Investor Sentiment, Beta, and the Cost of Equity Capital

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August 2, 2014

Abstract

Even though the security market line (SML) is unconditionally flat, it accords with the CAPM by taking on an upward slope in pessimistic sentiment periods. However, the SML is downward sloping during optimistic periods. We propose and investigate a behavioral explanation for this finding by arguing that periods of optimism attract equity investment by unsophisticated traders in high growth, high beta stocks, while such traders stay along the sidelines during pessimistic periods. In turn, high beta stocks become overpriced in optimistic periods, but during pessimistic periods, noise trading is reduced, so that rational beta pricing prevails. Unconditional on sentiment, these effects offset each other. Analyses using earnings expectations, fund flows, the probability of informed trading, and order imbalances provide evidence that noise traders are more bullish about high beta stocks when sentiment is optimistic, while investor behavior appears to accord more closely with rationality during pessimistic periods, supporting our hypothesis.

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The Capital Asset Pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966) posits that if traders are rational and sophisticated, expected returns increase linearly with asset betas, and is an integral element of capital budgeting decisions. In a seminal study, however, Fama and French (1992) show that beta is unrelated to returns, casting doubt on the applicability of the CAPM. Various explanations have been put forward to explain this puzzle ranging from mispecifications of risk (Jagannathan and Wang, 1996), to inefficiency of market proxies (Roll and Ross, 1994) to frictions (Black, 1972; Baker, Bradley and Wurgler, 2011). In this paper, we examine the relation between beta pricing and variations in the degree of unsophisticated trading due to the dynamics of investor sentiment.

The phrase "sentiment" refers to whether or not an agent possesses excessively positive or negative affect, and evidence from research in decision sciences shows that positive sentiment results in overly optimistic views, and vice versa (Bower 1981, 1991; Arkes, Herren, and Isen 1988; Wright and Bower 1992; Johnson and Tversky 1992). In financial markets, optimistic or pessimistic beliefs induced by sentiment should trigger unsophisticated ("noise") trading, as postulated by Black (1986), and thus affect financial asset prices. However, there are reasons to believe that such trading will not be symmetric across optimistic and pessimistic sentiment periods, but will be more prevalent during optimistic ones. For example, Amromin and Sharpe (2009) find that individuals expect higher returns from risky investments following good periods rather than following bad ones. Consistent with these views, Grinblatt and Keloharju (2001) and Lamont and Thaler (2003) document that unsophisticated investors are more likely to enter the stock market during prosperous periods. Taken together, these arguments suggest that unsophisticated trading will be more prevalent and impactful in optimistic periods. Further, Baker and Wurgler (2006) show that unsophisticated optimistic investors overweight positive outcomes and underweight negative ones in stocks that are harder to value, thus causing these stocks to become overpriced and subsequently underperform. This finding has firm grounding in the psychology of affect and risk perception (Loewenstein et al., 2001).

We propose that the above arguments can have implications regarding the validity of the CAPM. Specifically, if it is indeed the case that unsophisticated traders are active market participants during optimistic periods, and are attracted to high growth companies, which tend to have higher betas (Barber and Odean, 2000), they will overprice high beta stocks. If these investors, on the other hand, stay by the sidelines during pessimistic periods, then the behavior of financial markets may be more in line with neoclassical asset pricing theories, and beta will be positively related to returns.[1] On the whole these effects might cancel out, and an econometrician who does not condition on sentiment may observe that the beta-return relationship is flat. We build a simple model consistent with this intuition,[2] and provide empirical support for the above arguments, by providing evidence that the upward sloping security market line in pessimistic (but not optimistic) periods is also accompanied by lower levels of unsophisticated trading in high beta stocks during such periods.

In our base analysis, we use the Baker and Wurgler (2006) index, which is orthogonalized with respect to a set of macro variables. Confirming Stambaugh, Yu, and Yuan (2012, Tables 7 and 8),[3] we find that for the period 1966 to 2010, using the Fama and French (1992) methodology,

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[1] Moreover, arbitrage activity in pessimistic periods only entails long positions, which are generally not restricted. In optimistic periods, however, arbitrage requires short positions which entail additional costs.

[2] The model of Daniel, Hirshleifer, and Subrahmanyam (DHS) (2001) also suggests stronger beta pricing when the proportion of overconfident agents is low (see their Proposition 3). Our model accords with this implication, under the assumption that pessimistic periods are accompanied by a smaller proportion of unsophisticated, overconfident agents relative to optimistic ones. The DHS model does not, however, predict negative beta pricing during optimistic periods.

[3] Stambaugh, Yu, and Yuan (2012) test whether the explanatory power of various cross-sectional predictors, not explained by the Fama and French (1993) three factor model, vary with sentiment, and also present some evidence in relation to the beta-return relationship. However, they do not examine the sources of the flat beta-return relation, which represents an empirical failure of the CAPM.

a standard beta, while unconditionally insignificant, is positively related to returns during pessimistic periods with a Fama-Macbeth (1973) *t*-statistic of 2.42, while estimates of the market risk premium are reasonable and in line with intuition. Consistent with our prediction, the nullification of the beta-return relation stems from optimistic periods, where beta is negative with a *t*-statistic of -2.31. These results also hold using a portfolio approach. The prevalence of some anomalies in pessimistic periods, specifically short-run reversals and the size effect, shows that beta is not the sole determinant of expected returns, unlike what the classical version of the CAPM would predict.[4] However, like Stambaugh, Yu, and Yuan (2012), we find that the number of predictors reduces substantially in pessimistic periods, which supports the notion of more informational efficiency in these periods.

Next, we conduct several tests to examine whether the negative pricing of beta in optimistic periods reflects an overpricing due to optimistic noise traders, who are attracted to assets with uncertain valuations, as argued by Baker and Wurgler (2006).[5] First, we examine whether optimistic periods are generally associated with higher capital flows into equity mutual funds. Given that fund flows reflect active reallocation decisions of individual investors, higher inflows in these periods would signal that noise traders are more active and optimistic about equities. Our results confirm this prediction.

We then examine whether unsophisticated (noise) trading rises disproportionately for

[4] The two implications of the CAPM are that the market portfolio is mean-variance efficient, which implies that expected returns are linear in market betas, and that cross-sectional variations in expected returns are solely driven by variations in betas. Levy and Roll (2010) show that the efficiency of the market portfolio cannot be rejected for many common market proxies. They use the "reverse-engineering" method: given a particular market proxy, they investigate the minimum sample variations in parameters required to ensure that the chosen proxy remains mean/variance efficient. They find that with minor variations in parameters, well within estimation error bounds, suffice to ensure that ex ante efficiency of the market portfolio cannot be rejected. They acknowledge, however, that their approach does not "constitute a proof of the empirical validity of the model" (p. 2487). In contrast to their approach, we examine variation in the linear beta-return relation conditional on investor sentiment.

[5] The delay in correction may arise due to limited arbitrage capital (Shleifer and Vishny 1997) or risk aversion of arbitrageurs that prevents them from taking large enough positions to eliminate mispricing (DHS 2001).

higher beta stocks in optimistic periods, using different firm-level proxies for noise trading. Our first measure is the signed forecast error in sell-side analyst earnings forecasts. Since sell-side analysts exert a powerful impact on retail investor earnings expectations (Malmendier and Shanthikumar 2007), their relative optimism about high beta stocks can be used to capture the bullishness of noise traders. Secondly, we use the Frazzini and Lamont (2008) flow-based measure that captures whether a specific stock is in abnormally high demand by mutual fund investors. Frazzini and Lamont (2008) show that this measure negatively predicts returns, and suggest that it is indicative of the bullishness of noise traders for different stocks. Lastly, we use the probability of informed trading (the *PIN* measure of Easley, Hvidkjaer, and O'Hara 2002), as calculated in Brown and Hillegeist (2007). *PIN* is estimated from a structural model using intra-day order flow data and indicates whether the trading for a specific stock in a given month is likely to be driven by fundamental information. Relatively lower *PIN* levels for high beta stocks in optimistic sentiment periods would indicate higher noise trader activity. Our results across all three measures consistently show that noise traders are indeed relatively more bullish and active for high beta stocks when sentiment is optimistic, in line with our hypothesis.

Several studies show that small trades are likely to reflect the trading decisions of noise traders. For example, Hvidkjaer (2008) shows that stocks with high small trader sell-initiated volume subsequently outperform stocks with high small trader buy-initiated volume. Hvidkjaer (2006) shows that small traders underreact to news, and Malmendier and Shanthikumar (2007) show that small traders are naïve about the incentives of informational intermediaries. Along these lines, we use intra-day transactions data to estimate stock-by-stock small trader order imbalances (OIB), and test whether they indicate relatively more bullishness about high beta stocks in periods of optimism. We find that in optimistic periods small investors are net buyers (sellers) of high (low) beta stocks in the six-month period ending on portfolio formation date. No pattern is observed in pessimistic periods. Moreover, when comparing OIB for high beta stocks across sentiment periods, we find that small investors are significantly more bullish when sentiment is optimistic.

We also examine the response of small investors to earnings announcements and revisions to analyst recommendations and earnings forecasts associated with low and high beta stocks. We find that small investors are relatively more bullish (or less bearish) about high beta stocks when sentiment is optimistic. The OIB's from pessimistic periods in response to these events show little variation across beta portfolios, which suggests that in these periods rational investors largely anticipate the announcements or revisions. Overall these results provide further support to our hypothesis.

Optimistic noise traders are attracted to uncertainty because it allows more extreme positive outcomes, which are over-weighted. Uncertainty, however, can be manifested in a number of ways other than beta. Indeed, we believe that more direct metrics of firm-level uncertainty, which do not require specialized thinking, are more likely to attract attention by noise traders. To test this notion we add in our Fama and MacBeth (1973)-type regressions two additional variables that capture the degree to which a firm's valuation is subjective, namely idiosyncratic volatility and dispersion in analyst forecasts. According to our hypothesis we expect that the inclusion of such variables will absorb some of the significance of beta in optimistic periods, where noise traders are attracted to uncertainty more broadly, but should have no effect in pessimistic periods, where prices are set according to fundamentals. In this specification we find that beta continues to be significantly positive in pessimistic periods and that the two added variables are insignificant. A very different picture emerges in optimistic periods, however, since beta becomes insignificant, whilst the two added variables are significantly negative. This result provides further credence to our hypothesis that beta pricing as predicted by the CAPM is suppressed due to the tendency of noise traders to be attracted to stocks with subjective valuations (i.e., high growth/high beta stocks) when they are optimistic.

Finally, we conduct several double portfolio sorts, to examine whether the beta-return relation we document reflects (or relates to) broader facets of firm risk. Specifically, we consider institutional ownership (higher institutional ownership implies lower agency risk, viz. Gillian and Starks, 2000), analyst coverage (high coverage stocks have lower information quality risk in the sense of Arbel and Strebel 1983), and short ratio (stocks with a higher proportion of shares held short in relation to total shares outstanding are most likely cheaper to short sell and thus involve less noise trader risk, viz. Shleifer and Summers 1990). Our results indicate that positive beta pricing in pessimistic periods is preserved in all tables, which suggests that it reflects pricing of covariance risk. Conversely, the negative pricing of beta in optimistic periods, is stronger among stocks with lower analyst coverage and stocks which are more expensive to sell short. This further corroborates the view that the negative pricing of beta in optimistic periods arises from investors' behavioral biases and limits to arbitrage.

Our results hold when we account for the predictability of market returns from sentiment, if we measure sentiment using the Consumer Confidence Index compiled by the University of Michigan, whether orthogonalized with respect to macroeconomic variables or not, to different beta specifications, to controls for additional variables and to previous determinants of a time-varying security market line (SML). We discuss these robustness tests in later sections of the paper.

In other related work, Yu and Yuan (2011) report that the positive relationship between aggregate market volatility and market returns only exists in pessimistic periods. In independent work, Shen and Yu (2012) argue that stocks with high exposure to macroeconomic shocks carry a positive premium in pessimistic periods (see also Jouini and Napp (2011)). Investor sentiment has been linked to the post-earnings announcement drift (Livnat and Petrovic 2008), price momentum (Antoniou, Doukas, and Subrahmanyam 2013) and the relationship between ownership breadth and returns (Cen, Lu and Yang 2013). As already mentioned, Stambaugh, Yu, and Yuan (2012) examine whether the relation between various cross sectional predictors of stock returns varies with sentiment. Thus, existing literature has linked sentiment to both the rational risk-return tradeoff and anomalies left unexplained by rational pricing models. [6]

Our results add to the growing literature on how sentiment affects equity prices and influences thinking on the behavioral versus neoclassical finance debate. Since the seminal result of Fama and French (1992) that the empirical return-beta relation is flat,[7] various explanations have been put forward for why beta is not priced, such as the inefficiency of market proxies (Roll and Ross 1994), the inability of standard unconditional tests to properly measure systematic risk (Jagannathan and Wang 1996; Lettau and Ludvigson 2001), delegated portfolio management (Karceski 2002; Brennan, Cheng, and Li 2012), market frictions (Black, 1972; Baker, Bradley and Wurgler, 2011; Frazzini and Pedersen, 2013) and the omission of state variables (Acharya and Pedersen 2005; Campbell et al. 2012).

Other literature has also produced evidence that the slope of the SML is time varying. Cohen, Polk, and Vuolteenaho (2005) advance an argument based on money illusion, and show

[6]Other literature links more direct indicators of investor mood to stock returns. For example, Hirshleifer and Shumway (2003) use sunshine to capture investors' moods, and confirm that returns are higher on sunnier days. Edmans, Garcia, and Norli (2007) capture mood using sporting events, and find that after losses in international competitions, stock markets of losing nations fall. Kaplanski and Levy (2010) show that market returns are low after aviation disasters, which are highly publicized events and cultivate negative affect.

[7] Early investigations of the relation between average returns and covariance risk met with mixed results; see, for example, Douglas (1969), Black, Jensen, and Scholes (1972), Fama and MacBeth (1973), and Haugen and Heins (1975).

that riskier stocks earn higher returns when expected inflation is low. Similarly, Hong and Sraer (2012) propose that the underperformance of risky stocks relates to aggregate disagreement about the market factor and limits to arbitrage, and Frazzini and Pedersen (2013) show that in periods of tighter borrowing constraints the security market line is flatter. In our analysis we find that investor sentiment exerts an effect on the beta-return relation over and above the effects of inflation, aggregate disagreement, and the TED spread, in line with the notion of noise trading, as advanced by Black (1986). We show that the pricing of beta varies depending on market sentiment, even though the full-sample relationship is flat, and that this result is distinct from the findings of the aforementioned studies that document time-variation in the slope of the SML.[8]

1. A Simple Analytical Framework

We motivate our empirical tests by a stylized model. In keeping with the studies cited in the introduction, the model is based on the dual premises that pessimistic periods consist of rational investors and optimistic periods attract unsophisticated investors. We thus propose that capital market equilibria are different across optimistic and pessimistic periods.

Consider pessimistic periods first. These periods last for two dates, 0 and 1. Trade happens at Date 0 and securities are liquidated at Date 1. In pessimistic periods, Date 1 security payoffs follow a one-factor model:

$$\theta_i = \bar{\theta} + \beta_i f + \varepsilon_i, \tag{1}$$

where $\bar{\theta}$ and the β_i's are nonstochastic. Security payoffs are normally distributed and follow the usual independence assumptions of factor models. The random variables all have zero mean. There

[8] This observation has implications for when the CAPM is an appropriate model to use in setting the cost of capital. In an important survey, Graham and Harvey (2002) indicate that 74% of CFOs in the United States use CAPM to set required rates of return.

are risk averse agents of finite mass. Each agent has exponential utility with risk aversion coefficient A and each observes a noisy signal about the factor, and about each idiosyncratic security payoff. The factor signal is $f+\nu$, whereas the idiosyncractic signal i is $\varepsilon_i+\eta_i$. The random variables f and ε_i as well as the signal noise terms are normally distributed with zero mean, and mutually independent.

It follows that the equilibrium in pessimistic periods is the same as that in a standard CAPM with fully rational agents, who are risk averse and solve a standard portfolio problem with CARA utility and normally distributed payoffs. It is obtained by setting the overconfidence terms to zero in Eq. (25) of Daniel, Hirshleifer, and Subrahmanyam (2001), which results in their Eq. (27). In this setting, trading volume is zero, as all agents have homogeneous beliefs.

We propose that trading and equilibrium in optimistic periods are different from that in pessimistic periods. Optimistic periods also last for two dates, $0'$ and $1'$. Trade happens at Date $0'$ and securities are liquidated at Date $1'$. Date $1'$ security payoffs again follow a one factor model, as in Eq. (1). In order to contrast the role of fundamental/price ratios with that of beta, we propose that risk neutral, overconfident agents[9] observe two signals about ε_i, $\varepsilon_i+\eta_i$ and $\varepsilon_i+\delta_i$. For simplicity, we assume that no agent possesses information about the common factor f. Let v_ε, v_η, and v_δ denote the variances of ε_i, η_i, and δ_i, respectively, and assume that these variances are constant in the cross-section. We propose that the overconfident agents underassess the variance of η_i to be $v_c<v_\eta$.

Given the evidence from Barber and Odean (2000), and Harris and Marston (1994), that retail investors are attracted to high growth stocks, which tend to have high betas, we propose that

[9] As in Daniel, Hirshleifer, and Subrahmanyam (1998), the unsophisticated (overconfident) traders are assumed to be risk neutral for tractability. Felton, Gibson, and Sanbonmatsu (2003) show that optimism may be accompanied by a tendency to take risks, partially motivating this assumption (see also Kuhnen and Knutson, 2011).

overconfident agents are overly optimistic about high beta stocks. We capture this by proposing that the error term in the second signal $\delta_i = k\beta_i$ where $k > 0$.[10] The presence of these risk-neutral, overconfident agents implies that these agents are price-setters. We also assume that a class of noise traders with exogenous demand N_i trades in security i and these trades are absorbed by the risk-neutral, overconfident, agents. We assume that more agents are attracted to high growth, higher beta stocks, so that the total number of shares traded in security *i*, $N_i = \overline{N} + g\beta_i$, where *g>0.*

Now, since agents are risk netural and competitive, the price is given by

$$P_i = E_c[F \mid \varepsilon_i + \eta_i, \varepsilon_i + \delta_i].$$

where the subscript c denotes expectations under overconfidence. Under normality, it is easy to show that the price takes on a linear form:[11]

$$P_i = a_1\varepsilon_i + a_2\eta_i + a_3\delta_i, \tag{2}$$

where a_1, a_2, and a_3 are defined in Appendix A. We proxy for a fundamental/price ratio (such as book/market) by $\overline{\theta}$ - P_i. In our setting, owing to overconfidence, prices overreact to private information, so that fundamental/price ratios positively predict returns. On the other hand, since agents are overly optimistic about high beta stocks, beta negatively predicts returns. The proposition below (proved in Appendix A) formalizes this intuition:

Proposition 1

1. Under optimistic periods, the following two results hold:

[10] Our specification assumes that betas are stochastic during optimistic periods. Also, since δ_i is normally distributed, and is linearly related to β_i, the model allows for negative betas. While this issue should be noted, it is possible to have alternative specifications where δ_i has positive mean, and the probability of negative betas can be made arbitrarily small. Thus, our specification is without loss of generality.
[11] The price is independent of the common factor since nobody has information about this factor and the factor has a mean of zero.

A. In a bivariate regression, fundamental/price ratios positively predict stock returns.

B. In a multiple regression of stock returns on fundamental/price ratios and beta, if agents are sufficiently overconfident, the coefficient on the fundamental/price ratio is positive, and that on beta is negative.

2. In pessimistic periods, a standard CAPM holds, and expected returns are positively and linearly related to betas.

The simple model above forms the basis for our central empirical analysis. First, we investigate whether high beta stocks have lower returns in optimistic periods, and higher returns in pessimistic periods. Second, we examine whether noise traders are relatively more active and more bullish for high beta stocks in optimistic periods.

2. Data and Methodology

2.1 Sentiment Index

We measure sentiment using the annual index provided by Baker and Wurgler (2006). This index is constructed using six proxies of investors' propensity to invest in stocks (an indirect measure of their optimism or pessimism): trading volume (total NYSE turnover), the premium for dividend paying stocks, the closed-end fund discount, the number and first-day returns of IPOs, and the equity share in new issues. To remove the effect of economic fundamentals from these variables, Baker and Wurgler (2006) regress each of them on growth in industrial production, real growth in durable consumption, non-durable consumption, services consumption, growth in employment, and an NBER recession indicator, and use the first principal component of the residuals from the regressions as the Sentiment Index.[12] We define all observations in year *t* as optimistic

[12] In recent and independent work, Sibley, Xing, and Zhang (2012) show that the Baker and Wurgler index correlates with contemporaneous business cycle variables, but they do not rule out the possibility that these variables may also

(pessimistic) if the Sentiment Index is positive (negative) in year *t*-1 (Yu and Yuan 2012). The index is available from 1965 to 2010, so our sample covers the period 1966-2010.[13]

2.2 Asset pricing regressions

In our empirical tests we use all common stocks (share codes 10 and 11) listed on the NYSE, AMEX, and NASDAQ for which we have available data for each of the ensuing tests. Prices, returns, and shares outstanding are from the CRSP monthly files, while book values of equity are obtained from Compustat (as in Fama and French, 1992).

We start by estimating beta following the methodology of Fama and French (1992). Specifically, in June of year *t*, all NYSE firms are sorted by size (price x shares outstanding) to determine decile breakpoints. Using these breakpoints, we assign all firms in the sample in year *t* to 10 size portfolios. To allow for variation in beta that is unrelated to size, we further subdivide each size decile into 10 portfolios sorted on pre-ranking betas for individual stocks. These pre-ranking betas are calculated using 24 to 60 monthly returns (as available) ending in June of year *t*. We set beta breakpoints for each size decile using only NYSE stocks. This procedure yields 100 size-beta portfolios.

After assigning firms into size-beta portfolios in June, we obtain the equally-weighted returns of these portfolios from July of year *t* until June of year *t*+1. This yields 100 time series of returns, one for each size-beta portfolio, spanning our entire sample period. We estimate post-formation betas using the returns of these portfolios and the CRSP value-weighted return as a

capture sentiment. They also show that including the sentiment variable reduces pricing errors for 25 size and book/market-sorted portfolios relative to the Fama and French (1992) three-factor model. Unlike us, they do not focus on cross-sectional beta pricing across individual stocks.

[13] For more details on the construction of the index, see Baker and Wurgler (2006). We thank Malcolm Baker and Jeffrey Wurgler for making the Sentiment Index publicly available.

proxy for the market portfolio. As in Fama and French (1992), pre- and post-ranking betas are calculated as the sum of the slopes in the regression of returns on the current and lagged market return. These betas are then assigned back to individual stocks, depending on their size-beta classification. To make sure that all the information used to explain returns is known ex ante, we mainly focus on rolling betas using five years of data prior to the holding period in month *t*. However, we present results using the full sample betas in Section 6.2 to follow.

2.3 Summary statistics

Table 1 shows the time series averages of the post-formation rolling betas for each size-beta portfolio. Three important findings can be seen. First, post-ranking betas precisely reproduce the ranking of pre-ranking betas. In every size portfolio, post ranking betas increase monotonically with pre-ranking betas, which suggests that the results should be insensitive to whether pre- or post-ranking betas are used in our asset pricing tests. Second, there is sizable variation in betas that is unrelated to firm size. For example, for the small size portfolio, betas increase from 0.98 in the low-beta group to 2.01 for the high-beta group. And finally, betas are generally larger for smaller companies.

[Insert Table 1 here]

Table 2 shows some key characteristics of the beta-sorted portfolios. High-beta stocks tend to be smaller stocks with lower B/M ratios and return on assets, as well as higher total volatility and dispersion in analysts' earnings forecasts (i.e., analyst disagreement). These results are consistent with the notion that high-beta stocks tend to be growth-oriented companies with uncertain cash flows.

[Insert Table 2 here]

Our main analysis employs the Fama and MacBeth (1973) methodology. Thus, in each month *t* we run a cross-sectional regression of returns on post-formation betas and control variables. The time series average of the regression coefficients and its standard error provide standard tests of whether these variables are on average priced in the cross-section of stock returns. In the cross-sectional regressions, we control for variables that have been shown by prior research to predict returns. Specifically we control for firm size (Banz 1981), the book/market ratio of equity (Statman 1980), the return of stock *i* in month *t*-1 (Jegadeesh 1990), the cumulative return of stock *i* in the six months prior to month *t*-1 (Jegadeesh and Titman 1993), and the cumulative return of stock *i* in the six months prior to month *t*-7 (Novy-Marx 2012).

Table 3 provides descriptive statistics and pooled time series, cross-sectional, correlation coefficients for betas (rolling and full sample) and the control variables in Panels A and B, respectively. It can be seen that the summary statistics of the rolling and full sample betas are fairly similar. The mean and median values of the logarithm of firm size are close to each other, suggesting little skewness. The same is true for the log of the book-to-market ratio.

Panel B of Table 3 indicates that the correlation between the rolling and full sample betas exceeds 80%. Book/market and firm size are negatively correlated, whereas the correlations between the momentum and other variables are fairly low. Overall, the correlations suggest that multicollinearity is not likely a material issue in our statistical tests in that the correlations between beta and the other variables are quite modest (less than 0.3 in absolute terms).

[Insert Table 3 here]

3. Portfolio Results

We begin with a simple portfolio test. We rank stocks based on their pre-formation betas in deciles (using NYSE breakpoints) in June of year *t* and hold these portfolios for 12 months. We calculate their returns in each month *t* on a value-weighted basis. The time series averages of the monthly value-weighted returns for the beta portfolios are presented in Table 4. To label periods as optimistic or pessimistic, we follow the procedure outlined in the previous section, and average these monthly returns separately for optimistic and pessimistic months.

The first row of Table 4 presents unconditional results for our entire sample period. The results corroborate the findings of Fama and French (1992), who report that the relationship between beta and returns is flat. The difference in average monthly returns between the extreme beta deciles is a trivial -0.01% and is not statistically significant. Thus, we confirm the seminal results of Fama and French (1992) in our extended sample spanning twenty more years.

The second row of Table 4 presents the average monthly return of these portfolios in pessimistic sentiment months and indicates that stock returns increase with beta, as predicted by the CAPM. The average monthly return of the low-beta portfolio is 0.79% and is 1.88% in the high-beta portfolio. This is a return spread of more than 12% per year. A *t*-test for whether the return of the high-beta portfolio is greater than that of the low-beta portfolio, as predicted by theory, produces a *p*-value smaller than 5%. Figure 1 shows a graphical illustration of this result by demonstrating the upward-sloping nature of the empirical Security Market Line (SML) during pessimistic periods.[14]

[Insert Figure 1 here]

The third row in Table 4 shows the average monthly returns of the beta portfolios in optimistic sentiment periods. The results here are different. Low-beta stocks outperform high-beta stocks. The mechanism pointed out by Baker and Wurgler (2006) regarding noise trading and risk perception, and our model, provide an explanation for this finding. High-beta stocks are riskier

[14] We have verified that our results continue to hold if we terminate the analysis in 2006, and thus eliminate the financial crisis of 2007 and beyond. These results are available upon request.

stocks, and when investors are optimistic, the uncertainty that surrounds their valuations is perceived as an opportunity, not a threat.[15] Therefore, these high-risk stocks become overpriced and subsequently underperform. We provide evidence that supports this conjecture in Section 5.

[Insert Table 4 here]

4. Regression Analysis

The results in the previous section are indicative of a positive relationship between beta and stock returns in pessimistic periods. In this section, we provide more direct evidence using the regression approach of Fama and MacBeth (1973). As discussed earlier, we also control for various other characteristics that have been shown to affect returns.

Table 5 presents the regression results. The full sample findings appear in Panel A, while Panels B and C show results for pessimistic and optimistic periods, respectively. The full sample results are in line with previous research. Specifically, we find that beta is not priced in the cross-section of stocks, and that there is a significant size and value effect in the data. In addition, there is a strong monthly reversal effect, as well as a medium-horizon momentum effect and a 'delayed' continuation effect. These effects are all consistent with the original papers documenting the relevant phenomena: Jegadeesh (1990), Fama and French (1992), Jegadeesh and Titman (1993), and Novy-Marx (2012). Our findings provide confirmation of the original results in our extended sample spanning several more years than the former three studies.

In Panels B and C of Table 5 we observe sentiment-conditional patterns in the size and momentum effects. The size effect is present only in pessimistic periods (Baker and Wurgler 2006), while the momentum effect is present only in optimistic periods (Antoniou, Doukas, and

[15] As seen in Table 2, high-beta stocks are smaller, have lower B/M ratios, lower analyst coverage, and higher analyst disagreement. Baker and Wurgler (2006) suggest that such characteristics make the valuations of companies more subjective, and thus contribute to overpricing during periods of optimistic sentiment.

Subrahmanyam 2013). Since momentum has been hard to explain using traditional risk-return models (Fama and French 1996) and appears to be a pricing anomaly, this result is consistent with the notion that naïve traders (Hong and Stein 1999), whose actions cause momentum, are active mainly during optimistic periods. The value effect is present in both types of sentiment periods, but the regression coefficient is smaller in pessimistic periods than in optimistic ones.[16] Why the value effect prevails in both optimistic and pessimistic periods needs further analysis in future research. One potential explanation is that book/market captures a missing element of risk (e.g., Berk 1995; Campbell and Vuolteenaho 2004; Petkova and Zhang 2005; Campbell et al. 2012) that is priced in both optimistic and pessimistic periods. For example, it is plausible that investors will care about distress risk (captured by book/market) in both optimistic and pessimistic periods, but if they hope that growth-oriented high-beta stocks will deliver high returns during optimistic periods, they will negate the upward slope of the SML by overpricing high-beta stocks during such periods.[17] The monthly reversal and the delayed continuation effects are present in both optimistic and pessimistic periods, and the coefficients in both periods are quite similar for the variables capturing these effects.

Panel B of Table 5 shows that in pessimistic periods, beta is strongly positively related to returns, even in the presence of the various control variables. These variables reduce the size and significance of the coefficient on beta (especially the firm size variable), but beta is always positive and significant, with a *t*-statistic of at least 2.42.[18] Although the implied market premium is quite

[16] Appendix B presents the contrasting results for momentum and B/M in a portfolio setting.

[17] Fundamental/price ratios can also be priced due to behavioral reasons. Note that our theoretical model predicts overpricing of beta stocks (because investors are overconfident about high beta stocks) as well as a fundamental/price ratio effect (due to overconfidence). However, our model does not predict a fundamental/price ratio effect in pessimistic periods. The latter finding is consistent with the overconfidence-based model of Daniel. Hirshleifer, and Subrahmanyam (2001), which predicts positive pricing of both beta and fundamental/price ratios.

[18] In additional analysis, we replicate the above regressions controlling for liquidity using the Amihud (2002) measure [calculated using Equation (1) in Brennan, Huh, and Subrahmanyam (2013)]. To address issues arising from different calculations of NYSE/AMEX and NASDAQ volume, we add two Amihud measures in the regressions, IlliqNYAM

high when beta is the only variable, it is brought down to 0.8%-0.9% per month when control variables are included in the cross-sectional regression. While still higher than the 8.0%-8.5% annual premium documented in various sources (e.g., Allen, Brealey, and Myers 2010), this premium nonetheless is reasonable in terms of its magnitude.[19]

In untabulated analysis we regress the time series coefficients on beta on a constant and the level of sentiment in the previous year. We obtain a coefficient on sentiment equal to -0.52 with a Newey and West (1987)-corrected *t*-statistic equal to -2.42, which shows that our result continues to hold when we define sentiment as a continuous variable.

Panel C of Table 5 indicates that beta is negatively related to returns during optimistic periods. We argue using formal tests in Section 5 that this is because during optimistic periods risky stocks become overpriced and subsequently underperform.[20] A *t*-test for the difference between the two coefficients on beta across Panels B and C safely rejects the hypothesis that they are equal.[21,22]

To further confirm that the two betas obtained from optimistic and pessimistic periods are statistically different, we perform additional tests (available from the authors upon request). First, we regress the time-series of the Fama-MacBeth coefficients of beta (used in the last row of Table

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(IlliqNas), which takes the value implied by this equation if the company is listed on NYSE or AMEX (NASDAQ), and 0 otherwise. Because NASDAQ volume is not available prior to 1982, these tests are based on a smaller sample; however, the results are virtually unchanged.

[19] A risk premium of 8.5% is well within the one standard deviation band of our pessimistic period coefficient including all controls. Note that the standard deviation of the risk premium we obtain is comparable to those reported in Fama and MacBeth (1973) and Fama and French (1992).

[20] Preliminary results are supportive, however, as we find that stocks in the optimistic period high-beta portfolio (formed as in Table 7) outperform stocks in the low-beta portfolio in the period *t*-13 to *t*-36 by 62% (*t*-statistic = 5.77), where *t* is the portfolio formation month (recall that optimism is defined based on the sentiment index in the *past* year). The corresponding figure in pessimistic periods is 10% (*t*-statistic = 1.29).

[21] The medians of the betas in optimistic and pessimistic periods are also significantly different.

[22] Fama and McBeth (1973) find evidence that support the CAPM for the pre-1970 period. In unreported analysis we use the sentiment index provided by Baker and Wurgler that is available from 1934 ($SENT^{\wedge}$(old)), and perform the tests in Table 5 conditional on sentiment for the period 1934-1965. Qualitatively we obtain similar findings in relation to the pricing of beta as those in Table 5.

5) on a constant and a dummy that is one for pessimistic periods. The Newey and West (1987)-corrected *t*-statistic on the sentiment dummy with the beta coefficients as the dependent variable is 3.52.[23] In addition, we use our full panel dataset and run a regression of returns on a constant, the sentiment dummy, betas (used in Table 5), betas interacted with the dummy, and control variables. We calculate *t*-statistics by clustering the standard errors on the basis of time (month) and company. In this specification, we obtain a coefficient on beta equal to -0.68 (*t*-stat. = -1.90) and a coefficient on beta interacted with the sentiment dummy equal to 1.03 (*t*-stat. = 2.16). These results provide additional support for our baseline findings that the relationship between beta and returns is stronger in pessimistic periods.

[Insert Table 5 here]

5. Sentiment, Beta, and Noise Trading

While our baseline results show that high-beta stocks earn higher average returns than low-beta stocks in pessimistic periods, the reverse happens in optimistic periods. According to our arguments, this occurs because in optimistic periods noise traders are more active and more bullish for high-beta stocks. This leads to an overpricing of these stocks in optimistic periods, and therefore lower subsequent returns. In this section we test this conjecture using several proxies that capture noise trader activity.

Our starting point is the notion that for (presumably unsophisticated) retail investors, the principal avenue for broad-based stock market participation is through mutual funds.[24] This implies that fund flows can be used as a proxy for retail investor optimism, a point also made by earlier studies (Teo and Woo 2004; Baker and Wurgler 2007; Frazzini and Lamont 2008). In

[23] We also regress the portfolio return differentials between the highest and lowest beta deciles (used in the row marked "All" in Table 4) on a constant and the same dummy. The *t*-statistic on the dummy variable in this regression is 3.64.
[24] The Investment Company Institute estimates that 44% of U.S. households owned mutual funds in 2011, and that as a group households owned 89% of the mutual fund industry (2012 Investment Company Fact Book).

untabulated analysis, we estimate aggregate monthly fund flows (*AFLOW*) using the CRSP Mutual Fund Database and following the procedure in Akbas et al. (2012, Eq. (3), p. 12).[25] The results indicate that *AFLOW* is 0.61% in optimistic months versus 0.39% in pessimistic months, and that the difference is statistically significant at the 5% level. In dollar terms, mutual funds experience an average increase in inflows of $22 billion during optimistic months relative to pessimistic ones. This analysis corroborates the view that there is increased noise trader activity in optimistic periods.[26]

We continue with tests that examine more directly whether noise traders are particularly bullish about high beta stocks in periods of optimistic sentiment. Our first, and relatively direct, indicator, is a measure of optimism in earnings expectations, measured by analysts' signed earnings forecast errors. Hribar and McInnis (2012) show that analysts are susceptible to sentiment and produce more optimistic earnings forecasts for uncertain stocks when sentiment is high. Given that analyst forecasts likely impact retail investor expectations, "sentimental" analysts may also contribute to increased noise trading among high-beta stocks in optimistic periods.[27] Using the IBES summary files for one-year ahead forecasts we calculate average forecast error (*FE*) for every firm in June of year *t* (defined as (mean forecast – actual)/abs(actual)) and then take the average in the high- and low-beta portfolios conditional on sentiment. Higher *FE* values indicate increased noise trading.

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[25] The equation is $MFFLOW_{i,t} = \frac{\sum_{i=1}^{N}(TNA_{i,t} - TNA_{i,t-1} * (1 + MRET_{i,t}))}{\sum_{i=1}^{N} TNA_{i,t-1}}$, where *TNA* is the total net assets of fund *i* in month *t* and *MRET* is the return of fund *i* in month *t*.

[26] As an additional test of greater aggregate noise trading in optimistic periods, we examine the returns of the mispricing factor constructed by Hirshilefer and Jiang (2010) (we thank David Hirshleifer and Danling Jiang for making their factor publicly available). The results indicate that the monthly return to this factor in optimistic months is 1.10% versus 0.65% in pessimistic months. Although the difference is not statistically significant (*t*-statistic = 1.58), the point estimates support the notion of more noise trading in optimistic periods.

[27] Note that excessively *pessimistic* forecasts are not likely to trigger noise trading because they are likely to be uncommon, given the career concerns faced by sell-side analysts, viz. Hong and Kubik 2012).

The results are shown in Panel A of Table 6. *FE* is generally higher for high beta stocks. This is expected, since analyst bias is likely to be stronger in situations when uncertainty is higher. However, and consistent with the analysis of Hribar and McInnis (2012), we find that the relative increase in *FE* is much more pronounced in optimistic sentiment periods (0.11: *t*-stat 4.46). Moreover, we find that in optimistic periods *FE* reduces for low beta stocks and increases for high beta stocks, and that these differentials are statistically significant. This indicates higher relative noise trading among high beta stocks when sentiment is optimistic.

Our next set of proxies capture the bullishness of noise traders toward high beta stocks through their trading decisions. Frazzini and Lamont (FL) (2008) argue that stocks that are held by funds with a high positive difference between actual and hypothetical flows can be thought of as being in demand among noise traders, and are therefore overpriced. We thus compare actual with hypothetical flows into fund *i* in quarter *t*, where hypothetical flows are recursively proportional to fund *i*'s TNA relative to the entire mutual fund industry from three years ago. Stocks that are held by funds with a high positive difference between actual and hypothetical flows (we label this difference *FLOW*) can be thought to be in demand among noise traders, and are therefore overpriced.[28] Using Equations (1)-(8) in Frazzini and Lamont (2008), we calculate *FLOW* for each company every June of year *t*, and then take the average in the high and low beta portfolios conditional on sentiment. In this table observations are divided into optimistic (pessimistic) depending on whether the BW sentiment index is positive (negative) in year *t*. Higher *FLOW* values indicate increased noise trading.

From Panel C of Table 6, we find that in optimistic sentiment periods *FLOW* is negative for low beta stocks and positive for high beta stocks, and the difference is statistically significant

[28] To make these calculations, we use both the CRSP Mutual Funds Database and the CDA/Spectrum database provided by Thomson Financial. For more details about this methodology, see Frazzini and Lamont (2008).

(0.33: *t*-stat 4.05). This result shows that high beta stocks are relatively favored by noise traders during optimistic sentiment periods.[29] *FLOW* is higher for high beta stocks in pessimistic sentiment periods as well, but the difference is not statistically significant (0.12: *t*-stat 1.48). Moreover, the spread in *FLOW* between high and low beta stocks is significantly higher in optimistic sentiment periods (0.21: *t*-stat 1.90).

Our last indicator in this section of the analysis is the probability of informed trading (*PIN*), calculated in Brown and Hillegeist (2007).[30] *PIN* is estimated from a structural model using intra-day order flow data and indicates whether the trading for a specific stock in a given month is likely to be driven by fundamental information. For more details on *PIN* see Brown and Hillegeist (2007). Every firm in June of year *t* is assigned a *PIN* value, which we then average in the high- and low-beta portfolios conditional on sentiment. Lower *PIN* values indicate increased noise trading.

From Panel D we observe that *PIN* is generally higher for low beta stocks, which conforms to the notion that trading is likely to be more informed if fundamentals are more transparent. However, we again observe that the relative spread in *PIN* between high and low beta stocks is significantly higher when sentiment is optimistic (-0.017: *t*-stat -2.81). Moreover, and similarly with Panel C, we find that in optimistic periods *PIN* increases for low beta stocks and decreases for high beta stocks, which supports the notion that noise trading among high beta stocks is relatively higher in optimistic sentiment periods.

[Insert Table 6 here]

Previous research shows that small trades are likely to reflect the decisions of

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[29] The economic mechanism for this result is explained in Barberis and Shleifer (2003): during prosperous periods, high-beta stocks tend to do well, so noise traders flock into this "style" making it overpriced; therefore, the style subsequently underperforms. For evidence on return-chasing flows, see Chevalier and Ellison (1997), Sirri and Tufano (1998), and Teo and Woo (2004).

[30] We thank Stephen Brown and Stephen Hillegeist for making their data publicly available (http://www.rhsmith.umd.edu/faculty/sbrown/pinsdata.html).

unsophisticated traders (see for example, Hvidkjaer (2006; 2008) and Malmendier and Shanthikumar (2007)). In this section, we use intra-day transaction level data from the transaction and quotes database (TAQ) to calculate small investor net order imbalance (OIB), expecting to observe more bullishness for high beta stocks in periods of optimism. To calculate order flow proxies for small investors we follow the procedure in Hvidkjaer (2006).[31]

The results are shown in Table 7. In Panel A we calculate average daily OIB for each firm-month, and then report the rolling monthly average of high and low beta stocks ending in June of year *t*. Observations are divided into optimistic (pessimistic) depending on whether the BW sentiment index is positive (negative) in that year [this procedure is used for all analyses in Table 7]. We find that, in periods of optimism, small investors are net buyers of high beta stocks and net sellers of low beta stocks (0.009 vs. -0.005, with the spread significant at the 10% level). No spread is observed between high and low beta stocks in pessimistic periods. Moreover, when comparing the response of small investors toward high beta stocks across sentiment periods, we find that small investors are become net sellers in pessimistic periods (-0.021), with the spread being statistically significant (0.03: *t*-stat -4.77). These results support the notion that noise traders are attracted to high beta stocks in periods of optimism.[32]

In Panels B-D we examine the response of small investors to earnings announcements, and revisions to analyst recommendations and earnings forecasts. For earnings announcements we follow Livnat and Mendenhall (2006) and calculate quarterly surprises using the seasonal random

[31]The method involves using stocks size-based quintiles and computing the 99th stock price percentile. Small trades are trades whose dollar values are less than defined as one hundred times this percentile, and large trades are defined as those exceeding 200 times the percentile. Imbalances are market-adjusted by subtracting the market-wide aggregate imbalance for each trade category. See Hvidkjaer (2006) for details.

[32] In unreported analysis, we use *FLOW, FE* and *OIB* and the monthly BW sentiment index in month *t*, perform principal component analysis, and measure sentiment using the first principal component from this procedure. When we repeat the analysis of Table 5 using this alternative sentiment specification we find that the negative effect of beta on returns in optimistic periods increases substantially, which suggests that *FLOW, FE* and *OIB* do indeed relate to uninformed, noise-trader demand. These results are available on request.

walk model. We assign each event-firm in a beta portfolio using the beta classifications obtained in June of year *t* and rank firms within each beta group in 4 standardized unexpected earnings (SUE) groups in each fiscal period. We average daily small investor OIB in the window [-1,0], where 0 is the announcement date, reporting results for the low (SUE=1) and high (SUE=4) earnings surprise group. In Panels C and D we use annual analyst earnings forecast revisions and revisions to analyst recommendations, which we classify into upward and downward, repeating the analysis of Panel B.

From Panel B1 (SUE=4) we observe that small investors are significantly more bullish about high beta stocks when sentiment is optimistic (-0.005 vs. 0.054). There is a similar, but weaker, effect in pessimistic periods also (-0.047 vs. -0.007), and this effect is not statistically significant. Moreover, small investors are net buyers of high beta stocks in optimistic periods, but net sellers in pessimistic periods (0.054 vs. -0.023). Responses to negative surprises do not produce any significant results. In Panel C1, we again observe that small investors are net buyers of high beta stocks, but net sellers for low beta stocks during optimistic periods; but their behavior does not materially differ across high and low beta stocks during pessimistic periods. From Panel C2 we also see that they are significantly less bearish about high beta stocks after bad news (SUE=1) (-0.032 vs.-0.072). Finally, in Panel D1 we find that small investors are net sellers for both high and low beta stocks, but less so for the former than the latter. The spreads in OIB between high and low beta stocks across sentiment periods are not significant in this table, but the point estimates are generally consistent with our hypothesis. Collectively these results show that small investors respond more favorably to information about high beta stocks than low beta stocks when they are optimistic. On the contrary OIB's from pessimistic periods show little variation across beta portfolios, which suggests rational investors largely anticipate the announcements or revisions.

[Insert Table 7 here]

Our final test examines whether the negative beta-return relation in optimistic periods reflects a general overpricing of "uncertain" or "lottery-like" stocks, as argued by Baker and Wurgler (2006). To examine whether this is the case, we add into our Fama-MacBeth regressions additional variables that relate to firm uncertainty, expecting that these variables will help capture the overpricing of uncertainty in optimistic sentiment periods more accurately, and thus absorb some of the significance of beta.

Based on previous literature, we add two variables into our regressions, namely disagreement, measured by dispersion in analyst forecasts (*Disp*), and idiosyncratic volatility (*IVOL*). Diether, Malloy, and Scherbina (DMS) (2002) show that stocks with high disagreement earn lower returns and argue that this reflects an overpricing in the spirit of Miller (1977). Ang, Hodrick, Xing and Zhang (2006) (AHXZ) show that stocks with high idiosyncratic volatility earn significantly lower returns. Gao, Yu, and Yuan (2012) show this effect to be concentrated in optimistic sentiment periods, and suggest that it reflects an overpricing due to noise trading activity.

The regression results with disagreement (*Disp*) and idiosyncratic volatility (*IVOL*) are shown in Table 8. Note that analyst coverage data are only available from 1976 onwards, so the regressions that include the two additional variables span a shorter sample period relative to Table 5 (ten less years than the main sample, which begins in 1966). As in Table 5, we average the coefficients on the different variables for the whole sample (Panel A), and separately for the Pessimistic (Panel B) and Optimistic (Panel C) sentiment periods. Model 1 refers to a regression that includes the variables used in Table 5 for this slightly shorter sample and Model 2 is the expanded version for this same sample, which also includes disagreement and idiosyncratic volatility.

In Model 2 in Panel A of Table 8, we confirm DMS and AHXZ in that both *Disp* and *IVOL* are unconditionally negatively related to returns. In addition, once we partition on sentiment, this effect is concentrated in optimistic sentiment periods, consistent with the findings of Gao, Yu, and Yuan (2012). Comparing Models 1 and 2 in Panel C, the inclusion of these variables reduces the *t*-statistic on beta from -2.03 to -1.68. The beta-return relationship in pessimistic periods, however, is not affected, as shown in Panel B. This finding suggests that the relationship between beta and returns in optimistic periods captures a general overpricing of uncertain stocks, whereas in pessimistic periods it is likely to reflect fundamentals.

[Insert Table 8 here]

6. Beta-sorted Portfolios Cut Different Ways

In this section, we examine whether our central result is robust to firm characteristics that potentially capture dimensions of risk other than beta. Our aim is to ascertain if beta pricing might be proxying for some other risk source. Specifically, we consider institutional ownership (higher institutional ownership firms can be thought to involve lower agency risk as institutions effectively monitor the CEO—viz. Gillian and Starks 2000), analyst coverage (high coverage stocks have lower information quality risk in the sense of Arbel and Strebel 1983), and short ratio (stocks with a higher proportion of shares held short in relation to total shares outstanding are most likely cheaper to short sell and thus involve less noise trader risk-viz. Shleifer and Summers 1990). We subdivide our sample into two groups using these variables (High vs. Low, cutting at the median within each beta portfolio every June of year *t*), and perform the portfolio analysis shown in Table 4 separately for each group. If beta pricing is proxying for a missing risk characteristic, it should be less evident across high- and low-beta stocks within the high-risk group (i.e., the low ownership, low coverage, and low short ratio groups).

The results of the portfolio analysis are shown in Table 9. Our main result of positive beta pricing in pessimistic periods is preserved in all tables. Conversely, the result in optimistic periods, that lower beta stocks outperform higher beta stocks, is much less stable and seems to be stronger among higher uncertainty stocks, and stocks which are generally costlier to arbitrage. For example, as seen in Panels B2 and C2, the underperformance of high-beta stocks is only observed among stocks with low analyst coverage and those with low short ratio.[33]

[Insert Table 9 here]

7. Other Robustness Checks

In this section, we conduct a final set of tests to ascertain robustness of our results. First, we conduct the Fama-MacBeth regressions from Table 8 (model 2) while controlling for additional variables shown in Baker and Wurgler (2006) to affect stock returns conditional on sentiment. Specifically we include firm age (*AGE*), external finance (*EF*), growth in sales (*GS*), and profitability and dividend paying dummies (*PrD, DivD,* respectively). We define these variables following Baker and Wurgler (2006).

The results are shown in table 10. For brevity we only report findings for pessimistic (Panel A) and optimistic (Panel B) sentiment periods. We find that in pessimistic periods beta continues to be positive and significant (0.67: *t*-stat 2.34), whereas in optimistic periods it is negative but insignificant (-0.53; -1.49). In terms of the additional variables included in the regressions the results show that some have explanatory power, in line with the results in Baker and Wurgler

[33] We obtain similar results if, for each of the three partitioning variables, we perform a Fama-Mcbeth style regression with controls as in Table 5, using dummy variables to indicate the effect of beta on returns in the high and low sub-groups.

(2006), i.e., returns in optimistic periods reduce with firm age and external finance, and returns in pessimistic periods are lower for dividend paying stocks. Overall the results confirm that our findings are robust when controlling for a comprehensive set of thirteen variables.

A concern with the rolling beta approach is that, due to the cyclicality of sentiment, returns from past optimist periods are used to estimate betas, which are then related to returns in pessimistic periods. It is possible, therefore, that betas may in fact encapsulate to some extent the effects of past noise trading, and may not reflect pure systematic variation. In this section we perform two tests to alleviate this concern. Firstly, we use the methodology of Fama and French (1992) and calculate full sample betas, which we assign to individual stocks. Arguably, the full sample betas will be less affected by the noise trading since they are estimated in the full sample from both optimistic and pessimistic sentiment periods. Secondly, we use the same rolling beta approach but in the regressions to estimate pre and post-formation betas we include aggregate fund flows (as per Footnote 24). Since, as argued earlier, fund flows likely reflect the decisions of noise traders, this will reduce the effect of noise trading on the measurement of beta.[34]

The results are shown in Table 11. Both the full sample (Panel 1) and aggregate fund flow method (Panel 2) produce results consistent with those in the previous section. Beta is insignificant in the full sample but positive and significant in pessimistic periods. This suggests that our baseline result in pessimistic periods does not reflect the effect of past noise trading on beta.

We now consider whether our findings are robust to different specifications of investor sentiment. Specifically we replicate the Fama-MacBeth regressions of Table 5, while measuring sentiment with the Consumer Confidence Index compiled by the University of Michigan, which we orthogonalize with respect to the macroeconomic variables used by Baker and Wurgler (2006).

[34] Note that the time period for this test is shorter since aggregate flows are used after 1990.

To compile this survey, the University of Michigan randomly contacts 500 households asking questions related to their current financial situation and their outlook for the economy. Their responses are then amalgamated to an overall numerical index of consumer confidence.[35] Previous studies have argued that such survey-based indexes can be used to measure market sentiment (e.g., Brown and Cliff 2005; Lemmon and Portniaguina 2006). The time period for this test is 1978 to 2010, when monthly observations for the Index are available. As before, in the second step of the Fama and MacBeth procedure, we average the coefficients separately depending on whether month *t* was classified as optimistic or pessimistic (if the average of the orthogonalized index from month *t*-1 to *t*-7 is positive (negative), month *t* is classified as optimistic (pessimistic)).

As shown by Table 10 Panel 3, our main findings are robust to this alternative sentiment specification. When we average the coefficients of beta for the entire sample period, the relationship between beta and returns is flat. Once we partition on sentiment, however, we continue to observe that beta is positive and significant in pessimistic sentiment months and that the flat beta-return relationship (Panel A) is driven by investor sentiment in optimistic periods.

Because residual sentiment is estimated in a first stage regression, the analysis may contain a generated regressors problem. To control for this possibility we repeat the analysis using the raw Michigan index. We calculate the rolling average of the index from *t*-1 to *t*-7 and define the observation at time *t* as optimistic (pessimistic) if this rolling average is above (below) the sample median. The results are shown in Panel 4, and are in line with our baseline findings.[36]

Finally, we examine whether sentiment predicts the beta-return relationship once we

[35] For more information about the index, visit http://www.sca.isr.umich.edu/main.php.

[36] In unreported analysis we conduct an additional test to control for the generated regressors problem: we define sentiment using a 10 year rolling average, using the annual Baker-Wurgler index that is unadjusted with respect to macroeconomic variables, and repeat the analysis in Table 5. We obtain similar results as those in the paper. These results are available from the authors on request.

control for other factors that predict the slope of the security market line identified by other work, namely inflation (Cohen et al 2005), funding constraints (Frazzini and Pedersen 2013) and aggregate disagreement (Hong and Sraer 2012). For this test we define sentiment using the monthly Baker-Wurgler sentiment[37] index orthogonal to macroeconomic variables, which we further orthogonalize with respect to the inflation rate, two variables that capture leverage constraints (TED spread defined as the 3-month rate difference between LIBOR and the T-Bill rate and the BAB factor from Frazzini and Pedersen (2013)),[38] and two variables that capture aggregate disagreement (beta-weighted disagreement from analyst earnings forecasts as in Hong and Sraer 2012, and disagreement about market returns calculated using data from the Survey of Professional Forecasters (SPF) as in Anderson, Ghysels and Juergens (2009)).[39] We use the two different measures of disagreement to capture the potential influence of disagreement more robustly. Also, it is well known that sell-side analysts have incentives to promote the firms they follow (Jackson 2005), and our SPF-based measure, since it is generated from forecasts about the aggregate economy, is arguably less contaminated by such incentives.

When we regress sentiment on these variables we find that the coefficient on inflation is negative and insignificant, the coefficients on TED and BAB are positive and significant, the coefficient on disagreement from sell-side analysts is positive and significant and the coefficient

[37] We use the monthly index to get more variability in sentiment and perform a more robust orthogonalization with respect to TED, inflation and disagreement.

[38] Data on the BAB factor are available from Andrea Frazzini's website (http://www.econ.yale.edu/~af227/). We thank him for making the data publicly available.

[39] The data on the TED spread and inflation are from the Federal Reserve Bank of St Louis available at http://research.stlouisfed.org/fred2/. To calculate aggregate disagreement as in Hong and Sraer (2012) we obtain data from the IBES summary files on the standard deviation of long term growth earnings forecasts for individual stocks, taking a beta weighted sum at time *t* as the measure of aggregate disagreement. To calculate disagreement from SPF data we use forecasts on corporate profits and inflation, which we combine according to the procedure explained in Anderson et al (2009) to derive forecasts for aggregate market returns. See Anderson et al (2009) for details about this procedure.

on disagreement from SPF data is negative and significant.[40] We define optimistic and pessimistic sentiment averaging the residuals from this regression, as in Panels 3 and 4 of Table 11. Panel 5 presents the results, which are consistent with those in our baseline sentiment specification, and show that our finding is incremental in relation to these studies.[41]

Finally we examine whether our results are driven by the predictability of aggregate market returns from sentiment. To do this we perform two tests: Firstly, in a time series framework, we regress the spread between the high and low beta portfolios from Table 4 on excess market returns, separately in the two sentiment periods. If our hypothesis is correct we should observe that the intercept in this regression is insignificant in pessimistic periods, indicating that the CAPM holds, and negative and significant in optimistic periods, indicating that the CAPM does not hold.

Secondly, in a cross sectional framework, we regress returns on an intercept and an interaction between beta and market returns, and report the time series averages of these coefficients. With this specification the slope obtained from the Fama-MacBeth procedure is:

$$slope_{t+k} = (r_{t+k}^{m}\boldsymbol{\beta}_{t}'\boldsymbol{\beta}_{t}r_{t+k}^{m})^{-1}r_{t+k}^{m}\boldsymbol{\beta}_{t}'\boldsymbol{r}_{t+k}$$

If the CAPM holds, therefore the intercept should equal to 0 and the slope, which is now unrelated to sentiment, should equal 1. We expect this pattern to emerge in pessimistic periods but not optimistic ones.

The results from these tests are shown in Table 12 and support our hypothesis. In the time series test in Panel A we find that alpha is insignificant in pessimistic periods whereas it is negative

40 The opposing coefficients are interesting and deserve attention in future research. We do not try to investigate this further here since it is beyond the scope of our paper.

41 In unreported analysis, which is available on request, we orthogonalize the monthly sentiment index of Baker and Wurgler (2007) with respect to the first and second principal component derived from the full set of variables used by Sibley et al (2013) to capture the business cycle, and repeat the analysis in Panel 5 Table 11. Our baseline results continue to hold.

and highly significant in optimistic periods. Similarly, in the cross sectional test in Panel B, we find that in pessimistic periods the intercept is 0 and the slope is indistinguishable from 1, whereas this is not the case in optimistic periods. Overall these results suggest that the evidence of stronger CAPM pricing in pessimistic periods are not driven by the predictability of market returns from sentiment.

[Insert Tables 11 - 12 here]

8. Conclusion

Beta pricing varies with investor sentiment; the security market line is upward sloping only during pessimistic periods. To explain this phenomenon, we argue that unsophisticated traders will participate strongly in risky equities during optimistic periods, obscuring the positive pricing of covariance risk. However, in pessimistic periods these traders will stay along the sidelines, therefore prices will be closer to fundamentals. We demonstrate these arguments via a simple analytic framework.

Several empirical tests lend support to our hypothesis. We find that earnings expectations for high beta stocks are significantly more bullish in optimistic periods. Moreover, using the Frazzini and Lamont's (2008) fund-flow-based measure of noise trading, we show strong inflows of funds into high-beta stocks during optimistic periods, but no variation in flows across and high- and low-beta stocks during pessimistic periods. Lastly, using the probability of informed trading to measure noise trading, we find that noise traders are more active in high beta stocks during optimistic periods. Further confirming results obtain from analyzing the order imbalance for small investors as calculated from intra-day data. Small investors are net buyers (sellers) of high (low) beta stocks when sentiment is optimistic, but no variation is observed in order imbalance for pessimistic periods. Collectively the evidence presented supports the view that overly positive views on high beta stocks obscure the positive beta pricing posited by the CAPM.

These results have important implications for organizations, indicating that CFO's can use the CAPM for capital budgeting decisions in pessimistic periods, but not optimistic ones. Thus, during the latter periods, it may be more appropriate to derive valuations from model-free methods, using, for example, comparables, and price multiples such as the P/E ratio.

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Appendix A

Proof of Proposition 1: We use the well-known result (e.g., Anderson, 1984) that if there exist random vectors υ_1 and υ_2 such that

$$(\upsilon_1, \upsilon_2) : N\left[(\mu_1, \mu_2), \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \right]$$

then the conditional distribution of υ_1 given $\upsilon_2 = X_2$ is normal with a mean given by the vector

$$E(\upsilon_1 | \upsilon_2 = X_2) = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(X_2 - \mu_2),$$

and the variance-covariance matrix given by

$$var(\upsilon_1 | \upsilon_2 = X_2) = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}.$$

In our case, $\upsilon_1 = F$ and $\upsilon_2 = [\varepsilon_i + \eta_i, \varepsilon_i + \delta_i]$, and the relevant unconditional means are all zero. Thus, the coefficients a_1, a_2, and a_3 in Eq.(2) are given by

$$a_1 = \frac{v_\varepsilon(v_c + v_\delta)}{v_c(v_\delta + v_\varepsilon) + v_\delta v_\varepsilon},$$

$$a_2 = \frac{v_\varepsilon v_\delta}{v_c(v_\delta + v_\varepsilon) + v_\delta v_\varepsilon},$$

and

$$a_3 = \frac{v_\varepsilon v_c}{v_c(v_\delta + v_\varepsilon) + v_\delta v_\varepsilon}.$$

From the above expressions, taking cross-sectional (true) expectations to compute covariances, it follows that:

$$\operatorname{cov}(\theta_i - P_i, \bar{\theta} - P_i) = \frac{v_\delta^2 v_\varepsilon^2 (v_\eta - v_c)}{[v_c(v_\delta + v_\varepsilon) + v_\delta v_\varepsilon]^2} > 0.$$

Similarly, the true cross-sectional multivariate relation between stock returns (measured here as θ_i-P_i) and, in turn, the market price and δ_i, is given by the following conditional expectation:

$$E(\theta_i - P_i \mid P_i, \delta_i) = b_1 P_i + b_2 \delta_i, \tag{3}$$

where

$$b_1 = -\frac{v_\delta[(v_\eta - v_c)v_\delta - v_c^2]}{v_c^2 v_\varepsilon + 2v_c v_\delta v_\varepsilon + v_\delta^2(v_\varepsilon + v_\eta)},$$

and

$$b_2 = -\frac{v_c v_\varepsilon (v_c + v_\delta)}{v_c^2 v_\varepsilon + 2v_c v_\delta v_\varepsilon + v_\delta^2(v_\varepsilon + v_\eta)},$$

Note that b_1 will be negative if v_c is sufficiently small, and the sign of the coefficient on fundamental/price ratio (proxied by $\bar{\theta}$ -P_i) will be opposite to that of b_1 (recall that $\bar{\theta}$ is nonstochastic). Since $\delta_i = k\beta_i$, with $k > 0$, the sign of b_2 is the same as the sign of the cross-sectional regression which replaces the second conditioning variable in (3), δ_i, with β_i. This proves the proposition.

Appendix B

Momentum and book/market portfolios conditional on sentiment

In this appendix (Table A below), we show that the results we document in Table 6 in relation to momentum and value strategies carry through in a portfolio setting.

Table A: Returns of momentum and B/M-sorted portfolios

This table presents average monthly returns in percentages for price momentum strategies (Panel A) and B/M strategies (Panel B) involving all NYSE/AMEX/NASDAQ stocks. In panel A each month all stocks are ranked based on their cumulative returns over the previous six months. The winner stocks are bought and the loser stocks sold, and this position is held for six months. Monthly holding period returns come from overlapping strategies and are computed as an equal-weighted average of returns from strategies initiated at the beginning of this month, and the previous five months. Returns in each month are equally weighted. We allow one month between the end of the formation period and the beginning of the holding period, and delete all stocks that are priced less than one $1 at the beginning of the holding period. In Panel B, in each June of year *t*, we rank all stocks into deciles according to their book-to-market ratio (B/M), which is calculated as follows: B is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. Stocks with negative book values are not used. We allow a minimum of six months after the end of the fiscal period to match the book value to returns. *M* is the market value of equity as of December of *t*-1. Portfolio 1 includes growth stocks (low B/M) and portfolio 10 the value stocks (high B/M). Value stocks are bought and growth stocks are sold, and this position is held for 12 months. We delete all stocks that are priced less than one $1 at the beginning of the holding period. Returns in each month are equally weighted. IN both Panels we measure sentiment using the annual index provided by Baker and Wurgler (2006), orthogonalized with respect to macroeconomic variables. We define all holding-period return observations in year *t* as optimistic (pessimistic) if the sentiment index is positive (negative) in year *t*-1. We then average portfolio returns and spreads separately for optimistic and pessimistic months. Our sample covers the period 1966-2010. ** and * denote significance at the 5% and 10% levels, respectively.

	Losers	2	3	4	5	6	7	8	9	Winners	H-L
	Panel A: Momentum portfolios										
All (n=540)	0.47	0.78	0.94	1.11	1.16	1.21	1.29	1.36	1.45	1.60	1.13**
Pess. (n=276)	1.83	1.73	1.67	1.69	1.63	1.60	1.67	1.75	1.90	2.26	0.43
Opt.(n=264)	-0.95	-0.20	0.19	0.52	0.67	0.81	0.89	0.95	0.98	0.91	1.87**
	Panel B: B/M portfolios										
	Growth	2	3	4	5	6	7	8	9	Value	H-L
All (n=540)	0.66	0.95	1.00	1.17	1.22	1.31	1.37	1.50	1.63	1.78	1.12**
Pess. (n=276)	1.47	1.65	1.42	1.58	1.67	1.73	1.80	1.92	2.14	2.58	1.11**
Opt.(n=264)	-0.19	0.22	0.55	0.73	0.75	0.87	0.93	1.06	1.09	0.95	1.14**

Table 1: Post-formation rolling betas

This table reports the time series averages of post-formation betas that are assigned to individual stocks. In June of year *t*, all NYSE firms are sorted by size (price x shares outstanding) to determine decile breakpoints. Using these breakpoints, we assign all firms in the sample in year *t* into 10 size portfolios. We further subdivide each size decile into 10 portfolios of pre-ranking betas for individual stocks. These pre-ranking betas are calculated using 24 to 60 monthly returns (as available) ending in June of year *t*. We set beta breakpoints for each size decile using only NYSE stocks. This procedure yields 100 size-beta portfolios. We obtain the equally-weighted returns of these portfolios from July of year *t* until June of year *t*+1. We estimate post-formation betas using the returns of these portfolios and the CRSP value-weighted portfolio as a proxy for the market. Pre- and post-ranking betas in all the tables are calculated as the sum of the slopes in the regression of returns on the current and lagged market return. In this table, the post-formation betas are calculated in a rolling fashion by performing the regression each month using five years of past data, which produces an estimate of beta in each month for each size-beta portfolio. This table presents the time series average of these estimates. Our sample covers the period 1966-2010.

	Low β	2	3	4	5	6	7	8	9	High β
Small ME	0.98	1.01	1.18	1.23	1.39	1.44	1.56	1.64	1.82	2.01
2	0.90	1.03	1.10	1.23	1.31	1.41	1.51	1.59	1.72	1.98
3	0.86	0.96	1.05	1.12	1.18	1.27	1.40	1.53	1.56	1.95
4	0.82	0.93	0.98	1.12	1.19	1.29	1.37	1.48	1.72	1.94
5	0.77	0.87	1.00	1.09	1.12	1.20	1.36	1.44	1.49	1.83
6	0.64	0.74	0.95	1.02	1.11	1.18	1.22	1.32	1.47	1.78
7	0.66	0.74	0.95	1.04	1.12	1.21	1.27	1.29	1.37	1.73
8	0.58	0.75	0.95	0.99	1.09	1.09	1.18	1.21	1.38	1.64
9	0.60	0.71	0.84	0.88	0.98	1.02	1.06	1.14	1.25	1.59
Large ME	0.55	0.63	0.73	0.85	0.88	0.93	0.99	1.10	1.22	1.48

Table 2: Characteristics of beta-sorted portfolios

This table reports characteristics of portfolios sorted on betas. In June of year *t*, all NYSE firms are sorted into 10 portfolios by pre-ranking betas using NYSE breakpoints. These pre-ranking betas are calculated using 24 to 60 monthly returns (as available) ending in June of year *t*. Stocks priced less than one dollar in June of year *t* are deleted. *BM* is the book-to-market ratio calculated as follows: B is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. Stocks with negative book values are not used. *M* is the market value of equity as of December of *t*-1. *ME* is the company size (price x shares outstanding) measured at June of year *t*. Return on Assets (*ROA*) is calculated as earnings before interest and taxes divided by total assets. *Total volatility* is calculated as follows: Using daily data from CRSP we calculate monthly return standard deviation for each company (requiring a minimum of 10 daily observations). In each June of year *t*, we calculate the average monthly standard deviation for the preceding six months, including June of year *t*. We calculate *Analyst Disagreement* using the IBES summary files as standard deviation of outstanding forecasts (as reported by IBES) divided by the absolute value of the mean forecast in June of year *t*. The data for *Analyst Disagreement* start in 1976 when the IBES data become available. We average each characteristic for each portfolio every June of year *t*, and then report the time series average of these estimates.

	Low β	2	3	4	5	6	7	8	9	High β
log[BM]	-0.37	-0.35	-0.35	-0.35	-0.37	-0.38	-0.38	-0.41	-0.44	-0.63
log[ME[	4.84	5.10	5.10	5.06	5.01	4.98	4.79	4.61	4.40	4.03
ROA	0.06	0.09	0.09	0.09	0.09	0.08	0.08	0.07	0.06	0.01
Total Volatility	2.30%	2.14%	2.26%	2.34%	2.48%	2.61%	2.81%	3.03%	3.33%	4.06%
Analyst disagreement	0.13	0.16	0.14	0.15	0.17	0.21	0.27	0.25	0.30	0.37

Table 3: Descriptive statistics and correlation coefficients

This table reports descriptive statistics (Panel A) and Pearson correlation coefficients (Panel B). Post-formation betas (*Rolling betas*) are calculated using the returns of the size-beta sorted portfolios and the CRSP value-weighted portfolio as a proxy for the market. They are calculated as the sum of the slopes in the regression of returns on the current and lagged market return. *Rolling beta* is obtained by performing the regression each month using five years of past data. The full sample beta [*FF beta* – as used by Fama and French (1992)] is calculated by running one regression only for each size-beta portfolio using the data from the entire sample period. *ME* is the company size (price x shares outstanding) measured at June of year *t. BM* is the book-to-market ratio calculated as follows: B is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. Stocks with negative book values are not used. M is the market value of equity as of December of *t*-1. *ME* is the company size (price x shares outstanding) measured at June of year *t*. In the Fama-MacBeth regressions these variables are matched with CRSP returns for the months of July of year *t* to June of year *t*+1. *Ret1* is the return of stock *i* in month *t*-1. *Ret6* is cumulative return of stock *i* in the six months prior to month *t*-1, and *Ret12* is the cumulative return from of stock *i* in the six months prior to month *t*-7. Our sample covers the period 1966-2010.

Panel A: Descriptive Statistics

	Mean	Std. Dev.	Median	Q1	Q3
Rolling beta	1.31	0.46	1.24	0.98	1.57
FF beta	1.30	0.34	1.24	1.03	1.51
log[ME]	4.80	2.08	4.64	3.28	6.18
log[BM]	-0.44	0.90	-0.37	-0.94	0.13

Panel B: Correlation Coefficients

	Rolling beta	*FF beta*	*log[ME]*	*log[BM]*	*Ret1*	*Ret6*	*Ret12*
Rolling beta	1	0.81	-0.24	-0.05	0.008	0.036	0.04
		[<.0001]	[<.0001]	[<.0001]	[<.0001]	[<.0001]	[<.0001]
FF beta		1	-0.29	-0.07	0.01	0.03	0.05
			[<.0001]	[<.0001]	[<.0001]	[<.0001]	[<.0001]
log[ME]			1	-0.37	-0.04	-0.04	0.03
				[<.0001]	[<.0001]	[<.0001]	[<.0001]
log[BM]				1	0.03	0.08	-0.04
					[<.0001]	[<.0001]	[<.0001]
Ret1					1	-0.02	0.003
						[<.0001]	[<.0001]
Ret6						1	-0.01
							[<.0001]
Ret12							1

Table 4: Returns of Beta-Sorted Portfolios

This table reports the average return of beta-sorted portfolios. In June of year *t*, all firms are sorted into 10 portfolios by pre-ranking betas using NYSE breakpoints. These pre-ranking betas are calculated using 24 to 60 monthly returns (as available) ending in June of year *t*. Stocks priced less than one dollar in June of year *t* are deleted. We obtain value-weighted monthly returns for these portfolios from July of year *t* to June of year *t*+1, where size is measured at the end of June of year *t*. We measure sentiment using the annual index provided by Baker and Wurgler (2006), orthogonalized with respect to macroeconomic variables. We define all observations in year *t* as optimistic (pessimistic) if the sentiment index is positive (negative) in year *t*-1. We then average portfolio returns and spreads separately for optimistic and pessimistic months. Our sample covers the period 1966-2010. ** and * denote significance at the 5% and 10% levels, respectively.

	Low β	2	3	4	5	6	7	8	9	High β	H-L
All (*n*=540)	0.90	0.86	0.94	1.04	0.93	1.01	0.89	0.98	1.04	0.89	-0.01
Pess. (*n*=276)	0.79	0.77	0.87	1.12	1.25	1.12	1.35	1.39	1.67	1.88	1.09**
Opt.(*n*=264)	1.01	0.95	1.00	0.96	0.59	0.90	0.41	0.55	0.38	-0.15	-1.16**

Table 5: Fama-MacBeth regressions

This table reports the average slopes of each variable from the monthly regressions for the period 1966-2010. The *t*-statistic is the average slope divided by its time series standard error. We use Newey-West correction on the standard errors to control for heteroscedasticity and autocorrelation. Stocks priced less than one dollar in month *t*-1 are not included in the regressions. In Panel A we average the slopes for our entire sample period. In panels B and C we define each month *t* as pessimistic or optimistic, respectively, and average the slopes separately for each group. We measure sentiment using the annual index provided by Baker and Wurgler (2006) orthogonalized with respect to macroeconomic variables. We define all observations in year *t* as optimistic (pessimistic) if the sentiment index is positive (negative) in year *t*-1. Stocks are assigned into size-beta portfolios in June of year *t* and remain in that classification for 12 months. Stocks are assigned post formation rolling beta (β) in month *t*, which are obtained from the regression of size-beta portfolio returns on market returns using five years of data ending in month *t*-1. In panel D the post formation betas are calculated using the full sample as in Fama and French (1992). *ME* is the company size (price x shares outstanding) measured at June of year *t*. *BM* is the book-to-market ratio calculated as follows: B is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. Stocks with negative book values are not used. M is the market value of equity as of December of *t*-1. These variables are matched with CRSP returns for the months of July of year *t* to June of year *t*+1. *Ret1* is the return of stock *i* in month *t*-1. *Ret6* is cumulative return of stock *i* in the six months prior to month *t*-1, and *Ret12* is the cumulative return from of stock *i* in the six months prior to month *t*-7. In Panel A, the average number of companies in each cross sectional regression is 3,037, 2,894 in Panel B, and 3,186 in Panel C.

Panel A: All (*n*=540)						**Panel B: Pessimistic (*n*=276)**						**Panel C: Optimistic (*n*=264)**					
β	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*	β	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*	β	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*
0.31						1.46						-0.88					
[1.04]						[3.50]						[-2.64]					
0.04	-0.11					0.97	-0.21					-0.93	-0.02				
[0.16]	[-3.14]					[2.48]	[-3.99]					[-2.83]	[-0.34]				
0.18	-0.07	0.28				0.97	-0.17	0.20				-0.65	0.04	0.37			
[0.69]	[-1.81]	[4.26]				[2.59]	[-3.26]	[2.26]				[-2.23]	[0.86]	[4.15]			
0.16	-0.07	0.30	-0.05			0.97	-0.17	0.22	-0.06			-0.68	0.04	0.38	-0.04		
[0.63]	[-1.79]	[4.41]	[-11.11]			[2.54]	[-3.13]	[2.46]	[-8.13]			[-2.26]	[0.85]	[4.17]	[-8.03]		
0.10	-0.07	0.29	-0.05	0.005		0.84	-0.17	0.21	-0.06	0.001		-0.69	0.03	0.37	-0.04	0.009	
[0.40]	[-1.95]	[4.31]	[-11.23]	[2.31]		[2.42]	[-3.24]	[2.35]	[-8.24]	[0.21]		[-2.37]	[0.69]	[4.13]	[-8.10]	[4.30]	
0.11	-0.08	0.30	-0.05	0.004	0.006	0.85	-0.17	0.25	-0.06	0.000	0.005	-0.65	0.02	0.37	-0.04	0.009	0.007
[0.48]	[-2.17]	[4.76]	[-11.53]	[2.21]	[4.12]	[2.53]	[-3.37]	[2.79]	[-8.50]	[0.16]	[2.04]	[-2.31]	[0.50]	[4.40]	[-8.27]	[4.15]	[4.25]

Table 6: Noise trading and beta

In this table we report proxies of noise trading conditional on sentiment in low and high beta portfolios, formed using pre-formation betas every June of year t using NYSE breakpoints. .In Panel A we report average forecast error *FE*, calculated for each firm every June of year *t* as (Mean estimate – actual)/abs(actual) using data from the IBES summary files. For this test we only retain companies with December fiscal year ends and winsorize *FE* at the 5^{th} and 95^{th} percentile.
In Panel B we report average *Stock Specific Flow*, calculated for each company every June of year *t* following equations (1)-(8) in Frazzini and Lamont (2008). The time period for the *Flow* analysis is 1983 to 2010. In Panel C we report average probability of informed trading *PIN*, calculated for each firm every June of year *t* following Brown and and Hillegeist (2007) and obtained from Stephen Brown's website. The *t*-statistics are calculated by clustering observations on the firm level. In all Panels sentiment is defined as optimistic (pessimistic) if the Baker and Wurgler (2006) annual index is positive (negative) in the same year.

Panel A: Analyst Optimism				
	Low β	High β	H-L	t-stat
Opt.	0.18	0.43	0.25	14.73
Pess.	0.21	0.35	0.14	7.42
O-P	-0.03	0.08	0.11	
t-stat	-2.48	4.55	4.46	
Panel B: Stock Specific Flow				
	Low β	High β	H-L	t-stat
Opt.	-0.06	0.27	0.33	4.05
Pess.	0.52	0.64	0.12	1.48
O-P	-0.58	-0.37	0.21	
t-stat	-7.77	-5.56	1.90	
Panel C: PIN				
	Low β	High β	H-L	t-stat
Opt.	0.287	0.198	0.089	19.43
Pess.	0.278	0.206	0.072	16.13
O-P	0.009	-0.008	-0.017	
t-stat	2.26	-4.80	-2.81	

Table 7: Small Investor Order Imbalance

The table presents order imbalance (OIB) for small investors calculated from TAQ data for the low and high beta portfolios. For this test we use NYSE and AMEX stocks for the period 1980-2010.We follow Hvidkjaer (2006, 2008) to match trades to quotes, and to identify small and large investor trades. From the daily small investor OIB for each company we subtract the market-wide imbalance for small investors on that day. We delete top 1% of daily OIB observations according to small trader turnover and large trader turnover (buy volume +sell volume)/market value)). In Panel A we average daily OIB for each company and month, and then report the average monthly OIB for the 6 month period ending in June of year *t*. In Panel B we calculate earnings surprises using the seasonal random walk model. We assign a beta classification to each event-firm, and rank all event-firms in a given fiscal period and beta group in 4 standardized unexpected earnings groups (SUE). In panel B we report average OIB for the days [-1,0], where 0 is the earnings announcement date, for SUE groups 1 (negative surprise) and 4 (positive surprise). In Panel C (D) we follow the same procedure but the event analyzed is analyst recommendations (analyst earnings forecasts), which we split to upward and downward. In Panel D all revisions that exceed 100% in absolute value are deleted. T-statistics are calculated by clustering observations on the firm level. In all Panels sentiment is defined as optimistic (pessimistic) if the Baker and Wurgler (2006) annual index is positive (negative) in the same year.

Beta portfolio	Opt.	Pess.	Opt.-Pess.	t-stat	Opt.	Pess.	Opt.-Pess.	*t*-stat
Panel A: Beta Portfolios								
1	-0.005	-0.008	0.003	0.33				
10	0.009	-0.021	0.030	4.77				
10-1	0.014	-0.013	0.027	2.38				
t-stat	1.80	-1.58						
Panel B : Earnings announcements								
	B1:SUE=4				B2:SUE=1			
1	-0.023	-0.045	0.022	1.09	-0.077	-0.056	-0.021	-1.01
10	0.054	-0.005	0.059	2.51	-0.101	-0.072	-0.029	-1.24
10-1	0.077	0.040	0.037	1.17	-0.024	-0.016	-0.008	-0.26
t-stat	3.39	1.79			-1.06	-0.76		
Panel C: Analyst recommendations								
	C1: Upward				C2: Downward			
1	-0.039	-0.032	-0.007	-0.44	-0.070	-0.052	-0.018	-1.20
10	0.017	-0.013	0.030	2.03	-0.032	-0.042	0.010	0.65
10-1	0.056	0.019	0.037	1.61	0.038	0.010	0.028	1.22
t-stat	3.36	1.21			2.10	0.66		
Panel D: Analyst earnings forecasts								
	D1: Upward				D2: Downward			
1	-0.047	-0.062	0.015	1.39	-0.019	-0.043	0.024	2.10
10	-0.025	-0.05	0.025	2.46	-0.026	-0.041	0.015	1.47
10-1	0.022	0.012	0.01	0.51	-0.007	0.002	-0.009	-0.57
t-stat	1.63	0.97			-0.64	0.17		

Table 8: Expanded Fama-MacBeth regressions

This table reports the average slopes of each variable from the monthly Fama-MacBeth regressions for Models 1 and 2 for the period 2/1976-12/2010 for which *disp* is available from the IBES summary files. The *t*-statistic is the average slope divided by its time series standard error. We use Newey-West correction on the standard errors to control for heteroscedasticity and autocorrelation. Stocks priced less than one dollar in month *t*-1 are not included in the regressions. In Panel A, we average the slopes for our entire sample period. In Panels B and C, we define each month *t* as pessimistic or optimistic, respectively, and average the slopes separately for each group. We measure sentiment using the annual index provided by Baker and Wurgler (2006) orthogonalized with respect to macroeconomic variables. We define all observations in year *t* as optimistic (pessimistic) if the sentiment index is positive (negative) in year *t*-1. Stocks are assigned into size-beta portfolios in June of year *t* and remain in that classification for 12 months. Stocks are assigned post formation rolling beta (β) in month *t*, which are obtained from the regression of size-beta portfolio returns on market returns using five years of data ending in month *t*-1. *ME* is the company size (price x shares outstanding) measured at June of year *t. BM* is the book-to-market ratio calculated as follows: B is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. Stocks with negative book values are not used. M is the market value of equity as of December of *t-1*. These variables are matched with CRSP returns for the months of July of year *t* to June of year *t*+1. *Ret1* is the return of stock *i* in month *t-1*. *Ret6* is cumulative return of stock *i* in the 6 months prior to month *t*-1, and *Ret12* is the cumulative return from of stock *i* in the six months prior to month *t*-7. We calculate analyst disagreement (*Disp*) using the IBES summary files. *Disp* is standard deviation of outstanding forecasts (as reported by IBES) divided by the absolute value of the mean forecast in June in month *t-1*. *IVOL* is idiosyncratic volatility in *t-1* calculated as follows: Using daily data we run a monthly regression for each company of returns on MKT (value-weighted returns of the market from CRSP), HML (High minus Low) and SMB (Small minis Big) and save the residuals. *IVOL* is the monthly sum of the squared residuals for each company. The average number of firms per month in the regressions below is 1,888.

	B	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*	*Disp*	*IVOL*
				Panel A: All (*n*=419)				
Model 1	0.01	-0.09	0.18	-0.04	0.01	0.01		
	[0.05]	[-2.41]	[2.28]	[-8.66]	[2.07]	[3.68]		
Model 2	0.09	-0.12	0.17	-0.04	0.005	0.006	-0.08	-13.64
	[0.36]	[-3.44]	[2.10]	[-8.69]	[1.85]	[3.40]	[-2.07]	[-5.69]
				Panel B: Pessimistic (*n*=191)				
Model 1	0.81	-0.16	0.11	-0.04	0.00	0.002		
	[2.32]	[-2.84]	[1.00]	[-6.08]	[0.12]	[0.83]		
Model 2	0.83	-0.16	0.11	-0.04	0.00	0.002	-0.04	-4.82
	[2.42]	[-3.17]	[0.98]	[-6.26]	[0.20]	[0.82]	[-0.46]	[-1.30]
				Panel C: Optimistic (*n*=228)				
Model 1	-0.66	-0.03	0.24	-0.04	0.01	0.01		
	[-2.03]	[-0.72]	[2.26]	[-6.26]	[3.27]	[4.99]		
Model 2	-0.53	-0.09	0.21	-0.04	0.008	0.01	-0.12	-21.03
	[-1.68]	[-1.83]	[2.02]	[-6.10]	[2.83]	[4.47]	[-4.05]	[-7.63]

Table 9: Beta-sorted Portfolios Cut Different Ways

This table reports the average returns of double-sorted portfolios. Following the procedure of Table 4 we form beta portfolios across sentiment periods and classify them in groups based on institutional ownership, short ratio and analyst coverage. In panel A we calculate institutional ownership as of June of year *t* for each stock. We partition our sample in two groups based on institutional ownership (above and below median within each beta portfolio in each June of year *t*), and run the analysis separately for each group. The data for institutional ownership are from Thomson Reuters on WRDS. The time period for this test is 1981-2010. In Panel B we calculate for each stock monthly short ratio as follows: shares held short/shares outstanding, and then average the short ratio for each company in the 12 months ending in June of year *t*. We partition our sample in two groups based on short ratio (above and below median within each beta portfolio in each June of year *t*), and run the analysis separately for each group. The time period for this test is 1974-2010. Short sale data are from Compustat. In Panel C we calculate residual analyst coverage as follows: Each month *t* we run a cross sectional regression of Log(1+number of analysts)= a + b*log(Market Value) + e, where number of analysts is provided by the IBES summary files and MV is end of previous year end market value. The residual from this regression is our measure of analyst coverage in June of year *t*. We partition our sample in two groups based on residual analyst coverage (above and below median within each beta portfolio in each June of year *t*), and run the analysis separately for each group. The time period for this test is 1980-2010. In all Panels we obtain value-weighted monthly returns for these portfolios from July of year *t* to June of year *t*+1, where size is measured at the end of June of year *t*. ** and * denote significance at the 5% and 10% levels, respectively.

	Low β	2	3	4	5	6	7	8	9	High β	H-L
	Panel A1:Low Institutional Ownership										
Optimistic (*n*=210)	1.01	0.95	1.32	1.23	0.79	0.77	0.57	0.33	0.11	-0.85	-1.86**
Pessimistic (*n*=144)	1.01	1.14	1.26	1.41	1.22	1.85	1.97	2.43	2.00	2.28	1.27*
	Panel A2: High Institutional Ownership										
Optimistic (*n*=210)	1.07	0.94	1.00	1.01	0.57	0.89	0.32	0.52	0.29	-0.23	-1.30**
Pessimistic (*n*=144)	0.98	0.94	1.32	1.65	1.71	1.45	1.89	1.76	2.31	2.59	1.61**
	Panel B1: Low Short Ratio										
Optimistic (*n*=228)	1.07	1.01	0.96	0.92	0.67	0.71	0.70	0.59	0.43	-0.38	-1.45**
Pessimistic (*n*=210)	0.82	0.90	0.94	0.77	1.29	1.15	1.09	1.39	1.78	2.08	1.26**
	Panel B2: High Short Ratio										
Optimistic (*n*=228)	1.19	1.06	1.18	1.04	0.77	1.02	0.50	0.91	0.65	0.45	-0.74
Pessimistic (*n*=210)	0.98	0.85	1.15	1.59	1.61	1.63	1.78	1.71	2.09	2.40	1.42**
	Panel C1: Low Analyst Coverage										
Optimistic (*n*=222)	1.03	0.89	0.99	0.92	0.41	0.95	0.50	0.57	0.36	-0.40	-1.43**
Pessimistic (*n*=144)	1.02	0.77	1.39	1.66	1.51	1.54	2.04	1.60	2.37	2.50	1.48**
	Panel C2: High Analyst Coverage										
Optimistic (*n*=222)	1.07	1.09	1.18	1.13	0.94	0.93	0.62	0.64	0.83	0.14	-0.93
Pessimistic (*n*=144)	1.01	1.12	1.43	1.56	1.70	1.59	1.87	2.21	2.40	2.73	1.72**

Table 10: Controlling for additional variables

This table reports the average slopes of each variable from the monthly Fama-MacBeth regressions for Models 1 and 2 for the period 2/1976-12/2010 in optimistic and pessimistic sentiment periods. We measure sentiment using the annual index provided by Baker and Wurgler (2006) orthogonalized with respect to macroeconomic variables. We define all observations in year *t* as optimistic (pessimistic) if the sentiment index is positive (negative) in year *t*-1. The *t*-statistic is the average slope divided by its time series standard error. We use Newey-West correction on the standard errors to control for heteroscedasticity and autocorrelation. Stocks priced less than one dollar in month *t*-1 are not included in the regressions. We augment model 2 from Table 8 with the following variables: *Age* (the log of the number of years between the first date the firm appears in the CRSP files and month *t)*, *EF* (external finance defined as change in assets minus change in retained earnings divided by assets), *GS* (change in net sales divided by prior year sales), *PrD* (dummy variable which takes the value of 1 for firms with positive earnings (income before extraordinary items+ plus deferred taxes minus preferred dividends, as available) and 0 otherwise), and *DivD* (dummy variable which takes the value of 1 for firms with positive dividends per share at the ex-date and 0 otherwise.

β	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*	*Disp*	*IVOL*	*Age*	*EF*	*GS*	*PrD*	*DivD*
Panel B: Pessimistic (*n*=191)												
0.67	-0.13	0.14	-0.04	0.00	0.00	-0.01	-5.41	-0.01	-0.11	0.09	-0.18	-0.37
[2.34]	[-2.46]	[1.35]	[-6.22]	[0.19]	[0.77]	[-0.08]	[-1.44]	[-0.14]	[-0.62]	[1.20]	[-0.90]	[-2.69]
Panel C: Optimistic (*n*=228)												
-0.53	-0.13	0.21	-0.04	0.01	0.01	-0.11	-19.68	0.11	-0.29	0.04	0.18	0.08
[-1.49]	[-2.59]	[1.67]	[-6.04]	[3.03]	[4.08]	[-3.81]	[-6.47]	[2.49]	[-2.69]	[1.32]	[0.96]	[0.61]

Table 11: Alternative beta and sentiment specifications

This table reports the average slopes of each variable from the monthly Fama-MacBeth regressions. The *t*-statistic is the average slope divided by its time series standard error. We use the Newey-West correction to the standard errors. Stocks priced less than one dollar in month *t*-1 are not included in the regressions. In Panel A we average the slopes for our entire sample period. In Panels B and C, we define each month *t* as pessimistic or optimistic, respectively, and average the slopes separately for each group. In Panels 1 and 2 we measure sentiment using the Baker and Wurgler (2006) index as in Table 5. In Panel 1 post formation betas are calculated using the full sample methodology, as in Fama and French (1992). In Panel 2 we calculate post formation betas using the rolling methodology explained in Table 5, but in the regressions where we estimate both pre and post formation betas we also include contemporaneous aggregate equity fund flows (calculated as per footnote 24) in addition to the market variables. The time period for this test is June 1998 to December 2010. In Panels 3 and 4 all the variables are defined as in Table 5 except that we measure sentiment differently. In Panel 3 we use the consumer confidence index published by the University of Michigan orthogonalized with respect to the macroeconomic variables used by Baker and Wurgler (2006). To define sentiment in month *t* we average the residuals from *t*-1 to *t*-7 and define sentiment as optimistic (pessimistic) if this average is positive (negative). In panel 4 we use the raw Michigan index which we average from *t*-1 to *t*-7. If the rolling average ending at *t*-1 is above (below) the sample median rolling sentiment the observation in month *t* is defined as optimistic (pessimistic). The time period in Panels 3 and 4 is 1978-2010, when the Michigan index is available on a monthly basis. In Panel 5 we use the monthly Baker and Wurgler sentiment index orthogonalized with respect to macroeconomic variables, which we further orthogonalize with respect to the TED spread, inflation, aggregate disagreement calculated from analyst earnings forecasts (as in Hong and Sraer (2012), and disagreement about market returns using data from the Survey of Professional Forecasters (as in Anderson et al 2009). Because the latter measure of disagreement is available on quarterly basis we use linear interpolation to obtain monthly observations. To define sentiment in month *t* we average the residuals from *t*-1 to *t*-7 and define sentiment as optimistic (pessimistic) if this average is positive (negative). The time period for this test is 1986-2010, for which LIBOR data are available.

Panel A: All						**Panel B: Pessimistic**						**Panel C: Optimistic**					
β	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*	β	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*	β	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*
Panel 1: Full sample betas																	
		n=540						*n*=276						*n*=264			
0.07	-0.07	0.30	-0.05	0.04	0.006	0.82	-0.15	0.25	-0.06	0.00	0.005	-0.71	0.02	0.36	-0.04	0.009	0.007
[0.29]	[-1.89]	[4.76]	[-11.54]	[2.21]	[4.32]	[2.38]	[-2.84]	[2.84]	[-8.49]	[0.15]	[2.17]	[-2.38]	[0.39]	[4.35]	[-8.30]	[4.18]	[4.39]
Panel 2: Controlling for fund flows																	
		n=151						*n*=72						*n*=79			
0.52	-0.06	0.12	-0.02	0.00	0.00	2.10	-0.18	0.04	-0.02	-0.01	-0.01	-0.91	0.05	0.19	-0.01	0.008	0.004
[1.01]	[-0.87]	[0.89]	[-1.77]	[-0.07]	[-0.59]	[3.41]	[-2.22]	[0.21]	[-3.67]	[-1.01]	[-1.95]	[-1.36]	[0.46]	[1.07]	[-0.73]	[1.65]	[1.83]

Table 11: Continued

Panel A: All						**Panel B: Pessimistic**						**Panel C: Optimistic**					
β	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*	*β*	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*	*β*	*ln[ME]*	*ln[B/M]*	*Ret1*	*Ret6*	*Ret12*
Panel 3: Michigan consumer confidence index$^{\perp}$																	
		n=391						*n*=165						*n*=220			
0.12	-0.03	0.27	-0.04	0.005	0.005	0.85	-0.10	0.19	-0.04	0.001	0.003	-0.4	0.02	0.33	-0.03	0.008	0.006
[0.43]	[-0.81]	[3.72]	[-9.59]	[2.26]	[3.52]	[2.19]	[-1.90]	[1.76]	[-7.00]	[0.16]	[1.16]	[-1.11]	[0.41]	[3.42]	[-6.95]	[4.83]	[4.46]
Panel 4: Michigan consumer confidence index																	
		n=391						*n*=195						*n*=196			
0.12	-0.03	0.27	-0.04	0.005	0.005	0.81	-0.09	0.21	-0.04	0.001	0.003	-0.56	0.03	0.34	-0.03	0.009	0.006
[0.43]	[-0.81]	[3.72]	[-9.59]	[2.26]	[3.52]	[2.10]	[-1.80]	[2.16]	[-7.07]	[0.21]	[1.54]	[-1.47]	[0.53]	[3.15]	[-6.72]	[5.14]	[4.14]
Panel 5: Controlling for Inflation, Leverage Constraints and Disagreement																	
		n=295						*n*=181						*n*=114			
0.24	-0.01	0.25	-0.03	0.003	0.003	1.17	-0.06	0.06	-0.02	0.002	0.002	-1.10	0.06	0.52	-0.04	0.005	0.005
[0.72]	[-0.24]	[2.87]	[-7.20]	[1.19]	[1.73]	[2.56]	[-0.97]	[0.52]	[-4.20]	[0.42]	[0.72]	[-2.71]	[1.04]	[5.08]	[-6.18]	[2.43]	[2.44]

Table 12: Controls for Market Returns

This table reports the average return of beta-sorted portfolios. In June of year *t*, all firms are sorted into 10 portfolios by pre-ranking betas using NYSE breakpoints. These pre-ranking betas are calculated using 24 to 60 monthly returns (as available) ending in June of year *t*. Stocks priced less than one dollar in June of year *t* are deleted. We obtain value-weighted monthly returns for these portfolios from July of year *t* to June of year *t*+1, where size is measured at the end of June of year *t*. In Panel A we regress the spread between the high and the low beta portfolio at time *t* on a constant and the excess market return at time *t* separately in optimistic and pessimistic sentiment periods. In Panel B we run a Fama-McBeth cross sectional regression of returns on a constant and beta (defined as in Table 5) interacted with market returns and report the time series averages of these parameters. We measure sentiment using the annual index provided by Baker and Wurgler (2006), orthogonalized with respect to macroeconomic variables. We define all observations in year *t* as optimistic (pessimistic) if the sentiment index is positive (negative) in year *t*-1. In both Panels the *t*-statistics are calculated by correcting for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Panel A: Time series			**Panel B: Fama-McBeth**		
Parameter	Estimate	t-stat	Parameter	Estimate	t-stat
	Pessimistic			Pessimistic	
a	0.004	1.15	a	-0.08	-0.24
b	0.96	8.03	b	0.78	1.87
	Optimistic			Optimistic	
a	-0.01	-4.50	a	1.74	6.05
b	1.03	11.63	b	3.26	1.03

Figure 1: Beta, sentiment and returns

This figure depicts the relationships between beta and returns. The x-axis shows portfolio average returns and the y-axis average portfolio beta. To obtain beta portfolios in June of year *t*, all firms are sorted into 20 portfolios by pre-ranking betas using NYSE breakpoints. These pre-ranking betas are calculated using 24 to 60 monthly returns (as available) ending in June of year *t.* Stocks priced less than one dollar in June of year *t* are deleted. We obtain value-weighted monthly returns for these portfolios from July of year *t* to June of year *t+1*, where size is measured at the end of June of year *t.* We measure sentiment using the annual index provided by Baker and Wurgler (2006) orthogonalized with respect to macroeconomic variables. We define all observations in year *t* as optimistic (pessimistic) if the sentiment index is positive (negative) in year *t*-1. We then average portfolio returns separately for optimistic and pessimistic months. The left panel shows the relationship between beta and returns for the entire sample period and the right Panel only in pessimistic sentiment periods.