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Constantinos Antoniou, John A. Doukas, Avanidhar Subrahmanyam

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Investor Sentiment, Beta, and the Cost of Equity Capital

Constantinos Antoniou
Warwick Business School, University of Warwick, Coventry CV4 7AL, United Kingdom,
constantinos.antoniou@wbs.ac.uk

John A. Doukas
Strome College of Business, Old Dominion University, Norfolk, Virginia 23529; and
Judge Business School, University of Cambridge, Cambridge CB2 1TN, United Kingdom,
doukas@odu.edu

Avanidhar Subrahmanyam
Nanjing University School of Management and Engineering, Nanjing Jiangsu 210093, China; and
UCLA Anderson School of Management, University of California, Los Angeles, Los Angeles, California 90095,
subra@anderson.ucla.edu

The security market line accords with the capital asset pricing model by taking on an upward slope in pessimistic sentiment periods, but is downward sloping during optimistic periods. We hypothesize that this finding obtains because periods of optimism attract equity investment by unsophisticated, overconfident, traders in risky opportunities (high beta stocks), whereas such traders stay along the sidelines during pessimistic periods. Thus, high beta stocks become overpriced in optimistic periods, but during pessimistic periods, noise trading is reduced, so that traditional beta pricing prevails. Unconditional on sentiment, these effects offset each other. Although rational explanations cannot completely be ruled out, analyses using earnings expectations, fund flows, the probability of informed trading, and order imbalances do provide evidence that noise traders are more bullish about high beta stocks when sentiment is optimistic, whereas investor behavior appears to accord more closely with rationality during pessimistic periods, supporting our hypothesis.

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1. Introduction

The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) is an integral element of capital budgeting decisions. It posits that if traders are rational and sophisticated, expected returns increase linearly with asset betas. 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 et al. 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 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 et al. 1988; Wright and Bower 1992; Johnson and Tversky 1983).[1] 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, as shown by Amromin and Sharpe (2009), individual investors expect higher stock returns, and thus participate in equities more strongly, following good periods rather than following bad ones. Similarly Grinblatt and Keloharju (2001) and Lamont and Thaler (2003) find that unsophisticated investors are more likely to enter the stock market during prosperous periods. Taken together, these arguments suggest that unsophisticated trading

[1] For related work in experimental economics on the effect of sentiment on financial decisions, see Kuhnen and Knutson (2011) and Andrade et al. (2014).

will be more prevalent and impactful in optimistic periods.[2]

We argue that the heightened noise trader activity in optimistic periods will not affect all companies equally, but will be disproportionately concentrated among high beta stocks. The general preference of individual investors toward high beta stocks has been documented by Barber and Odean (2000), who show that the market beta of the aggregate retail investors' portfolio exceeds unity. Furthermore, Barber and Odean (2001, Table 3) show that this preference is particularly strong among unsophisticated retail investors (i.e., those who trade the most and earn the lowest returns—young, single males). These observations indicate that the enhanced unsophisticated trading during optimistic periods would be more prevalent in high beta stocks. Further, if unsophisticated traders are optimistic about the aggregate stock market but face leverage constraints or are simply averse to borrowing or shorting, high beta stocks are a natural vehicle for them to act on this optimism.

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-beta companies, 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. On the whole, these effects can cancel out, flattening the unconditional beta-return relationship. We provide empirical support for the above arguments, by showing 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 (BW) to capture sentiment, which is orthogonalized with respect to a set of macro variables. Confirming Stambaugh et al. (2012, Tables 7 and 8),[3] we find that for the period from 1966 to 2010, using the Fama and French (1992) methodology, a standard beta, although unconditionally insignificant, is positively related to returns during pessimistic periods, whereas 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 negatively related to returns.

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 high beta stocks. First, since mutual fund flows reflect active reallocation decisions of individual investors, we examine whether optimistic periods are associated with higher capital flows into equity mutual funds. Our results confirm this prediction.

We then examine whether unsophisticated (noise) trading rises disproportionately for 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. Lastly, we use the probability of informed trading (the *PIN* measure of Easley et al. 2002), as calculated in Brown and Hillegeist (2007), which indicates whether the trading for a specific stock in a given month is likely to be driven by fundamental information. 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, which is in line with our hypothesis.

Several studies show that small trades are likely to reflect the trading decisions of noise traders (Hvidkjaer 2006, 2008; Malmendier and Shanthikumar 2007). Along these lines, we use intraday transactions data to estimate stock-by-stock small trader order imbalances (SOIBs), and we test whether they indicate 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, whereas no pattern is observed in pessimistic periods. Moreover, when examining SOIBs around earnings announcements and analyst forecasts, we find that small investors are relatively more bullish (or less bearish) about high beta stocks when sentiment is optimistic. The SOIBs from pessimistic periods in response to these events show little variation across beta portfolios, which suggests that in these periods rational investors largely anticipate these announcements. Overall these results provide further support to our hypothesis.

[2] Furthermore, pessimistic investors need to engage in short selling to express their views, and empirical evidence shows that individual investors are generally reluctant to sell short (Barber and Odean 2008). This aversion to short selling can also contribute to decreased noise trading in pessimistic sentiment periods.

[3] Stambaugh et al. (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.

Since our argument is that increased noise trading in optimistic sentiment periods leads to the underperformance of high beta stocks, by augmenting the BW sentiment index to include information from our proxies of noise trading, we should be better able to capture periods in which high beta stocks are overpriced. To test this notion, we perform principal component analysis using the BW sentiment index and our proxies for noise trading, and we define sentiment using the first principal component from this procedure. We find that the augmented index is a more powerful predictor of the underperformance of high beta stocks in optimistic periods compared to the original BW index, whereas both indices perform similarly in pessimistic periods. This finding supports our hypothesis that heightened noise trading activity leads to negative beta pricing in optimistic sentiment periods.

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; see 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; see 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 that are more expensive to sell short, which suggests 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, 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.

Of course, there is always the possibility that the Baker and Wurgler (2006) measure of sentiment captures a state variable related to macroeconomic risk, and that beta and its pricing dynamically vary with this state variable. Although this possibility cannot completely be ruled out, Lewellen and Nagel (2006) argue that variation in conditional betas would need to be implausibly large to explain asset pricing anomalies.[4] Further, in our context, a rational argument would also need to explain why a traditional beta is negatively priced during optimistic periods, which seems like a daunting task. Finally, as we mention in §8, we find that our results continue to hold when we use betas conditional on sentiment. Thus, we believe that, if rational channels play a role in our findings, it is likely that they do so in conjunction with behavioral channels.

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 (2013) 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 various cross-sectional predictors of stock returns (Livnat and Petrovits 2008, Antoniou et al. 2013, Cen et al. 2013, Stambaugh et al. 2012). Thus, existing literature has linked sentiment to both the rational risk-return trade-off and anomalies left unexplained by rational pricing models.

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,[5] 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 et al. 2012), market frictions (Black 1972, Baker et al. 2011, Frazzini and Pedersen 2014), 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 et al. (2005) advance an argument based on money illusion, and show that riskier stocks earn higher returns when expected inflation is low. Similarly, Hong and Sraer (2014) propose that the underperformance of risky stocks relates to aggregate disagreement about

[4] Specifically, Lewellen and Nagel (2006) show that if a conditional CAPM holds, a stock's alpha depends primarily on the covariance between beta and the market risk premium, which is bounded above by the product of the standard deviations of beta and the premium. The empirical standard deviations are not nearly high enough to explain the alphas achieved from predictor variables corresponding to common asset pricing anomalies.

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

the market factor and limits to arbitrage, and Frazzini and Pedersen (2014) show that in periods of tighter borrowing constraints the security market line is flatter. In our analysis we find that, while controlling for these predictors of the SML's slope, investor sentiment influences the beta–return relation, in line with the notion of noise trading, as advanced by Black (1986).

2. Hypotheses

Our hypotheses are 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.

The studies cited in the introduction (Amromin and Sharpe 2009, Grinblatt and Keloharju 2001, Lamont and Thaler 2003) all suggest that individual investors may be more prone to investing in risky assets during optimistic periods. We thus propose that unsophisticated investors stay by the sidelines during pessimistic periods, so that these periods consist of utility-maximizing risk-averse agents. This implies that a standard CAPM holds during these periods.

We propose periods of optimism attract unsophisticated agents who hold unduly optimistic beliefs about market returns. We argue that these agents exploit their signal only in high beta stocks. We motivate this assumption as follows. Barber and Odean (2000) show that the typical retail investor's portfolio is tilted toward higher beta stocks (they document a loading of 1.1 of the aggregate retail investor portfolio on the market factor). Furthermore, Barber and Odean (2001) show that the most unsophisticated investors (young, single males, who lose the most from investing, and are the most susceptible to overconfidence), also prefer to be long on riskier (higher beta) stocks. We note that if optimistic investors are averse to shorting or borrowing, they would prefer to buy stocks with high exposure to the market, as these promise higher perceived benefits from trading.

Under the condition that the optimism of unsophisticated traders is expressed primarily in high beta stocks, such stocks will become overvalued during optimistic periods.[6] All of the above arguments lead to the following hypotheses:

Hypothesis 1. *Under optimistic periods, stocks with high betas are overpriced. Specifically, the expected return difference between high beta and low beta stocks is negative.*

Hypothesis 2. *During pessimistic periods, a standard CAPM obtains, so that beta is positively priced.*

Hypotheses 1 and 2 form the bases for our empirical analyses. 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 more bullish for high beta stocks in optimistic periods.

3. Data and Methodology

3.1. Sentiment Index

We measure sentiment using the annual index provided by Baker and Wurgler (2006).[7] This index is constructed using six proxies of investors' propensity to invest in stocks: 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, nondurable 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.[8] We define all observations in year t as optimistic (pessimistic) if the Sentiment Index is positive (negative) in year $t-1$ (Yu and Yuan 2011). The index is available from 1965 to 2010, so our sample covers the period 1966–2010.

3.2. 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 Centre for Research in Security Prices (CRSP) monthly files, and 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 × shares outstanding) to determine decile breakpoints. Using these breakpoints, we assign all firms in the

[6] Simple analytical frameworks demonstrating these points are available upon request. We thank the associate editor for suggesting another mechanism: Unsophisticated investors may be overconfident about a (valid) positive market signal during optimistic periods, and overinvest in high beta stocks, as leverage constraints might preclude a large investment in the market index. This phenomenon would also lead to overvaluation of high beta stocks.

[7] We thank Malcolm Baker and Jeffrey Wurgler for making the Sentiment Index publicly available.

[8] In recent and independent work, Sibley et al. (2013) show that the Baker and Wurgler (2006) index correlates with contemporaneous business cycle variables, but they do not rule out the possibility that these variables may also 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.

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 preranking betas for individual stocks. These preranking betas are calculated using 24–60 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 postformation betas using the returns of these portfolios and the CRSP value-weighted return as a proxy for the market portfolio. As in Fama and French (1992), pre- and postranking 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 §7.2 to follow.

Our main analysis employs the Fama and MacBeth (1973) methodology. Thus, in each month t we run a cross-sectional regression of returns on postformation 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 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).

3.3. Summary Statistics

Table 1 shows the time-series averages of the postformation rolling betas for each size-beta portfolio, with three important findings emerging. First, postranking betas precisely reproduce the ranking of preranking betas, second, there is sizable variation in betas that is unrelated to firm size, and third, betas are generally larger for smaller companies.

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 riskier companies with more speculative cash flows.

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 and the book-to-market ratio are close to each other, suggesting little skewness. Panel B of Table 3 indicates that the correlation between the rolling and full sample betas exceeds 80%. Overall, the correlations are quite modest suggesting that multicollinearity is not likely a material issue in our statistical tests.

Table 1 **Postformation Rolling Betas**

	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

Notes. This table reports the time-series averages of postformation betas that are assigned to individual stocks. In June of year t, all NYSE firms are sorted by size (price × 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 preranking betas for individual stocks. These preranking betas are calculated using 24–60 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 postformation betas using the returns of these portfolios and the CRSP value-weighted portfolio as a proxy for the market. Pre- and postranking 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 postformation 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. Our sample covers the period 1966–2010.

Table 2 Characteristics of Beta-Sorted Portfolios

	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

Notes. This table reports characteristics of portfolios sorted on betas. In June of year t, all NYSE firms are sorted into 10 portfolios by preranking betas using NYSE breakpoints. These preranking betas are calculated using 24–60 monthly returns (as available) ending in June of year t. Stocks priced less than one dollar in June of year t are deleted. The book-to-market ratio, *BM*, is calculated as the book value of stockholders' equity, *B*, 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. Market value of equity, *M*, is measured at December of $t-1$. Company size (price $\times$ shares outstanding), *ME*, is 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 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 we report the time-series average of these estimates.

4. Portfolio Results

We begin with a simple portfolio test. We rank stocks based on their preformation 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.

Table 3 Descriptive Statistics and Correlation Coefficients

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*]	*Ret*1	*Ret*6	*Ret*12
Rolling beta	1	0.81	−0.24	−0.05	0.008	0.036	0.04
		[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
FF beta		1	−0.29	−0.07	0.01	0.03	0.05
			[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
log[*ME*]			1	−0.37	−0.04	−0.04	0.03
				[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
log[*BM*]				1	0.03	0.08	−0.04
					[< 0.0001]	[< 0.0001]	[< 0.0001]
*Ret*1					1	−0.02	0.003
						[< 0.0001]	[< 0.0001]
*Ret*6						1	−0.01
							[< 0.0001]
*Ret*12							1

Notes. This table reports descriptive statistics (panel A) and Pearson correlation coefficients (panel B). Postformation betas (*Rolling beta*) 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. The book-to-market ratio, *BM*, is calculated as the book value of stockholders' equity, *B*, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Stocks with negative book values are not used. Market value of equity, *M*, is measured at December of $t-1$. Company size (price $\times$ shares outstanding), *ME*, is 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 $t+1$. The return of stock i in month $t-1$ is indicated as *Ret*1; *Ret*6 is cumulative return of stock i in the six months prior to month $t-1$; and *Ret*12 is the cumulative return of stock i in the six months prior to month $t-7$. Our sample covers the period 1966–2010.

Table 4 Returns of Beta-Sorted Portfolios

	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
Pessimistic ($n = 276$)	0.79	0.77	0.87	1.12	1.25	1.12	1.35	1.39	1.67	1.88	1.09**
Optimistic ($n = 264$)	1.01	0.95	1.00	0.96	0.59	0.90	0.41	0.55	0.38	−0.15	−1.16**

Notes. This table reports the average return of beta-sorted portfolios. In June of year t, all firms are sorted into 10 portfolios by preranking betas using NYSE breakpoints. These preranking betas are calculated using 24–60 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.
**Denotes significance at the 5% level.

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. 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 SML during pessimistic periods.[9]

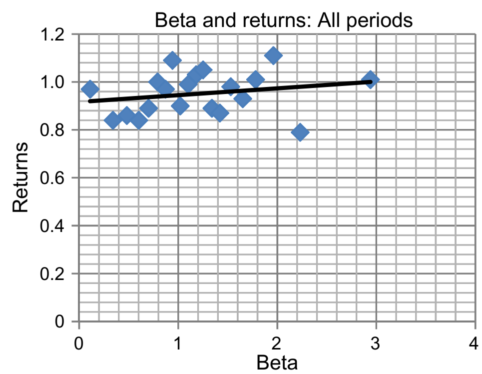
The third row in Table 4 shows the average monthly returns of the beta portfolios in optimistic sentiment periods. In these periods, low beta stocks outperform high beta stocks. According to our hypothesis, this occurs because noise traders overprice high beta stocks when they are optimistic. We conduct several tests to directly test this proposition in §6.

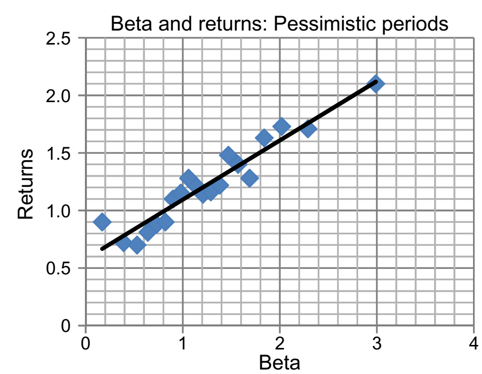
5. Regression Analysis

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 previously discussed, 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, and 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

Figure 1 (Color online) Beta, Sentiment, and Returns





Notes. 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 preranking betas using NYSE breakpoints. These preranking betas are calculated using 24–60 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 upper panel shows the relationship between beta and returns for the entire sample period and the lower panel only in pessimistic sentiment periods.

[9] 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.

Table 5 Fama–MacBeth Regressions

Panel A: All ($N=540$)						Panel B: Pessimistic ($n=276$)						Panel C: Optimistic ($n=264$)					
β	ln[*ME*]	ln[*B/M*]	*Ret*1	*Ret*6	*Ret*12	β	*ln[ME]*	ln[*B/M*]	*Ret*1	*Ret*6	*Ret*12	β	ln[*ME*]	ln[*B/M*]	*Ret*1	*Ret*6	*Ret*12
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]

Notes. 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 postformation 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 $t-1$. Company size (price $\times$ shares outstanding), *ME*, is measured at June of year t. The book-to-market ratio, *BM*, is calculated as the book value of stockholders' equity, *B*, 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. Market value of equity, *M*, is measured at December of $t-1$. These variables are matched with CRSP returns for the months of July of year t to June of year $t+1$. The return of stock i in month $t-1$ is indicated as *Ret*1; *Ret*6 is cumulative return of stock i in the six months prior to month $t-1$; and *Ret*12 is the cumulative return of stock i in the six months prior to month $t-7$. The average number of companies in each cross-sectional regression is 3,037 in panel A, 2,894 in panel B, and 3,186 in panel C.

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 et al. 2013). The value effect is present in both types of sentiment periods, but the regression coefficient is smaller in pessimistic periods than in optimistic ones. 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.[10] 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.[11] Although the implied market premium is quite 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. Although still higher than the 8.0%–8.5% annual premium documented in various sources (e.g., Allen et al. 2010), this premium nonetheless is reasonable in terms of its magnitude.[12]

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 §6 that this is because during optimistic periods risky stocks become overpriced and subsequently underperform.[13] 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.[14, 15] We conduct several additional tests to establish the significance of this differential, which are available from the authors upon request.

We would like to stress, however, an issue that is common to papers that use the sentiment index of Baker and Wurgler (2006). Specifically, the sentiment index is a principal component extracted from several time series, and as such, requires full sample information for construction. This implies that our approach is not amenable to estimation in real time. It would be valuable for researchers and practitioners if future research were to identify an alternative sentiment proxy based only on historical information.

6. Sentiment, Beta, and Noise Trading

Whereas 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 bullish for high beta stocks. This leads to an

[10] 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.

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

[12] 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).

[13] Preliminary results are supportive, however, as we find that stocks in the optimistic period high beta portfolio 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 $= 1.29$).

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

[15] Fama and MacBeth (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^(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.

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.[16] 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 untabulated analysis, we estimate aggregate monthly fund flows (*AFLOW*) using the CRSP Mutual Fund Database and following the procedure in Akbas et al. (2015, Equations (3), p. 11).[17] 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.

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 forecasts for stocks with more uncertain valuations 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.[18] Using the Institutional Brokers' Estimate System (IBES) summary files for one-year-ahead forecasts, we calculate the 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 beta and low beta portfolios conditional on sentiment. Higher *FE* values indicate increased noise trading.

[16] The Investment Company Institute (2012) 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.

[17] The equation is

$$MFFLOW_{i,t} = \frac{\sum_{i=1}^{N}(TNA_{i,t} - TNA_{i,t-1} * (1 + MRET_{i,t}))}{\sum_{i,t}^{N} TNA_{i,t-1}},$$

where TNA is the total net assets of fund i in month t and $MRET$ is the return of fund i in month t.

[18] 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 (see Hong and Kubik 2003).

Table 6 Noise Trading and Beta

	Low β	High β	H-L	t-statistic
Panel A: Analyst optimism				
Optimistic	0.18	0.43	0.25	14.73
Pessimistic	0.21	0.35	0.14	7.42
Optimistic − Pessimistic	−0.03	0.08	0.11	
t-statistic	−2.48	4.55	4.46	
Panel B: Stock specific flow				
Optimistic	−0.06	0.27	0.33	4.05
Pessimistic	0.52	0.64	0.12	1.48
Optimistic − Pessimistic	−0.58	−0.37	0.21	
t-statistic	−7.77	−5.56	1.90	
Panel C: PIN				
Optimistic	0.287	0.198	0.089	19.43
Pessimistic	0.278	0.206	0.072	16.13
Optimistic − Pessimistic	0.009	−0.008	−0.017	
t-statistic	2.26	−4.80	−2.81	

Notes. This table measures noise trading activity in low and high beta portfolios, conditional on investor sentiment. The beta portfolios are formed using preformation 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 5th and 95th 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 from 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 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.

The results are shown in panel A of Table 6. High beta stocks generally have higher *FE*. This is expected, since analyst bias is likely to be stronger in situations when uncertainty is higher. However, 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-statistic = 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 captures the bullishness of noise traders toward high beta stocks through their trading decisions. Frazzini and Lamont (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.[19] 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 (0.33: t-statistic = 4.05). This result shows that high beta stocks are relatively favored by noise traders during optimistic sentiment periods.[20] *FLOW* is higher for high beta stocks in pessimistic sentiment periods as well, but the difference is not statistically significant (0.12: t-statistic = 1.48). Moreover, the spread in *FLOW* between high and low beta stocks is significantly higher in optimistic sentiment periods (0.21: t-statistic = 1.90).

Our last indicator in this section of the analysis is the probability of informed trading (*PIN*), calculated in Brown and Hillegeist (2007).[21] *PIN* is estimated from a structural model using intraday order flow data and indicates whether the trading for a specific stock in a given month is likely to be driven by fundamental information. 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 of Table 6 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-statistic = −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.

Previous research shows that small trades are likely to reflect the decisions of unsophisticated traders (see, e.g., Hvidkjaer 2006, 2008; Malmendier and Shanthikumar 2007). In this section, we use intraday transaction level data from the transaction and quotes database (TAQ) to calculate small investor net order imbalance (SOIB), 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).[22]

The results are shown in Table 7. In panel A we calculate the average daily SOIB 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 become net sellers in pessimistic periods (−0.021), with the spread being statistically significant (0.03: t-statistic = −4.77). These results support the notion that noise traders are attracted to high beta stocks in periods of optimism.

In panels B–D of Table 7, we examine the response of small investors to earnings announcements, revisions to analyst recommendations, and earnings forecasts. For earnings announcements we follow Livnat and Mendenhall (2006) and calculate quarterly surprises using the seasonal random 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 four standardized unexpected earnings (SUE) groups in each fiscal period. We average the daily small investor SOIB 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.

[19] 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).

[20] 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).

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

[22] 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 100 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.

Table 7 Small Investor Order Imbalance

Beta portfolio	Optimistic	Pessimistic	Optimistic − Pessimistic	*t*-statistic	Optimistic	Pessimistic	Optimistic − Pessimistic	*t*-statistic
			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-statistic	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-statistic	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-statistic	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-statistic	1.63	0.97			−0.64	0.17		

Notes. This table presents order imbalance (SOIB) 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 SOIB for each company, we subtract the market-wide imbalance for small investors on that day. We delete the top 1% of daily SOIB observations according to small trader turnover and large trader turnover ((buy volume + sell volume)/market value)). In panel A we calculate the average daily SOIB for each company and month, and then report the average monthly SOIB for the six-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 four standardized unexpected earnings groups (SUE). In panel B we report the average SOIB 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. 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.

From panel B1 (SUE = 4) of Table 7, 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. −0.070). 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 the SOIB 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, SOIBs from pessimistic periods show little variation across beta portfolios, which suggests rational investors largely anticipate the announcements or revisions.

Our next test examines whether noise traders are attracted to high beta stocks because they allow market bets or because they are more speculative. To examine this, we add into our Fama–MacBeth regressions two additional variables that relate to firm uncertainty, namely disagreement, measured by dispersion in analyst forecasts (*Disp*), and idiosyncratic volatility (*IVOL*). Diether et al. (2002) show that stocks with high disagreement earn lower returns and argue that this reflects an overpricing in the spirit of Miller (1977). Ang et al. (2006) show that stocks with high idiosyncratic volatility earn significantly lower returns. Gao et al. (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 onward, so the regressions that include the two additional variables span a shorter sample period relative to Table 5 (10 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 Diether et al. (2002) and Ang et al. (2006) 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 et al. (2012). Comparing models 1 and 2 in panel C, the inclusion of these variables reduces the coefficient on beta in optimistic periods from −0.66% to −0.53% and its t-statistic from −2.03 to −1.68, which suggests

Table 8 Expanded Fama–MacBeth Regressions

	β	ln[*ME*]	ln[*B/M*]	*Ret*1	*Ret*6	*Ret*12	*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]

Notes. This table reports the average slopes of each variable from the monthly Fama–MacBeth regressions for models 1 and 2 for the period February 1976 to December 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 postformation 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 $t-1$. Company size (price × shares outstanding), ME, is measured at June of year t. The book-to-market ratio, BM, is calculated as the book value of stockholders' equity, B, 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. Market value of equity, M, is measured at December of $t-1$. These variables are matched with CRSP returns for the months of July of year t to June of year $t+1$. The return of stock i in month $t-1$ is indicated as *Ret*1; *Ret*6 is cumulative return of stock i in the six months prior to month $t-1$; and *Ret*12 is the cumulative return of stock i in the six months prior to month $t-7$. We calculate analyst disagreement (*Disp*) using the IBES summary files. Dispersion, *Disp*, is the standard deviation of outstanding forecasts (as reported by IBES) divided by the absolute value of the mean forecast in June in month $t-1$. Idiosyncratic volatility in $t-1$, *IVOL*, is 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 minus big) and save the residuals. Then in each month and for each company, *IVOL* is the sum of the squared residuals. The average number of firms per month in the regressions below is 1,888.

Table 9 Augmented Sentiment Index

Panel A: Returns on beta-sorted portfolios			
	Low β	High β	H-L
Pessimistic ($n = 212$)	0.91	1.97	1.06**
Optimistic ($n = 113$)	1.11	−1.16	−2.27**

Panel B: Fama–MacBeth regressions					
β	ln[*ME*]	ln[*B/M*]	*Ret*1	*Ret*6	*Ret*12
B1: Pessimistic ($n = 212$)					
0.87	−0.04	0.14	−0.03	0.002	0.001
[2.38]	[−0.76]	[1.29]	[−5.47]	[0.68]	[0.50]
B2: Optimistic ($n = 113$)					
−1.27	0.08	0.53	−0.04	0.008	0.01
[−3.04]	[−1.34]	[5.00]	[−6.37]	[2.88]	[3.69]

Notes. In this table we use the monthly Baker and Wurgler (2007) sentiment index in month t, and the average *Stock specific flow*, *FE*, and *SOIB* for high beta in the same month (defined as in Tables 6 and 7, respectively), perform principal component analysis, and retain the first principal component as an augmented sentiment index. To define sentiment in month t, we average the augmented sentiment index from $t-1$ to $t-7$ and define sentiment as optimistic (pessimistic) if this average is positive (negative). Using this index in panel A, we repeat the analysis conducted in Table 4, and in panel B the analysis of Table 5, using the same methodology as in those tables. The time period for this test is 1984–2010.

**Denotes significance at the 5% level.

that both the aforementioned channels contribute to the negative pricing of beta in optimistic periods. As shown by panel B, the beta return relationship in pessimistic periods is not affected, which suggests that in those periods prices are set according to fundamentals.

Next, we test the notion that an augmented sentiment index using information from noise trading proxies can better predict the underperformance of high beta stocks in optimistic periods. We use the monthly sentiment index of Baker and Wurgler (2007) orthogonalized to macroeconomic variables in month t, and the average *Stock specific flow*, *FE*, and *SOIB* for high beta stocks (defined as in Tables 6 and 7, respectively) in the same month, perform principal component analysis, and retain the first principal component as an augmented sentiment index.[23] We average this augmented index for the months $t-1$ to $t-7$, and if this rolling average is positive (negative) we define sentiment in month t as optimistic (pessimistic). Using this index we repeat our baseline analysis in Tables 4 and 5. The time period for this test is shorter, due to the fact that the noise trading proxies are not available for the earlier part of the sample.

The results are shown in Table 9. Indeed, we find that the augmented sentiment index is better able to predict the negative pricing of beta in optimistic sentiment periods. From panel A, in a portfolio setting, we observe that the return spread between high and low beta stocks is −2.27% per month, considerably larger than the −1.16% shown in Table 4. However, the spread in pessimistic periods is not materially altered. In panel B, in a Fama–MacBeth setting, we observe that the coefficient of beta in optimistic sentiment periods with the augmented sentiment index is −1.27 (t-statistic = −3.04). When we repeat this analysis for the same time period using the original Baker and Wurgler (2007) index we find that the coefficient of beta is −0.70 (t-statistic = −2.02) (unreported result). Therefore, controlling for other variables, the underperformance of high beta stocks reduces by 0.57% per month when the augmented index is used. In pessimistic sentiment periods, the coefficient on beta under the original sentiment index is 0.99 (t-statistic = 2.16), not very different from the coefficient of 0.87 (t-statistic = 2.38) shown in Table 9, panel B. This finding confirms that expanding the sentiment index to include information from the noise trading proxies improves the capacity of the index to identify optimistic sentiment, and therefore predict the negative pricing of beta in optimistic periods. The fact that the noise trading proxies do little to the predictability of returns from beta in pessimistic sentiment periods suggests that in those periods noise trading is less impactful and prices are set according to fundamentals.[24]

[23] The correlation between this first principal component and the original sentiment index is 79%.

[24] In unreported analysis, we use the augmented sentiment index to replicate the analysis of Tables 8 and 11, and we obtain very similar results as those in Table 9. These results are available from the authors upon request.

Table 10 Beta-Sorted Portfolios Cut Different Ways

	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**

Notes. 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 Wharton Research Data Services. 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 $\log(1 + \textit{Number of analysts}) = a + b * \log(\textit{Market value}) + e$, where number of analysts is provided by the IBES summary files and *Market value* 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.

7. 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; see 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; see Shleifer and Summers 1990). We subdivide our sample into two groups using these variables (high versus 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 10. 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 that 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.[25]

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

Table 11 Controlling for Additional Variables

β	ln[*ME*]	ln[*B/M*]	*Ret*1	*Ret*6	*Ret*12	*Disp*	*IVOL*	*AGE*	*EF*	*GS*	*PrD*	*DivD*
						Panel A: 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 B: 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]

Notes. This table reports the average slopes of each variable from the monthly Fama–MacBeth regressions for models 1 and 2 for the period from February 1976 to December 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 that 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 that takes the value of 1 for firms with positive dividends per share at the ex-date and 0 otherwise.

8. 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 11. 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-statistic = 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 (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 13 variables.

One issue is whether our differential results for beta pricing during optimistic and pessimistic periods obtain because of variation in beta conditional on sentiment. To address this, we estimate conditional betas using the technique of Jagannathan and Wang (1996), using the BW sentiment index as the conditioning variable. The analysis indicates that these conditional betas are also positively priced in pessimistic periods and negatively priced during optimistic periods. The results are not reported here for brevity, but are available upon request.

A concern with the rolling beta approach used in the main tests is that, because of 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. First, 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. Second, we use the same rolling beta approach, but in the regressions to estimate preformation and postformation betas we include aggregate fund flows (as per Footnote 17). 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.[26]

The results are shown in Table 12. Both the full sample (panel A) and aggregate fund flow method (panel B) 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

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

Table 12 Alternative Beta and Sentiment Specifications

All						Pessimistic						Optimistic					
β	ln[*ME*]	ln[*B/M*]	*Ret*1	*Ret*6	*Ret*12	β	ln[*ME*]	ln[*B/M*]	*Ret*1	*Ret*6	*Ret*12	β	ln[*ME*]	ln[*B/M*]	*Ret*1	*Ret*6	*Ret*12
Panel A: 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 B: 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]
Panel C: Michigan consumer confidence index$^{\top}$																	
$N = 391$						$n = 163$						$n = 228$					
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 D: 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 E: 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]

Notes. 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 the columns labeled "all," we average the slopes for our entire sample period. In the columns labeled "pessimistic" and "optimistic," we define each month t as pessimistic or optimistic, respectively, and average the slopes separately for each group. In panels A and B we measure sentiment using the Baker and Wurgler (2006) index as in Table 5. In panel A postformation betas are calculated using the full sample methodology, as in Fama and French (1992). In panel B we calculate postformation betas using the rolling methodology explained in Table 5, but in the regressions where we estimate both preformation and postformation 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 C and D all the variables are defined as in Table 5 except that we measure sentiment differently. In panel C 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 D 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 C and D is 1978–2010, when the Michigan index is available on a monthly basis. In panel E 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 2014), 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 a 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.

of Michigan, which we orthogonalize with respect to the macroeconomic variables used by Baker and Wurgler (2006). 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.[27] 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–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 panel C of Table 12, 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 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 D of Table 12, and are in line with our baseline findings.[28]

We next examine whether sentiment predicts the beta-return relationship once we 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 2014), and aggregate disagreement (Hong and Sraer 2014). For this test we define sentiment using the monthly BW sentiment[29] index orthogonal to macroeconomic variables, which we further orthogonalize with respect to the inflation rate, two variables that capture leverage constraints (the TED spread, defined as the three-month rate difference between LIBOR and the T-Bill rate and the BAB factor from Frazzini and Pedersen 2014),[30] and two variables that capture aggregate disagreement (beta-weighted disagreement from analyst earnings forecasts as in Hong and Sraer 2014, and disagreement about market returns calculated using data from the Survey of Professional Forecasters (SPF) as in Anderson et al. 2009).[31] 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 on disagreement from SPF data is negative and significant.[32] We define optimistic and pessimistic sentiment averaging the residuals from this regression, as in panels C and D of Table 12. Panel E presents the results, which are consistent with those in our baseline sentiment specification, and shows that our finding is incremental in relation to these studies.[33]

Finally, we examine whether our results are driven by the predictability of aggregate market returns from sentiment. To do this, we perform two tests: First, in a time-series framework, we regress the spread between the high and low beta portfolios from Table 4 on excess

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

[28] 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 we repeat the analysis in Table 5. We obtain similar results as those in the paper. These results are available from the authors upon request.

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

[30] 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.

[31] 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 (2014), 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.

[32] 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.

[33] In unreported analysis, which is available upon 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 we repeat the analysis in Table 5. Our baseline results continue to hold.

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.

Second, 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 the coefficients on this term. Let r_{t+k} denote the expected return at time t over a k period horizon, with the superscript m denoting the market. Further, let β_t denote the beta vector at time t. With this specification, the slope obtained from the Fama–MacBeth procedure is

$$slope_{t+k} = (r^m_{t+k}\boldsymbol{\beta}'_t\boldsymbol{\beta}_t r^m_{t+k})^{-1} r^m_{t+k}\boldsymbol{\beta}'_t\mathbf{r}_{t+k} = (r^m_{t+k}\boldsymbol{\beta}_t)^{-1}\mathbf{r}_{t+k}.$$

Therefore, if the CAPM holds and returns are only proportional to betas ($\mathbf{r}_{t+k} = \boldsymbol{\beta}_t r^m_{t+k}$), the intercept should equal 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 13 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 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 is not driven by the predictability of market returns from sentiment.

Table 13 **Controls for Market Returns**

Panel A: Time series			Panel B: Fama–MacBeth		
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
	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

Notes. This table reports the average return of beta-sorted portfolios. In June of year t, all firms are sorted into 10 portfolios by preranking betas using NYSE breakpoints. These preranking betas are calculated using 24–60 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–MacBeth 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 and West (1987) estimator.

9. 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.

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 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 intraday 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.

Although we cannot rule out the possibility that our sentiment measure captures variations in a macroeconomic state variable, and that beta and its pricing covary with this variable, such an explanation should also accord with negative beta pricing during optimistic periods, which is challenging. Collectively, the evidence presented thus 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 CFOs can use the CAPM for capital budgeting decisions in pessimistic periods, but not optimistic ones, assuming such periods can be identified in real time. Thus, for real investments undertaken during periods of optimism, it may be more appropriate to derive valuations from model-free methods, using, for example, comparables, and price multiples such as the price/earnings ratio.

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