\theta^*, \sigma_\theta^2), \text{ for all } t,$$

where $\theta^* \neq \theta$. Thus, noise traders' knowledge of earnings growth is not only imprecise but also systematically biased. In noise traders' view, expected earnings grows at a constant rate that is different from θ

$$E_{t+s}[X^n_{t+s+2}] = \theta_{t+s} E_{t+s}[X^n_{t+s+1}], \text{ for } s = 0, 1, \ldots. \tag{3}$$

It is tempting to label θ_t (or θ_t - θ) as investor sentiment.[10] The later analysis, however, shows that the mean of noise traders' misperception about growth, θ^*, asserts a greater impact on stock price than the realization θ_t. I come back to the point after deriving the explicit form of the price.

The existence of investor sentiment and its shifts have a wide variety of social and psychological roots. Shiller (1984) discusses social movements, such as fashions, whims, rumors, and so on, which are generally considered unrelated to economic fundamentals. Sentiment may as well be the manifestation of numerous cognitive biases to which investors are not immune. Overconfidence, representative heuristics, conservatism, just name a few.

The process (3) indicates that noise traders use the realized (incorrect) growth rate to forecast future earnings. At first glance such specification is rather simplifying. It, however, can be partially justified if the growth rate is broadly interpreted as an input to forecasting earnings, instead of a quantity to mechanically extrapolate future earnings

[10] In the current setup, obviously, only noise traders exhibit sentiment. In the reality, however, it is not clear whether an observed measure, provided it captures some aspect of sentiment, shall be attributed to specific group or general market participants.

from a base. In this regard, only the observable and realized quantity is of economic relevant. Moreover, empirical findings show that sentiment measures, however they are constructed, are fairly persistent (e.g., Brown and Cliff 2005). That suggests that a random walk reasonably approximate the true data-generating process of sentiment. The specification in (3) is consistent with such a premise.

Neither rational investors nor noise traders have perfect foresights of future sentiment, i.e., the growth rate perceived by noise traders. As De Long *et al.* (1990) point out, such uncertainty about future sentiment represents an extra type of risk -- noise trade risk. When this risk is correlated across investors, as in the current setup, the equilibrium price will contain compensation for the risk. The price thus differs from the benchmark case in which noise trade risk does not exist.

Other than the growth rate of future earnings, noise traders and rational investors share common knowledge, including the distribution of θ_t, the conditional distribution of future earnings and the second moment of stock payoffs. In particular, both types of agents agree on the forecasts of t+1 earnings which they make at time t

$$E_t[X_{t+1}] = E_t[X^n_{t+1}] \ .$$

The assumption is reasonable given the wide availability of analyst earnings forecasts and that analyst forecasts of near-term earnings are rather accurate.

If the final wealth W_{t+1} in (1) is normally distributed (which turns out to be true in the equilibrium I consider), the expected utility maximization problem reduces to the particularly simple mean-variance maximization problem[11]:

$$E_t[W_{t+1}^i] - \rho \mathrm{var}_t[W_{t+1}] ,$$

subject to the constraint (1). Substituting wealth in the objective function with (1), and simplifying, one obtains

$$(E_t[P_{t+1}] + E_t[X_{t+1}^i] - R \cdot P_t)\lambda_t^i - \rho\sigma_{\bar{p},t}^2(\lambda_t^i)^2 , \text{ for } i \in \{n, r\}, \tag{4}$$

where $\sigma_{\bar{p},t}^2 \equiv \mathrm{var}_t[P_{t+1} + X_{t+1}]$.

For rational investors, the first-order condition for an interior maximization of (4) gives the optimal stock holding λ_t^r

$$\lambda_t^r = \frac{E_t[P_{t+1}] + E_t[X_{t+1}] - R \cdot P_t}{2\rho\sigma_{\bar{p},t}^2}. \tag{5}$$

The optimal stock holding by noise traders λ_t^n can be derived similarly

$$\lambda_t^n = \frac{E_t[P_{t+1}] + E_t\,[X_{t+1}^n] - R \cdot P_t}{2\rho\sigma_{\bar{p},t}^2}. \tag{6}$$

Both (5) and (6) have intuitive interpretations. For risk-averse agents of both types, their stock holdings increase with expected excess payoffs (i.e., risk premium), and decrease with risk, which comes from the two sources: the t+1 earnings and noise trader's future misperception about earnings growth.[12]

Equilibrium

The equilibrium price clears the stock market: the demands for the stock by both

[11] The variance term does not have the superscript i because I assume noise traders correctly perceive the second moment.

[12] λ_t^r and λ_t^n can be negative, which means agents are allowed to short sell the stock. Moreover, the current setup does not rule out the possibility of negative final wealth.

types of agents must equal to the supply

$$1 = \mu \lambda_t^n + (1-\mu)\lambda_t^r .$$

Substituting (5) and (6) into the equation above, and solving for P_t, one obtains the equilibrium price

$$P_t = \frac{1}{R}\left(E_t[P_{t+1}] + (1-\mu)E_t[X_{t+1}] + \mu E_t\,[X_{t+1}^n] - 2\rho\sigma_{\tilde{p},t}^2\right). \tag{7}$$

Equation (7) is a generalization of the standard no-arbitrage formula. Letting $\mu = 0$, i.e., all agents are rational, Equation (7) reduces to

$$P_t = \frac{E_t[P_{t+1} + X_{t+1}]}{R} - \frac{2\rho\sigma_{\tilde{p},t}^2}{R} .$$

That is, the current price equals to the next period payoff, discounted at the risk free rate, and adjusted for risk. Higher future payoff increases the current price while the more volatile payoffs reduce the price. The price decreases with risk aversion of agents.

The next goal is to derive a price function that does not contain the endogenous $E_t[P_{t+1}]$. I consider the steady-state equilibria in which the (conditional) distribution of P_{t+1} and X_{t+1} are identical across periods. As shown in the appendix, the equilibrium valuation, expressed as the price-to-forward earnings ratio (FPE), only depends on exogenous earnings flows and model fundamentals -- the earnings growth rate, noise traders' sentiment, agents' risk attitude, the risk-free rate, and the volatility of future stock payoffs.

Proposition. The price-to-forward earnings ratio based on the equilibrium price is

$$FPE_t = \frac{1-\mu}{R-\theta} + \frac{\mu}{R-\theta^*} + \frac{\mu(\theta_t - \theta^*)}{R(R-\theta^*)} - \frac{2\rho\hat{\sigma}^2_{\bar{p},t}}{r}, \tag{8}$$

where

$FPE_t \equiv P_t / E_t[X_{t+1}]$,

$\hat{\sigma}^2_{\bar{p},t} \equiv \sigma^2_{\bar{p},t} / E_t[X_{t+1}]$.

Equation (8) shows that both rational and noise traders' beliefs influence the stock valuation in equilibrium. It is made possible by the assumption that both types of agents must sell their holdings in the next period. The short horizon assumption is critical to limit rational traders' arbitrage which would otherwise offset mispricing.

Equation (8) closely relates to the standard expression for the "price-fundamental" ratio. To see that, setting $\mu = 0$ reduces (8) to the familiar Gordon Growth Formula

$$FPE_t = \frac{1}{R-\theta} - \frac{2\rho\hat{\sigma}^2_{\bar{p},t}}{r}.$$

Testable Implications

First, the mean of noise traders' belief about future earnings growth θ^* has a greater effect on the valuation than a particular realization θ_t does. In fact, any realization θ_t only transiently affects the price. That is because in the current setup neither noise traders nor rational investors have perfect foresights about future sentiment. So any contemporary sentiment only influences the price (by a discounted amount) over one period. By contrast, the mean of noise traders' belief influences all future earnings flows perceived by noise traders (rational traders take this fact into account as well). The impact of the mean belief accumulates and thus shows up in the equilibrium valuation.

The presence of both parameters θ^* and θ_t in the equilibrium valuation suggests that there are at least two types of sentiment effects. The first one is a pure "fad", which shifts frequently. Such high-frequent change in sentiment is unlikely to be particularly of economics interest because its nature is not different from background noise. The second type of sentiment is investors' attitude and psychology over a longer timeframe. Slow shifts in average opinions of market participants are far more important in understanding stock valuation, as argued above. I will mainly focus on the mean θ^* in comparative static analysis.

Second, equation (8) confirms the first-cut investment principle -- the price-forward-earnings ratio increases with expected growth but decreases with risk.[13] To versify the first half of the statement, consider comparative statics of the equilibrium valuation with respect to noise traders' and rational investors' growth beliefs, separately:

$$\frac{\partial FPE_t}{\partial \theta} = \frac{1-\mu}{(R-\theta)^2} > 0 \ , \tag{9}$$

$$\frac{\partial FPE_t}{\partial \theta^*} = \frac{\mu \theta_t}{R(R-\theta^*)^2} > 0 \ . \tag{9'}$$

A similar positive relation between FPE and the average belief about earnings growth ($\mu\theta^* + (1\text{-}\mu)\theta$) follows immediately.

Equation (8) corresponds to the common empirical specification in the valuation literature (e.g., Cragg and Malkiel 1982; Penman 1996; Thomas and Zhang 2006). The empirical counterpart of $\partial PFE_t/\partial\theta$ or $\partial PFE_t/\partial\theta^*$ is the slope in a regression of the

[13] The second half of the statement is trivial because in (8) PFE_t is negatively proportional to $\hat{\sigma}^2_{\bar{p},t}$.

forward P/E ratio on expected growth. It reflects investors' willingness to pay for expected growth. Therefore, $\partial PFE_t/\partial\theta$ or $\partial PFE_t/\partial\theta^*$ is the valuation of growth as termed in this study.

Third, the valuation of growth increases with investor optimism, as made clear below:

$$\frac{\partial Val\ Grw_t}{\partial\theta^*}=\frac{\mu\theta_t}{(R-\theta^*)^3}>0\ , \qquad (10)$$

where $Val\ Grw_t = \partial FPE/\partial(\mu\theta^*+(1-\mu)\theta)$. The relation is another way to describe the convexity between the forward P/E ratio and sentiment-inflicted (average) growth belief. As a consequence of capitalization the forward P/E ratio tends to fluctuate more dramatically than expected growth.

Even though the model is essentially static, the prediction can be tested using the time-variation in the valuation of growth. I distinguish between the cross-sectional valuation of growth and the valuation of aggregate growth. The former involves a growth premium for individual stock valuation in the cross section. The latter is a growth premium assigned to equity as a whole.

Justification of a Consumption-based Sentiment Measure

Here I show the link between consumption willingness and investment decision. The model presented above is a special case of the intertemporal consumption-based asset pricing model. Because all agents must consume all their wealth in the second period, future stock payoffs perceived by agents will have a direct effect on the future consumption they perceive. Let the *irrational* consumer confidence (or consumer sentiment) be

$$E_t[W_{t+1}{}^n] - E_t[W_{t+1}]\ ,$$

where $E_t[W_{t+1}^n]$ is the expected consumption/wealth when the equilibrium price is determined in the presence of noise traders, and $E_t[W_{t+1}]$ is the expected consumption/wealth when the price is determined by only rational investors. It is easy to verify that irrational consumer confidence co-moves with noise traders' mean perception about earnings growth.

Corollary. The irrational consumer confidence increases with θ^*.

The statement justifies the approach to extract an investor sentiment measure from consumer confidence surveys. Fisher and Statman (2003) document that consumer confidence measures (such as the Index of Consumer Confidence by University of Michigan) are correlated with direct survey measures of investor sentiment[14]. Lemmon and Prtniaguina (2006) show that consumer confidence and its sentiment component help to explain the size premium. In the rest empirical analysis I follow Lemmon and Prtniaguina (2006) to construct a sentiment component of consumer confidence, which is unrelated to macroeconomic variables. For the comparison and robustness purpose, I also report the test results using a sentiment index developed by Baker and Wurgler (2006).

[14] Such include the measure based on the survey conducted by the American Association of Individual Investors and an index constructed from surveying investment newsletter writers.

IV. EMPIRICAL APPROACH AND DATA

Empirical Approach

The analysis in the previous section leads to the main prediction: variation in the valuation of growth can be explained by changes in investor sentiment, unwarranted by economic fundamentals, i.e., relation (10). Due to social, psychological, or institutional reasons, sentiment shifts between bullish and bearish.[15] Waves of sentiment inevitably affect investor attitudes towards growth and their willingness to pay for growth.

When sentiment is high, investors are optimistic about general conditions of stock markets. With such optimism, investors may find high future earnings growth a particularly attractive trait. Some behave so simply because they believe exceptional growth may actually substantiate in a favorable environment. Others favor high growth stocks because these stocks are good targets for speculation. Regardless of exact rationales, optimistic investors bid up prices for high growth stocks, whereas depress prices of stocks whose earnings are expected to only grow modestly: growth becomes "expensive".

When sentiment is low, investors are skeptical to rosy growth stories. Rather, many follow the strategy of "flight to quality": buy stable, mature, acyclical stocks with only modest growth and sell stocks whose high growth is unlikely to realize. The reallocating of funds results in the narrowing valuation gap between high and low growth stocks. Consequently, a lower valuation of growth is observed.

Because broad-based sentiment displays its variation in time series, I test the

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[15] This study does not attempt to explicate sources of sentiment. See Barberis and Thaler (2003) for a review of the psychological phenomena that are relevant to stock markets.

prediction using time-series analysis:

$$Valuation\ of\ Growth_t = f(Sentiment_t, Controls)\ . \qquad (11)$$

The valuation of growth can be measured both in the cross section of individual stocks and at the aggregate market level. In the former case, the LHS of model (11) is the Growth Response Coefficient (GRC for short), which can be conveniently estimated at each date using a cross-sectional regression similar to (8). The estimated GRC is then regressed against sentiment measures time serially. So the hypothesis is tested in the exact form of model (11). In the latter case, the market level data does not allow one to obtain a GRC-like measure. Instead, I test the *conditional* effect of sentiment when examining the time-series relation between market valuation and expected growth in aggregate earnings.

Sample

The firm-level data are from the merged CRSP-COMPUSTAT-IBES database. The final sample contains all common stock issuers, excluding financial institutions and utilities, between 1982 and 2005.[16] Admittedly, the sample is biased towards large-cap stocks. But Baker and Wurgler (2006) show evidence that large-cap stocks are less sensitive to sentiment. So the sample bias works against rejecting the null hypothesis. Another concern is that IBES coverage changes over time. To address this issue, I repeat all analyses over non-financial/utility S&P 500 stocks, which IBES consistently covers throughout the sample period. The results are qualitatively similar.

[16] 1982 is the first year when IBES provided long-term growth forecasts (LTG).

Measure the Cross-Sectional Valuation of Growth

I estimate the cross-sectional valuation of growth, i.e., the sensitivity of stock valuation to expected growth, from a cross-sectional regression

$$FEY_{it} = \gamma_{1t} LTG_{it} + \gamma_{2t} RISK_{it}, \tag{12}$$

where FEY is the forward earnings yield, LTG is the consensus (median) long-term growth forecasts. RISK controls for systematic risk. Both price and forecast data are obtained at the third month of each calendar quarter. Regression (11) is an empirical version of equation (8) in the previous section.

The forward earnings yield is the one-year-ahead forward EPS divided by stock price. Its inverse, the forward P/E ratio, has become the primary valuation metric in practice. Using forward earnings rather than trailing earnings is justified on the ground that forward earnings are *the* attribute that investors (should) focus on. The one-year-ahead forward EPS is extrapolated from earnings forecasts over various horizons, whenever data available. This adjustment ensures that forward earnings contain as much forecast information as possible. [17] Using the forward earnings yield ensures the dependent variable to be continuous even when forward earnings happen to be zero.

I use consensus (median) long-term growth forecasts (LTG) to proxy for expected earnings growth that investors may consider during the valuation process. Some may question the validity of LTG on the grounds that (i) analyst forecasts may not adequately

[17] EPS forecasts that IBES surveyed at a time close to the end of a fiscal year are not entirely forward-looking, but a mixture of realizations and forecasts. For example, in a consensus forecast for 2004 annual EPS surveyed in November, 2004, the fourth quarter component is a forecast. The components for the rest three quarters are already realized.

proxy for market's expectation of earnings growth, and (ii) they are documented to be irrational (i.e., La Porta 1996; Dechow *et al.* 2001; Chan *et al.* 2003). I, however, contend that these concerns are less a problem in the current setting. For the first concern, the validity of this proxy does not hinge on the assumption that LTG exactly surrogates the stock market expectation. Rather, the proxy is sensible as long as investors use LTG as an input in valuation decision.[18] For the second concern, the irrationality in analyst forecasts reduces the test power. So the findings of rejecting the null hypothesis remain robust despite the bias. Figure 1 depicts the level and volatility of the forward-earnings yield and LTG over time. The co-movement of the two variables is clearly visible.

[Insert Figure 1 here]

The coefficient for LTG, γ_{1t}, is the measure for the cross-sectional valuation of growth at date t, which I refer to as the *Growth Response Coefficient* (GRC for short). GRC is expected to have a *negative* sign: investors must give up short-term payoff (in terms of the earnings yield) for long-term benefits (in terms of long-term earnings growth). The larger the magnitude of GRC is, the more expensive growth is priced.

GRC serves as a desirable measure for the cross-sectional valuation of growth for several reasons. First, GRC captures the key tradeoff that investors must make: giving up near-term benefit (i.e., the forward earnings yield) for future payoffs (i.e., long-term earnings growth). Second, GRC is unit-free and unrelated to the level of growth, making comparisons straightforward. Third, GRC can be conveniently estimated using a cross-

[18] Related, LTG is not meant to be the number which one can literally extrapolate future earnings from a base. Instead, one should consider LTG as an indicator of investors' expectation on growth. LTG may potentially summarize a spectrum of aspects related to growth, say, precision in growth expectation, robustness of growth, growth horizon, and so on.

sectional regression.[19]

Two sets of systematic risk proxies are used in model (12): (a) market beta (BETA); and (b) factor loadings from the Fama-French three factor model (i.e., loadings on market, size, and B/M). Both sets of risk proxies are estimated over rolling 36-month windows.

[Insert Table 1 here]

[Insert Figure 2 here]

Model (12) is estimated quarterly from 1982: I to 2005: IV, separately for each set of risk proxies. The resulting two series are described in Table 1 and plotted in Figure 2. These plots show that GRC fluctuates considerably over the sample period.[20] The peaks and troughs of the estimated GRC are visually aligned with anecdotal accounts of bull and bear markets. Take Panel A, which plots the GRCs controlling for market beta. GRC reaches its peak in the first half of 1987, leading to the market crash in October of that year. The bear market turned out to be swift and stock markets advanced with resilience. This recovery process is captured by an upward curve up to early 1990s. GRC bottoms again in 1998 when stock markets were depressed by the ripple of the financial crisis in South-East Asia and Russia. Under the Fed's strong intervention, stock markets soon rebound and became the most spectacular bull market in recent history, which is clearly identified by the highest peak in the sequence.

I formally test the stability of the estimated GRC. For each quarter between 1982 and

[19] At the market level, it is not feasible to obtain a GRC-like measure. However, the concept of the valuation of aggregate growth remains well defined and bears the similar interpretation as GRC. See Section VI for further discussion.

[20] The GRC plotted in Figure 1 is the absolute value of the original estimates. The transformation facilitates interpretation.

2005, the following pair of regressions is jointly estimated using the Seemingly Unrelated Regression (SUR):

$$\begin{aligned} FEY_{it} &= \gamma_{1t} LTG_{it} + \gamma_{2t} RISK_{it} \\ FEY_{i,t-4} &= \gamma_{1,t-4} LTG_{i,t-4} + \gamma_{2,t-4} RISK_{i,t-4} \,. \end{aligned} \tag{13}$$

The null hypothesis is $\gamma_{1t} = \gamma_{1t\text{-}4}$. I then count the occasions of rejecting the null. As shown in Panel D in Table 1, the null is rejected in 77% of 92 pairs of adjacent years below or at the 10% significance level, for both GRC measures. The results provide formal support to the casual observation that investors change attitude to growth over time.

The estimated GRC is rather persistent. The first-order autocorrelation of GRC_M over the whole sample period equals 0.79. But the autocorrelation declines reasonably fast and becomes statistically insignificant after 4 lags. Both series are stationary, as shown in the augmented Dickey-Fuller test.

Descriptive statistics in Panel C in Table 1 reveal other features of the estimates. First, the two sequences of GRC obtained with different risk controls are almost indistinguishable. It offers some comfort that the measurement of GRC is not sensitive to systematic risk control. Second, both GRC_M and GRC_3F are reliably negative, suggesting that model (12) is empirically sensible. Third, the average R^2 from all cross-sectional regressions remains low (8% for GRC_M and 11% for GRC_3F). It suggests that factors other than expected growth and systematic risk play important roles in determining stock valuation in the cross section. Model (12), at most, is a crude approximation to the underlying valuation function.

The sign of GRC is somehow arbitrary. GRC is negative under the specification of regression (12), and is accordingly interpreted as a short- vs. long-term tradeoff. But the negative-signed GRC is inconvenient when one wants to talk about whether growth is cheap or expensive. Also notice that the GRC estimates remain reliably negative. So taking the absolute value transforms the original series monotonically, and does not affect the validity of the inference I intend to draw.

Investor Sentiment Measures

I rely on the finance literature to select measures for investor sentiment. Prior research has used two types of measures for market-wide investor sentiment: survey and trading data. Studies using survey measures for sentiment include Fisher and Statman (2002), Lemmon and Portniaguina (2006); studies using trading measures include Lee *et al.* (1991), Baker and Wurgler (2000), Lowry (2003), Baker and Stein (2004), Baker and Wurgler (2004). Brown and Cliff (2005) compare and evaluate multiple sentiment measures. The literature, however, has yet reached consensus on which measure (or which type of measure) should be favored.

In this study I use both types of measures: a measure based on consumer confidence survey (Lemmon and Portniaguina 2006) and a composite index based on trading variables (Baker and Wurgler 2006, 2007). My choice is necessarily a balance between intuitiveness, existing empirical support, and data accessibility.

The choice of the consumer confidence-based measure follows the findings in Lemmon and Portniaguina (2006). First, the authors find that both consumer confidence and its sentiment component (i.e., unrelated to fundamentals) explain the time variation in size premium. The findings suggest that optimistic investors overvalue small stocks relative to large stocks and vise versa. Second, the authors report that stocks with low (high) institutional ownership have low (high) future returns following initial high measured sentiment. Third, consumer confidence has been shown to be correlated with direct surveys of investor sentiment (Fisher and Statman 2002; Qiu and Welch 2006) and to predict aggregate market returns (Charoenrook 2002). Following Lemmon and Portniaguina (2006), I regress the Index of Consumer Expectation from the University of Michigan's Consumer Confidence Survey on a set of macroeconomic variables. The residual is used as a proxy for investor irrational sentiment, which is referred to as the *Sentiment Component of Consumer Confidence* (SC).[21]

The trading measure for sentiment is the composite index developed by Baker and Wurgler (2006, 2007), referred to as the *Sentiment Index* (SI). According to the authors, the measure is the first principle component of six sentiment proxies, including closed-end fund discount, stock market turnover, IPO numbers and first-day returns, the share of equity issues in total capital raising, and dividend premium.

These proxies have been suggested in the literature to proxy for sentiment. For example, Lee *et al.* (1991) argues that closed-end fund discount varies with individual investor sentiment. Baker and Stein (2004) model trading activities such that high liquidity (turnover) results from irrational investor optimism. IPO activities have long been considered to reflect investor sentiment (i.e., Ritter 1991; Lowry 2003). Baker and Wurgler (2000) find the more equity in total capital raising predicts low market returns. Baker and Wurgler (2004) show that firms' initialization and omission of dividends

[21] Appendix B details the construction of the SC measure.

relates to dividend premium, a proxy for investor uninformed demand for dividend paying stocks.

Using the Sentiment Index, the authors show that cross-sectional future return patterns change according to ex ante sentiment, consistent with the hypothesis that sentiment asserts differential influence in the cross section. Additionally, to the extent that each underlying variable captures some aspect of investor sentiment, the SI measure has the advantage of compressing rich information. To remove the influence of economic fundamentals, before putting underlying variables into forming the SI measure, the authors regress each variable on a set of macroeconomic variables (i.e., orthogonization). I obtain the monthly orthogonalized SI series from Jeffrey Wurgler (http://www.stern.nyu.edu/~jwurgler/).

Both SC and SI measures are as of the second month of each calendar quarter. Because GRC is measured at the quarter end, using lagged sentiment measures helps address the concern that it is sentiment that causes GRC to fluctuate, and not vise versa.

[Insert Table 2 here]

[Insert Figure 3 here]

Table 2 summarizes both SC and SI measures.[22] The first impression is that there is significant variation in both measures over the sample period. The autocorrelation in both the sequences are strong. Similar to GRC, the autocorrelation declines to reasonable level after four quarters. Unfortunately, the two measures are not particularly highly correlated, despite the statistical significance (see Table 3). The visual inspection of Figure 3

[22] Both measures are scaled by 10 to be quantitatively comparable to the magnitude of GRC.

suggests that SC seems to lead while SI lags. This pattern is consistent with the idea that belief leads trading behaviors.

V. CROSS-SECTIONAL VALUATION OF GROWTH

This section seeks to answer whether the fluctuation in the cross-sectional valuation of growth can be attributed to changes in investor sentiment. I first describe the empirical regression, along with discussing estimation issues. Empirical results are presented next.

Regression Model

To test the prediction that growth becomes more expensive as sentiment grows increasingly optimistic, I use the following time-series regression:

$$GRC_t = a_1 SENTIMENT_t + a_2 INT_t + a_3 VOL_t + a_4 ANAFLW_t + a_5 GDPG_t \ . \qquad (14)$$

Here GRC is the Growth Response Coefficient, estimated from the cross-sectional regression (12) in the previous section. I use two series of GRC, which differ in risk controls in regression (12): (i) GRC_M is the LTG slope controlling for market beta; (ii) GRC_3F is the LTG slope controlling for loadings on the Fama-French three factors (market, size, and B/M).

Regression (14) uses the *absolute value* of the estimated GRC (they are originally negative; see section IV). Using positive GRC facilitates interpretation: The larger GRC is, the more expensive expected earnings growth is priced.

The coefficient for investor sentiment (SENTIMENT), a_1, is my main focus. I predict a_1 to be *positive*: to the extent that sentiment measures capture factors contributing mispricing, the high (low) GRC is a manifestation of overpricing (underpricing) of growth. I use two measures for sentiment: the Sentiment Component of Consumer Confidence (SC) and the Sentiment Index (SI).

Regression (14) controls for fundamental factors that may contribute to the variation in GRC, which I describe below. Interest rates have a major impact on stock stocks. The regression controls for *real* interest rates because stocks are claims to real productive capital and their valuation is hedged against inflation. In economic theory, real interest rates rise in expansions and drop in recessions. Thus, I predict a positive relation between real interest rates and GRC.[23] Real interest rates (INT) is measured as the three-month Treasury bill yield, minus the inflation rate.

I also include market volatility (VOL) in regression (14). Stock market volatility is shown to positively relate to expected returns, either as a risk proxy (French *et al.* 1987), or through volatility feedback (Campbell and Hentschel 1992). To the extent that market volatility causes stock prices to drop more than it does to earnings growth expectations, market volatility should negatively relate to GRC. Following French *et al.* (1987), I measure VOL as *ex ante* volatility, the GARCH estimate of the volatility in the value-weighted CRSP stock index.

GRC may fluctuate along with stock market information environments. Specifically, long-term growth forecasts better explain the cross-sectional variance in the forward earnings yield when the former contains more value-relevant information. At the extreme, GRC would drop to zero when long-term growth forecasts contain pure noises. Higher analyst following indicates that more resources are devoted to information processing and that forecasts may be more informative (e.g., Alford and Berger 1999; Frankel and Li

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[23] Heuristically, during an expansion large demands for capital by companies push interest rates high. Conversely, in a recession low capital demands cause interest rates to fall. Alternatively, one may also predict a negative relation between real interest rates and GRC. Both variables reflect economic agents' tradeoffs between current and future. During periods when current consumption is valued more (i.e., real interests rates are high), investors should also be reluctant to give up too much for future earnings (i.e., GRC is low). Of course, the effect of interest rates on real economy, capital market, and agent expectation is far more complex than described here and the issue remains unsolved even in economics. A full-fledged discussion of the topic is beyond the scope of this paper.

2004). Thus I include the average number of analysts following the sample stocks (ANAFLW) in the regression.

Some may be still concerned that the sentiment measures used here reflect economic fundamentals, despites the efforts of isolating such influences when constructing these measures. In particular, if sentiment measures merely track expansions and contractions of the economy, it would not be surprising that GRC comoves with sentiment measures.[24] To address the issue, I include growth in real gross domestic product (GDPG) as an indicator of business cycles. The variable is calculated as the change in log real per capita GDP, times 100.

GRC and sentiment measures are persistent, even though the autocorrelation decays to a modest level beyond the fourth lag (see descriptive statistics in Table 1 and Table 2). Preliminary estimations of regression (14) reveal that OLS residuals are correlated. These data features, taken as a whole, suggest that OLS standard errors for coefficients are likely to be biased downwards and that the null hypothesis is rejected too often. Following Lemmon and Portniaguina (2006), I report the *t*-statistics constructed from Newey-West standard errors (with four lags). Alternatively, I (i) include an autoregressive term to account for residual serial correlation; (ii) bootstrap to correct biases in OLS coefficients and generate standard errors. The results are qualitatively similar.

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[24] When business conditions are good, high expected growth is likely to realize, and meanwhile, investors may become less risk averse. Both lead to a wider gap in the valuation between high and low growth stocks, i.e, a large GRC. When business conditions are poor, high growth becomes less feasible. Rational investors valuate high growth stocks less, resulting in a small GRC. Following the similar logic, Johnson (1999) finds that earnings persistence and earnings response coefficients are higher in expansion periods than in contraction periods.

Empirical Results

Table 4 presents the regression results. Over the sample period 1982 - 2005, there exits a positive and significant relation between GRC and the sentiment measures, indicating that growth becomes more expensive as sentiment increases.[25] Browsing across columns reveals that the relation between GRC and sentiment is robust to using different measures. Comparing the two measures for sentiment, the SI measure appears statistically more significant. This comes as no surprise because the measure is directly constructed from trading patterns, and thus is more likely to capture factors influencing stock valuation. To examine the economic significance of coefficient, take the first column as an example. One-SD increase in sentiment (measured in terms of SC) is associated with a 37%-SD increase in GRC_M. Such increase in GRC means that investors now must give up extra 16 basis points (in forms of the earnings yield) in exchange of one extra percentage point of expected growth.

[Insert Table 4 here]

The adjusted R^2 for the regression is about 0.22~0.25, quite stable across the columns. The incremental contribution to adjusted R^2, after including sentiment as an additional explanatory variable, is 0.12 and 0.06, for GRC_M and GRC_3F, respectively. The noticeable drop in the incremental R^2 between the two GRC measures comes as no surprise if one accepts the behavioral explanation for the size and book-to-market factors.

[25] Despite the contemporaneous regression design here, I cautiously make the causal inference for two reasons. First, behavioral finance theory treats investor sentiment as the cause of mispricing (e.g., Barberis and Thaler 2003). The causality follows to the extent that sentiment measures capture the theorized factors. Second, sentiment is measured at the 2nd month of a quarter, whereas GRC is estimated at the 3rd month. Because sentiment measures predate GRC, it is less plausible that the causality goes from GRC to sentiment.

Alternatively, if one buys into rational explanations (elaborated in section VIII), the sentiment measures are probably contaminated by fundamental factors. Taken as a whole, the sizeable improvement in the model fitness reinforces the prediction that sentiment contributes to the fluctuation in GRC.

Control variables largely behave as predicted. Real interest rates (INT) positively relate to GRC and are by far the most significant explanatory variable. Market volatility has a negative coefficient (for the GRC_3F columns), consistent with the notion that high perceived risk makes investors less willing to pay for future growth. Average analyst following and GDP growth are in the right sign, but statistically insignificant.

Overall, results in Table 4 support the main prediction that changes in market-wide sentiment explain fluctuations in the *cross-sectional* valuation of growth. The statistical relation documented suggests that bullish investors are willing to pay lofty price for (likely inflated) rosy expectations on future earnings growth. In contrast, bearish investors are reluctant to do so and thus growth appears to be cheap.

VI. VALUATION OF AGGREGATE GROWTH

This section investigates the influence of investor sentiment on the valuation of growth at the market level. This analysis is in interest of its own: it captures how investors' attitude to equity as a broad asset class may be influenced by sentiment. In addition, the cross-sectional effect of sentiment reported above raises the concern that if the sentiment effect is largely idiosyncratic, it might be canceled out through diversification. The market-level analysis helps clarify this issue.

The valuation of aggregate growth is the *intertemporal* sensitivity of market-level valuation to expected growth in aggregate earnings. The construct is qualified by the slope for aggregate growth forecasts in the following time-series regression

$$FPE_t^m = \theta_1 LTG_t^m + \theta_2 RISK_t^m, \tag{15}$$

where FPE^m is the market P/E, the ratio of the aggregate market value to aggregate forward earnings; both components are summed over sample stocks. LTG^m is the aggregate growth forecast, constructed as follows

$$LTG_t^m = \left(\frac{\sum_i (1 + LTG_t^i)^5 AE_t^i}{\sum_i AE_t^i} \right)^{1/5}.$$

Here AE_t^i is stock i's reported earnings for the most recent fiscal year, available by the end of quarter t. LTG_t^i is the stock's long-term growth forecasts reported by IBES. This way of aggregation is the so-called "bottom-up" approach in practice. Both FPE^m and LTG^m are in natural logarithm. The sample includes all industrial stocks in the merged CRSP-COMPUSTAT-IBES database over the period 1982 - 2005.

Unlike GRC, the growth slope θ_1 in regression (15) pertains to the valuation of aggregate growth over the *entire* sample period, not a point in time. For this reason, a time-series regression like (14) is not viable for the market-level analysis. Instead, I modify regression (15) into the following "conditional" regression:

$$FPE_t^m = a_0 + a_1 LTG_t^m + a_2 SENTIMENT_t \times LTG_t^m + a_3 SENTIMENT_t \\ + a_4 NINT_t + a_5 PREM_t \,. \tag{16}$$

The regression is so-called because the response of FPE^m to LTG^m is conditional on the contemporaneous level of sentiment. In other words, the valuation of aggregate growth $a_1 + a_2 SENTIMENT_t$ becomes a (linear) function of investor sentiment. My main interest is the coefficient a_2, the conditional effect of sentiment on the valuation of aggregate growth. The higher is sentiment, the more expensive is aggregate growth valued. Hence I predict a_2 to be positive.

Regression (16) controls for nominal interest rates (NINT) and equity risk premium (PREM), both related to the discount factor in valuation. I use the nominal ten-year Treasury bond yield, partially motivated by the empirical relation between the equity yield and nominal interest rates (also known as the "Fed" model. See Asness 2003; Campbell and Vuolteenaho 2004). Equity risk premium is measured as the future return in the CRSP stock index, in excess of the three-month Treasury bill return. Both variables are expected to be negative, as a large discount factor reduces equity valuation, given a level of expected growth. I estimate regression (16) with respect to both measures for investor sentiment: the Sentiment Component of Consumer Confidence (SC) and the Sentiment Index (SI).

Estimation and Inference are taken into account the persistence of variables and error autocorrelation. As in the previous section, t-statistics are constructed from Newey-West standard errors (for 4 lags). A close inspection of the data reveals that FPE^m and LTG^m

have unit roots: the p-values of the augmented Dickey-Fuller test is 0.45 and 0.29, for FPE^m and LTG^m, respectively. Nevertheless, I argue that this data feature can be reasonably excluded on the ground of economic theory. Rational investors would certainly not expect the rate of growth in future earnings to explode. Instead, the growth rate should revert to a "normal" level. A similar argument can be made for the market P/E. (In fact, the existence of nonstationarity in these financial ratios may be a manifestation of mispricing.) Campbell and Yogo (2006) have a similar discussion regarding the dividend yield. To verify the validity of inference based on standard statistical methods, I take seasonal difference on FPE^m and LTG^m, which results in both series to be stationary. Inferences are qualitatively similar when I re-estimated regression (16) (with a slight modification to the specification) using the differenced series.

[Insert Table 5 here]

The first column of Panel C in Table 5 reports the results, when SC is a sentiment measure. The interaction term between sentiment and aggregate growth forecast ($SENTIMENT_t \times LTG_t^m$) is positive and significant at the 1% level. It provides formal support to the prediction: when sentiment is high, aggregate growth forecast is priced with a premium; the valuation of aggregate growth declines when sentiment falls. In economic terms, when sentiment (measured by SC) is one standard deviation above the "no-sentiment" case, aggregate growth is valued, *on the margin*, 42% higher (See Panel D in Table 5). Comparing the two sentiment measures, SC vs. SI, one may notice that the trading-based measure SI appears less significant than the survey-based SC. It is likely caused by the stronger persistence of SI. Judging from incremental R^2, SI clearly provides more explanatory power than SC. The rest variables behave as expected: aggregate growth (LTG^m) remains positive and significant, whereas nominal interest rates (NINT) and risk premium (PREM) are negative.

The findings in this section suggest that aggregate earnings growth is also valued differently, depending on sentiment regimes. It implies that sentiment has broad effect on stock valuation, beyond the cross-sectional effect documented in the previous section. Aggregation/ diversification does not completely diminish the sentiment effect. These findings corroborate those in Brown and Cliff (2005) and Lamont and Stein (2004, 2006), which show that sentiment contributes the inefficiency at the market level.

VII. IS GROWTH MISPRICED?

Sorting on LTG

The behavioral explanation for the findings in the previous sections is that expected growth is mispriced under the influence of sentiment. While intriguing, such explanation is subject to criticism: The inference largely hinges on the validity of sentiment measures. To gain further insight on the mispricing of growth, I examine cross-sectional patterns of stock returns that can be identified by expected growth. La Porta (1996) documents future returns are predictable by ex ante LTG. Baker and Wurgler (2006) examine predictability patterns in returns, *conditional* on sentiment, an approach I follow here. They, however, didn't examine expected earnings growth.

I predict that changes in sentiment over time and differential expected growth in the cross section combine to create rich patterns in returns.[26] Specifically, when sentiment is high, stocks with high expected growth tend to be more overvalued than stocks with low expected earnings growth. Subsequently, the former underperforms the latter as overpricing is gradually corrected. In contrast, when sentiment is low, over-pessimistic investors take defensive actions by selling high growth stocks and holding "quality" stocks. So subsequently high growth stocks outperform low growth stocks.

[Insert Table 6 here]

Table 6 sorts sample stocks both on LTG and on *ex ante* SI measure for sentiment. Specifically, I first sort stocks into ten equal-weighted deciles on the basis of LTG at the

[26] Baker and Wurgler (2006) argue that some stocks are sensitive to sentiment influence and are faced with large market frictions that prevent arbitrageurs from stabilizing price. In the current setting, stocks with high expected growth are valued inherently with more subjectivity, and thus their valuations are more sensitive to sentiment. Meanwhile, these same stocks are often small, young, and less liquid, factors that all deter arbitrageurs from betting against mispricing.

end of each calendar quarter between 1982:I and 2005:IV.[27] Portfolio returns are cumulated over three-, six- and twelve-month periods subsequent to formation. Next, I group LTG portfolios based on the sentiment level at the formation date. A sentiment level is identified as high if the reading of the IS measure is above the 60th percentile of the measure's historical distribution, and low if below the 40th percentile.

As shown in Panel B in Table 6, raw returns of LTG deciles exhibit the predicted conditional cross-sectional patterns. For example, following initial low sentiment, the top (highest growth) decile outperforms the bottom (lowest growth) decile by 2.5% over subsequent six months. The relative performance reverses following high sentiment: The top decile underperforms the bottom decile by 9.4%. The performance reversal is consistent with the prediction that growth stocks are more prone to sentiment influence and to be mispriced. The nonparametric Wilcoxon test confirms that the reversal of relative performance between high and low growth stocks is statistically significant.

It is also noticeable that return spreads are larger (in magnitude) following high sentiment than following low sentiment. The asymmetry may reflect the institutional nature of short-sells constraint: pessimistic investors are prohibited from short selling in down-turn markets.

The sentiment effect can also be observed for individual portfolios. The bottom

[27] The decile breakpoints are based on all stocks available, rather than NYSE stocks only. Prior studies use NYSE breakpoints to ensure that extreme portfolios are not dominated by stocks traded at one particular exchange. However, LTG for NYSE stocks in recent quarters are not well dispersed. Sorting stocks into deciles based on NYSE breakpoints would result in too many ties, and in some quarters, fails to form middle portfolios. To verify that the sorting results do not depend on the choice of breakpoints, I also analyzed the decile and quintile portfolios formed using NYSE breakpoints. The results remain largely unchanged.

decile performs virtually the same across sentiment regimes (the return spread between the two regimes is only -0.4% over six moths). The spread widens when moving towards the upper deciles and reaches the maximum 11.5% for the top decile. Examining other characteristics (see Panel A in Table 6) reveals distinctions between high and low LTG stocks. The lower deciles are big-cap, dividends-payers. These are "safe" stocks whose valuation can be anchored around objective and proven track records. The upper deciles are small-cap, investment intensive, and currently less profitable. Because these stocks' valuation heavily relies on expected growth, it is hardly a surprise that they are sensitive to sentiment.

The conditional effect of sentiment on cross-sectional return patterns is robust to return period and return measurement. Expanding return horizon makes the conditional effect more prominent. For example, over one year, the return spread between the top and bottom deciles is 4.0% following low sentiment, whereas the spread is -21.8% following high sentiment. In Panel C in Table 6, the conditional effect remains qualitatively similar when abnormal returns from the market model are used.

[Insert Figure 4 here]

Figure 4 illustrates Panel B and C graphically. Other than the inferences drawn above, it reveals two more interesting patterns. First, returns across deciles are on average lower following high sentiment (solid bars) than following low sentiment (clear bars). The result is consistent with prior findings that sentiment (weakly) predicts market returns (e.g., Brown and Cliff 2004; Baker and Wurgler 2007). Second, the upward pattern of the difference in conditional returns (solid lines) appears inconsistent with the U-shaped curve reported by Baker and Wurgler (2006, Panel J, Figure 2, pp. 1663). But they form deciles based on historical sales growth. Such sorting may leave risky, speculative stocks on the two tails and stable, mature stocks in the middle. Forecasted growth is more likely to reveal the sentiment impact because sentiment inherently pertains to (otherwise rational) growth expectations.

Sorting on the PEG Ratio

The reported predictability power of LTG comes from two sources: erroneous *expectation* on growth and erroneous *valuation of growth*. A sharper design would examine whether *ex ante* valuation of growth relates to subsequent returns. The PEG (price/earnings-to-growth) ratio can be considered as capturing a relation between the forward P/E and growth for individual stocks. Sorting on the PEG ratio thus better focuses on the valuation of growth, not growth expectation itself. The ratio has gained some acceptance as a valuation metric in practice, which also warrants a careful examination of its merits.

[Insert Table 7 here]

Table 7 reports the sorting results based on the PEG ratio and the SI measure of sentiment. The PEG ratio is the stock price, dividend by one-year-ahead forward earnings and LTG (in percentage). Panel A reports characteristics of the PEG deciles. Despite that the sorting produces a wide range for the PEG ratio, it is also apparent that the forward earnings yield and LTG exhibit the opposite trends across portfolios. Stocks in the bottom decile have depressed prices relative to LTG and forward earnings, while stocks in the top decile have high prices relative to LTG and forward earnings. These two groups are apparently anomalous considering the usual positive relation between the forward earnings yield and LTG. Decile 6 has the PEG ratio close to one, the textbook benchmark of correct valuation. Except decile 10, average size increases monotonically from the bottom to top. Readings from other characteristics give rise to conflicting pictures of constituent stocks as well. For example, stocks in the bottom decile have high historical EPS growth, low dividend payout, high B/M, and stock prices performed poorly in the past. In light of these characteristics, high LTG of these stocks are likely to be biased/ outdated forecasts by analysts. The top decile stocks performed equally disappointing, in terms of both fundamentals and stock prices. Stocks on both tails possess such characteristics that they are sensitive to sentiment influence.

[Insert Figure 5 here]

Figure 5 illustrates raw (abnormal) returns for PEG portfolios, conditional on formation-date sentiment (also reported in Panel B (C) of Table 7). Compared to the sorting based on LTG, two main patterns emerge. First, unconditional future returns exhibit a U-shape. That is, both tails tend to underperform to the middle deciles. Second, the difference between conditional returns is a reversed U-shape. This is consistent with the early observation that stocks on the two tails are sensitive to sentiment, and thus more susceptible to mispricing.

In summary, the results from sorting on LTG/PEG are consistent with the hypothesis that growth can be mispriced under the influence of sentiment: mispricing occurs among stocks with fast growth and stocks whose growth is valued extremely. As prevailing sentiment shifts between pessimism and optimism, these stocks go through from undervaluing to overvaluing.

VIII. ALTERNATIVE EXPLANATIONS

In this section I examine rational explanations for the fluctuation in the valuation of growth, as alternatives to the sentiment explanation. The alternative explanations in the rational framework look at either (rational) risk premium or rational growth expectations. Evidence exists that risk premium indeed changes over time (e.g., Ferson and Harvey 1991). It also seems plausible that rational investors change their expectations on growth upon available information. While each single piece of evidence can be reconciled with some rational explanation, no coherent rational theory exits which explain all the evidence collectively.

Growth and risk are so closely related that it is almost self-evident that high growth means high risk and vise versa. Thus, at the first glance, risk should play some role in driving the changing valuation of growth. A more careful analysis, however, reveals that a classic rational setting can not account for the time-varying valuation of growth reported in section V and VI.

First, consider the valuation of growth for the aggregate market. The market P/E ratio rises when the risk premium declines. High expected growth and low risk premium are likely to concur during good business conditions. However, despite that regression (16) controls for risk premium, the conditional effect of sentiment on the valuation of aggregate growth remains significant (see Panel C of Table 5).

Second, GRC may vary with time-varying risk premium. Low risk premium means low discount rates; future growth will be discounted less and valuation grows higher. So GRC moves opposite to risk premium. To examine the risk premium explanation, I include measures for risk premium in the time-series regression (12) and examine whether the sentiment measure retains incremental explanatory power. Drawing upon prior finance literature I consider two sets of measures for risk premia. The first set includes spreads for empirical risk factors: market, B/M, size, and momentum.[28] The second set is associated with economic state variables identified by Chen *et al.* (1986) – industrial production (replaced by GDP growth), default spread, and term spread.[29]

[Insert Table 8 here]

Table 8 shows the results. Both the SC and SI measures of sentiment remain largely significant, albeit weaker. Risk premium measures are mostly insignificant.

Changes in the risk premium cannot explain the future return patterns documented in Section VII. I maintain the heuristic "high growth means high risk." Now suppose high (low) sentiment periods coincide with low (high) risk premium. It follows that the spread in expected returns between high and low growth stocks is narrow (wider) in high (low) sentiment periods. The results in Table 6 and Table 7 do not support this prediction. Contradictorily, the spread is larger following high sentiment. The risk premium explanation runs into further difficulty in light of the reversal in the spread following different sentiment regimes.

It seems even less plausible to attribute fluctuations in the valuation of growth to investors' rational expectations. The irrationality of analyst growth forecasts is well documented in the literature (e.g., La Porta 1996; Dechow *et al.* 2000; Chan *et al.* 2003;

[28] I caution that exact economic interpretations for the empirical risk factors remain unsettled; the behavioral explanation has gained increasing acceptance.

[29] These variables are merely *state variables*, neither risk factors or risk premia. Estimating a time-series of risk premium is empirically challenging. Common estimation methods rely on overlapped observations and, as a result, introduce autocorrelation into estimates. Resulting estimates are often very noisy. For these reasons, I use the state variables themselves. The inference is made on the assumption that the time-variation in state variables is correlated to the time-variation in underlying risk premia.

Hughes *et al.* 2008). Rational investors would discount rather than overreact to analyst growth forecasts when such forecasts become extreme. The results in this study are in sharp contrast to such a scenario.

IX. CONCLUSIONS

Fundamental analysis centers on the P/E ratio and expected growth. The relation between the two, called the *valuation of growth* in this study, matters to both investors and management. In the root, the valuation of growth relates to the underlying valuation process. This study seeks to understand why expected earnings growth is valued differently over time. Specifically, I examine the behavioral hypothesis that sentiment-induced mispricing causes growth to be priced differently.

The empirical findings confirm that the valuation of growth varies with investor sentiment, both in the cross section of individual stocks and at the aggregate market level. I also find that cross sections of future returns vary with initial sentiment. The patterns are intriguing. Following a period of high sentiment, stocks whose growth is likely to be mispriced (i.e., high LTG, and extreme PEG) underperform stocks insensitive to sentiment. Following periods of low sentiment, cross-sectional return patterns reverse. Collectively, these results are consistent with the behavioral view in which sentiment causes the mispricing of growth. Overly optimistic investors pay too much for good growth prospects, despite the fact that expected growth is likely to be biased. Pessimistic investors behave in the opposite. I consider the alternative explanations that changes in risk premia or rational growth expectations drive the valuation of growth. However, these explanations cannot explain the findings as a whole.

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APPENDIX A

DERIVATION OF THE PRICE FUNCTION (8)

The appendix derives equation (8) in Section III. First assume the (conditional) distribution of P_{t+1}, X_{t+1}, and $X_{t+1}{}^n$ are identical across periods. The assumption enables me to iterate equation (7) forward. In doing so, note that X_{t+1}, and $X_{t+1}{}^n$ follow different processes in expectation, defined by (2) and (3), respectively. I also assume that for all s, θ_{t+s} and $E_{t+s}[X.^n]$ are conditionally independent so that

$$
\begin{aligned}
& E_t[\ldots E_{t+s}[E_{t+s+1}[X_{t+s+2}{}^n]]\ldots] \\
&= E_t[\ldots E_{t+s-1}[\theta_{t+s}E_{t+s}[X_{t+s+1}{}^n]]\ldots] \\
&= E_t[\ldots E_{t+s-2}[\theta^* E_{t+s-1}[X_{t+s+1}{}^n]]\ldots] \\
&= \ldots \\
&= (\theta^*)^s \theta_t E_t[X_{t+1}], \qquad \text{for } s = 0,1,\ldots.
\end{aligned}
$$

Equation (7) then becomes

$$
\begin{aligned}
P_t = {} & R^{-T}E_t[P_{t+T}] + (1-\mu)\left(\sum_{s=1}^{T} R^{-s}\theta^{s-1}\right)E_t[X_{t+1}] \\
& + \mu\left(\theta_t \sum_{s=2}^{T} R^{-s}(\theta^*)^{s-2} + R^{-1}\right)E_t[X_{t+1}] - 2\rho\sigma_{\bar{p},t}^2 \sum_{s=1}^{T} R^{-s}.
\end{aligned}
$$

When $T \to \infty$, and the transversality condition $\lim_{T\to\infty} R^{-T}E_t[P_{t+T}] = 0$ is satisfied, the equation can be further simplified into

$$
\frac{P_t}{E_t[X_{t+1}]} = \frac{1-\mu}{R-\theta} + \frac{\mu}{R-\theta^*} + \frac{\mu(\theta_t - \theta^*)}{R(R-\theta^*)} - \frac{2\rho\sigma_{\bar{p},t}^2}{rE_t[X_{t+1}]}\,. \tag{8}
$$

APPENDIX B

CONSTRUCT THE SC MEASURE FOR SENTIMENT

I follow the method in Lemmon and Portniaguina (2006, LM for short) to estimate a sentiment component of consumer confidence (SC). Specifically, I regress consumer confidence measures on a set of macroeconomic variables that the literature has suggested as the basis of rational expectations. The regression residual will be used to proxy for irrational investor sentiment.

Among various measures of consumer confidence, I choose the Index of Consumer Expectation (ICE), issued by the University of Michigan Survey Research Center.[30] The index is constructed from survey questions, which ask consumers about their views on future personal financial condition and economy.[31] Thus the index is forward looking, targets over a long (five-year) horizon, and closely relates to business conditions. For its importance in forecasting and understanding changes in the national economy, the U.S. Department of Commerce includes the index in the Leading Indicator Composite Index.

This study focuses on an irrational component of consumer confidence that is unrelated to economic fundamentals, i.e., the sentiment component (SC). Regress of the series of ICE on a set of macroeconomic variables and their lags (i.e., equation (1) in LM)

$$ICE_t = \alpha_1 GDP_t + \alpha_2 CONS_t + \alpha_3 LABOR_t + \alpha_4 UR_t + \alpha_5 DEF_t + \alpha_6 TERM + \alpha_7 YLD3_t + \alpha_8 INF_t + \alpha_9 DY_t\,, \qquad \text{(A.1)}$$

where the independent variables include GDP growth (GDP), personal consumption growth (CONS), labor income growth (LABOR), unemployment rate (UR), default

---

[30] The Survey Research Center started conducting the quarterly Survey of Consumers since 1946 and switched it to monthly from 1978 on. Minimum of 500 households are interviewed in each survey. See Charoenrook (2003) for additional detail regarding the survey.

[31] Each question is assigned a relative score, the difference between the percent of favorable and unfavorable replies, plus 100. The three relative scores then compose to ICE.

spread (DEF), term spread (TERM), risk-free rate (YLD3), inflation rate (INF) and dividend yield (DY). The data is quarterly from 1962:II to 2005:IV.[32] See Table A.1 for variable definitions and descriptive statistics.

[Insert Table A.1 here]

The Sentiment Component (SC) is the residual from the regression (A.1). To facilitate the comparison with the Sentiment Index (Baker and Wurgler 2006), I standardize the SC measure such that it has zero mean, and unit standard deviation.

[32] I run the regression over the full period between 1962:II and 2005:IV to increase the reliability of estimation. Using the shorter period between 1982:I and 2005:IV produces qualitatively similar results.

TABLE 1

Growth Response Coefficient (GRC), 1982:I - 2005:IV

Panel A. Variables for Estimating GRC

	Obs	Mean	Std	Min	Q1	Med	Q3	Max
FEY	163,316	0.08	0.04	0.00	0.05	0.07	0.09	0.98
Pre-1993	61,799	0.09	0.04	0.00	0.06	0.08	0.11	0.95
Post-1993	101,517	0.07	0.04	0.00	0.04	0.06	0.08	0.98
LTG	163,316	0.18	0.09	0.00	0.12	0.15	0.20	1.00
Pre-1993	61,799	0.16	0.08	0.00	0.11	0.15	0.20	1.00
Post-1993	101,517	0.18	0.09	0.00	0.12	0.16	0.22	0.99
BETA	161,784	1.19	0.73	-1.76	0.72	1.11	1.56	5.74
MKT	161,784	1.12	0.71	-2.08	0.68	1.06	1.49	5.19
SIZE	161,784	0.76	1.00	-3.70	0.09	0.66	1.33	6.68
BM	161,784	-0.02	1.22	-6.50	-0.69	0.07	0.75	4.65

All variables are at the end of calendar quarter. FEY is the forward earnings yield, in which forward earnings is median EPS forecasts for the coming 12 months. LTG is consensus (median) long-term growth forecasts. FEY and LTG are truncated between 0 and 1. BETA is estimated from the market model over 36 months. MKT, SIZE, and BM are loadings on the Fama-French three factors: market, size, and book-to-market, estimated from the three-factor model over 36 months. Risk proxies are truncated by 0.5% at both tails. The sample excludes financial institutions and utility companies.

Panel B. Correlation

	FEY	LTG	BETA	MKT	SIZE	BM
FEY		-0.24***	-0.11***	-0.03***	0.03***	0.13***
LTG	-0.30***		0.30***	0.12***	0.19***	-0.23***
BETA	-0.11***	0.30***		0.76***	0.14***	-0.28***
MKT	-0.03***	0.12***	0.74***		0.08***	0.24***
SIZE	0.04***	0.21***	0.13***	0.07***		0.15***
BM	0.14***	-0.23***	-0.28***	0.25***	0.15***	

The low and upper triangular report Pearson and Spearman correlation, respectively. *** indicates significance at 1%.

TABLE 1 (Continued)

Panel C. Estimated GRC, 1982:I - 2005:IV

$FEY_{it} = \gamma_{1t}LTG_{it} + \gamma_{2t}RISK_{it}$

	Obs	Mean	Std	Min	Q1	Med	Q3	Max	Avg. R^2	Autocorrelation 1	2	4	6	Unit Root
GRC_M	96	-0.11	0.04	-0.25	-0.14	-0.10	-0.08	-0.05	0.08	0.79*	0.60*	0.27	0.00	<.001
Pre-1993	44	-0.12	0.03	-0.20	-0.15	-0.12	-0.10	-0.06	0.06	0.73*	0.62*	0.49	0.24	
Post-1993	52	-0.10	0.04	-0.25	-0.11	-0.09	-0.08	-0.05	0.10	0.79*	0.55*	0.08	-0.19	
GRC_3F	96	-0.11	0.03	-0.20	-0.13	-0.11	-0.09	-0.04	0.11	0.73*	0.59*	0.32	0.10	<.001
Pre-1993	44	-0.13	0.03	-0.20	-0.15	-0.12	-0.11	-0.06	0.08	0.67*	0.56*	0.38	0.07	
Post-1993	52	-0.10	0.03	-0.20	-0.12	-0.10	-0.08	-0.04	0.14	0.68*	0.50*	0.10	-0.06	

The model is estimated by OLS over the cross section at the end of each calendar quarter. The slope for LTG (γ_1) is the Growth Response Coefficient (GRC). GRC_M is the estimated GRC when RISK is market beta (BETA). GRC_3F is the estimated GRC when RISK includes loadings on the Fama-French three factors (MKT, SIZE, BM). Avg. R^2 is the mean of adjusted R^2 from quarterly cross-sectional regressions. * indicates being greater than two standard errors. Unit Root reports the p-value from the augmented Dickey-Fuller test with the null hypothesis that there exists a unit root with a drift.

TABLE 1 (Continued)

Panel D. Stability of GRC						
		Confidence Level for the Stability Test				
Model		**< 1%**	**1 - 5%**	**5 - 10%**	**> 10%**	**Total**
GRC_M	Count	48	18	5	21	92
	%	52	20	5	23	100
GRC_3F	Count	55	13	3	21	92
	%	60	14	3	23	100

Between 1982 and 2005, the following pair of regressions is jointly estimated using the Seemingly Unrelated Regression (SUR)

$$FEY_{it} = \gamma_{1t}LTG_{it} + \gamma_{2t}RISK_{it}$$

$$FEY_{it\text{-}4} = \gamma_{1t\text{-}4}LTG_{it\text{-}4} + \gamma_{2t\text{-}4}RISK_{it\text{-}4}\,.$$

The null hypothesis is $\gamma_{1t} = \gamma_{1t\text{-}4}$. The table reports the count (percentage) of rejecting the null under various confidence levels.

TABLE 2

Measures for Investor Sentiment, 1982:I - 2005:IV

	Obs	Mean	Std	Min	Q1	Med	Q3	Max	Autocorrelation 1	2	4	6	Unit Root
The Sentiment Component of Consumer Confidence (SC)													
Overall	96	0.00	0.10	-0.28	-0.04	0.01	0.07	0.22	0.41*	0.34*	0.30*	0.19	0.03
Pre-1993	44	0.01	0.10	-0.23	-0.04	0.01	0.08	0.21	0.51*	0.49*	0.39	0.24	
Post-1993	52	-0.00	0.10	-0.28	-0.04	-0.00	0.07	0.22	0.33*	0.23	0.18	-0.01	
The Sentiment Index (SI)													
Overall	96	0.02	0.07	-0.13	-0.04	0.01	0.06	0.30	0.74*	0.61*	0.36	0.25	0.02
Pre-1993	44	0.02	0.08	-0.13	-0.04	0.02	0.07	0.28	0.84*	0.72*	0.52	0.47	
Post-1993	52	0.02	0.07	-0.08	-0.03	0.00	0.05	0.30	0.63*	0.46*	0.15	-0.01	

The data is quarterly as of months 2, 5, 8, 11. The Sentiment Component of Consumer Confidence (SC) is the residual from regressing the Index of Consumer Expectation on a set of macroeconomic variables. See Appendix A for the construction of the measure. The monthly Sentiment Index (SI) series is kindly provided by Jeffery Wurgler. SI is the first principal component of six variables: closed-end fund discount, NYSE turnover, numbers and first-day returns of IPOs, the equity share in total raised capital, and dividend premium. All contributing variables are first regressed on a set of macroeconomic variables to control for macroeconomic conditions. See Baker and Wurgler (2006, 2007) for further detail. Both measures are scaled by 10. * indicates being greater than two standard errors. Unit Root reports the p-value from the augmented Dickey-Fuller test with the null hypothesis that there exists a unit root with a drift.

TABLE 3

Variable Correlation, 1982:I – 2005:IV

	GRC_M	GRC_3F	SC	SI	INT	VOL	ANAFLW	GDPG
GRC_M		0.86***	0.34***	0.45***	0.36***	0.04	0.05	0.05
GRC_3F	0.88***		0.24**	0.37***	0.40***	-0.17	0.13	0.14
SC	0.19*	0.18*		0.36***	-0.06	0.15	-0.11	0.17*
SI	0.38***	0.26***	0.41***		0.31***	0.12	-0.19*	0.20*
INT	0.45***	0.40***	-0.01	0.31***		-0.02	0.10	-0.07
VOL	-0.06	-0.23**	0.20**	0.08	-0.02		-0.35***	-0.12
ANAFLW	0.11	0.14	-0.09	-0.22**	0.10	-0.28***		-0.11
GDPG	0.04	0.09	0.15	0.19*	0.05	-0.15	-0.13	

The data is quarterly. GRC_M (GRC_3F) is the Growth Response Coefficient, controlling for market beta (loadings on the Fama-French three factors). SC is the Sentiment Component of Consumer Confidence. SI is the Sentiment Index. INT is the real interest rate. VOL is the *ex ante* market volatility. ANAFLW is the average number of analysts following the sample stocks. GDPG is growth in real gross domestic product. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

TABLE 4

Time Series Regression of GRC on Investor Sentiment, 1982:I - 2005:IV

$$GRC_t = a_1SENTIMENT_t + a_2INT_t + a_3VOL_t + a_4ANAFLW_t + a_5GDPG_t$$

	Predicted Sign	GRC_M		GRC_3F	
		SC	**SI**	**SC**	**SI**
SENTIMENT	(+)	0.148***	0.216***	0.090**	0.131***
		(2.40)	(3.63)	(2.28)	(2.85)
INT	(+)	0.018***	0.011***	0.017***	0.012***
		(4.51)	(2.58)	(4.39)	(3.70)
VOL	(-)	0.028	0.079	-0.337	-0.306
		(0.08)	(0.20)	(-1.25)	(-1.13)
ANAFLW	(+)	0.004	0.008	0.004	0.007
		(0.31)	(0.77)	(0.43)	(0.74)
GDPG	(+)	0.004	0.001	0.014*	0.013
		(0.28)	(0.08)	(1.29)	(1.12)
Adj. R^2		0.22	0.23	0.24	0.25
Incremental R^2		0.12	0.13	0.06	0.07
Obs		96	96	96	96

The data is quarterly. The dependent variable is the Growth Response Coefficient (GRC). Two sets of GRC are estimated, different in risk control: (i) market beta (GRC_M); (ii) loadings on the Fama-French three factors (GRC_3F). Regression uses the absolute value of GRC. Investor sentiment (SENTIMENT) is measured by: (i) the Sentiment Component of Consumer Confidence (SC); (ii) the Sentiment Index (SI). INT is the real interest rate, measured as the three-month Treasury bill yield, minus the inflation rate. VOL is the *ex ante* market volatility, proxied by the GARCH estimate of the volatility of the value-weight CRSP stock index. ANAFLW is the average number of analysts following sample stocks. GDPG is growth in real gross domestic product. *t*-statistics are in parentheses, using Newey-West standard errors (lag = 4). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using a one-sided test. Incremental R^2 reports the improvement in adjusted R^2 after including sentiment measures.

TABLE 5

Valuation of Aggregate Growth and Investor Sentiment, 1982:I - 2005:IV

Panel A. Summary Statistics

	Obs	Mean	Std	Min	Q1	Med	Q3	Max
FPE^m	96	15.52	5.08	6.17	11.74	14.95	19.03	27.03
LTG^m	96	0.13	0.01	0.11	0.12	0.13	0.14	0.16
NINT	96	0.02	0.04	-0.06	-0.01	0.02	0.05	0.16
PREM	96	0.02	0.08	-0.25	-0.02	0.03	0.07	0.20

The data is quarterly. FPE^m is the market P/E ratio, where total market value and forward earnings are aggregated over all sample stocks. LTG^m is the annualized growth for forecasted aggregate earnings over a five-year period

$$LTG_t^m = \left(\frac{\sum_i (1 + LTG_t^i)^5 AE_t^i}{\sum_i AE_t^i} \right)^{1/5}.$$

NINT is the nominal ten-year Treasury bond yield. PREM is the excess return on the value-weight CRSP stock index, minus the three-month Treasury bill yield. PREM is one quarter ahead of the rest variables.

Panel B. Autocorrelation

	1	4	6	8	12	Unit Root
FPE^m	0.92*	0.74*	0.68*	0.60	0.38	0.48
LTG^m	0.85*	0.62*	0.52*	0.32	-0.00	0.29
ΔFPE^m	0.71*	-0.06	0.03	-0.00	-0.20	0.01
ΔLTG^m	0.59*	-0.10	0.15	0.09	-0.19	0.10

ΔFPE^m and ΔLTG^m are the seasonal difference of log FPE^m and log LTG^m. * indicates being greater than two standard errors. Unit Root reports the p-value from the augmented Dickey-Fuller test with the null hypothesis that there exists a unit root with a drift.

TABLE 5 (Continued)

Panel C. Time-Series Regression of the Market P/E on Aggregate Growth Forecast, Conditional on Investor Sentiment, 1982:I - 2005:IV

$$FPE_t^m = a_1 LTG_t^m + a_2 SENTIMENT_t \times LTG_t^m + a_3 SENTIMENT_t + a_4 NINT_t + a_5 PREM_t$$

	Sign	SC	SI
LTG^m	(+)	1.625***	2.190***
		(3.39)	(4.82)
$SENTIMENT \times LTG^m$	(+)	6.847***	6.829*
		(2.51)	(1.66)
SENTIMENT	(+)	13.432***	11.876*
		(2.49)	(1.49)
NINT	(-)	-1.559**	-1.563***
		(-2.34)	(-2.87)
PREM	(-)	-0.224	-0.226
		(-0.85)	(-1.10)
Adj. R^2		0.37	0.50
Incremental R^2		0.03	0.16
Obs		96	96

The data is quarterly. FPE^m and LTG^m are in natural logarithm. See Panel A for variable definitions. t-statistics are in parentheses, using Newey-West standard errors (lag = 4). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using a one-sided test. Incremental R^2 reports the improvement in adjusted R^2 after including sentiment terms SENTIMENT and $SENTIMENT \times LTG^m$.

Panel D. Conditional Effect of Sentiment in Economic Terms

		Valuation of Aggregate Growth	
Sentiment Level	**Formula**	**SC**	**SI**
Base Case: Sentiment = 0	$\hat{a}_1$	1.63	2.19
One SD above the Base	$\hat{a}_1 + \hat{a}_2 SENTIMENT$	2.31	2.67

Coefficient estimates are from Panel C.

TABLE 6

Portfolios Formed on LTG, 1982:I – 2005:IV

Panel A: Properties of Portfolios

Characteristics	1 Low	2	3	4	5	6	7	8	9	10 High	All
LTG	0.08	0.11	0.13	0.14	0.17	0.18	0.21	0.24	0.28	0.41	0.18
FEY	0.07	0.08	0.08	0.07	0.07	0.06	0.06	0.05	0.04	0.02	0.06
B/M	0.88	0.72	0.64	0.62	0.58	0.52	0.49	0.46	0.42	0.36	0.60
Size ($ Mil)	4191	4144	4291	2773	2179	1907	1986	1692	1153	1038	2781
Five-Year EPS Growth	0.01	0.05	0.08	0.08	0.14	0.16	0.19	0.26	0.29	0.39	0.13
Fraction of Profitability	0.74	0.82	0.85	0.83	0.82	0.81	0.80	0.78	0.71	0.59	0.78
Dividend Payout	0.59	0.51	0.55	0.25	0.30	0.11	0.13	0.10	0.05	0.06	0.31
R&D Intensity	0.17	0.02	0.03	0.04	0.04	0.05	0.08	0.46	0.18	1.64	0.21
Raw Returns	10.42	12.06	14.29	15.00	16.32	18.86	21.60	20.83	27.94	33.95	17.76
Abnormal Returns	-2.93	-0.88	1.36	-1.25	2.97	1.89	4.93	6.12	9.50	16.46	2.84

At the end of June of each year, 10 equal-weighted portfolios are formed on the basis of consensus (median) long-term growth forecasts (LTG). FEY is the forward earnings yield. B/M is the ratio of the book value of common equity (plus balance sheet deferred taxes) to market value. Size is the total market value of common equity, in millions. Five-Year EPS Growth is the slope of a fitted line over the past five-year positive EPS. Fraction of Profitability is the proportion of firms with positive earnings. Dividend Payout is the ratio of common dividends to earnings, if earnings are positive, or 0.08×common equity otherwise. R&D Intensity is the ratio of R&D expense to sales. Returns are cumulated over one year prior to formation (in percentage). Abnormal returns are calculated from the market model. The sample includes all industrial stocks in the merged CRSP-COMPUSTAT-IBES database, with LTG between 0 and 1. Accounting data from the fiscal year t-1 are matched to stock price and forecast data of year t.

TABLE 6 (Continued)

Panel B. Future Raw Returns by Sentiment and LTG

Sentiment	1 Low	2	3	4	5	6	7	8	9	10 High	Comparison 10 – 1	10 - 5	5 – 1
3 Months													
Low	5.04	5.11	5.34	5.91	4.94	7.76	6.63	6.13	6.49	7.81	2.76	1.90	1.44
High	4.19	3.95	4.25	3.34	4.37	5.00	2.71	2.96	0.93	0.28	-3.91	-3.93	0.10
Low - High	0.85	1.15	1.09	2.57	0.57	2.76	3.92	3.16	5.56	7.53**	6.67***	5.83**	1.34*
6 Months													
Low	8.68	8.21	8.50	8.74	8.10	10.24	8.59	8.56	8.91	11.15	2.47	2.78	1.27
High	9.04	9.01	9.15	7.79	9.00	9.00	5.73	5.40	2.27	-0.40	-9.44	-8.75	-0.25
Low - High	-0.36	-0.80	-0.65	0.95	-0.90	1.24	2.86	3.16	6.65	11.5***	11.9***	11.5***	1.52**
12 Months													
Low	17.05	15.51	16.68	16.66	17.84	21.01	16.24	17.33	18.05	21.08	4.03	4.93	2.73
High	18.31	18.88	18.56	16.19	17.20	15.43	11.28	8.77	2.73	-3.47	-21.8	-20.3	-1.48
Low - High	-1.26	-3.37	-1.88	0.48	0.64	5.58	4.96	8.57	15.32	24.6***	25.8***	25.2***	4.21***

At the end of each calendar quarter, 10 equal-weighted portfolios are formed based on LTG. The sentiment level at the formation date is identified as low if the SI measure (refer to TABLE 2 for the definition) is below the 40 percentile of the measure's historical distribution, and high if it is above the 60 percentile. The panel reports average post-formation portfolio returns (in percentage), over formation dates of low sentiment, formation dates of high sentiment, and the difference between these two averages. I test whether Low-High differs significantly from zero for decile 1, 5, 10, and the three comparisons. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using the one-sided Wilcoxon test.

TABLE 6 (Continued)

Panel C. Future Abnormal Returns by Sentiment and LTG

	1									10	Comparison		
Sentiment	**Low**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**10 – 1**	**10 - 5**	**5 – 1**
						3 Months							
Low	-0.03	-0.14	0.02	0.48	0.58	0.19	0.81	-0.09	-0.08	1.23	1.26	0.74	1.02
High	1.47	1.24	1.36	0.76	1.22	2.00	-0.51	-0.47	-2.45	-3.64	-5.11	-4.83	-0.26
Low - High	-1.50**	-1.38	-1.35	-0.28	-0.64	-1.81	1.32	0.38	2.37	4.87***	6.37***	5.57***	1.27*
						6 Months							
Low	0.32	-0.56	-0.31	-0.20	-0.03	-1.38	-0.29	-1.68	-1.79	0.18	-0.14	0.66	0.48
High	3.70	3.67	3.57	2.48	2.96	3.51	-0.48	-1.26	-4.47	-7.75	-11.4	-10.4	-0.74
Low - High	-3.4***	-4.23	-3.88	-2.67	-2.99**	-4.89	0.20	-0.42	2.68	7.92***	11.3***	11.1***	1.22*
						12 Months							
Low	0.58	-1.68	-0.62	-0.79	0.74	-0.49	-1.38	-2.39	-2.55	-0.04	-0.63	0.87	1.08
High	7.71	8.19	7.46	5.14	5.36	4.60	-0.99	-4.23	-11.1	-18.0	-25.7	-23.6	-2.39
Low - High	-7.1***	-9.88	-8.07	-5.93	-4.62**	-5.09	-0.39	1.84	8.54	18.0***	25.1***	24.5***	3.48***

Abnormal returns are calculated from the market model.

TABLE 7

Portfolios Formed on the PEG Ratio, 1982:I – 2005:IV

Panel A: Properties of Portfolios

Characteristics	**≤ 0**	**1 Low**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 High**	**All**
PEG	N/A	0.40	0.58	0.69	0.80	0.90	1.01	1.14	1.31	1.62	4.33	1.00
LTG	0.23	0.26	0.22	0.20	0.18	0.17	0.16	0.15	0.14	0.14	0.13	0.18
FEY	N/A	0.13	0.09	0.09	0.08	0.08	0.07	0.07	0.06	0.06	0.04	0.06
B/M	0.82	0.71	0.64	0.59	0.56	0.55	0.54	0.52	0.51	0.55	0.73	0.60
Size ($ Mil)	841.1	428.3	652.2	932.9	1375	2020	2372	3160	4835	6883	5314	2771
Five-Year EPS Growth	0.07	0.25	0.21	0.19	0.18	0.16	0.13	0.12	0.09	0.06	0.00	0.13
Fraction of Profitability	0.17	0.81	0.85	0.87	0.88	0.87	0.87	0.87	0.85	0.80	0.59	0.78
Dividend Payout	0.17	0.12	0.11	0.11	0.21	0.31	0.21	0.34	0.43	0.67	0.58	0.31
R&D Intensity	2.47	0.05	0.04	0.05	0.11	0.03	0.03	0.03	0.03	0.04	0.05	0.21
Raw Returns	-0.70	2.24	10.03	16.27	19.54	21.02	22.73	23.69	25.95	25.32	18.12	17.66
Abnormal Returns	-16.2	-13.8	-5.62	1.50	4.71	6.27	8.18	8.96	11.40	10.79	3.48	2.74

At the end of June each year, 10 equal-weighted portfolios are formed on the basis of the PEG ratio. The PEG ratio is stock price, divided by one-year-ahead forward earnings and LTG (in percentage). LTG is consensus (median) long-term growth forecasts. FEY is the forward earnings yield. B/M is the ratio of the book value of common equity (plus balance sheet deferred taxes) to market value. Size is the total market value of common equity, in millions. Five-Year EPS Growth is the slope of a fitted line over the past five-year positive EPS. Fraction of Profitability is the proportion of firms with positive earnings. Dividend Payout is the ratio of common dividends to earnings, if earnings are positive, or 0.08×common equity otherwise. R&D Intensity is the ratio of R&D expense to sales. Returns are cumulated over one year prior to formation (in percentage). Abnormal returns are calculated from the market model. The sample includes all industrial stocks in the merged CRSP-COMPUSTAT-IBES database, with LTG between 0 and 1. Accounting data from the fiscal year t-1 are matched to stock price and forecast data of year t.

TABLE 7 (Continued)

Panel B. Future Raw Returns by Sentiment and the PEG Ratio

		1									**10**	**Comparison**		
Sentiment	**≤ 0**	**Low**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**10 – 1**	**10 - 5**	**5 – 1**
						3 Months								
Low	7.31	6.43	6.12	6.16	6.41	6.09	5.95	5.54	5.15	4.66	5.02	-1.42	-1.07	-0.34
High	2.05	2.09	2.90	3.40	4.00	3.95	3.46	3.94	3.74	3.32	2.10	0.01	-1.84	1.86
Low – High	5.26	4.34**	3.22	2.77	2.40	2.15	2.49	1.61	1.41	1.33	2.92	-1.43*	0.77	-2**
						6 Months								
Low	11.11	8.33	8.89	8.99	9.50	9.34	9.44	8.67	8.28	7.63	7.99	-0.34	-1.34	1.01
High	3.55	4.46	6.47	7.20	8.25	8.19	7.48	8.15	7.99	7.53	4.84	0.38	-3.35	3.73
Low – High	7.56**	3.87**	2.43	1.79	1.25	1.14	1.96	0.52	0.29	0.10	3.15*	-0.71	2.01	-3***
						12 Months								
Low	22.94	15.29	16.80	16.25	17.61	18.00	17.65	17.17	16.17	16.17	17.94	2.65	-0.07	2.72
High	4.31	9.67	14.16	15.71	15.69	16.89	14.83	15.55	15.36	13.24	7.42	-2.25	-9.47	7.22
Low – High	19***	5.62*	2.64	0.54	1.92	1.11	2.82	1.62	0.80	2.92	10.5**	4.90	9.4***	-4.50*

At the end of each calendar quarter, 10 equal-weighted portfolios are formed based on the PEG ratio. The sentiment level at the formation date is identified as low if the SI measure (refer to TABLE 2 for the definition) is below the 40 percentile of the measure's historical distribution, and high if it is above the 60 percentile. The panel reports average post-formation portfolio returns (in percentage), over formation dates of low sentiment, formation dates of high sentiment, and the difference between these two averages. I test whether Low - High differs significantly from zero for decile 1, 5, 10, "≤ 0", and the three comparisons. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using the one-sided Wilcoxon test.

TABLE 7 (Continued)

Panel C. Future Abnormal Returns by Sentiment and the PEG Ratio

		1									10	Comparison		
Sentiment	**≤ 0**	**Low**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**10 – 1**	**10 - 5**	**5 – 1**
							3 Months							
Low	0.88	0.67	0.53	0.50	0.73	0.40	0.30	-0.01	-0.39	-0.83	-0.60	-1.27	-1.00	-0.27
High	-1.17	-1.26	-0.40	0.23	0.95	0.98	0.54	1.01	0.79	0.22	-0.83	0.43	-1.81	2.24
Low – High	2.04	1.93**	0.93	0.26	-0.22	-0.58	-0.24	-1.02	-1.18	-1.05	0.23	-1.7**	0.82	-3***
							6 Months							
Low	0.68	-1.19	-0.41	-0.47	0.10	0.05	0.14	-0.51	-0.94	-1.44	-1.10	0.09	-1.15	1.24
High	-2.57	-1.92	0.25	1.17	2.17	2.35	1.74	2.44	2.18	1.69	-1.07	0.85	-3.42	4.27
Low – High	3.25*	0.73	-0.66	-1.63	-2.07	-2.3**	-1.60	-2.95	-3.12	-3.12	-0.03	-0.76	2.28	-3***
							12 Months							
Low	2.82	-2.91	-1.11	-2.03	-0.63	-0.22	-0.66	-0.98	-1.70	-1.71	-0.22	2.70	0.00	2.69
High	-7.63	-3.53	1.59	3.40	3.46	5.19	3.38	4.19	3.94	1.91	-3.68	-0.15	-8.87	8.72
Low – High	10.5**	0.61	-2.70	-5.43	-4.09	-5***	-4.04	-5.16	-5.64	-3.62	3.46	2.85	8.9***	-6.0**

Abnormal returns are calculated from the market model.

TABLE 8

Time Series Regression of GRC on Sentiment, Controlling for Risk Premia, 1982:I – 2005:IV

$$GRC_t = a_1 SENTIMENT_t + a_2 VOL_t + a_3 ANAFLW_t + a_4 GDPG_t + RISK\ PREM$$

	GRC_M				GRC_3F			
	SC		SI		SC		SI	
SENTIMENT	0.14***	0.12**	0.29***	0.24***	0.08**	0.07**	0.18***	0.18***
(+)	(2.45)	(1.69)	(4.07)	(3.34)	(1.82)	(1.75)	(2.96)	(2.99)
VOL	-0.036	-0.139	0.127	-0.044	-0.361	-0.458	-0.294	-0.397*
(-)	(-0.07)	(-0.29)	(0.27)	(-0.09)	(-0.92)	(-1.29)	(-0.82)	(-1.29)
ANAFLW	0.006	-0.003	0.012	0.005	0.006	0.000	0.010	0.007
(+)	(0.56)	(-0.26)	(1.11)	(0.42)	(0.71)	(0.01)	(1.03)	(0.59)
GDPG	0.002	0.007	-0.003	0.003	0.015	0.021*	0.010	0.017*
(+)	(0.11)	(0.44)	(-0.16)	(0.22)	(1.11)	(1.66)	(0.78)	(1.39)
Risk Premium								
RMRF	-0.067		-0.000		-0.037		-0.003	
	(-0.84)		(-0.00)		(-0.56)		(-0.05)	
SMB	0.096		0.037		-0.057		-0.091	
	(0.87)		(0.37)		(-0.71)		(-1.15)	
HML	-0.035		-0.085		0.022		-0.020	
	(-0.30)		(-0.86)		(0.24)		(-0.26)	
UMD	0.079		0.098*		0.038		0.043	
	(0.93)		(1.49)		(0.61)		(0.88)	
DEF		0.087		0.043		0.053		0.017
		(1.08)		(0.58)		(0.90)		(0.32)
TERM		0.001		0.001		0.002**		0.002**
		(0.65)		(1.10)		(1.82)		(2.09)
Adj. R^2	0.08	0.11	0.21	0.20	0.08	0.12	0.17	0.21

TABLE 8 (Continued)

The data is quarterly. GRC_M and GRC_3F are defined in TABLE 1 and SC and SI are in TABLE 2. VOL is the *ex ante* market volatility, measured as the GARCH estimate of CRSP index return variance. ANAFLW is the average number of analysts following the sample stocks. GDPG is growth in real gross domestic product. RMRF is the excess return of the value-weight CRSP index over the risk-free rate. SMB is the return spread between small and large ME portfolios. HML is the return spread between high and low BM portfolios. UMD are the return spread between high and low momentum portfolios. (These portfolios are taken from Ken French's website and are described in more detail there.) DEF is the default spread, measured as the yield difference between Moody's Baa- and Aaa-rated corporate bonds. TERM is the term spread, measured as the yield spread between a ten-year Treasury bond and a one-month Treasury bill. All returns are holding period. *t*-statistics are in parentheses, using Newey-West standard errors (lag = 4). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using a one-sided test.

TABLE A.1

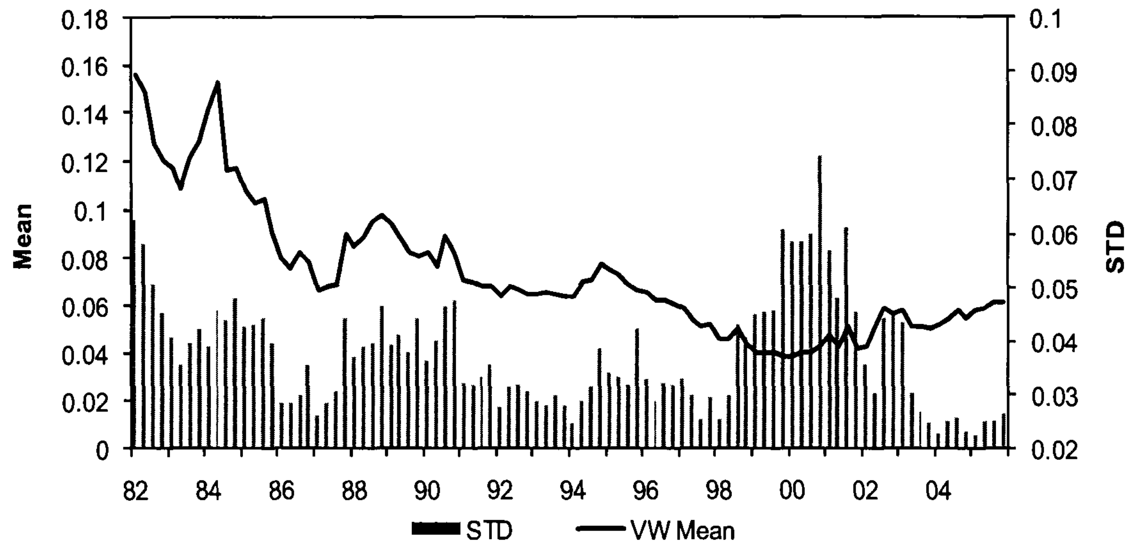
Variables for Estimating the Sentiment Component of Consumer Confidence

	Obs	Mean	Std	Min	Q1	Med	Q3	Max
ICE	178	81.78	13.84	45.30	71.50	83.55	91.50	107.8
GDP	178	0.35	0.36	-0.89	0.17	0.35	0.54	1.68
CONS	178	0.26	0.31	-1.11	0.10	0.27	0.44	1.09
LABOR	178	0.22	0.46	-1.15	0.01	0.23	0.42	2.22
UR	178	5.87	1.47	3.40	4.93	5.68	6.87	10.67
DEF	178	0.25	0.11	0.08	0.18	0.22	0.30	0.67
TERM	178	0.41	4.26	-9.61	-2.12	-0.25	2.67	14.11
YLD3	178	1.53	0.76	0.24	1.03	1.40	1.90	4.25
INF	178	1.08	0.86	-1.01	0.53	0.93	1.53	4.43
DY	178	3.25	1.10	1.45	2.50	3.08	4.05	6.11

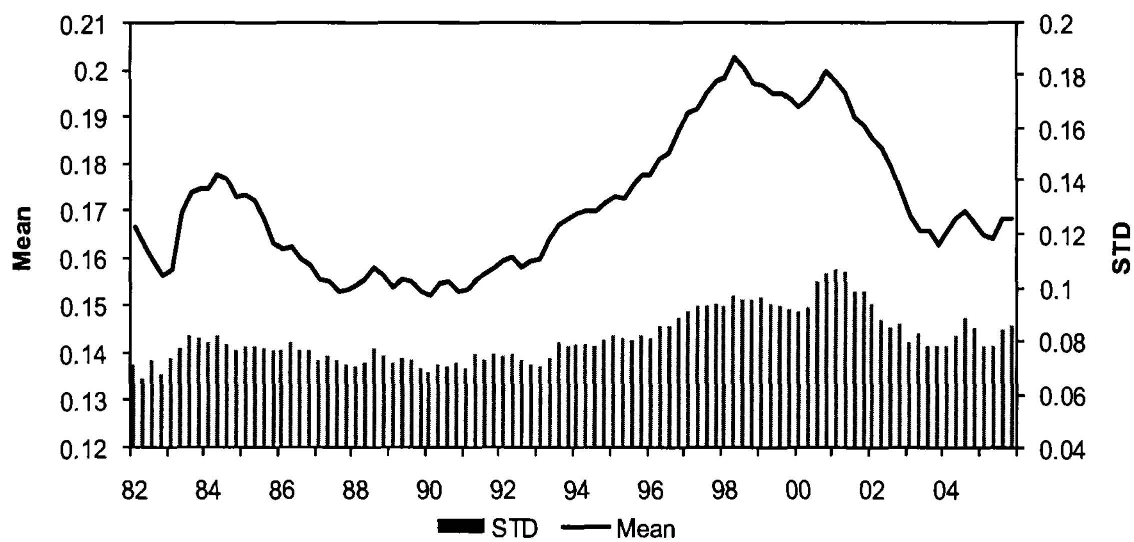
All data are quarterly as of months 3, 6, 9, 12, expect ICE (2, 5, 8, 11). ICE is the Index of Consumer Expectation issued by the University of Michigan. GDP is growth in gross domestic product, measured as the change in log real GDP, times 100. CONS is personal consumption growth, measured as the change in log personal expenditures (real and per capita), times 100. Personal expenditures include spending on durable goods, nondurable goods, and services, LABOR is labor income growth, measured as the change in log labor income (real and per capita), times 100. Labor income is measured as total personal income, net of dividends and interests. UR is the unemployment rate, averaged over three months in each quarter. DEF is the default spread, calculated as the difference in yields of Moody's Baa- and Aaa-rated corporate bonds. TERM is the term spread, calculated as the difference in the yields of a ten-year Treasury bond and a one-month Treasury bill. YLD3 is the 3-month Treasury bill yield. INF is the inflation rate, measured as the change in CPI. DY is the dividend yield for all CRSP stocks. All returns are holding period.

FIGURE 1

Variables for Estimating GRC, 1982:I – 2005:IV



A. Time Plot of the Forward Earnings Yield

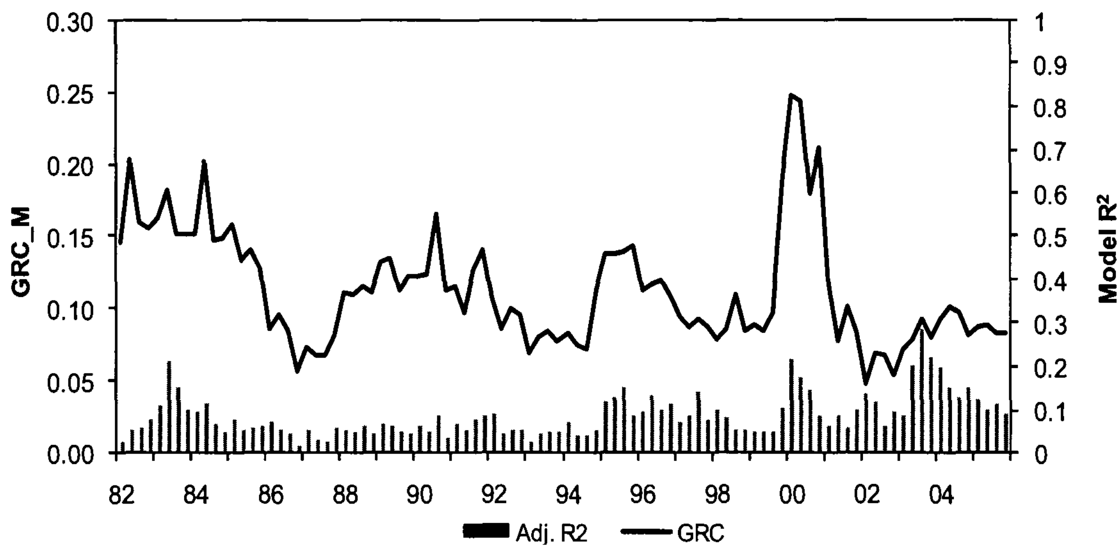


B. Time Plot of the Analyst Long-Term Growth Forecasts

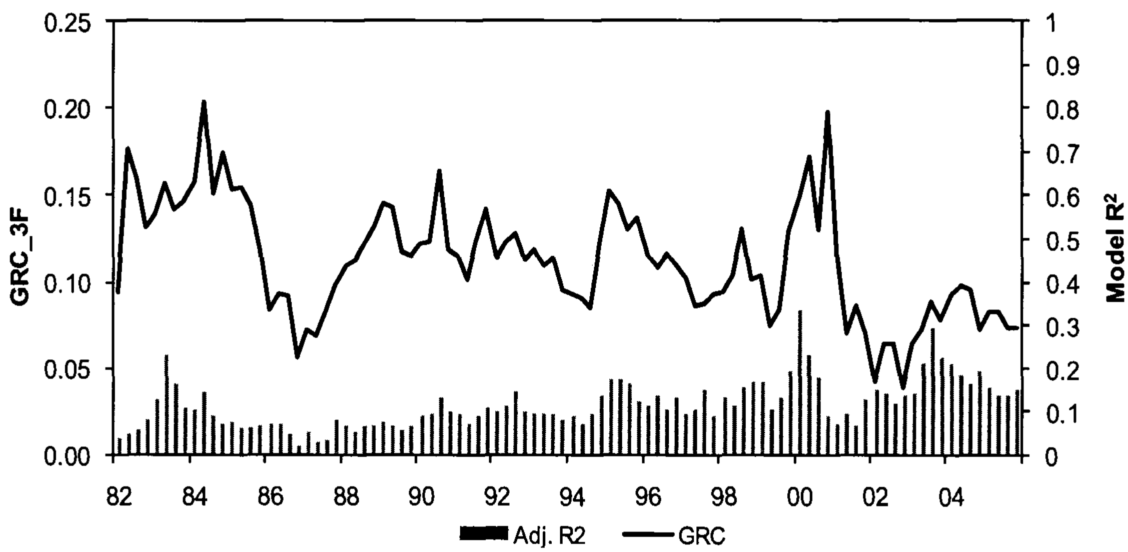
The forward earnings yield (FEY) is the one-year-ahead forward EPS divided by stock price. Long-term growth forecasts (LTG) are consensus (median) forecasts in IBES.

FIGURE 2

Time Plot of Estimated GRC, 1982:I – 2005:IV



A. Controlling for Market Beta



B. Controlling for Loadings on the Fama-French Three Factors

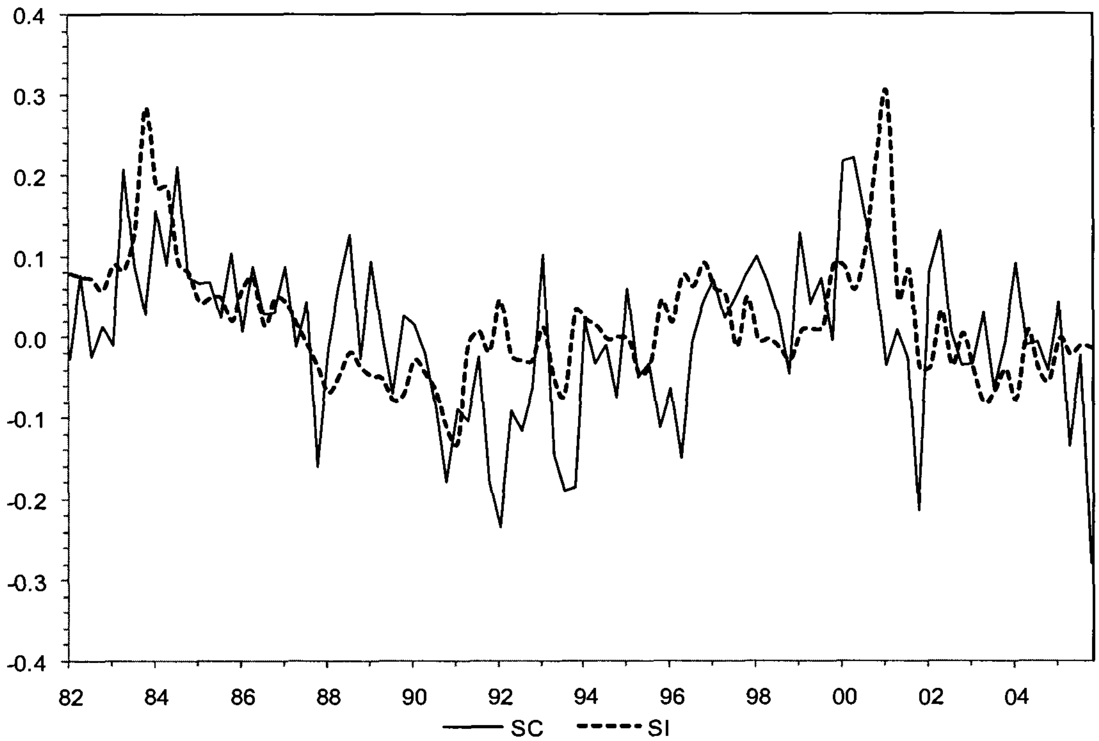
At each calendar quarter end, the following cross-sectional model is estimated using OLS

$$FEY_{it} = \gamma_{1t}LTG_{it} + \gamma_{2t}RISK_{it},$$

where FEY is the forward earnings yield and LTG is long-term growth forecasts. The Growth Response Coefficient (GRC) is the regression slope for LTG (γ_1). Panel A (B) shows GRC_M (GRC_3F), estimated with market beta (loadings on the Fama-French three factors, i.e., market, size and B/M). The solid line is GRC (left axis). The columns are regression R^2 (right axis).

FIGURE 3

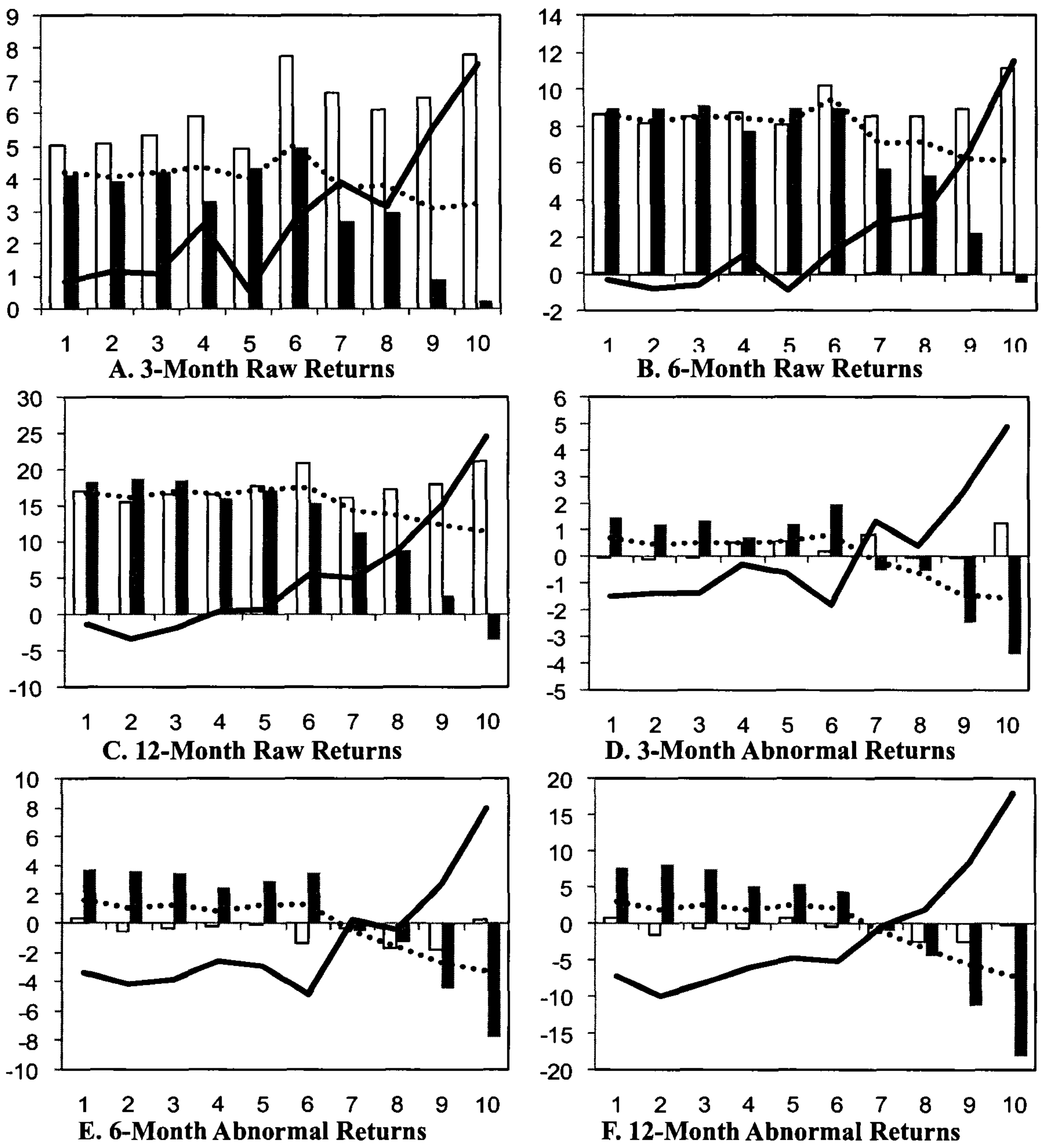
Measures for Investor Sentiment, 1982:I – 2005: IV



The data is quarterly as of months 2, 5, 8, 11. The Sentiment Component of Consumer Confidence (SC) is the residual from regressing the Index of Consumer Expectation on a set of macroeconomic variables. See Appendix A for the construction of the measure. The monthly Sentiment Index (SI) series is kindly provided by Jeffery Wurgler. SI is the first principal component of six variables: closed-end fund discount, NYSE turnover, numbers and first-day returns of IPOs, the equity share in total raised capital, and dividend premium. All contributing variables are first regressed on a set of macroeconomic variables to control for macroeconomic conditions. Both measures are scaled by 10.

FIGURE 4

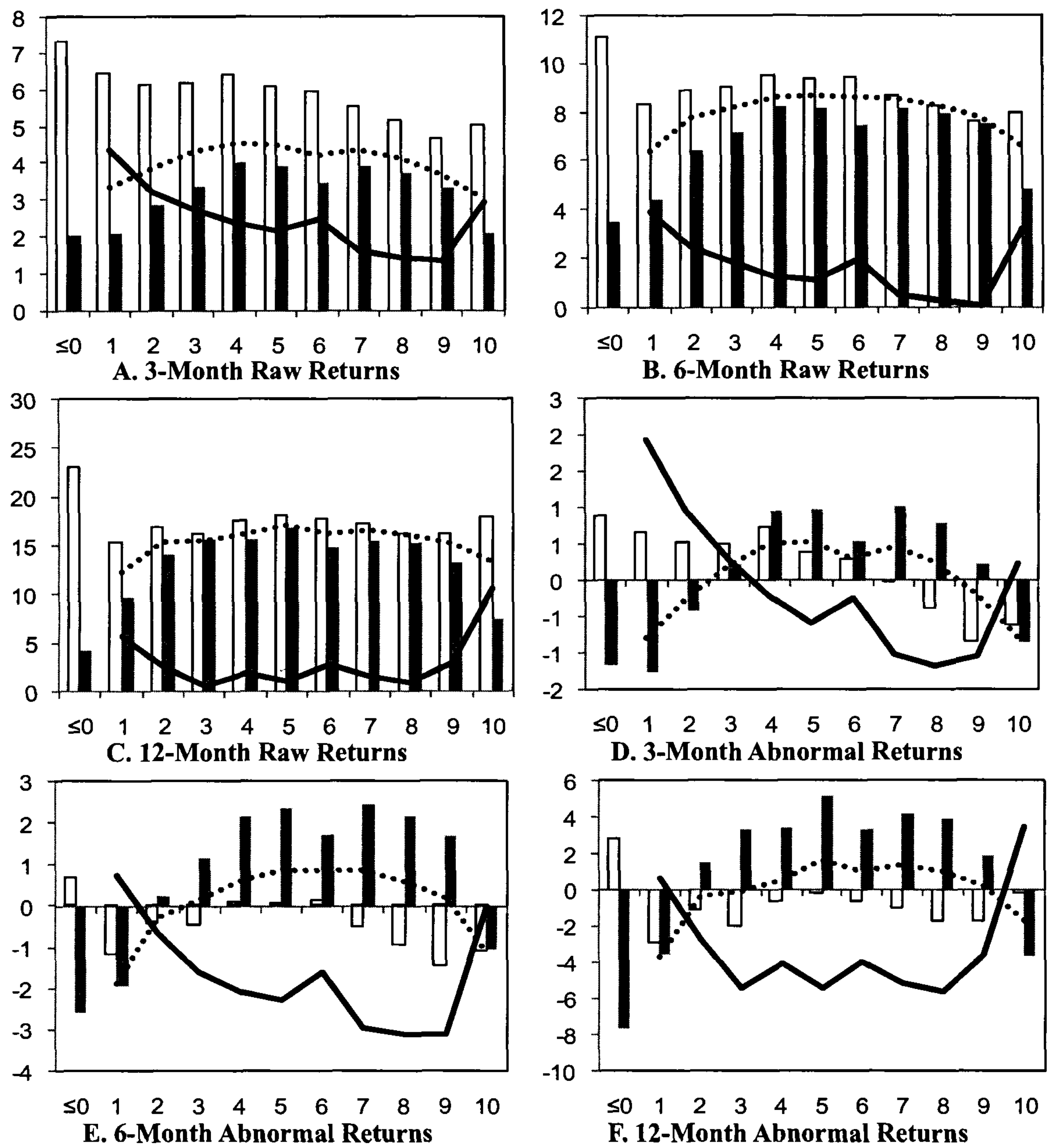
Two-Way Sorts by Sentiment and LTG: Future Returns, 1982:I – 2005: IV



At each calendar quarter end, 10 equal-weighted portfolios are formed based on LTG. The formation-date sentiment is low if the SI measure is below the 40 percentile of the measure's historical distribution, and high if it is above the 60 percentile. The clear (solid) bars are returns following low (high) sentiment. The dashed line is the average across both regimes of sentiment and the solid line is the difference. Returns are in percentage.

FIGURE 5

Two-Way Sorts by Sentiment and PEG: Future Returns, 1982:I – 2005: IV



At each calendar quarter end, 10 equal-weighted portfolios are formed based on the PEG ratio. The formation-date sentiment is low if the SI measure is below the 40 percentile of the measure's historical distribution, and high if it is above the 60 percentile. The clear (solid) bars are returns following low (high) sentiment. The dashed line is the average across both regimes of sentiment and the solid line is the difference. Returns are in percentage.