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Betting against beta and investor sentiment

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Miikka Hakala
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Abstract of master's thesis

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Background and objectives

CAPM implies positive relation between the beta of a stock and its future returns. However, empirical studies do not support this proposition because low-beta stocks do better and high-beta stocks worse than expected. Moreover, Frazzini and Pedersen (2014) show that a betting against beta (BAB) factor buying low-beta assets while shorting high-beta assets provides robustly positive returns in the U.S. stock market from 1926 to 2012 as well as in 20 international stock markets, Treasuries, corporate credits, and futures. There is an ongoing effort to uncover the beta anomaly. In this quest, the behavioral-finance approach seems most promising. While market frictions such as benchmarking and leverage constraints probably are important, there is also something about high-beta stocks that makes them attractive for individual investors.

My paper takes a conservative approach in studying does the betting against beta exists in the stock market by combining empirical elements that have produced modest results in the previous studies. If the betting against beta is found, data mining etc. seem unlikely explanations. Secondly, I investigate whether high-beta stocks have certain characteristics that make them the most affected by investor sentiment, which measures the collective mood and trust of individual investors. Most importantly, I study does investor sentiment explain the betting against beta phenomenon in the stock market.

Data and methodology

I use stock return data from CRSP between 1984 and 2011 to sort stocks into quintile portfolios based on beta. To find out whether the betting against beta exists in the stock market I study the portfolio returns on both absolute and risk-adjusted basis. Secondly, I use an index of investor sentiment (Baker and Wurgler, 2007) to answer the question does investor sentiment explain the betting against beta. First, I divide the sample period into high and low sentiment, and secondly, utilize the index as an explanatory variable in multifactor regressions.

Main findings

I find that the betting against beta exist in the stock market. Empirical security market line is too flat and Sharpe ratios as well as CAPM alphas decline monotonically in beta. The results are generally robust to traditional multifactor models. Furthermore, investor sentiment influences the performance of the betting against beta. Following high sentiment the returns are monotonically declining in the beta quintiles, and following low sentiment the pattern completely reverses. My results also reveal a "flight-to-quality" phenomenon within stocks. Lastly, the results are robust to controls for market, popular empirical style factors, and alternative measures of sentiment. Additional robustness checks show that investor sentiment influences the betting against beta also contemporaneously and that the results are not specific to the time period because investor sentiment influences also the BAB-factor returns during a longer time period from 1965 to 2011.

Keywords Betting against beta, BAB factor, CAPM, Investor sentiment, Sentiment, Individual investors, Retail investors, Limits of arbitrage, Flight-to-quality, Stock market, Speculation

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Tausta ja tavoitteet

CAPM ennustaa positiivista suhdetta osakkeen beta-kertoimen ja tuoton välillä. Empiiriset tutkimukset kuitenkin osoittavat, että alhaisen betan osakkeet tuottavat enemmän ja korkean betan osakkeet vähemmän kuin pitäisi. Frazzini ja Pedersen (2014) näyttävät, että markkinaneutraali BAB faktori, joka ostaa alhaisen ja myy korkean betan osakkeita tuottaa ylisuuria tuottoja niin Yhdysvaltain osakemarkkinalla vuosina 1926 - 2012 kuin 20 kansainvälisellä osakemarkkinalla, Yhdysvaltain valtionvelkakirjoissa, yritysluotoissa ja futuureissa. Empiirinen rahoitustutkimus on erityisesti viime vuosina ottanut aiheen omakseen ja varsinkin käyttäytymisrahoitukseen pohjautuva lähestymistapa on tuottanut lupaavia tuloksia. Erityisesti rahastoille asetetut suoritusmittarit ja velanoton rajoitteet näyttäisivät ohjaavan kysyntää korkean betan osakkeisiin. Toisaalta erityisesti yksityissijoittajat näyttävän olevan kiinnostuneita korkean betan osakkeista.

Tässä työssä otan konservatiivisen lähtökohdan beta-anomalian tutkimiseen yhdistämällä empiirisiä aineksia, jotka ovat aikaisemmissa tutkimuksissa tuottaneet heikompia tuloksia. Jos beta-anomalia tästä huolimatta näyttäytyy, on se katsottava vakaaksi. Toiseksi tutkin, onko korkean betan osakkeilla ominaisuuksia, jotka tekevät ne alttiiksi sijoittajasentimentille, joka mittaa yksityissijoittajien kollektiivista uskoa ja luottamusta markkinoihin. Pääasiallinen tutkimuskysymykseni onkin: vaikuttaako sijoittajasentimentti beta-anomaliaan.

Aineisto ja menetelmät

Aineisto koostuu CRSP-tietokannan osaketuottodatasta vuodesta 1984 vuoteen 2011, minkä perusteella osakkeille lasketaan beta-kerroin. Beta-kertoimen perusteella jaan osakkeet viiteen portfolioon. Käytän niin absoluuttisia kuin riskikorjattuja tuottoja beta-anomalian olemassaolon selvittämiseen. Sijoittajasentimentin vaikutusta tutkiessani hyödynnän sijoittajasentimentti-indeksiä (Baker and Wurgler, 2007). Ensinnäkin jaan sen perusteella otosperiodin korkeaan ja alhaiseen sentimenttiin. Toiseksi käytän indeksiä selittävänä muuttuja monimuuttujaregressiossa.

Tulokset

Tulokset vahvistavat beta-anomalian olemassaolon osakemarkkinoilla. Empiirinen osakemarkkinasuora on liian loiva ja Sharpe-kertoimet sekä CAPM alfat laskevat monotonisesti betan kasvaessa. Myöskään monimuuttujamallien käyttäminen ei tee tuloksista mitättömiä. Lisäksi, sijoittajasentimentti vaikuttaa beta-anomaliaan. Korkean sentimentin jälkeen tuotot laskevat monotonisesti betan kasvaessa ja matalan sentimentin jälkeen kasvavat. Tulokset paljastavat myös ”turvasatama” ilmiön osakemarkkinoilla. Sijoittajasentimentti on niin ikään erillinen markkina-efektistä sekä perinteisistä osaketuottokontrolleista. Tulokset ovat niin ikään vakaat vaihtoehtoisille sentimenttimittareille. Lopuksi näytän, että sijoittajasentimentti vaikuttaa osakkeiden tuottoihin kolmea kuukautta pidemmillä jaksoilla ja että tulokset pätevät myös pidemmällä ajanjaksolla 1965 – 2011.

Avainsanat Beta-anomalia, Beta-kerroin, Sijoittajasentimentti, Sentimentti, Yksityissijoittajat, Ei-ammattimaiset sijoittajat, Arbitraasi, Arbitraasirajoite, Turvasatama, Osakkeet, Spekulointi

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1 Introduction

1.1. Background

CAPM-implied positive relation between beta and return is empirically flat or even negative in the stock market (e.g. Frazzini and Pedersen, 2014). Low-beta stocks provide higher and high-beta stocks lower than expected returns. This beta anomaly has been branded as *betting against beta* in the literature and Baker, Bradley, and Wurgler (2011) dub it as “the greatest anomaly in finance”.

Indeed, it is disturbing that the most widely used measure of risk in finance is unrelated to returns. The missing link between beta and return implies that beta is not a good risk measure or that prices are not right. Furthermore, the challenge for the traditional efficient market theories is to explain why low-beta stocks are riskier than high-beta stocks, which could be insurmountable.

Fortunately, behavioral finance has emerged during the past two or three decades to complement the traditional theories of financial markets. Behavioral finance allows the possibility of market frictions and irrational demand playing a role in the financial markets. It is possible, for example, that prices deviate from fundamentals due to non-fundamental demand and that the forces of arbitrage are not always sufficient to correct the deviations.

The best explanations for the betting against beta also have behavioral roots. First of all, there seems to be important market frictions such as benchmarking (e.g. Baker, Bradley, and Wurgler, 2011) and leverage constraints (e.g. Black et al., 1972) that make high-beta stocks more attractive. Furthermore, psychology and especially lottery demand (e.g. Bali et al., 2014) stories have strong explanatory power. Importantly, the explanations are not mutually exclusive and probably most of them have a role to play.

Behavioral finance theories often make a distinction between rational (e.g. hedge funds, mutual funds) and irrational investors (e.g. retail investors, individual investors). While the first group makes decisions in a rational manner, the second group is humanly flawed. For example, individual investors suffer from biases (e.g. overconfidence, representativeness, and anchoring), herd (e.g. herding, peer learning), and focus too much on the strength of the information rather than weight of the information (Barberis, Shleifer, and Vishy, 1998).

Importantly, the behavior of retail investors is systematically correlated (e.g. Kumar and Lee, 2006). In finance, this systematically correlated behavior is labeled as investor sentiment. Furthermore, Baker and Wurgler (2006) develop an index of investor sentiment and show that investor sentiment has asset pricing implications. They show e.g. that there is time-variation in the returns of small stocks that can be explained by time-variation in the investor sentiment.

Barberis, Shleifer, and Wurgler (2005) propose a “category” or “habitat” view of financial markets, according to which different stocks move together because they have similar characteristics or clientele. According to their view some stock have positive returns over others because a certain sub-group of investors becomes bullish and drives up the prices of those stocks. Moreover, Baker and Wurgler (2007) discuss that individual and retail investors prefer certain characteristics over others (e.g. growth and volatility). Therefore if stocks have those characteristics they are most affected by investor sentiment.

Where there are limits-to-arbitrage, the investor sentiment implied mispricing is not arbitraged away and will be persistent. In the case of high-beta stocks, characteristics such as volatility, extreme growth, and small size could make it harder to arbitrage any mispricing. Furthermore, benchmarking, leverage constraints, and time-horizon most likely limit the arbitrage opportunities as well as arbitrage capital

1.2. Results

In this paper, I study first whether the betting against beta exist in the U.S. stock market between July 1984 and January 2011. While the previous studies generally support the existence, the results are somewhat sensitive to empirical choices. Moreover, Bali and Cakici (2008) show that the relation between idiosyncratic volatility and future returns is not robust to different empirical settings. Because beta and volatility anomalies are related, I choose a conservative setting in this study. Particularly, sample breakpoints, rebalancing frequency, weighting scheme, and risk-measure estimation used in this paper have provided weaker results in the previous studies.

I compare the average returns across five beta-sorted portfolios and investigate whether the betting against beta exists on absolute return basis. The average returns are flat across the beta quintiles and the return on a portfolio going long the lowest beta quintile while shorting the highest beta quintile is not statistically significant.

Furthermore, I investigate whether the betting against beta exists on risk-adjusted basis. Monotonically declining Sharpe ratios in beta, flat empirical security market line, and positive return on a risk-parity portfolio conceptually similar to BAB factor of Frazzini and Pedersen (2014) support unanimously the existence of the betting against beta. CAPM-regression alphas are also monotonically declining in beta. Lastly, variables known to explain cross-sectional stock returns (e.g. size, value, and momentum) do have explanatory power but the role of sentiment remains significant.

Secondly, I study does the investor sentiment influence the betting against beta. This is done in two steps. In the first step I study whether the high-beta stocks have the characteristics that individual and retail investors prefer according to Baker and Wurgler (2007). Based on previous literature and six-factor model loadings I conclude that high-beta stocks have the important characteristics.

In the next step I divide the sample period into high and low sentiment and study whether the returns on beta-sorted portfolios and long-short strategies are different following high and low sentiment. Furthermore, I make good use of the investor sentiment index (Baker and Wurgler, 2006) by including it as an explanatory variable in multifactor time-series regressions. This should capture more formally the effect of investor sentiment over and above market effect as well as popular empirical style factors.

The results support clearly the proposition that investor sentiment influences the betting against beta in the stock market. Following high investor sentiment the returns are monotonically declining in the beta quintiles. Moreover, following low investor sentiment the pattern completely reverses and high-beta stocks outperform low-beta stocks. Investor sentiment also affects the high-beta stocks the most. Furthermore, the results reveal a “flight-to-quality” phenomenon within equities because contrary to all the other stocks and overall market portfolio that have higher average returns following low investor sentiment the returns for low-beta stocks are lower following low investor sentiment. Therefore investors seem to look for safety during low sentiment. Finally, the multifactor regressions reveal that the effect of investor sentiment is distinct from the market effect and popular empirical style factors although they do diminish the effect of investor sentiment somewhat.

I examine the robustness of the results in several ways. First I study how investor sentiment influences the performance of BAB factor (Frazzini and Pedersen, 2014) during a longer time period from August 1965 to January 2011. The use of BAB factor makes it possible to utilize the whole monthly investor sentiment data in the Jeffrey Wurgler's website and provides a valuable out-of-sample evidence. The results are similar to the main results. Secondly, I construct three other measures of investor sentiment and show that the results are robust to the alternative measures. Thirdly, to provide further evidence that during high investor sentiment high-beta stocks become overvalued and during low investor sentiment undervalued, I show that increasing investor sentiment influences the performance of betting against beta *contemporaneously*. Increasing investor sentiment shows up as higher returns for high-beta stocks and decreasing investor sentiment shows up as lower returns for high-beta stocks. Lastly, I show that while the level of market and the level of investor sentiment are correlated, the effect of investor sentiment is distinct from the market effect. Especially, investor sentiment affects different stocks differently in the cross-section, while market affects all stocks similarly.

1.3. Contribution

The paper adds to the existing literature in several ways. First of all, it shows that the betting against beta is robust in the U.S. stock market. Although the empirical setting is conservative, the security market line is too flat and the low-beta stocks outperform the high-beta stocks on risk-adjusted basis. Secondly, this is the first paper to study how macro-level "top-down" investor sentiment influences the betting against beta in the stock market. This deepens the understanding about the dynamics of the betting against beta. Especially the role of investor sentiment as a non-fundamental demand factor in a traditional behavioral finance framework is valuable. Furthermore, the results highlight the importance of behavioral factors in a complete explanation of the betting against beta. More broadly, the paper adds to the growing evidence that investor sentiment has an important role in the study of financial markets.

1.4. Limitations

On the other hand, the applicability of the results beyond stock market is not within the reach of this study. Frazzini and Pedersen (2014) find that the betting against beta exist not only in the U.S. stock market but also in 20 international stock markets, Treasury bonds, corporate bonds, and futures. While investor sentiment influences the betting against beta in the stock market, other explanations might be more important in other markets. Moreover, at the moment there are multiple explanations for the betting against beta. While my study provides evidence that investor sentiment plays a significant role, it does not clearly distinguish between different explanations.

It is common in the asset pricing literature to study both value-weighted and equally weighted returns. This might or might not provide additional insights in this study because I use only equal-weighting. My approach is conservative in the sense that the betting against beta is stronger in the studies that use value-weighting. On the other hand, investor sentiment affects small stocks more than large stocks. However, I control the size effect explicitly in the multifactor regressions and the effect of sentiment remains significant.

Finally, high-beta stocks should have certain characteristics for the investor sentiment to influence them. I study the previous literature comprehensively and conduct a six-factor regression providing evidence about the characteristics. However, I acknowledge that more direct investigation could provide insights not captured by the previous literature and the six-factor regression loadings. Especially firm age and dividend data could provide more direct evidence. On the other hand, there are sensible reasons to assume that high-beta stocks are young and do not pay dividends. Also, the previous literature is consistent with the characteristics and I do not have much of a reason to doubt those results.

1.5. Structure

This paper proceeds as follows. Next I review the most important literature on the betting against beta and briefly for investor sentiment. In Section 3 I build the hypotheses. Section 4 introduces data and variables. Section 5 studies whether the betting against beta exists in the U.S. stock market. Section 6 studies whether the investor sentiment influences the betting against beta and provides robustness checks. Section 7 concludes the paper.

2 Literature review

2.1. Background

According to the efficient market hypothesis (Fama, 1970) stock prices "fully reflect" available information. When prices reflect all the available information investors can only seek higher than average returns by assuming higher than average risk by investing higher proportion of their assets in risky securities or levering up their portfolio. Although Grossman and Stiglitz (1980) show that prices are only efficient to the point where marginal cost of information gathering equals marginal benefit of higher future returns, it should still be the case that higher risk securities provide higher returns.

Capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Black (1972) provides the most popular analytical framework for assessing the nature of the risk-return relationship of a stock. According to CAPM, a stock's sensitivity to market portfolio or "beta" determines its expected return. The sensitivity is measured as the slope of a linear regression of the stock's excess return on the excess return of the market. Other risk is deemed irrelevant, because it is diversifiable. Moreover, there are no other risk factors in the CAPM framework.

The empirical success of CAPM, however, has been limited and other factors have been shown to explain the cross-section of stock returns better. Factors such as market capitalization (Banz, 1981), book-to-market (Fama and French, 1992), liquidity (Pastor and Stambaugh, 2003), profitability (Novy-Marx, 2013), and previous year's returns (Jegadeesh and Titman, 1993), just to mention few, have been shown to explain cross-sectional stock returns consistently.

Furthermore, later papers have not found empirically reliable and robust link between beta and future stock returns (e.g. Frazzini and Pedersen, 2014). Low-beta stocks produce higher than expected returns and high-beta stocks provide lower than expected returns. This beta anomaly has been branded as *betting against beta* in the finance literature and Baker, Bradley, and Wurgler (2011) dub it as "the greatest anomaly in finance". To be precise, they dub the low-risk anomaly as the greatest anomaly in finance. Low-risk anomaly refers to the combination of beta and volatility anomalies. Volatility anomaly refers to the empirical finding that low-volatility stocks provide higher returns than high-volatility stocks (e.g. Blitz and van Vliet, 2007; Ang et al., 2008).

2.2. Betting against beta

It is hard to think of any other anomaly questioning the risk-return paradigm in finance as much as the proposition that the most widely used risk measures are not related to returns. The finding implies that prices are not right or that the risk measures are wrong. Moreover, for traditional efficient market theories the finding implies a challenging task: to explain why high-beta and high-volatility stocks are riskier. Perhaps it is possible that more advanced risk-estimation techniques, time-varying discount rates, time-varying risk aversion or multiple risk factors will provide alternative explanations for beta and volatility anomalies. Nevertheless, the challenge is huge.

Fortunately, behavioral finance has emerged during the past three decades to provide alternative explanations for some poorly understood empirical findings in finance. Behavioral finance allows the possibility of prices deviating from fundamentals as well as market frictions. Moreover, it treats critically some important assumptions like perfect arbitrage and horizontal demand curves. Most importantly from the point of this study, behavioral finance also provides the most successful explanations for the betting against beta as well as for the volatility anomaly.

There is empirical and theoretical work to document and explain the betting against beta and volatility anomaly. Moreover, they are often studied together, first of all, because they are the two most important risk measures in finance, and secondly, because of high cross-sectional correlation between the two variables and empirical patterns that resemble each other.

Having this in mind, I first review the most novel and important empirical literature on the low-risk anomaly, including beta, total volatility, and idiosyncratic volatility. While the emphasis is on the betting against beta, I believe that reviewing the empirical literature on low-risk anomaly provides insights not captured by only studying the literature on the betting against beta. Foremost, this broadens the empirical literature considerable. Later I review the most prominent theoretical frameworks proposed to explain the betting against beta and present the betting against beta through a behavioral finance framework. Lastly, review the literature on investor sentiment for the part that directly concerns my study. This focus allows me to quite brief in that regard.

2.2.1. Empirical evidence

One of the earliest papers to notice that risk is not appropriately rewarded is Black et al. (1972). They study the CAPM implied linear relation between a beta of a stock and returns in U.S. stock market between 1931 and 1965 and find that the expected excess return on a stock is not strictly proportional to its beta. In other words, the empirical security market line is too flat relative to the one implied by CAPM. Low-beta stocks produce higher than expected returns whereas the opposite is true for high-beta stocks.

More recent papers have studied the low-risk anomaly more extensively. Blitz and van Vliet (2007) show that total volatility predicts stock returns negatively among global large caps. They study the volatility effect in the stock markets of U.S., Germany and Japan between 1985 and 2006 and find that especially the two highest volatility deciles produce abysmal returns and the return difference between the lowest and highest volatility deciles is 5.9 % per year. Moreover, they find that Sharpe ratios and Fama and French (1993) alphas are monotonically declining in volatility. The return difference between the lowest and highest volatility-decile alphas is 12.0 % per year and statistically significant. They show similar results using only U.S. stocks. Blitz and van Vliet (2007) also report the average betas of the volatility deciles. Interestingly, beta is monotonically increasing in volatility, and thus clearly negatively related to future stock returns.

Baker, Bradley, and Wurgler (2011) demonstrate that low-risk has produced better than expected returns during the latter part of the 20th century. They find that both total volatility and beta are associated with low returns in the U.S. stock market from January 1968 to December 2012. Excess returns and CAPM alphas are monotonically declining across risk quintiles using both total volatility and beta as the risk measure. Especially the performance of the highest volatility quintile is bad. Furthermore, their results hold also among a smaller sample of 1 000 largest U.S. firms by market capitalization.

Frazzini and Pedersen (2014) show that betting against beta effect exist not only in the U.S. stock market but in 20 international equity markets and other asset classes (e.g. treasuries and corporate bonds). Their U.S. stock return data covers the period from January 1926 to March 2012. They find that overall low-beta stocks do not produce excess returns compared to high-beta stock but on risk-adjusted basis low-beta portfolios offer superior performance compared to their high-beta counterparts. Most three-, four-, and five-factor alphas[1] are statistically significant and monotonically decreasing in beta. Volatility also increases monotonically in beta deciles.

Furthermore, Frazzini and Pedersen (2014) construct a BAB (betting against beta) factor going long low-beta stocks while shorting high-beta stocks. They lever the low-beta portfolio and de-lever the high-beta portfolio to have a beta of one, so that the BAB factor becomes market neutral. The BAB factor realizes positive and statistically significant returns in both excess return and risk-adjusted terms. The idea behind the BAB factor is that to profit from the betting against beta, one needs to lever up the low-beta stocks to capitalize their attractive risk-return feature. Lastly, Asness, Frazzini, and Pedersen (2014) show that the profitability of the BAB factor is not driven by exposure to value effect or industry bets.

Bali et al. (2014) further show that beta is not appropriately rewarded in the U.S. stock market between August 1963 and December 2012. They find that excess returns are similar across beta deciles and the highest beta decile produces slightly worse than average returns. Moreover, Carhart (1997) alphas are monotonically declining in beta. Their unlevered lowest beta-decile minus highest beta-decile portfolio also produces statistically significant and positive risk-adjusted returns.

Novy-Marx (2014b) provides similar findings using beta and total volatility sorted portfolios in the U.S. stock market from January 1968 to December 2013. He finds returns to be flat across volatility and beta quintiles. Only the highest volatility portfolio produces very bad returns. CAPM alphas are positive for the return difference between the lowest and the highest risk quintiles. However, Fama and French (1993) alpha is only significant for the low minus high volatility quintile return, but not for the low minus high beta quintile return.

Ang et al. (2008) use previous month's idiosyncratic volatility as their measure for risk and show that idiosyncratic volatility is negatively related to future stock returns in 23 developed stock markets between January 1980 and December 2013. The Fama and French (1993) alphas

[1] Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and five-factor model including liquidity factor (Pastor and Stambaugh, 2003).

decrease with idiosyncratic volatility. However, their results are weaker when they estimate idiosyncratic volatility using longer time horizon.

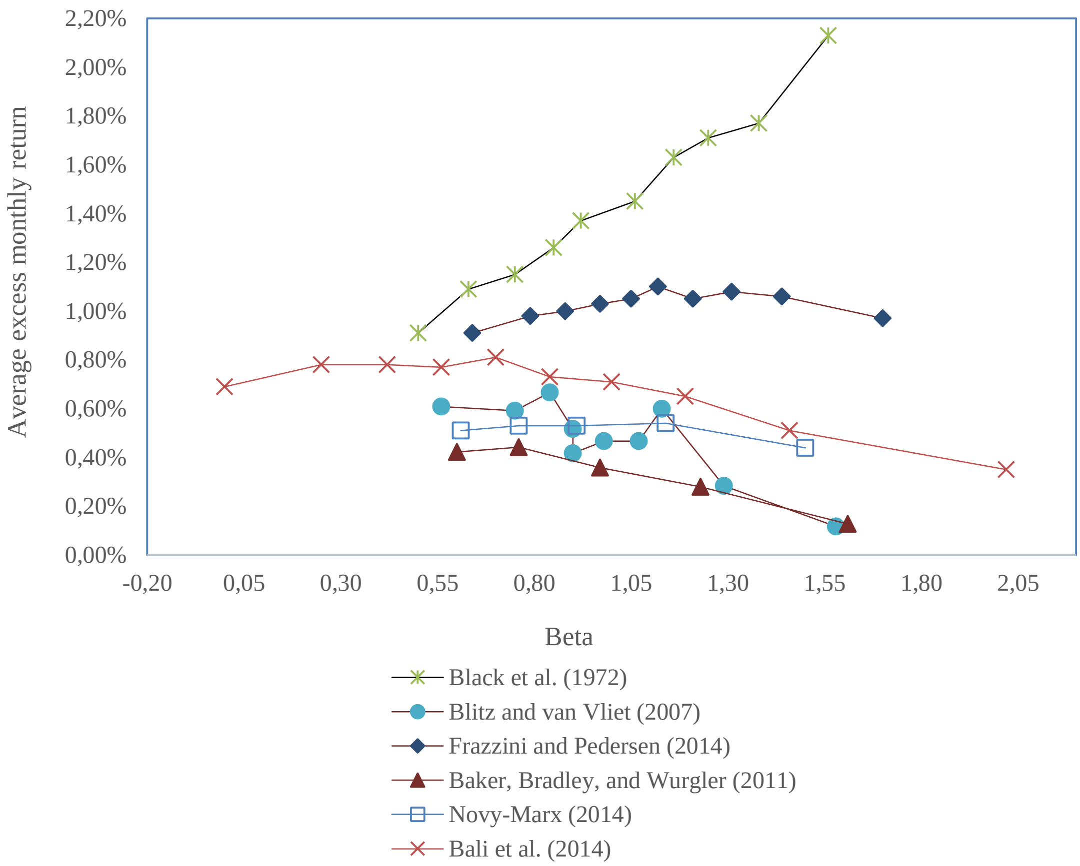

Fig. 1. Beta-return relation in the previous literature. This figure plots the beta-return relation from six previous studies. All the six studies use the portfolio approach of Black et al. (1972). The dots, squares etc. represent beta-return pairs of beta-sorted portfolios. Average excess monthly return is the portfolio return over risk-free rate. Beta is the average beta of the portfolio. The details of the portfolio construction naturally differ between the studies.

Bali and Cakici (2008) study further the robustness of the negative relation between idiosyncratic volatility and expected stock returns. They find that together with the period used to estimate idiosyncratic volatility, weighing scheme to calculate portfolio returns, sample, and breakpoints all affect the relation. In fact, the negative relation only exist in excess return terms when they use i) daily data from the previous month to estimate idiosyncratic volatility ii) value-weighting in calculating the returns, iii) NYSE/Nasdaq/Amex sample, and iv) CRSP breakpoints. Furthermore, when they use i) previous 60-month returns to estimate idiosyncratic volatility, ii) equal-weighting, iii) NYSE sample, and iv) NYSE breakpoints, they find a positive although not statistically significant relation between idiosyncratic volatility and future stock returns.

2.2.2. Robustness

As Bali and Cakici (2008) show in the case of idiosyncratic volatility, different empirical settings provide different empirical results. However, they only considered different empirical setting with respect to idiosyncratic volatility. I review here briefly the methods and their effect on the results of the most important empirical papers studying the low-risk anomaly and especially the betting against beta. It turns out that the sample period, breakpoints to sort stocks into portfolios, and rebalancing frequency affect the results. Weighting scheme and the way the risk measure is calculated might have additional effect. These effects are important to consider when evaluating empirical results on betting against beta or low-risk anomaly generally. Especially one should be on alert if all the factors point to the same direction because that can magnify the results significantly. Finally, this review is merely suggesting.

Sample period. The betting against beta seems to be stronger after 1968. Black et al. (1972) document flatter than expected but still positive beta-return relation between 1931 and 1965. However, Baker, Bradley, and Wurgler (2011), Bali et al. (2014), and Novy-Marx (2014b) show the beta-return relation to be flat or even reversed after 1968. Moreover, Frazzini and Pedersen (2014) show that the beta-return relation is flat or modestly increasing during the longer sample period from 1926 to 2012 highlighting the positive relation during the earlier century.

Breakpoints. The extreme returns of the highest beta and volatility quintiles are stronger using CRSP breakpoints, when comparing the results of Baker, Bradley, and Wurgler (2011) and Novy-Marx (2014b) who use CRSP and NYSE breakpoints, respectively. Bali et al. (2014) show similar findings to Novy-Marx (2014b) using portfolios containing equal number of stocks but they also excluded low-priced stocks. Bali and Cakici (2008) also find CRSP breakpoints to provide stronger results in the case of idiosyncratic volatility.

Rebalancing frequency. Generally the literature on low-risk anomaly uses monthly rebalancing and not much can be said on how long the abnormal returns would last. However, if the effect diminishes quickly, transaction costs might be an important limitation to arbitraging the anomaly. In a rare work, Garcia-Feijoo, Li, and Sullivan (2014) find that Fama and French

(1993) adjusted returns do not last beyond the first month and are eliminated by excluding low-priced stocks (i.e. share price below $ 5).

Weighting scheme. Value-weighing seems to provide stronger results than equal-weighting when calculating the monthly returns. Bali and Cakici (2008) show that value-weighting clearly results as larger difference between low and high idiosyncratic volatility portfolios because the highest risk stocks do especially badly using value-weighting. However, it is not clear whether this is the case for beta-sorted portfolios. Value- and equally weighted portfolios provide similar results in Novy-Marx (2014b) and Bali et al. (2014). However, Garcia-Feijoo, Li, and Sullivan (2014) provide supporting evidence for value-weighting to provide stronger results.

Risk measure estimation. There is some evidence that shorter-estimation period produces stronger results. Unfortunately, this evidence is again for idiosyncratic volatility (Ang et al., 2008; Bali and Cakici, 2008) as beta estimation has been rather similar across studies. On the other hand, longer beta estimation period can be thought of as providing more stable beta estimates and therefore requiring less turnover when the portfolios are rebalanced.

2.2.3. Theoretical explanations

Blitz and van Vliet (2007) provide a couple of reasons for the betting against beta effect although their empirical work focuses on documenting it. Firstly, many real investors face *leverage constraints*. As the empirical literature documents, there does not exist a clear link between beta and future return. Thus taking advantage of the better risk-return characteristics of the low-beta stocks requires leverage. Borrowing restrictions were already suggested by Black (1972). Secondly, the effect could be a result of *decentralized investment approach*. In the first phase capital is allocated to asset classes and next the managers invest within asset classes. Within asset classes they seek extra returns by investing in high-beta stocks (as they assume CAPM holds even partially) driving prices and returns to the observed patterns. Thirdly, *psychology* makes individuals seek “a shot at riches” and higher volatility and beta give the possibility of high returns.

Frazzini and Pedersen (2014) present an equilibrium model where some investors are *leverage and margin constrained*. Leverage constrained investors seek higher returns by overweighting high-beta assets driving their prices up and future returns down. Other investors are not constrained by leverage but face margin constraints, which makes them sensitive to liquidity shocks. Finally, there are unconstrained investors who use leverage or short sell high-beta securities to buy low-beta securities. The biggest investors such as mutual funds are likely to belong to the first group of leverage-constrained investors. Supporting this view, they tabulate the holdings of investors by beta. They report that constrained investors, such as mutual funds and individuals hold securities having betas significantly over one and less leverage constrained LBO funds and Berkshire Hathaway having betas significantly below one.

Baker, Bradley, and Wurgler (2011) consider *benchmarking* to be integral for the persistence of the betting against beta. Typically institutional equity managers have a mandate to maximize information ratio[2]. They go on to show, that this mandate or benchmark, makes managers to neglect considerable profit opportunities among low-beta stocks and prefer high-beta stocks. Sensoy (2009) point out that almost 95 % of the U.S. mutual funds are benchmarked to some popular U.S. index. Moreover, benchmarking could be the reason why big institutional investors do not arbitrage away the betting against beta.

Table 1
Summary of explanations for the betting against beta.

Table summarizes the proposed explanations in the literature for the betting against beta.

Explanation	Source
Borrowing restrictions	Black (1972) Blitz and van Vliet (2007) Frazzini and Pedersen (2014)
Benchmarking	Baker, Bradley, and Wurgler (2011)
Decentralized investment approach	Blitz and van Vliet (2007)
Psychology (e.g. overconfidence, representativeness, lottery demand)	Blitz and van Vliet (2007) Baker, Bradley, and Wurgler (2011) Bali, Brown, Murray, and Tang (2014)

Bali et al. (2014) show that the betting against beta can be explained by *lottery demand* in the stock market. They create FMAX factor proxying lottery demand and show that it explains, first of all, the abnormal returns of portfolios sorted by beta, and secondly, the abnormal return of the BAB factor of Frazzini and Pedersen (2014). Their theory goes that the lottery demand

[2] *Information ratio = Excess return over benchmark / Volatility of the excess return*

falls heavily on high-beta stocks making them overpriced. Supporting this view, they show that retail ownership is more common among high-beta stocks than low-beta stocks, which have a higher proportion of institutional ownership. Furthermore, they show that the betting against beta only exist following the months in which the cross-sectional correlation between beta and lottery demand is high. Lastly, they document that beta and idiosyncratic volatility are positively related to future returns, when lottery demand is controlled for.

2.3. Behavioral finance framework

Taken together the theoretical and empirical literature indicates that the betting against beta is best viewed through a behavioral finance framework of non-fundamental demand and limits-to-arbitrage. Classical behavioral finance framework relies on the interplay of non-fundamental demand driving prices away from fundamentals and some limits-to-arbitrage preventing rational investors from exploiting these deviations. In the context of betting against beta, non-fundamental demand has been explained to be the result of psychological factors such as representativeness, overconfidence, and lottery demand. Furthermore, benchmarking and leverage constraints provide important limits-to-arbitrage. Next I view the betting against beta through the behavioral finance framework. The papers reviewed this far are in the center of the discussion.

Table 2
Behavioral finance framework for the betting against beta.

Table constructs a behavioral finance framework for the betting against beta. Traditional behavioral finance framework is made of two components, non-fundamental demand and limits of arbitrage. This table groups the main explanations proposed for the betting against beta into these components.

Non-fundamental demand	Limits of arbitrage
Lottery demand	Leverage constraint
Representativeness	Benchmarking, delegated portfolio management
Overconfidence	Noise-trader risk
Decentralized investment approach	Time horizon
	Funding liquidity risk
	Transaction costs
	Volatility

2.3.1. Non-fundamental demand

Lottery demand seems to be an important driving force for the lower-than-expected returns for the high-beta stocks. The success of FMAX factor to explain the BAB returns as well as the high concentration of retail ownership among the highest beta stocks provides a great story with empirical backing (Bali et al., 2014). Furthermore, Kumar (2009) identifies stock-specific volatility among stock-specific skewness and low price as the main proxies for lottery stocks. The disappearance of the betting against beta after excluding the low-priced stocks in Garcia-Feijoo, Li, and Sullivan (2014) also supports the lottery demand explanation.

High-sales growth firms and low book-to-market firms are often *representative* of good investments in the minds of individual investors (Kaustia, Laukkanen, and Puttonen, 2009). Good investments are also perceived as technology stocks with big upside potential because people can remember the success and huge growth of firms such as Microsoft and Google more easily without understanding of the base group of *all* technology start-ups (also *availability* heuristic). All these stocks are more likely to be high-beta and high-volatility stocks.

According to Baker, Bradley, and Wurgler (2011) *overconfidence* might play a role as an explanation because high-beta stocks, which are also more likely high-volatility stocks, have often a wider range of opinions about the fundamental value and people suffer from setting too narrow confidence intervals to their guesses (Kaustia and Perttula, 2012). Moreover, overconfidence together with unwillingness or lack of ability to short-sell leads to a situation where the optimists actually set the prices (Miller, 1977) leading to bad future returns.

The *decentralized investment approach* (Blitz and van Vliet, 2007) also provides a non-fundamental demand shock in the absence of leverage. As already discussed, the desire to beat other fund managers by overweighting high-beta stocks and believing CAPM holds even partially puts pressure on prices of high-beta stocks and shows as a below average returns in the data.

2.3.2. Limits of arbitrage

In addition to non-fundamental demand distorting the beta-return relation there needs to be a force that prevents rational investors to take advantage of the distortions and bringing prices back to fundamentals. To some degree this dichotomy is arbitrary as for example the *leverage constraint* problem both drives prices of high-beta stocks up as investors seek higher returns, and simultaneously, prevents exploiting the deviations by leveraging. Moreover, *noise-trader risk* plays both roles. On the one hand it increases the prices of some stocks above fundamentals, and on the other hand acts as a limit-to-arbitrage because it might continue to drive the prices to the wrong direction for unknown time resulting in losses.

Besides leverage constraints and noise-trader risk, other common limits-to-arbitrage arguments are also applicable to the betting against beta. For example, the *time-horizon* of the investor is important. The high-beta stocks tend to outperform their low-beta during up markets. Therefore a hedge fund investing in the low-beta stocks might have to report lower than average returns for some time and justify the losses to investors. If the underperformance lasts long, investors might get uncomfortable and redeem their funds, forcing the hedge fund to realize its long-run profitable positions in the short-run with losses (Shleifer and Vishny, 1997).

If the investor is able to leverage himself, the positive returns are more stable, but now he becomes sensitive to the *funding liquidity risk*. Frazzini and Pedersen (2014) show that BAB factor is indeed more sensitive to funding liquidity as measured by TED spread and volatility of the TED spread. Funding liquidity risk increases the risk of arbitrage positions of big hedge funds, because the unconstrained investors and those who have margin constrains need to de-leverage or increase margins during increasing funding liquidity. This makes it harder to arbitrage the anomaly. Hombert and Thesmar (2014) summarize good ways for overcoming some limits of arbitrage.

Benchmarking (Baker, Bradley, and Wurgler 2011) also acts as an important limit to arbitrage. In a world of delegated portfolio management and performance evaluation based on information ratio, demand falls heavily on higher yielding assets. This fact combined with the notion that benchmarking is more prevalent within an asset class than across asset classes is interesting, because the risk-return relation only seem to break within asset class. However, across asset classes it holds much better.

The benchmarking problem becomes even more harmful in a world with limits to leverage and short selling. Practically believable but also empirically documented (Sensoy, 2009), most of the biggest institutional investors are not allowed to leverage themselves. Furthermore, mutual funds must prepare for redemptions and hold some of their assets in cash, which obviously eats returns compared to benchmark stock index. As Frazzini and Pedersen (2014) theorize, these investors seek returns by overweighting high-risk assets driving their prices up and expected returns down in the cross-section and leading to the observed beta-return relation.

Garcia-Feijoo, Li, and Sullivan (2014) report that the profits from beta arbitrage (simple low-minus-high portfolio) do not usually last beyond the first month. Therefore profiting from the anomaly requires monthly rebalancing which might be costly. Furthermore, as the anomaly returns are usually higher the shorter the estimation period for the risk-measure, higher profits equal higher turnover in the beta portfolios and therefore higher *transaction costs*. However, they only consider the simple low-minus-high risk strategy. Again, if the investor can leverage himself, the profits are more long-term.

Lastly, there is some evidence that the high-risk stocks are on average *hard-to-arbitrage stocks* in the sense of Baker and Wurgler (2007). Hard-to-arbitrage stocks are more likely young, non-dividend paying, small, illiquid, and unprofitable. Additionally, they have extreme growth opportunities and higher volatility. By definition, in the papers of Ang et al. (2008) and Bali and Cakici (2008) the high-risk stocks have high idiosyncratic volatility. Furthermore, Bali and Cakici (2008) show that stocks with high idiosyncratic volatility have lower market capitalization and share price. They are also illiquid and their returns are positively skewed. However, portfolios sorted by idiosyncratic volatility do not show variation in the book-to-market measure. Furthermore, Novy-Marx (2014b) reports that volatility is negatively correlated with size, value, and profitability. In effect, less volatile firms tend to be bigger and profitable value firms. Beta, on the other hand, is negatively associated with size and value, positively with liquidity and volatility, and not meaningfully with profitability.

2.4. “Top-down” investor sentiment

Investor sentiment is the belief about future cash flows and investment risks that is not justified by the facts at hand. There are two approaches to measuring it. Firstly, the “bottom-up” approach is based on biases in individual investor psychology, such as overconfidence, representativeness, and conservatism. These biases explain some errors that people do in their investment decisions. Furthermore, these biases should appear the same way among *most* individuals. Classical example being, that high-growth technology stocks should represent good investments in the minds of *most* individual investors. This drives the price of high-growth technology stocks up in the cross-section. The second approach is “top-down” or macroeconomic, and focuses on the measurement of reduced form, aggregate sentiment and traces its effects to market returns and individual stocks (Baker and Wurgler, 2007). In this paper, when I talk about investor sentiment, I refer to the "top-down" approach.

There are two important aspects to consider in investor sentiment. First of all, investor sentiment mainly refers to the behavior or mood of retail and individual investors. Institutional investors are, on the other hand, assumed to be unaffected by sentiment. The more general models of behavioral finance (e.g. De Long et al., 1990) refer to irrational or noise traders and rational arbitrageurs when they make this distinction. Therefore, when I talk about the investor sentiment being high or low, I mean the sentiment of the noise traders. Secondly, it is important in the "top-down" approach to make the distinction between high and low sentiment because the sentiment affects both contemporaneous and expected returns. When sentiment is high, the demand from noise traders drives the prices of stocks up and expected returns down, and when it is low, stocks become cheaper but expected to produce higher returns.

Baker and Wurgler (2006, 2007) make the important notion, that not all stocks are equally affected by investor sentiment. Investor sentiment affects stocks asymmetrically meaning that some firms are more sensitive to it. Consequently this means that individual and retail investors prefer some stocks over others when they trade during high and low sentiment. Furthermore they, show that small stocks, young stocks, unprofitable stocks, non-dividend paying stocks, distressed stocks, extreme-growth stocks, and volatile stocks are most affected by investor sentiment. For example, following high investor sentiment the returns on small stocks are significantly lower than following low investor sentiment.

Small stocks, young stocks, unprofitable stocks, non-dividend paying stocks, distressed stocks, extreme-growth stocks, and volatile stocks have on average two important features, hardness-to-value and hardness-to-arbitrage. These features are important because in the classical behavior finance framework the prices of stocks deviate from fundamental values due to two forces, non-fundamental demand and limits-to-arbitrage. Within this framework investor sentiment acts as a non-fundamental demand shock, and moreover, the investor sentiment affected stocks are also hard-to-arbitrage. Therefore prices may deviate from fundamentals without arbitrage correcting them. This also makes the returns on these stocks predictable conditioning on investor sentiment. However, this does not mean that it is easy to tell whether investor sentiment is high or low beforehand. In summary, because the same stocks that are affected by investor sentiment are also hard-to-arbitrage their returns are to some degree predictable conditioning on investor sentiment. In the next chapter I discuss why I believe the high-beta stocks are affected by investor sentiment and why they are also hard-to-value and hard-to-arbitrage.

3 Hypothesis building

The hypotheses are constructed to answer the two research question of the study. The first research question is, does the betting against beta exists in the stock market. The second is, does investor sentiment influence the betting against beta.

3.1. Betting against beta in the stock market

The empirical literature supports the proposition that the betting against beta exists in the stock market (e.g. Black et al., 1972; Frazzini and Pedersen, 2014). However, Bali and Cakici (2008) show that the empirical robustness of idiosyncratic volatility anomaly is sensitive to empirical choices. This is important because the beta and volatility anomalies are related and there exists a high cross-sectional correlation between them. I also discussed that different empirical settings provide somewhat different results for the betting against beta. Therefore, in this study, I take a conservative approach in studying the betting against beta by combining empirical elements that have produced modest results previously. An interesting question is whether the betting against beta still exists in the stock market considering this conservative approach. Furthermore, these results provide a comparison when I study the relation between the betting against beta and investor sentiment.

The empirical approach in my study differs from the previous work in some important ways. First of all, I use annual rebalancing in the portfolios whereas the previous literature has used almost exclusively monthly rebalancing. My approach has certain benefits as well as drawbacks. The annual rebalancing produces less costs if an investor wants to benefit monetarily from the anomaly as it requires trading once a year compared to 12 times.

On the other hand, it is arguable whether portfolios formed at the end of June of year t based on previous 60- and 36-month betas reflect their betas during the following 12 months. However, all historical beta measures are only rough estimates and forward-looking measures are hard to find. Moreover, there is no certainty that even the forward-looking betas are accurate estimators. I do believe, however, that the combination of 60- and 36-month beta estimation periods mitigate this concern, and that the beta exposures are rather stable during one year.

Particularly, the ranking of betas to sort stocks into portfolios should be similar during the estimation and return-calculation periods.

Secondly, the combination of i) having equal number of shares in a portfolio compared to CRSP breakpoints, ii) equal-weighting in calculating the portfolio returns compared to value-weighting, iii) long estimation period of beta, and iv) the exclusion of the most illiquid stocks (share price) is unique and provides a further robustness test to validate the existence of the betting against beta in the stock market. All the above empirical choices have provided less significant results in the previous tests, which means that if the betting against beta is found in my sample, it is robust.

The definition of the betting against beta so far has been vague. It has simply meant any situation where low (high) beta has provided better (worse) than expected returns. But compared to what? To clarify, I make a distinction between excess returns and risk-adjusted returns when studying the betting against beta. Therefore, the first hypothesis is stated as,

Hypothesis 1. Betting against beta does exist on absolute return basis

The betting against beta has been more significant on risk-adjusted basis in the literature. Still it is somewhat ambiguous what is meant by risk. There are hundreds of factors in the finance literature (Harvey et al., 2015; Novy-Marx, 2014a) supposedly explaining stock returns and not all of them represent risk exposures. Moreover, risk-adjusted or factor-adjusted returns are sensitive to the chosen factors. In my paper, CAPM as well as the most traditional multifactor models[3] are used to assess whether low (high) beta provide positive (negative) alpha.

The multifactor regression approach follows Black et al. (1972) and Fama and French (1993). Monthly excess returns of stock portfolios are regressed on the excess return on market and returns on zero-cost strategies based on empirical factors known to explain stock returns. The approach provides a well-defined test for an asset-pricing model. A model claiming to explain the average stock returns should produce intercepts undistinguishable from zero because of the

[3] Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and six-factor model including liquidity (Pastor and Stambaugh, 2003) and profitability (Novy-Marx, 2013) factors.

use of excess returns and returns on zero-cost strategies. Most importantly, the approach gives a simple measure to detect abnormal returns by focusing on the regression alpha.

Hypothesis 2. Betting against beta does exist on risk-adjusted basis

In summary, the existence of the betting against beta is studied from both absolute and risk-adjusted angles and compared to the existing literature. Next I start building my main hypothesis that links the betting against beta and investor sentiment. Hardness-to-value and hardness-to-arbitrage are important concepts in linking the betting against beta and investor sentiment.

3.2. Hardness-to-value and hardness-to-arbitrage

Hypothesis 3. High-beta stocks are hard-to-value and hard-to-arbitrage stocks

Small stocks, young stocks, unprofitable stocks, non-dividend paying stocks, distressed stocks, extreme-growth stocks, and volatile stocks are hard-to-value and hard-to-arbitrage stocks (Baker and Wurgler, 2007). High-volatility stocks are thus partly by definition hard-to-value and hard-to-arbitrage stocks. It is much less clear that high-beta stocks are also hard-to-value and hard-to-arbitrage.

Based on existing studies, high-beta stocks tend to be growth stocks and even extreme growth stocks (e.g. Novy-Marx, 2014b; Bali et al., 2014), volatile stocks (e.g. Frazzini and Pedersen, 2014; Bali et al., 2014; Novy-Marx, 2014b), and small stocks (e.g. Novy-Marx, 2014b; Bali et al., 2014). However, they tend to be liquid stocks (e.g. Garcia-Feijoo, Li, and Sullivan, 2014; Bali et al., 2014), and at least not clearly unprofitable stocks (Novy-Marx, 2014b). Lastly, I was not able to find papers documenting whether they are young and non-dividend paying stocks, although rather strong correlations with all the variables have been documented.

The existing evidence leads to a question, can I make the hypothesis three based on these characteristics from existing literature even though they do not fully fit the characteristics of hard-to-value and hard-to-arbitrage stocks? I believe the answer to the question is a cautious *yes*. This is because some characteristics are more important than others when hardness-to-value and hardness-to-arbitrage are considered. One such characteristic is volatility and high-beta stocks are unambiguously more volatile than their low-beta counterparts.

For example, when individuals are overconfident they are more likely to think their information or analysis is superior to the information of others. This creates more differences of opinions on valuations among the group of firms that are hard-to-value and also creates trading because of those differences. Trading, on the other hand, creates volatility. Volatility is thus a characteristic of hard-to-value firms.

Furthermore, volatility makes arbitrage risky. The arbitrageurs cannot always take large enough positions to eliminate the mispricing because taking large positions means taking more risk. Highly volatile stocks may deviate much to the wrong direction causing losses and margin calls. Moreover, in the case of highly volatile firms, the arbitrageurs are often less sure about the fundamental value. They can never be absolutely sure about the true value and may question their own analysis and information if the price deviates too much from their own value estimate. This makes arbitrageurs less willing to act on their information and analysis.

However, I am not fully confident to accept the view that high-beta stocks are hard-to-value and hard-to-arbitrage. Hence I perform my own empirical analysis about the characteristics of the low- and high-beta stocks in Section 6.1. I am much more willing to accept that high-beta stocks are hard-to-value and hard-to-arbitrage stocks if the results provide support for the "right" characteristics of the low- and high-beta stocks. It is also important to verify the characteristics in my sample.

3.3. Betting against beta and investor sentiment

Given the hypothesis three is not rejected and high beta is associated with the characteristics of hard-to-value and hard-to-arbitrage stocks, and thus, most affected by investor sentiment, I make the claim that investor sentiment is an important element in explaining the betting against beta[4].

Hypothesis 4. Investor sentiment influences the betting against beta in the stock market

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[4] It is not actually necessary for the betting against beta to show up unconditionally for there to be a conditional effect from investor sentiment.

Fig. 2. suggests an indirect channel for investor sentiment to affect the betting against beta. However, it is not entirely impossible that beta is also one such salience characteristics that retail investors demand. Beta is easily available from Internet and often reported by stock brokers. Neither does understanding what beta means and its implication on investing decisions require substantial investor sophistication. During high sentiment retail investors might seek "easy extra returns" by buying high-beta stocks unaware of the cross-sectional effect on the expected returns of their combined activity (e.g. Kumar and Lee, 2006).

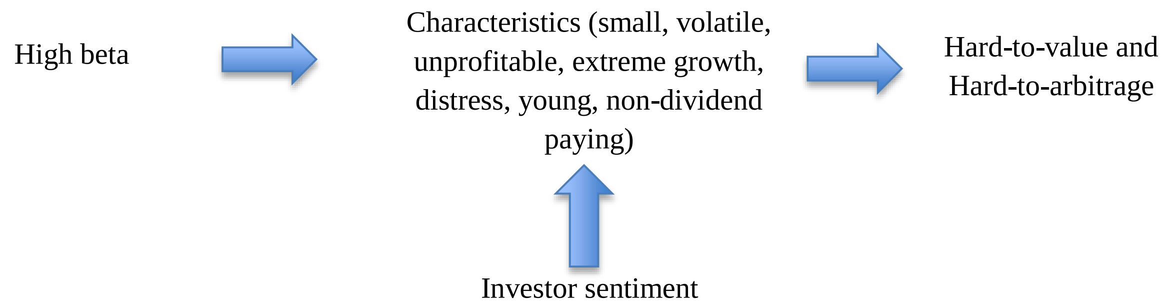


Fig. 2. Structure of the hypotheses three and four. Figure illustrates the structure of hypotheses three and four. The figure shows that if high beta stocks belong to the group of stocks having the right characteristics, then they are hard-to-value and hard-to-arbitrage (hypothesis three). Furthermore, the figure shows that investor sentiment affects the group of stocks having the right characteristics. Therefore, if high-beta stocks belong to the group of stocks having the right characteristics, they are also affected most by investor sentiment (hypothesis four).

4 Data and variables

4.1. Data

Monthly stocks return data is from Center for Research in Security Prices (CRSP). This covers all stocks in NYSE, Nasdaq, and Amex. The returns are collected from July 1979 to June 2011. This covers 32 years of return data in total. I have excluded stocks with prices below $ 5 and above $ 1000.

BAB factor returns are from Lasse Pedersen's website[5]. The BAB returns are monthly returns on a zero-cost portfolio that goes long in low-beta stocks and shorts high-beta stocks. The BAB factor is levered to beta of zero to make it market neutral. The details of constructing the BAB factor can be found in Frazzini and Pedersen (2014). The data covers the period from April 1929 to March 2012 for U.S. equities.

Fama and French (1993) and momentum factor returns as well as risk-free rates and excess market return are from Kenneth French's website[6]. The details of constructing these factors can be found on the website. Briefly, these are the returns on zero-cost portfolios that try to mimic the underlying exposures to book-to-market, size, and momentum effects. The data consist of monthly return data and covers the period from July 1926 to January 2015.

Profitability factor returns are from Robert Novy-Marx's website[7]. The profitability factor goes long in profitable stocks while shorting the least profitable of stocks. His data is monthly return data from July 1963 to December 2012. Profitability is measured by gross profitability-to-assets[8].

Liquidity data is from Lubos Pastor's website[9]. More specifically, it contains the monthly returns on traded liquidity factor (Pastor and Stambaugh, 2003). The data covers a period from January 1968 to December 2013.

The investor sentiment data is from Jeffrey Wurgler's website[10]. The data includes monthly time-series values of the sentiment index introduced in Baker and Wurgler (2006, 2007). Their sentiment index combines six investor-sentiment proxies to create one that captures the effects of them all. Briefly it contains i) a proxy for closed-end fund discount, ii) ratio of reported share

[5] http://www.lhpedersen.com/data

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[7] http://rnm.simon.rochester.edu/data_lib/index.html

[8] Gross profitability = (Revenues - COGS) / Assets. Assets is the balance sheet item, not the market value.

[9] http://faculty.chicagobooth.edu/lubos.pastor/research/

[10] http://people.stern.nyu.edu/jwurgler/

volume to average shares listed in NYSE, iii) number and iv) first-day returns on IPOs, v) gross equity issuance divided by total gross long-term capital issuance, and vi) the log difference of the average market-to-book ratios of dividend payers and non-payers.

Baker and Wurgler (2006, 2007) actually introduce two indexes of which I use the one that is orthogonalized to growth in industrial production, the growth in durable, nondurable, and services consumption, the growth in employment, and a flag for NBER recessions (SENTIMENT$^{\perp}$). More detailed analysis of the index composition and construction can be found in Baker and Wurgler (2006). The sentiment data is on a monthly basis and covers the period from July 1965 to December 2010.

4.2. Beta-sorted and zero-cost portfolios

The returns on the beta-sorted quintile portfolios are composed from the monthly stock return data from CRSP. At the end of June each year stocks are sorted into quintile portfolios[11] based on their past 60- and 36-month betas. Next, an equally weighted average return is calculated for the following 12 months. The returns on the beta-sorted portfolios are available from July 1984, because the monthly return data starts in July 1979 and I need 60 months to estimate betas. The return data ends in June 2011 but I mostly do not need it beyond January 2011, because the investor sentiment data ends in December 2010 and I use it to explain the next month's stock returns. Average number of stocks and average beta of the stocks in each quintile portfolio are reported in **Appendix A**.

The returns on the levered and unlevered zero-cost beta portfolios (B15L and B15UL) are constructed from the lowest and highest beta portfolios. More specifically, the monthly return on the zero-cost portfolio is the monthly return on the lowest quintile portfolio minus the monthly return on the highest quintile portfolio. Furthermore, in the case of the levered portfolio (B15L), both the highest and the lowest beta portfolio are leveraged to have a beta of one. Beta exposures of the lowest and highest beta quintiles are used to lever and de-lever the portfolios. Beta is the coefficient from a simple regression of the portfolio excess returns against the value-weighted excess market returns from Kenneth French's website. While the unlevered portfolio

[11] Each of the five portfolios contains equal number of stocks.

(B15UL) has strong negative market exposure during the sample period, the levered portfolio (B15L) is by construction market neutral. The return on the levered portfolio (B15L) is conceptually comparable to the BAB factor but there are differences in the details of their construction. The formulas for the levered (B15L) and unlevered (B15UL) portfolios are following,

$$B15UL = R_L - R_H \tag{1}$$

$$B15L = \frac{R_L - R_f}{B_L} - \frac{R_H - R_f}{B_H} \tag{2}$$

,where $B15UL$ is the return on simple high-minus-low strategy in month t, $B15L$ is the return on the levered portfolio in month t. R_L and R_H are the returns on the lowest and the highest beta portfolios, respectively. B_L and B_H are the betas of the lowest and highest beta portfolios, respectively. Lastly, R_f is the risk-free rate.

4.3. Beta estimation

To sort stocks into quintile portfolios I need an estimate of a beta for each individual stock. The beta is the covariance of the excess return of a stock with the excess return of a value-weighted stock market index divided by the variance of the return of the value-weighted stock-market index during the estimation period. Value-weighted market return is from Kenneth French's website. The beta-estimation period is either 60 or 36 months throughout this study.

The beta estimate should reflect the actual beta during the period in which the returns are calculated. For example, the lowest beta portfolio should include the quintile of stocks that has the lowest beta exposures during each 12-month period in which the returns are calculated. At the very least, there should be real differences between the ex-post beta exposures of the quintile portfolios. If betas are extremely time-varying or if the betas were measured with great inaccuracy, the estimates might be less useful.

Blume (1975) shows that betas regress to mean even after controlling for the fact that betas are measured with error, which produces too wide a range of betas. While this might lead e.g. some high-risk stocks to move down from the highest beta quintile, there are at least three reasons why this is not very important. First of all, it is not believable that a lot of stocks would change their beta exposures a lot. Secondly, even if there were stocks with extremely time-varying betas, the portfolio sizes in my study are big. As more stocks are added to the stock exchange the portfolio sizes increase from about 200 stocks in 1984 to almost 500 stocks in 2010 (**Appendix A.1.**). The marginal effects should not matter. Lastly, the estimation period of beta is long and Bali and Cakici (2008) show for idiosyncratic volatility that the longer the estimation period the closer the predicted and realized values are each other.

Buss and Vilkov (2012), on the other hand, use forward-looking information from option prices to estimate betas. They find a beta-return relation consistent with linear-factor models. According to their view, beta and return are linearly related, and the historical beta estimates are simply bad predictions of realized betas. Their approach is an interesting extension in the beta-estimation literature, and while it might affect the results considering the existence of the betting against beta, it should not affect the relation between investor sentiment and beta-sorted portfolios.

Some authors (e.g. Vasicek, 1973) use also beta-compression methods to exclude outliers in the data. However, the usefulness of the beta estimates relies on the assumption that the ranking of the ex-ante betas is similar to the ranking of ex-post betas and not their actual values. As these methods do not affect the ranking of betas, they are not relevant from the point of view of my study

4.4. Other considerations

The quintile-portfolio returns are equally weighted. Therefore, the smaller stocks have a bigger impact on the quintile-portfolio returns than if value-weighting was used. Betting against beta has been stronger using value-weighting, which makes my approach conservative in that respect. On the other hand, investor sentiment affects small stocks more than big stocks. However, multifactor-regression models used in this study explicitly control the size effect.

I also require the stocks to have return data each month during the beta-estimation period. This naturally excludes some of the youngest firms in the sample. The portfolios that use 36 months to estimate betas mitigate this problem and create a valuable comparison group.

5 Betting against beta in the stock market

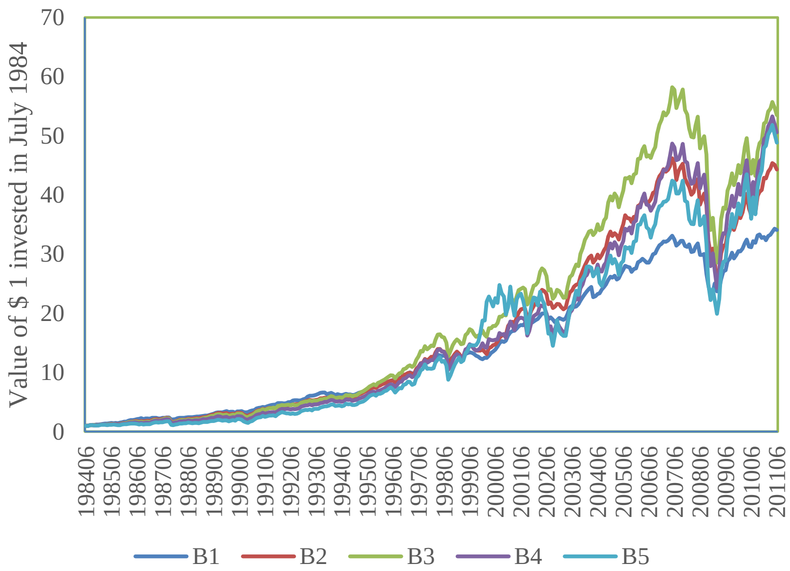
In this chapter I study empirically whether the betting against beta exists in the U.S. stock market between July 1984 and June 2011. The question is viewed from two angles. First I check whether the anomaly exists on an absolute return basis and secondly the returns are studied from a risk-adjusted perspective.

5.1. Absolute returns

Fig. 3 shows mixed evidence on the profitability of taking higher risk. Panel A shows that an investor who invested \$ 1 in the highest beta portfolio in July 1984 has accumulated a wealth of \$ 49 at the end of June 2011 whereas another investor who invested the same amount in the lowest beta portfolio has accumulated \$ 34 during the same period and the difference is even bigger if he used previous 36 months to estimate beta (Panel B). However, an investor who invested his money in the middle-risk portfolio (B3) has accumulated a wealth of \$ 53 during the same period, almost 10 % more than the highest beta investor. If the investor used data from previous 36 months to construct his beta portfolios (Panel B), higher risk has generally resulted in more wealth over the years. Still, an investor who invested his money in the relatively low-risk B2 portfolio has gained 13 % and 20 % more wealth than an investor who put his money in the rather risky, B3 and B4 portfolios, respectively. Taking more risk clearly did not mean that the investor was certain to beat his more risk-averse friend.

Fig. 4 enables to investigate the quintile-portfolio performance further. While monthly arithmetic average returns are more or less monotonically increasing in the beta quintiles (from 1.13 % to 1.44 %), the geometric returns are flat across the portfolios (from 1.09 % to 1.21 %) . Only the lowest beta-portfolio produces lower geometric average returns during the sample period. The reason for the differences between the arithmetic and geometric average returns is the high cross-sectional correlation between beta and volatility. Volatility eats the higher arithmetic average returns of the high-beta investors.

Panel A: Portfolios sorted by previous 60 month beta



Panel B: Portfolios sorted by previous 36 month beta

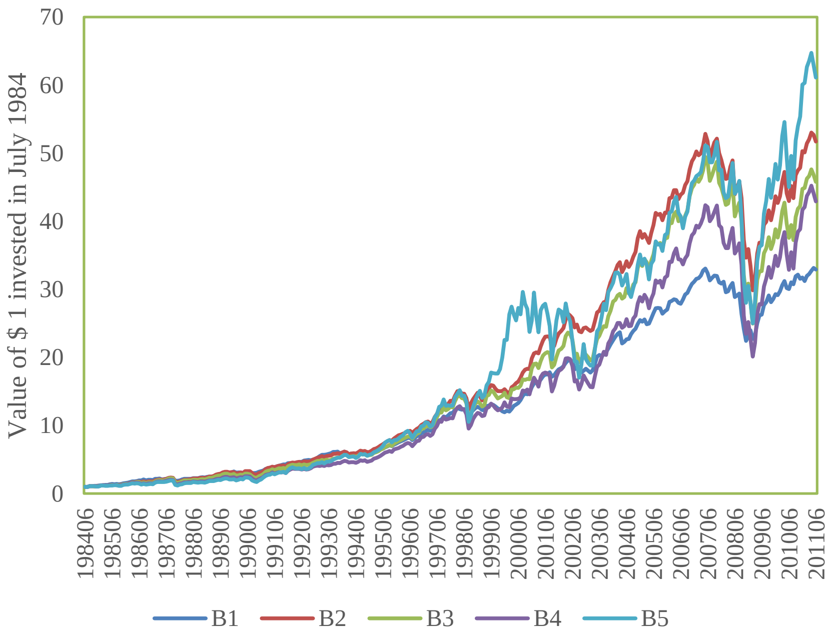
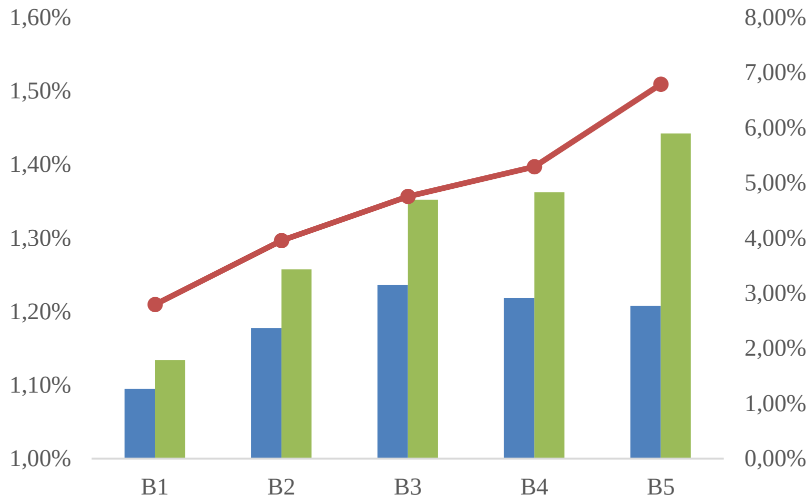


Fig. 3. Cumulative returns of the quintile portfolios. Figure shows the value of $ 1 invested in the quintile portfolios from July 1984 to June 2011. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 (Panel A) and 36 (Panel B) month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months.

Panel A: Portfolios sorted by previous 60 month beta



Panel B: Portfolios sorted by previous 36 month beta

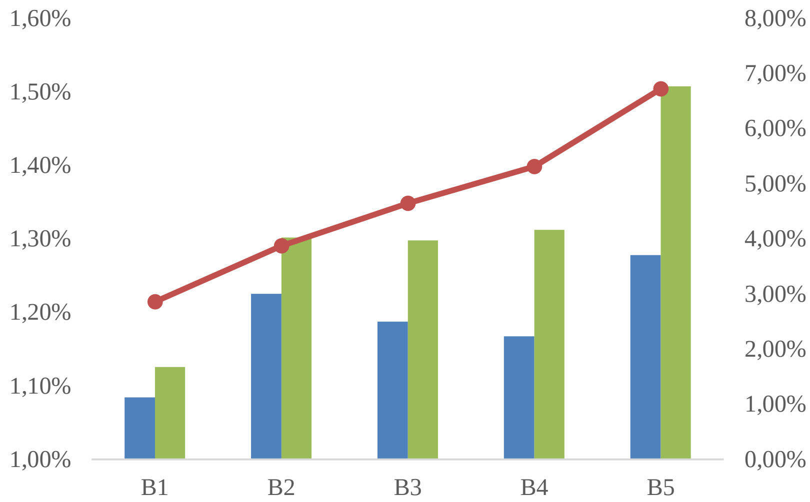


Fig. 4. Arithmetic and geometric average return and volatility of the quintile portfolios. Figure shows the arithmetic and geometric average returns as well as volatilities of the quintile portfolios from July 1984 to June 2011. The two bars show the arithmetic and geometric returns, respectively (LHS vertical axis). The line shows the volatility of the quintile portfolios (RHS vertical axis). B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 (Panel A) and 36 (Panel B) month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months.

Table 3 shows the summary statistics for the quintile portfolios. While it shows the monotonically increasing arithmetic returns and volatility in beta quintiles and flat geometric returns, it also shows that the return difference between the lowest and highest beta portfolio (B15UL) has not been statistically significant. Panel A and B show that the return difference has been -0.31 % (t-value, -1.01) and -0.38 % (t-value, -1.33) per month using the 60 month

Table 3
Summary statistics of the quintile and zero-cost portfolios.

Table shows summary statistics of the quintile portfolios and zero-cost strategies from July 1984 to June 2011. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 (Panel A) and 36 (Panel B) month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months. B15UL is the return on the lowest beta portfolio minus the return on the highest beta portfolio. B15L is the return on return on the lowest beta portfolio minus the return on the highest beta portfolio, where both portfolios are levered or de-levered to have a beta of one. BAB factor is from Frazzini and Pedersen (2014).

Arithmetic and geometric returns are the arithmetic and geometric average of the monthly returns over the sample period, respectively. Excess return is the arithmetic average return over the risk-free rate, volatility is the monthly standard deviation of the return, beta is the sensitivity of the portfolio to the value-weighted market portfolio during the sample period, and Sharpe is the arithmetic average excess return divided by volatility.

I report t-statistic in the parenthesis. Furthermore, statistically significant values are bolded and highlighted using asterisks when deemed important (***, **, and * denote statistical significance at the 1 %, 5%, and 10 % levels).

All the figures are monthly values or calculated from monthly values. For example, the arithmetic return of the B1 portfolio is 1.13 % per month. In total, there are 324 monthly observations.

Panel A: Portfolios sorted by previous 60 month beta and BAB factor

	B1	B2	B3	B4	B5	B15UL	B15L	BAB
Arithmetic return	1.13	1.26	1.35	1.36	1.44	-0.31	1.07	0.89
Geometric return	1.09	1.18	1.24	1.22	1.21	-0.46	0.93	0.82
Excess return	0.78	0.91	1.00	1.01	1.09	-0.31 (-1.01)	**1.07***** **(3.69)**	**0.89***** **(4.27)**
Volatility	2.79	3.95	4.75	5.29	6.79	5.51	5.21	3.77
Beta	0.42	0.75	0.94	1.07	1.37	-0.95	0.00	-0.18
Sharpe	0.28	0.23	0.21	0.19	0.16	-0.06	0.20	0.24

Panel B: Portfolios sorted by previous 36 month beta

	B1	B2	B3	B4	B5	B15UL	B15L
Arithmetic return	1.13	1.30	1.30	1.31	1.51	-0.38	0.83
Geometric return	1.08	1.23	1.19	1.17	1.28	-0.52	0.73
Excess return	0.78	0.95	0.95	0.96	1.16	-0.38 (-1.33)	**0.83***** **(3.33)**
Volatility	2.86	3.87	4.64	5.31	6.72	5.18	4.48
Beta	0.46	0.74	0.92	1.08	1.36	-0.90	0.00
Sharpe	0.26	0.23	0.18	0.15	0.14	-0.07	0.18

and 36 month beta-estimation period, respectively. The result would be non-existent if we were to calculate the difference between the returns of, for example, B2 and B5 portfolios, because the lowest beta portfolio produces the worst returns.

The results in **Table 3** support the message from previous literature that there is no robust link between beta and return. Average returns are rather flat and the return on B15UL portfolio is not statistically significant. However, there are a couple of interesting differences. First of all, **Table 3** shows upward sloping beta-return relation which is demonstrated by the negative return on B15UL portfolio whereas the difference has been previously positive (e.g. Baker, Bradley, and Wurgler, 2011; Novy-Marx, 2014b; Bali et al., 2014) or at least there has been a tilt in the highest beta portfolio (e.g. Black et al., 1972; Frazzini and Pedersen, 2014). Thus, the relation has been closer to the expected in my sample. Secondly, the level of excess return has been higher between July 1984 and June 2011 than in the samples covering the period from 1960s until yearly 2000s. The level of excess returns in my study is closer to the ones reported in Black et al. (1972) and Frazzini and Pedersen (2014) who cover the longer period beginning from 1930s.

The finding of no link between beta and return in my study is not surprising because I exclude the most illiquid stocks, use equal-weighting in calculating the portfolio returns, longer estimation period for beta, and less frequent rebalancing, which all have tended to provide less impressive results for the betting against beta. These results also mean that the first hypothesis is rejected because there is no economically or statistically significant link between beta and absolute returns. It is still possible, however, that the betting against beta exists on risk-adjusted basis.

5.2. Risk-adjusted returns

Now I study whether the betting against beta exists on risk-adjusted basis. First I consider whether Sharpe ratios and security market line reflect what would be expected. The returns on levered B15L portfolio and BAB factor also provide evidence on the question. As discussed, these portfolios are levered to have equal risk and standard finance theory suggest equal expected returns. Secondly, I study the returns of the quintile portfolios and zero-cost strategies against CAPM as well as three-, four-, and six-factor models to see how the betting against beta behaves relative to the most popular factors known to explain stock returns.

Sharpe ratios. **Table 3** shows that low-beta portfolios provide very attractive risk-return features because Sharpe ratios are monotonically declining in beta. Using the 60 month beta-estimation period Sharpes decline from 0.28 to 0.16 (Panel A), and using the 36 month beta-estimation period they decline from 0.26 to 0.14 (Panel B). Monotonically decreasing Sharpe ratios mean that extra unit of volatility has not produced sufficient extra return. The Sharpe ratios in my paper correspond rather well to those in the previous literature being slightly higher on average and showing less extreme divergence between the quintile portfolios. For example, Frazzini and Pedersen (2014) report Sharpe ratios varying from 0.20 to 0.08 for lowest and highest beta decile, respectively.

Risk-parity portfolios. Taking beta risk has not been rewarded. While beta of the B5 portfolio is over three times that of the B1 portfolio, the return is only slightly higher. Moreover, the returns on B15L strategy and BAB factor should be zero. However, the monthly return on B15L portfolio is positive and statistically significant being 1.07 % (t-value, 3.69) and 0.83 % (t-value, 3.33) using 60 and 36 month beta-estimation periods, respectively. The 0.89 % return on BAB factor (t-value, 4.27) also supports the notion that beta risk has not been adequately rewarded.

Security market line. **Fig. 5** shows the flatness of the empirical security market line. Low-beta portfolios have provided higher returns and high-beta portfolios lower returns than would be expected based on CAPM implied security market line. The empirical line has an intercept of 0.66 compared to zero of the theoretical line. Moreover, the slope of 0.33 is approximately third of the 0.96 implied by theory. Although this clearly demonstrates the betting against beta, the flatness is still less pronounced than in some previous studies (e.g. Blitz and van Vliet, 2007; Baker, Bradley, and Wurgler, 2011) that show an inversed security market line.

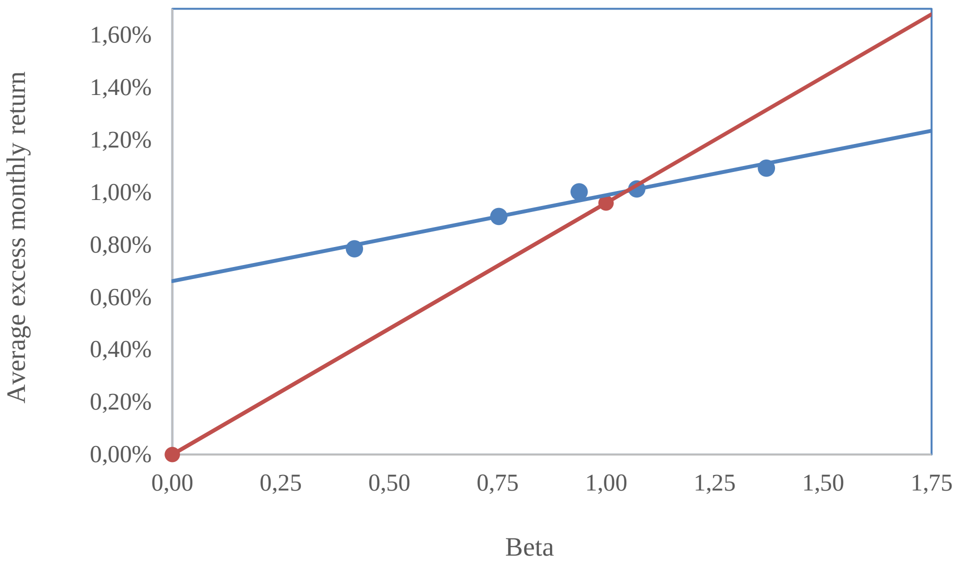


Fig. 5. Theoretical and empirical security market lines. The figure shows theoretical and empirical security market lines from July 1984 to June 2011. Red line shows the theoretical security market line, where the intercept is zero and slope is 0.96 % (equity premium). Market portfolio is an equally weighted return of the quintile portfolios. Risk-free rate is from the Kenneth French's website. Beta of a quintile portfolio is the slope from a regression of the excess portfolio returns on the excess market returns. The blue dots correspond to each beta-sorted portfolio (B1-B5) and the blue line shows the interpolated empirical security market line. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months.

5.3. Factor-model regressions

Until now I have only considered market risk. Next I study whether the betting against beta exists after controlling for other variables known to explain the cross-section of stock returns. These variables are size, value, momentum, liquidity, and profitability. Specifically, the excess returns of the quintile portfolios and returns on zero-cost strategies are regressed on excess market return as well as three-, four-, and six-factor models including additional factor proxies for each of the five variables. Using the linear factor models provides a clear and direct measure to evaluate the abnormal performance of a portfolio or long-short strategy by focusing on the regression alpha. First I explain the factor models and then discuss the regression results.

5.3.1. Factor models

The dependent variable in all the models [(*3*), (*4*), (*5*), and (*6*)] is the excess return over risk-free rate of a beta-sorted portfolio (B1, B2, B3, B4, and B5) or a zero-cost strategy (B15L, B15UL, and BAB). I only use the 60 month portfolios here, because the previous results were quite similar for portfolios constructed using the previous 60 month and 36 month betas. The explanatory variables are excess market return and returns on long-short strategies.

Alpha is the intercept of the regression. In economic terms alpha implies return that is not explained by risk factors or factors known to explain the cross-section of stocks returns. The question whether variables such as size or value represent risk are left to reader. My aim is simply to provide a benchmark against which to assess the returns of the beta-sorted portfolios and zero-cost strategies.

Capital asset pricing model (market) uses the sensitivity of a stock or portfolio to the market in explaining the returns. MRKT is the excess return on the market over the risk-free rate.

$$R_{jt} = a_j + b_j MRKT_t + \varepsilon_t \tag{3}$$

Three-factor model (market, size, value) (Fama and Frech, 1993) includes factors for excess market return (MRKT), size (SMB), and value (HML). SMB is the return on small stocks minus the return on big stocks, HML is the return on high book-to-market stocks minus the return on low book-to-market stocks.

$$R_{jt} = a_j + b_j MRKT_t + s_j SMB_t + h_j HML_t + \varepsilon_t \tag{4}$$

Four-factor model (market, size, value, momentum) (Carhart, 1997) is similar to the three-factor model but includes an additional variable for momentum (MOM). MOM is the return on the best-performing stocks minus the return on the worst-performing stocks over a period from t-12 to t-2, where t is month.

$$R_{jt} = a_j + b_j MRKT_t + s_j SMB_t + h_j HML_t + m_j MOM_t + \varepsilon_t \tag{5}$$

Six-factor model (market, size, value, momentum, liquidity, profitability) contains all the same factors as the four-factor model and adds two factors for liquidity and profitability. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). PMU is the return on the most profitable firms minus the return on the least profitable firms. Profitability is measured by gross profitability to assets.

$$R_{jt} = a_j + b_j MRKT_t + s_j SMB_t + h_j HML_t + m_j MOM_t + l_j LIQ_t + p_j PMU_t + \varepsilon_t \tag{6}$$

5.3.2. Regression results

Table 4 provides alphas of the multifactor-model regressions. It shows that the betting against beta exist on risk-adjusted basis. In Panel A, alphas are generally declining in beta. The relation is monotonically decreasing for portfolios from B1 to B4. B1 always outperforms the other four portfolios, B2 always outperforms B3 and B4, and B3 always outperforms B4. However, the highest beta portfolio actually performs relatively well on factor-model basis. It outperforms B4 on three-factor basis, and B4, B3, and B2 on four and six-factor basis.

More specifically, CAPM adjusted alphas are monotonically declining in beta and statistically significant for the B1, B4, and B5 portfolios. The difference of 0.60 % (t-value, 3.70) between CAPM alphas of the lowest and highest beta portfolio is similar to those reported in the previous studies. For example, Baker, Bradley, and Wurgler (2011) and Novy-Marx (2014b) report alpha differences of 0.64 % and 0.50 %, respectively.

Furthermore, three-, four-, and six-factor alphas are monotonically declining between portfolios from B1 and B4, but B5 performs better than expected on three-, four-, and six-factor basis. It even produces positive alpha in four- and six-factor basis even though neither is statistically significant. Secondly, the alpha difference is positive for all the multifactor models varying from 0.36 % to 0.14 % for three- and six-factor models, respectively, but statistically significant only for the three-factor model (t-value, 2.72). This is somewhat in line with previous studies, as e.g. Bali et al. (2014) and Novy-Marx (2014b) report four- and three-factor alphas of 0.51 % and 0.28 %, respectively. The more significant four-factor alpha in Bali et al. (2014) is the results of very bad performance of the highest beta decile in their study. Lastly, B5 performs relatively well on a multifactor-model basis, and when I compare multifactor-model alpha differences between B1 and B4 portfolios the differences are highly statistically significant t-values varying from 3.94 to 2.65 (not reported). The results strongly suggest that the betting against beta exists on risk-adjusted basis.

Panel B in **Table 4** shows the results for zero-cost portfolios and provides further evidence for the betting against beta. All the B15L and BAB alphas are positive and statistically significant, t-statistics varying from 4.86 to 2.41. The B15L alpha drops from 1.07 % (CAPM) to 0.64 % (four factor) and the BAB alpha from 1.00 % (CAPM) to 0.45 % (six factor) per month.

Table 4
Factor-model regression alphas.

This table shows the average monthly alphas from factor-model regressions from July 1984 to June 2011. Column 1 shows the dependent variables that are excess returns on the beta-sorted portfolios (Panel A) and zero-cost strategies (Panel B). B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months. B15UL is the return on the lowest beta portfolio minus the return on the highest beta portfolio. B15L is the return on the lowest beta portfolio minus the return on the highest beta portfolio, where both portfolios are levered or de-levered to have a beta of one. BAB factor is from Frazzini and Pedersen (2014).

Columns 2-5 show the linear factor model alphas for the quintile portfolios and zero-cost strategies. The factor models are CAPM, Fama and French (1993) three-factor model, four-factor model of Carhart (1997), and six-factor model including additional factors for liquidity (Pastor and Stambaugh, 2003) and profitability (Novy-Marx, 2013). More details about the factor models are in Section 5.3.1.

I report t-statistic in the parenthesis. Furthermore, statistically significant values are bolded and highlighted using asterisks when deemed important (***, **, and * denote statistical significance at the 1 %, 5%, and 10 % levels).

All the figures are monthly values or calculated from monthly values. For example, the CAPM alpha of B1 portfolio is 0.31 % per month. In total, there are 324 monthly observations.

	CAPM	Three factor	Four factor	Six factor
Panel A: Beta-sorted portfolios				
B1	**0.31*** (3.25)**	**0.26*** (2.77)**	**0.19** (2.04)**	**0.25*** (2.62)**
B2	0.09 (1.49)	0.02 (0.45)	-0.04 (-0.78)	**-0.08* (-1.68)**
B3	0.00 (-0.06)	-0.05 (-1.24)	**-0.08* (-1.87)**	**-0.13*** (-2.97)**
B4	**-0.11** (-2.30)**	**-0.12** (-2.44)**	**-0.09* (-1.81)**	**-0.14*** (-2.76)**
B5	**-0.29** (-2.20)**	-0.10 (-1.11)	0.02 (0.21)	0.11 (1.13)
B1-B5	**0.60*** (3.70)**	**0.36*** (2.72)**	0.17 (1.31)	0.14 (1.05)
Panel B: Zero-cost portfolios				
B15L	**1.07*** (3.65)**	**0.81*** (3.06)**	**0.64** (2.42)**	**0.69** (2.54)**
BAB	**1.00*** (4.86)**	**0.78*** (4.17)**	**0.56*** (3.13)**	**0.45** (2.41)**

Overall the results in this chapter indicate that the betting against beta exists in the U.S. stock market on risk-adjusted basis and the hypothesis two is not rejected. Monotonically declining Sharpe ratios and CAPM alphas as well as the flatness of the empirical security market line all highlight the fact that taking beta risk has not produced enough, if any, extra return. Moreover, the lowest beta portfolio produces statistically significant alpha even after controlling with size, value, momentum, liquidity, and profitability factors known to explain the cross-section of stock returns well.

Some ambiguity is still left as it is not the case that high beta stock do extremely badly when controlling with these other factors and alphas are not entirely monotonically decreasing in beta using the multi-factor models. However, the high monthly returns of strategies (B15L, BAB) taking advantage of the attractive risk-return features of the low-beta portfolios by leveraging them up provides strong support for the betting against beta. Moreover, these strategies provide robustly positive and statistically significant alpha after controlling with size, value, momentum, liquidity, and profitability factors.

6 Betting against beta and investor sentiment

In this chapter I study whether investor sentiment influences the betting against beta found in the stock market. It is preferable that the high-beta stocks have certain characteristics because investor sentiment has the biggest impact on these stocks (hypothesis three). This is also my proposed channel for investor sentiment to influence the betting against beta in the stock market (hypothesis four).

6.1. Characteristics of the beta-sorted portfolios

I considered some of the previously documented characteristics of the high-beta stocks in Section 3.2. Now I study and discuss the characteristics more thoroughly. While the previous literature provides evidence about the characteristics of beta-sorted portfolios, I find it important to provide further empirical support because the characteristics are very important in providing a habitat and speculative demand based story (Barberis, Shleifer, and Wurgler, 2005; Baker and Wurgler, 2007) for the relation between investor sentiment and the betting against beta.

Panel A in **Table 5** provides the six-factor model loadings of the quintile portfolios. It shows that high beta is associated positively with SMB, and negatively with HML, MOM, LIQ and

Table 5
Six-factor model loadings of the quintile portfolios**.**

This table shows the six-factor model loadings of the quintile portfolios during the sample period from July 1984 to June 2011. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months.

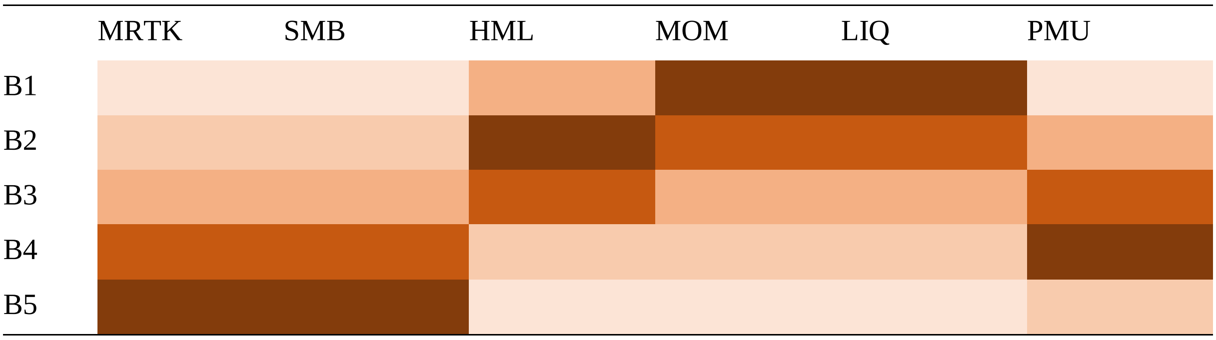
The excess returns on the quintile portfolios are regressed on the excess market return and SMB, HML, MOM, LIQ, and PMU factors known to explain cross-sectional stocks returns. These factors mimic underlying economic or behavioral exposures to market capitalization, book-to-market, momentum, liquidity, and profitability. The actual multifactor model used is Carhart (1997) including additional factors for liquidity (Pastor and Stambaugh, 2003) and profitability (Novy-Marx, 2013).

Panel A shows formally the results of the six-factor model regression and Panel B provides a graphical illustrations of the six-factor model loadings. Darker shade indicates higher exposure to a factor. All the figures are monthly values or calculated from monthly values. For example, the alpha of B1 portfolio is 0.25 % per month. In total, there are 324 monthly observations for each portfolio. I report t-statistics in the parenthesis below the regression coefficients. Last column in Panel A provides the adjusted R-squared value.

Panel A: Results of the six-factor regression

	alpha	MRKT	SMB	HML	MOM	LIQ	PMU	Adj. R^2
B1	0.25	0.55	-0.11	0.11	0.07	0.05	-0.17	69 %
	(2.62)	(25.82)	(-3.78)	(3.43)	(3.53)	(2.22)	(-4.11)	
B2	-0.08	0.90	-0.05	0.19	0.06	0.00	0.09	96 %
	(-1.68)	(79.65)	(-3.15)	(11.63)	(5.89)	(-0.15)	(4.24)	
B3	-0.13	1.08	-0.05	0.14	0.03	0.00	0.10	98 %
	(-2.97)	(109.45)	(-3.51)	(9.94)	3.00	(-0.20)	(5.12)	
B4	-0.14	1.17	-0.01	0.03	-0.03	0.00	0.10	98 %
	(-2.76)	(101.18)	(-0.49)	(1.67)	(-3.07)	(-0.24)	(4.53)	
B5	0.11	1.30	0.22	-0.46	-0.12	-0.04	-0.12	95 %
	(1.13)	(60.55)	(7.31)	(-15.03)	(-6.36)	(-1.90)	(-2.93)	

Panel B: Graphical illustration of the six-factor model loadings



PMU factors. Low-beta, on the other hand, is positively associated with HML, MOM, and LIQ, and negatively with SMB and PMU factors. While the relation between beta and SMB, MOM, and LIQ is clearly monotonic, higher loading on HML and PMU seem to be associated with middle-beta portfolios. Both the lowest and highest beta portfolios have significant and negative PMU loadings of -0.17 (t-value, -4.11) and -0.12 (t-value, 2.93), respectively. The highest beta portfolio is also associated with very low (-0.46) and statistically significant (t-value, -15.03) exposure to the HML factor. Panel B illustrates graphically the factor loadings of the quintile portfolios. Finally, three- and four-factor regressions provide almost identical factor loadings to the six-factor regression and are not reported.

Factor loadings do not tell directly about the characteristics of the portfolios. For example, positive SMB loading does not mean a stock is small or neither is it true that all small stocks have positive SMB loadings. However, this is not needed for my purposes as long as a positive SMB loading of a portfolio implies that the portfolio stocks are small on average. This is important because individual investors do not consciously demand stocks that have certain SMB, HML, and PMU loadings but they might very well demand stocks that are small and unprofitable growth stocks with a lot of potential to improve. Effectively, the results in **Table 5** imply that high-beta stocks are small, liquid, and unprofitable growth stocks with negative momentum. Low-beta stocks, on the other hand, are large, illiquid, and unprofitable value stocks with positive momentum.

It is hard to believe that individual investors demand certain factor loadings of stocks. At least this is most likely true for the sample period in this study. However, individual investors do not live in a different world than academics (e.g. access to Google scholar, news, etc.), and as the knowledge about the abnormal return on these factors spreads across wider population, individuals might start to demand these factors as they seek returns.

Already, the huge growth of mutual funds and ETFs mimicking value and growth strategies shows that academic factors do have an impact on investor behavior. As long as these funds and ETFs invest in corresponding physical securities such as value stocks this behavior does have cross-sectional impact. This just shows that the so-called characteristics that individual investors demand are not stable over time but change in response to the general perceptions to e.g. what has been successful in the past. Lastly, but not surprisingly, Blackrock launched a minimum-volatility ETF in 2011 investing in low-volatility stocks[12]. Importantly, it holds physical securities.

For the hardness-to-arbitrage argument it is preferable that high-beta stocks are illiquid. Although this is not the case either in my study or in the previous ones, I review here explicitly the two papers providing the most comprehensive account of the relation between beta and illiquidity to my knowledge. Firstly, Bali et al. (2014) provide unambiguous evidence on the negative relation between illiquidity and beta. They show a monotonically decreasing illiquidity measure (Amihud, 2002) for ten beta-sorted portfolios. Furthermore, the Fama and MacBeth (1973) regression coefficient for the same illiquidity measure is negative. Finally, the liquidity coefficient of Pastor and Stambaugh (2003) is positive although not significant in a linear regression against the BAB factor that goes long low-beta stocks and shorts high-beta stocks.

Secondly, Garcia-Feijoo, Li, and Sullivan (2014) investigate the liquidity characteristic of high-beta stocks. They find that high-beta stocks have higher share price, higher percentage of non-zero trading days, and higher average dollar volumes. Traditionally, low but not high share price is associated to illiquidity although a very high share price can also create illiquidity. Furthermore, the more there are non-zero trading days the more possibilities there are to trade. Also, the average dollar volume, which is higher for high-beta stocks, proxies the ease-of-trading. Interestingly, higher beta was associated with a higher value of illiquidity measure of Amihud (2002). All their liquidity measures also had very low correlations with each other. In summary, the high-beta stocks are not illiquid using traditional measures of illiquidity.

Lastly, the illiquidity of high-beta stocks may not be a big issue. Illiquidity is most of all a characteristic of hard-to-arbitrage stocks, and there are other limits to arbitrage than illiquidity in the context of the betting against beta. While previous literature proposes some limits of arbitrage already discussed, I show later empirically that time-horizon of fund managers most likely limits some arbitrage activity. Furthermore, we can speculate whether liquidity measures based on trading actually capture the "bad state" liquidity very well. It can be that it is exactly the excessive trading of the individual investors during increasing sentiment that creates the so-

[12] iShares MSCI USA Minimum Volatility ETF (CUSIP: 46429B697)

called liquidity. For example, many speculative bubbles seem to burst not long after the collective feeling of there always being a new buyer with higher price. Thus, it could be useful to investigate the time-varying liquidity of the high-beta stocks.

Table 6 summons up the required and empirical characteristics of the high-beta stocks from this and previous studies. My results (column four) indicate that high-beta stocks are small, liquid, volatile, and unprofitable growth stocks. This is in line with previous work (column three) other than the fact that my study shows clearly that high-beta stocks are unprofitable stocks whereas the previous studies have given mixed evidence. The difference is mainly methodological because e.g. Novy-Marx (2014b) reports negative correlation between beta and profitability and thus misses the non-linear relation between the two variables.

Table 6

Summary of the required and empirical characteristics of the high-beta stocks.

This table summarizes the required and empirical characteristics of the high-beta stocks. First column shows the characteristic in question. Second column tells the required value of the characteristic of a stock to be hard-to-value and hard-to-arbitrage by Baker and Wurgler (2007). Third column shows the findings by Novy-Marx (2014b), Bali et al. (2014), Frazzini and Pedersen (2014), and Garcia-Feijoo, Li, and Sullivan (2014) for the character values for high-beta stocks. Fourth column shows the results from this paper. The character values that correspond to the required ones are bolded.

Market capitalization is a company's share price multiplied by shares outstanding. Book-to-market measures the company's book value of equity to the market value of equity, and profitability is ratio of gross profitability to assets. Liquidity is measured differently in the studies. My paper uses the factor loading of the highest beta portfolio against the liquidity factor of Pastor and Stambaugh (2003). Liquidity measures in the previous literature are the traded liquidity factor of Pastor and Stambaugh (2003), Amihud (2002), share price, number of non-zero trading days, and dollar volume. Volatility is either total volatility or idiosyncratic volatility from the Fama and French (1993) three-factor regression. Dividends mean whether a company pays dividends or not. Age is company age.

Characteristic	Required	Literature	This paper
Market cap	Small	**Small**	**Small**
Book-to-market	Extreme growth	**Extreme growth**	**Extreme growth**
Profitability	Unprofitable	Mixed	**Unprofitable**
Liquidity	Low	High	High
Volatility	High	**High**	**High**
Dividends	No	N/A	**No (?)**
Age	Young	N/A	**Young (?)**

Table 6 also shows the characteristic-value pairs (first and second column) for the characteristics required for investor sentiment to have an effect as proposed by Baker and Wurgler (2007). Apart from illiquidity, high-beta stocks have all the characteristics required although data on firm age and dividends is not available. However, it is most likely that because high-beta stocks tend to be smaller, they also tend to pay less dividends and be younger. Only large firms tend to pay dividends and on average firms grow in size as they mature.

To sum up the results in this chapter so far, I am willing to accept the proposition that high-beta stocks are hard-to-value and hard-to-arbitrage stocks because they are small, unprofitable and volatile growth stocks. There are also good reasons to believe that they are younger and pay less dividends. Thus, they should be most affected by investor sentiment.

6.2. Betting against beta and investor sentiment

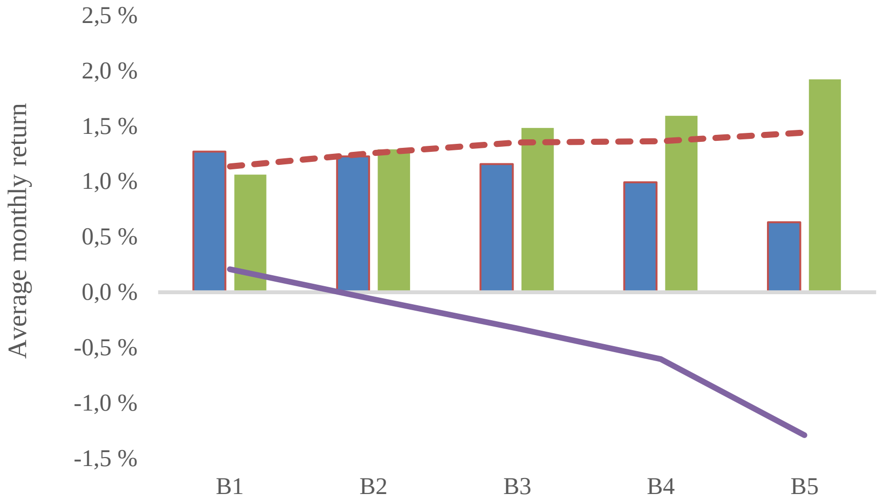
Section 6.1 showed that high-beta stocks have the characteristics that individual investors demand. Therefore high-beta stocks should be most affected by investor sentiment. During high sentiment the demand falls heavily on high-beta stocks and drives their prices up leading to abnormally low future returns. During low sentiment the demand for high-beta stocks decreases driving their prices down and future returns up and investors may even fly to quality by buying less risky stocks. Consequently, following high sentiment the betting against beta should be stronger and following low sentiment it should be weaker. In this chapter I study whether there is any empirical support for this reasoning.

To test whether investor sentiment influences the betting against beta, I first divide the whole sample period to low- and high-sentiment periods based on average level of the sentiment index. This enables me to observe whether the return patterns are different following different sentiment levels. The returns are also compared to the average returns during the whole period. Secondly, I study the returns using the multifactor models introduced previously while also including an additional factor for investor sentiment. The multifactor regressions are also performed both following high and low sentiment.

6.2.1. Return differences following low and high sentiment

Fig. 6 shows the main results for the quintile portfolios graphically. LHS (RHS) bar shows the average return following high (low) sentiment. Dashed line is the average return during the whole period and solid line describes the difference between returns following high and low

Panel A: Portfolios sorted by 60 month beta



Panel B: Portfolios sorted by 36 month beta

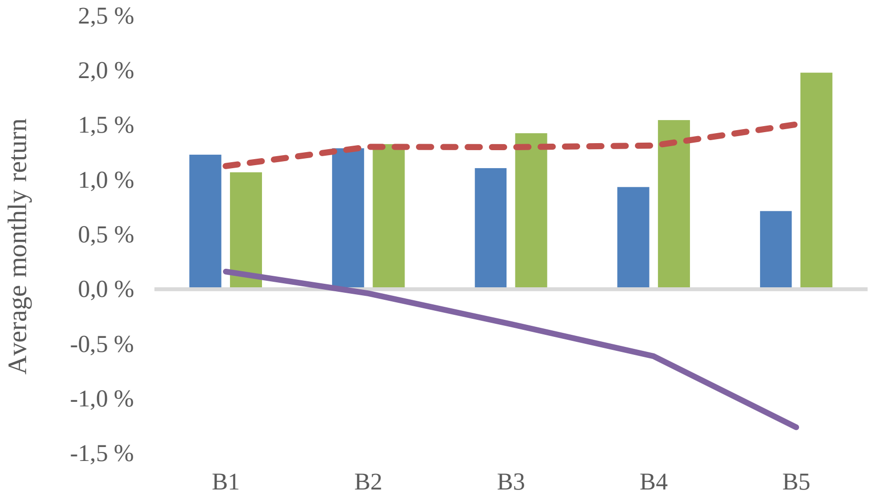


Fig. 6. Average returns of the quintile portfolios following high and low sentiment. Figure shows the average returns of the quintile portfolios following high and low sentiment. The LHS bar is the return of a portfolio following high sentiment and RHS bar the return following low sentiment. Solid line is the difference between the returns following high and low sentiment. Dashed line is the average return during the full sample period. The sample period from July 1984 to January 2011 is divided to two based on average level of investor sentiment. High (low) contains the months when the previous month's level of investor sentiment index is above (below) average. Panels A and B show the results for portfolios constructed by sorting stocks based on their previous 60 and 36 month betas, respectively. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 (Panel A) and 36 (Panel B) month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months. In total there are 319 observations. Details about the index of investor sentiment are in Baker and Wurgler (2006).

sentiment. Dashed line shows the previously documented flat average returns across the quintile portfolios. Strikingly, however, the bars show that average returns are increasing in beta following low sentiment and decreasing in beta following high sentiment. Furthermore, the solid line shows that high-beta stocks are more sensitive to investor sentiment than low-beta stocks. Lastly, the patterns are identical for portfolios sorted by previous 60- and 36-month betas in Panels A and B, respectively.

Table 7 shows the average returns of the quintile portfolios and zero-cost strategies following high and low sentiment more formally. It shows that following high sentiment, the average returns decline monotonically as beta increases. It shows also that following low sentiment the pattern completely reverses and high-beta stocks outperform their low-beta counterparts. Panel A shows the results for the portfolios sorted by previous 60-month betas. Following high sentiment the monthly return decreases from 1.27 % to 0.63 % when we move from the lowest beta to the highest beta portfolio. Moreover, following low sentiment the monthly return increases for the same portfolios from 1.06 % to 1.92 %.

Panel B shows similar results for the portfolios sorted by previous 36-month betas. Following high sentiment, monthly returns decrease from 1.23 % to 0.72 % for the highest and lowest beta portfolios, respectively. Following low sentiment, monthly returns increase from 1.07 % to 1.98 % for the same portfolios. The level of investor sentiment clearly predicts the performance of the betting against beta.

The last two columns in **Table 7** provide further support for the investor sentiment to influence the betting against beta. In Panel A, the return difference of the lowest and highest beta portfolios (B15UL) is 0.64 % and -0.86 % following high and low sentiment, respectively. Moreover, the difference of 1.50 % between the returns on B15UL strategy following high and low sentiment is statistically significant (t-value, 2.17). Panel B shows similar results using the 36 month beta-estimation period.

It is also interesting to see how the levered B15L strategy produces positive return in all sentiment conditions. It produces highly statistically and economically significant monthly return of 1.86 % (t-value, 3.26) following high sentiment and a decent return of 0.60 % (t-value, 1.84) following low sentiment. This also means that while investor sentiment does predict the returns of the betting against beta, it is not sufficient alone to explain why the betting against beta is so strong unconditionally.

Furthermore, **Table 7** shows that especially high-beta stocks are affected by investor sentiment. The quintile portfolio return differences between high and low sentiment clearly increase in

Table 7
The performance of the quintile and zero-cost portfolios following high and low sentiment.

Table shows the returns on the quintile portfolios and zero-cost strategies following high and low sentiment. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 (Panel A) and 36 (Panel B) month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months. B15UL is the return on the lowest beta portfolio minus the return on the highest beta portfolio. B15L is the return on return on the lowest beta portfolio minus the return on the highest beta portfolio, where both portfolios are levered or de-levered to have a beta of one.

The sample period from July 1984 to January 2011 is divided to two based on average level of investor sentiment. High (low) contains the months when the previous month's level of investor sentiment index is above (below) average. Average is the unconditional average return during the whole sample period. In total there are 319 observations. Details about the index of investor sentiment are in Baker and Wurgler (2006).

I report t-statistic in the parenthesis. Furthermore, statistically significant values are bolded and highlighted using asterisks when deemed important from the point of view of discussion (***, **, and * denote statistical significance at the 1 %, 5%, and 10 % levels).

All the figures are monthly values or calculated from monthly values. For example, the return on B1 portfolio following high sentiment is 1.27 % per month.

Panel A: Portfolios sorted by 60 month beta

	B1	B2	B3	B4	B5	B15UL	B15L
High	1.27	1.22	1.16	0.99	0.63	0.64	**1.86*** **
						(1.06)	(3.26)
Average	1.13	1.26	1.35	1.36	1.44	-0.31	**1.07*** **
						(-1.01)	(3.69)
Low	1.06	1.29	1.48	1.59	1.92	**-0.86** **	**0.60* **
						(-2.49)	(1.84)
High - Low	0.21	-0.06	-0.33	-0.60	-1.29	**1.50** **	**1.26* **
	(0.57)	(-0.12)	(-0.54)	(-0.90)	(-1.49)	(2.17)	(1.91)

Panel B: Portfolios sorted by 36 month beta

	B1	B2	B3	B4	B5	B15UL	B15L
High	1.23	1.29	1.11	0.93	0.72	0.51	**1.53*** **
						(0.92)	(3.14)
Average	1.13	1.30	1.30	1.31	1.51	-0.38	**0.83*****
						(-1.33)	(3.33)
Low	1.07	1.33	1.43	1.54	1.98	**-0.91*** **	0.41
						(-2.77)	(1.45)
High - Low	0.16	-0.04	-0.32	-0.61	-1.26	**1.42** **	**1.12** **
	(0.43)	(-0.08)	(-0.54)	(-0.91)	(-1.47)	(2.20)	(1.99)

beta as well as the statistical significance. The monthly return difference is 0.21 % for the lowest beta portfolio whereas it rises to -1.29 % for the highest beta portfolio, although none of these differences is statistically significant in normal confidence levels. However, later in **Table 10** I use alternative investor sentiment measures and the return difference becomes statistically significant for the two highest beta portfolios.

While investor sentiment influences cross-sectionally some stocks more than others, average returns of the quintile portfolios are higher following low sentiment. The equally weighted monthly market return is 0.42 %[13] higher following low than high sentiment. Furthermore, the value-weighted monthly market return is 0.76 %[14] higher following low than high sentiment. This implies that investor sentiment does affect the expected returns also on a market level.

However, it could be that the level of investor sentiment and the level of market are just highly correlated and that the over and undervaluation of the market is actually the primary source of the patterns in the quintile portfolio and zero-cost strategy returns. **Appendix B.2**. shows the correlation argument to have some validity. I discuss the effect of market on the robustness of my results in Section 6.3.4. For now it is sufficient to say that while following high level of market the returns on *all* stocks are lower, and following low level of market the returns on all stocks are higher, the level of market does not fully explain the cross-sectional return differences of the beta-sorted stocks.

Interestingly, contrary to the overall market and the other quintile portfolios the lowest beta portfolio produces higher returns following high-sentiment. The monthly return on B1 portfolio is 1.27 % following high level of investor sentiment and 1.06 % following low level of investor sentiment. Although the difference is not statistically significant, **Table 10** shows that it is robust to the use of alternative sentiment measures.

Most importantly, this indicates that there is a “flight-to-quality” effect *within* equities, and when investors seek safety they also look for the safest stocks and not just safer assets. On other words, during high sentiment low-beta stocks become undervalued whereas during low

[13] Equally weighted market return = Average return on the quintile portfolios

[14] Value-weighted market return is from Kenneth French’s website

sentiment they become overvalued contrary to higher beta stocks that become overvalued during high sentiment and undervalued during low sentiment. Furthermore, this implies that the lowest beta stocks are affected by investor sentiment in an important way. All this discussion paints a very frantic picture of the stock market, in which individual investors dash from speculative high-beta stocks to safe low-beta stocks as their sentiment changes.

Finally, undervaluation should be interpreted loosely here because undervaluation is less likely than overpricing as it is easier to buy stocks than to sell them short. Thus undervaluation should be interpreted to describe the relative valuations between high and low beta stocks, and between high and low sentiment.

6.2.2. Factor-model regressions

Next I run the factor-model regressions including a sentiment proxy for the whole sample period from July 1984 to January 2011. Fortunately, the sentiment proxy is of continuous nature and can be included in the regression models. The use of factor-model regression allows to conduct formal significance tests and study whether the effect of sentiment is distinct from other well-known variables known to explain stocks returns. I only consider the quintile portfolios sorted by previous 60 month beta because the results were similar for 60 and 36 month portfolios in the previous section. Lastly, I also conduct factor-model regressions following high and low sentiment and report the alphas in **Appendix B.4.**

6.2.2.1. Factor models

The regression models are below. They are comparable to the one-, three-, four-, and six-factor models introduced in Section 5.3.1. The difference is that the models here include an additional explanatory factor for sentiment (SENTIMENT or SENT). SENT is the beginning of period level of investor sentiment index from Baker and Wurgler (2007). The dependent variables are monthly returns on levered B15L and unlevered B15UL strategies that go long in low-beta stocks while shorting high-beta stocks. The first model studies the sole impact of the beginning of period investor sentiment on next month’s stock returns without any controls.

$$R_{jt} = a_j + d_j SENTIMENT_{t-1} + \varepsilon_t, \tag{7}$$

Capital asset pricing model (market) uses the sensitivity of a stock or portfolio to the market in explaining returns. MRKT is the excess return on the market over the risk-free rate.

$$R_{jt} = a_j + d_j SENTIMENT_{t-1} + b_j MRKT_t + \varepsilon_t, \tag{8}$$

Three-factor model (market, size, value) (Fama and Frech, 1993) contains factors for excess market return (MRKT), size (SMB), and value (HML). SMB is the return on small stocks minus the return on big stocks, HML is the return on high book-to-market stocks minus the return on low book-to-market stocks.

$$R_{jt} = a_j + d_j SENTIMENT_{t-1} + b_j MRKT_t + s_j SMB_t + h_j HML_t + \varepsilon_t, \tag{9}$$

Four-factor model (market, size, value, momentum) (Carhart, 1997) is similar to the three-factor model but includes an additional variable for momentum (MOM). MOM is the return on the best-performing stocks minus the return on the worst-performing stocks over a period from t-12 to t-2, where t is month.

$$R_{jt} = a_j + d_j SENTIMENT_{t-1} + b_j MRKT_t + s_j SMB_t + h_j HML_t + m_j MOM_t + \varepsilon_t, \tag{10}$$

Six-factor model (market, size, value, momentum, liquidity, profitability) contains all the same factors as the four-factor model and adds two factors for liquidity and profitability. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). PMU is the return on the most profitable firms minus the return on the least profitable firms. Profitability is measured by gross profitability to assets.

$$R_{jt} = a_j + d_j SENTIMENT_{t-1} + b_j MRKT_t + s_j SMB_t + h_j HML_t + m_j MOM_t + l_j LIQ_t + p_j PMU_t + \varepsilon_t, \tag{11}$$

6.2.2.2. Regression results

Panel A in **Table 8** shows the results of the multifactor regressions including the sentiment proxy for the levered B15L strategy. It shows that the beginning of period sentiment level influences the performance of the B15L strategy. The estimates for sentiment coefficient (SENT) vary from 1.52 % for CAPM to 0.88 % for the four-factor model. All the coefficients are also statistically significant t-values varying from 2.93 to 1.90 for CAPM and four-factor model, respectively.

Moreover, the coefficient estimates are all positive and economically significant meaning that higher level of investor sentiment predicts positive returns for B15L strategy. For example, the coefficient of SENT in the CAPM regression indicates that a one-unit increase in SENT

Table 8

The results of the multifactor regressions including sentiment proxy, zero-cost portfolios.

Table shows the results from multifactor regressiond including a sentiment proxy. The factor models are Sentiment that includes only the sentiment proxy, CAPM, Fama and French (1993) three-factor model, four-factor model of Carhart (1997), and six-factor model including additional factors for liquidity (Pastor and Stambaugh, 2003) and profitability (Novy-Marx, 2013). Furthermore, the models include a factor for beginning of period sentiment. The beginning of period sentiment (SENT) is the previous month's value of investor sentiment index from Baker and Wurgler (2007). The index is not standardized. The mean and standard deviation of SENT are 0.14 and 0.56, respectively.

The dependent variables are monthly returns on zero-cost strategies. B15L (Panel A) is the return on the lowest beta portfolio minus the return on the highest beta portfolio, where both portfolios are levered or de-levered to have a beta of one. B15UL (Panel B) is the return on the lowest beta portfolio minus the return on the highest beta portfolio.

The sample covers the period from July 1984 to January 2011. It includes monthly values for dependent and explanatory variables. In total there are 319 observations. I report t-statistic in the parenthesis. Furthermore, statistically significant values are bolded and highlighted using asterisks when deemed important (***, **, and * denote statistical significance at the 1 %, 5%, and 10 % levels). All the figures are monthly values or calculated from monthly values. For example, the alpha of B15L strategy using CAPM is 0.82 % per month. Adjusted R^2 is reported in the last column.

Panel A: Levered B15L portfolio

	alpha	SENT	MRKT	SMB	HML	MOM	LIQ	PMU	Adj. R^2
Sentiment	0.84	**1.50*** **							2 %
	(2.80)	(2.92)							
CAPM	0.82	**1.52*** **	0.02						2 %
	(2.71)	(2.93)	(0.31)						
Three factor	0.63	**1.03** **	0.19	-0.29	0.62				20 %
	(2.31)	(2.18)	(3.13)	(-3.36)	(6.66)				
Four factor	0.49	**0.88* **	0.24	-0.30	0.68	0.19			23 %
	(1.79)	(1.90)	(3.89)	(-3.50)	(7.32)	(3.14)			
Six factor	0.56	**1.09** **	0.24	-0.31	0.61	0.19	0.15	-0.34	26 %
	(2.02)	(2.32)	(4.03)	(-3.73)	(6.35)	(3.46)	(2.14)	(-2.83)	

Panel B: Unlevered B15UL portfolio

	alpha	SENT	MRKT	SMB	HML	MOM	LIQ	PMU	Adj. R2
Sentiment	-0.54	**1.48*** **							2 %
	(-1.69)	**(2.72)**							
CAPM	0.17	**0.67** **	-0.94						63 %
	(0.84)	**(1.98)**	(-22.78)						
Three factor	0.09	0.45	-0.81	-0.52	0.25				76 %
	(0.56)	(1.63)	(-23.05)	(-10.33)	(4.66)				
Four factor	-0.08	0.28	-0.75	-0.53	0.33	0.22			79 %
	(-0.54)	(1.08)	(-22.51)	(-11.35)	(6.42)	(7.41)			
Six factor	-0.04	0.38	-0.75	-0.54	0.29	0.22	0.06	-0.17	80 %
	(-0.26)	(1.48)	(-22.77)	(-11.58)	(5.48)	(7.49)	(1.63)	(-2.56)	

provides 1.52 % higher monthly returns for B15L strategy. The sentiment index has a mean of 0.14 % per month and standard deviation of 0.56 % (not standardized). This means that a one-standard deviation increase in the index predicts 0.85 % higher return next month.

The alphas of the multifactor regressions including a proxy for sentiment are also slightly lower and less significant compared to the alphas of the multifactor regressions without the sentiment proxy. The coefficient estimates for the other factors are almost identical to those without SENT (**Appendix B.1.**).

Considering the positive and statistically significant coefficients for SENT in all the multifactor regressions, it seems that sentiment plays an important role in explaining the returns on B15L strategy and that the role is not greatly diminished after controlling for other variables known to explain cross-sectional stock returns.

Panel B in **Table 8** shows the results of the multifactor regressions including the sentiment proxy for the unlevered B15 strategy. It shows mixed evidence for the sentiment to explain the returns on the unlevered B15UL strategy. All the coefficients of SENT are positive varying from 1.48 % to 0.28 % for the sole SENT regression (Sentiment) and four-factor model, respectively. Furthermore, SENT is statistically significant in the CAPM regression as well as in the regression where it is the only explanatory variable. SENT is also close to being statistically significant in the three-factor and six-factor regressions (p-values of 10.4 % and 13.9 %, respectively) but using the four-factor model it becomes irrelevant.

Other coefficient estimates are almost identical in sign, magnitude and statistical significance to the coefficient estimates in the regressions without SENT (**Appendix B.1.**). Compared to B15L strategy, MRKT, SMB, and MOM become more significant in the B15UL regressions.

Overall, the results of the multifactor regressions in **Table 8** support the *hypothesis four* that investor sentiment influences the betting against beta. The SENT coefficient is always positive and mostly statistically significant in the B15L and B15UL regressions although the empirically-motivated factors (e.g. SMB and MOM) diminish the magnitude and significance of the coefficient somewhat, especially in the B15UL regression.

6.3. Robustness checks

Earlier investigations imply that the level of investor sentiment predicts the performance of the betting against beta. In this chapter I conduct additional tests to study the robustness of these findings. First of all I study the influence of investor sentiment on the returns of BAB factor of Frazzini and Pedersen (2014). The use of BAB factor makes it possible to utilize the whole monthly investor sentiment data from July 1965 to December 2011 available in the Jeffrey Wurgler's website. Secondly, I construct alternative measures of investor sentiment to verify that the results are not specific to one measure of investor sentiment. Thirdly, the investor sentiment index data enables to study how changes in investor sentiment affect the betting against beta contemporaneously. As investor sentiment builds up, the individual investor demand should fall on high-beta stocks and increase their returns contemporaneously. Finally, I study whether the effect of investor sentiment is just a market effect in disguise by studying the betting against beta performance following high and low levels of market. The multifactor regressions conducted this far also provide evidence on the significance of sentiment over and above market.

6.3.1. Longer time series

To study the robustness of investor sentiment as an explanation for the betting against beta I conduct multifactor regressions during a longer time series from August 1965 to January 2011 for which the investor sentiment index data is available. The BAB factor (Frazzini and Pedersen, 2014) is also available during the period and is conceptually similar to the B15L strategy used in this study. The multifactor models are the same used previously and discussed in detail in Section 6.2.2.1.

Table 9 shows the results of the multifactor regressions including a sentiment proxy (SENT) as an explanatory variable and BAB factor as the dependent variable. SENT is the previous month's level of investor sentiment from Baker and Wurgler (2007). The table shows that investor sentiment influences the betting against beta also during a longer time series from July 1965 to January 2011.

Importantly, all the SENT coefficients are positive and statistically significant. The monthly coefficient estimates vary from 0.42 % (t-value, 2.96) for the regression including only SENT to 0.22 % (t-value, 1.67) for the six-factor model. The index is standardized meaning that for example a one-unit increase (i.e. one standard deviation) in SENT using CAPM predicts 0.40 % higher next month returns.

On the other hand, adding more RHS variables decreases the SENT coefficient as well as its statistical significance somewhat. Especially HML and MOM factors are important in explaining the BAB returns. However, the positive and significant SENT coefficients provide evidence that the earlier results are not specific to chosen time period. Furthermore, the use of BAB factor provides valuable out-of-sample evidence.

Table 9

The results of the multifactor regressions including sentiment proxy, BAB factor.

Table shows the results of the multifactor regression including a sentiment proxy from August 1965 to January 2011 (sentiment index is available from July 1965). The factor models are Sentiment that includes only the sentiment proxy, CAPM, Fama and French (1993) three-factor model, four-factor model of Carhart (1997), and six-factor model including additional factors for liquidity (Pastor and Stambaugh, 2003) and profitability (Novy-Marx, 2013). The six-factor model is run from January 1968 to January 2011, because the liquidity factor is available since January 1968. Furthermore, the models include a factor for beginning of period sentiment (SENT). The beginning of period sentiment is the previous month's level of investor sentiment index from Baker and Wurgler (2007). The sentiment index is standardized. The mean and standard deviation of SENT are 0 and 1, respectively. Details about the index of investor sentiment are in Baker and Wurgler (2006). There are 546 monthly observations for the first four models, and 516 monthly observations for the six-factor model.

The dependent variable is the monthly return on BAB factor (Frazzini and Pedersen, 2014). BAB factor is market neutral self-financing portfolio that goes long low-beta stocks while shorting high-beta stocks.

I report t-statistic in the parenthesis. Furthermore, statistically significant values are bolded and highlighted using asterisks when deemed important (***, **, and * denote statistical significance at the 1 %, 5%, and 10 % levels).

All the figures are monthly values or calculated from monthly values. For example, the alpha of BAB strategy using CAPM is 0.93 % per month. Adjusted R^2 is reported in the last column.

	alpha	SENT	MRKT	SMB	HML	MOM	PMU	LIQ	Adj. R2
Sentiment	0.91	**0.42*** **							1 %
	(6.46)	(2.96)							
CAPM	0.93	**0.40*** **	-0.06						2 %
	(6.62)	(2.83)	(-1.87)						
Three factor	0.71	**0.35*** **	0.04	0.01	0.47				17 %
	(5.38)	(2.70)	(1.18)	(0.21)	(10.13)				
Four factor	0.53	**0.34*** **	0.07	0.01	0.53	0.19			23 %
	(4.09)	(2.75)	(2.41)	(0.22)	(11.67)	(6.63)			
Six factor	0.45	**0.22***	0.08	0.03	0.56	0.21	0.08	0.09	25 %
	(3.31)	(1.67)	(2.60)	(0.65)	(11.48)	(7.30)	(1.43)	(2.40)	

6.3.2. Alternative measures of sentiment

Until now the chosen sentiment measure has been the previous month's level of the sentiment index from Baker and Wurgler (2007). While the measure takes account broad range of sentiment proxies[15] and should be the best measure available, I formulate other sentiment measures to verify that my results are not specific to one measure by constructing three-, six-, and twelve-month moving averages of the same sentiment index.

Table 10 shows the returns of the quintile portfolios and zero-cost strategies following high and low sentiment using alternative measures of sentiment. It shows that the main results are robust to measuring the investor sentiment with three-, six-, and twelve-month moving averages. Panels from A to C show that following high sentiment low-beta portfolios outperform high-beta portfolios and following low sentiment high-beta portfolios outperform low-beta portfolios. This is illustrated by the returns on B15UL strategy that produces positive returns following high sentiment (from 0.77 % to 1.04 %), and negative returns following low sentiment (from -0.91 % to -1.08 %). The difference of returns on B15UL strategy following high and low sentiment varies from 1.67 % (Panel A) to 2.12 % (Panel C) depending on sentiment measure. The differences are also highly statistically significant. Moreover, the results in **Table 10** are larger in magnitude and statistical significance than the main results in **Table 7**. Overall these results are supportive for the level of investor sentiment predicting the betting against beta performance.

6.3.3. Changes in investor sentiment

The sentiment index makes it possible to test another important proposition of how investor sentiment influences the betting against beta. Until now I have investigated and found that different *levels* of investor sentiment tell about over and undervaluation of beta-sorted stocks and *predict* future performance. However, it should also be the case that *changes* in investor sentiment should explain *contemporaneously* the returns of beta-sorted stocks. Moreover, the

[15] The closed-end fund discount, NYSE share turnover, the average first-day IPO returns, the number of IPOs, the equity share in total equity and debt issues, and the dividend premium.

Table 10
Alternative measures of sentiment.

Table shows the returns on the quintile portfolios and zero-cost strategies following high and low sentiment. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months. B15UL is the return on the lowest beta portfolio minus the return on the highest beta portfolio. B15L is the return on the lowest beta portfolio minus the return on the highest beta portfolio, where both portfolios are levered or de-levered to have a beta of one.

The sample period from July 1984 to January 2011 is divided to two based on average level of investor sentiment. High (low) contains the months when the previous t month's average level of investor sentiment index is above (below) t month average during the sample period, where t ∈ (3, 6, 12). The averages are moving averages and thus overlapping. For example, In Panel A, stocks are sorted to high and low sentiment based on the previous three months average level of the investor sentiment index. In total there are 319 observations. Details about the index of investor sentiment are in Baker and Wurgler (2006).

I report t-statistic in the parenthesis when appropriate. Furthermore, statistically significant values are bolded. Statistical significance is also highlighted using asterisks (*** = 1 %; ** = 5 %; * = 10 %).

All the figures are monthly values or calculated from monthly values. For example, the return on B1 portfolio following high sentiment is 1.35 %.

Panel A: Three-month moving average

	B1	B2	B3	B4	B5	B15UL	B15L
High	1.35	1.34	1.26	1.05	0.59	0.77	**2.10*** **
						(1.26)	(3.53)
Low	1.02	1.22	1.42	1.56	1.93	**-0.91*** **	0.49
						(-2.65)	(1.56)
Difference	0.33	0.12	-0.17	-0.51	-1.34	**1.67** **	**1.60** **
	(0.90)	(0.23)	(-0.27)	(-0.75)	(-1.53)	(2.40)	(2.38)

Panel B: Six-month moving average

	B1	B2	B3	B4	B5	B15UL	B15L
High	1.32	1.22	1.13	0.92	0.28	**1.03* **	**2.25*** **
						(1.74)	(3.84)
Low	1.04	1.29	1.49	1.63	2.11	**-1.07*** **	0.39
						(-3.12)	(1.25)
Difference	0.28	-0.07	-0.36	-0.71	**-1.82** **	**2.11*** **	**1.86*** **
	(0.76)	(-0.14)	(-0.58)	(-1.05)	(-2.11)	(3.07)	(2.80)

Panel C: Twelve-month moving average

	B1	B2	B3	B4	B5	B15UL	B15L
High	1.19	0.98	0.82	0.62	0.16	**1.04* **	**2.07*** **
						(1.65)	(3.34)
Low	1.10	1.42	1.67	1.80	2.19	**-1.08*** **	0.48
						(-3.35)	(1.64)
Difference	0.09	-0.44	-0.85	**-1.18* **	**-2.03** **	**2.12*** **	**1.58** **
	(0.24)	(-0.85)	(-1.37)	(-1.74)	(-2.32)	(3.00)	(2.31)

returns of high-beta stocks should actually be higher as changes in investor sentiment are positive because the price pressure from individual investors falls on high-beta stocks.

Table 11 shows how changes in investor sentiment affect the returns on the quintile portfolios and zero-cost strategies contemporaneously. I measure one-, three-, six-, and twelve-month absolute changes in the investor-sentiment index and returns on the quintile portfolios and zero-cost strategies during the same months in Panels A to D, respectively. Positive means positive absolute change and negative means negative absolute changes in the level of investor sentiment.

While change in investor sentiment is not related to the returns on high-beta stocks on one- and three-month basis (Panels A and B), it has an effect on six- and twelve-month basis. Especially the high-beta stocks are affected. For example, the highest beta quintile produces 0.71 % (t-value, 2.18) higher returns during six-month positive change in investor sentiment than during six-month negative change in investor sentiment. Furthermore, the results are stronger during twelve-month change in investor sentiment and also apply to other quintile portfolios.

Importantly, the differences are bigger for higher beta portfolios. Panels C and D show that the return difference rises in beta. This is also demonstrated in the B15UL portfolio returns during six- and twelve-month change. For example, the difference between lowest and highest beta portfolio returns during six-month positive and negative changes are -0.79 % and 0.17 % respectively. The difference of -0.96 % (t-value, -3.56) is also highly statistically significant. Lastly, the performance of B15L portfolio is affected by changes in investor sentiment. The betting against beta is clearly stronger during negative than positive change in sentiment.

Finally, the “flight-to-quality” phenomenon shows up in **Table 11**. The returns of the lowest beta portfolio are higher during negative changes in investor sentiment implying that investors look for safety and bid up the lowest beta stocks. Importantly, the results here are in line with the earlier results that showed low average returns for the lowest beta portfolios following low level of investor sentiment.

Although at first glance it is not clear from **Table 11** whether changes in investor sentiment imply changes in contemporaneous returns for beta-sorted stocks, overall the story is clear. Changes in investor sentiment do not lead to over- or undervaluation immediately (Panels A and B). For investor sentiment to have cross-sectional implications it is necessary that a rather

Table 11
Changes in investor sentiment and contemporaneous returns.

Table shows the how changes in investor sentiment relate to contemporaneous returns on the quintile portfolios and zero-cost strategies. The first column shows whether the changes in sentiment are positive or negative during the period in question. Changes in sentiment are positive if the change is non-negative and negative if the change is negative. Changes are measured in absolute terms during the observation period. Details about the index of investor sentiment are in Baker and Wurgler (2006). Sample period is from July 1984 to December 2010 because the index of investor sentiment is available until December 2010.

Panel A shows how a change in the level of investor sentiment during one month affects the quintile portfolio and zero-cost strategy returns in that same month. Panel B shows how the change in the level of investor sentiment during a three-month period influences the quintile portfolio and zero-cost strategy returns during the same three month period. Panels C and D show similarly how the change in the level of investor sentiment during six- and twelve-month period affect the quintile portfolio and zero-cost strategy returns during the same six- and twelve-month periods.

B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months. B15UL is the return on the lowest beta portfolio minus the return on the highest beta portfolio. B15L is the return on return on the lowest beta portfolio minus the return on the highest beta portfolio, where both portfolios are levered or de-levered to have a beta of one.

I report t-statistic in the parenthesis when appropriate. Furthermore, statistically significant values are bolded. Statistical significance is also highlighted using asterisks (*** = 1 %; ** = 5 %; * = 10 %).

All the figures are monthly values or calculated from monthly values. For example, the return on B1 portfolio in Panel A following positive change in the level of investor sentiment index is 1.08 % per month. Furthermore, multi-month returns (i.e. three-, six, and twelve-month returns) are expressed in monthly terms to simplify comparison. Monthly returns are simple averages of the multi-month returns. For example, a three-month return is divided by three to get the monthly return. Panels A, B, C, and D contain 318, 316, 313, and 307 observations, respectively.

Panel A: One-month contemporaneous changes

	B1	B2	B3	B4	B5	B15UL	B15L
Positive	1.08	1.03	1.03	1.03	1.03	0.05 (0.11)	**1.25***** 2.81)
Negative	1.21	1.53	1.73	1.76	1.92	-0.71 (-1.54)	**0.87**** (2.29)
Positive - Negative	-0.13 (-0.41)	-0.51 (-1.12)	-0.70 (-1.29)	-0.73 (-1.21)	-0.89 (-1.14)	0.75 (1.21)	0.38 (0.65)

Panel B: Three-month contemporaneous change

	B1	B2	B3	B4	B5	B15UL	B15L
Positive	1.08	1.21	1.31	1.31	1.38	-0.30 (-1.18)	**1.04***** (3.49)
Negative	1.24	1.37	1.47	1.47	1.58	-0.33 (-1.20)	**1.18***** (4.82)
Positive - Negative	-0.17 (-0.82)	-0.16 (-0.59	-0.16 (-0.50)	-0.16 (-0.46)	-0.20 (-0.43)	0-03 (0.08)	-0.14 (-0.37)

Table 11 *(continued)*

Panel C: Six-month contemporaneous changes							
	B1	B2	B3	B4	B5	B15UL	B15L
Positive	1.05	1.34	1.56	1.64	1.84	**-0.79***** (-4.05)	**0.62***** (3.11)
Negative	1.30	1.26	1.25	1.17	1.13	0.17 (0.90)	**1.63***** (7.52)
Positive - Negative	-0.25 (-1.56)	0.08 (0.41)	0.30 (1.29)	**0.47*** (1.87)	**0.71**** (2.18)	**-0.96***** (-3.56)	**-1.20***** (-3.45)
Panel D: Twelve-month contemporaneous changes							
	B1	B2	B3	B4	B5	B15UL	B15L
Positive	1.20	1.49	1.72	1.76	1.98	**-0.78***** (-5.00)	**0.91***** (5.60)
Negative	1.22	1.19	1.18	1.09	1.05	0.18 (1.40)	**1.44***** (7.33)
Positive - Negative	-0.02 (-0.15)	**0.30**** (2.02)	**0.53***** (3.26)	**0.67***** (4.02)	**0.94***** (4.08)	**-0.96***** (-4.76)	**-0.53**** (-2.07)

large group of investors joins the wagon as the capital of one individual is hardly ever enough to move prices. The results in Panels B and C indicate that it takes somewhere between three to six months for changes in investor sentiment to have price effects. For example, the returns for high beta stocks are clearly higher during six-month positive change in sentiment than during negative change in sentiment, whereas there is no difference during three-month positive and negative change in the level of sentiment.

Changes in investor sentiment are most likely associated with market returns. First of all, positive market returns feed up investor sentiment and because high-beta stocks tend to do better during up than down market (**Table 13**) this shows simultaneous increase in investor sentiment and higher returns for high-beta stocks. However, investor sentiment also has price implications because during increasing investor sentiment individuals start buying stocks en masse, and this speculative buying concentrates on high-beta stocks[16]. Trough psychological factors such as self-attribution bias and overweighting of personal experience (e.g. Kaustia and Knüpfer, 2008) investor sentiment grows further. At some point, the overvaluation is revealed

[16] An alternative explanation to speculative demand focusing on the characteristics could be that investors only chase returns. According to this view, individual investors buy high-beta stocks because they have appreciated the most recently.

leading to lower returns for high-beta stocks. The starting point of this sort of “cycle” is e.g. a fundamental shock.

I also conducted regressions (unreported) that include contemporaneous *six-month market return* and *six-month absolute change in the level of investor sentiment* as explanatory variables, and *returns on quintile portfolios* and *zero-cost strategies* during the same months as dependent variables. The results show that the sentiment coefficients have the expected signs and that investor sentiment is statistically and economically distinct from market effect. Furthermore, I study next whether the investor sentiment is distinct from market effect in predicting the performance of the betting against beta.

6.3.4. Up- and down-market performance

As discussed in Section 6.2.1, investor sentiment seems to predict aggregate market returns as well as cross-sectional stock returns. The monthly equally weighted and value-weighted market returns are 0.42 % and 0.76 % higher following low than high sentiment, respectively. Therefore the effect of investor sentiment could be just a demonstration of under and overvaluation of the market in general because the variables are correlated. In effect, high level of market is associated with high level of investor sentiment and low level of market is associated with low investor sentiment. If the sentiment effect is just the market effect in disguise, the patterns following high and low level of market should be similar to those following high and low sentiment reported in **Table 7**.

Table 12 shows that the returns of the quintile portfolios and zero-cost strategies following up and down market. Up is the return following a month in which the level of market is above its linear (Panel A) or exponential (Panel B) trend. Down is the return following a month when the level of market is below its linear or exponential trend. The table shows that the average returns following up and down market resemble those following high and low investor sentiment. For example, the monthly equally weighted market returns are 0.73 % (Panel A) and 0.53 % (Panel B) higher following low level of market[17].

[17] This is the average return of the quintile portfolios following down market minus the average return following up market.

Table 12
Average returns of the quintile and zero-cost portfolios following up and down market.

Table shows the performance of the quintile and zero-cost portfolios following up and down market from July 1984 to June 2011. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months. B15UL is the return on the lowest beta portfolio minus the return on the highest beta portfolio. B15L is the return on return on the lowest beta portfolio minus the return on the highest beta portfolio, where both portfolios are levered or de-levered to have a beta of one.

In Panel A, up market is defined as the level of market that is above its linear growth curve during the sample period. Down market is defined as the level of market that is below the linear curve. In Panel B, up (down) market is defined as the level of market that is above (below) its exponential growth curve during the sample period. There are 324 observations in the sample. Up – Down is the average return following up market minus the average return following down market.

I report t-statistic in the parenthesis when appropriate. Furthermore, statistically significant values are bolded. Statistical significance is also highlighted using asterisks (*** = 1 %; ** = 5 %; * = 10 %).

All values are monthly values or calculated from monthly values. For example, in Panel A the average return on B1 portfolio following up market is 1.02 % per month.

Panel A: Linear trend

	B1	B2	B3	B4	B5	B15UL	B15L
Up	1.02	1.09	1.08	1.00	0.82	0.21	**1.19****
						(0.45)	(2.49)
Down	1.23	1.40	1.59	1.67	1.98	**-0.75***	**0.96*****
						(-1.87)	(2.76)
Up - Down	-0.20	-0.30	-0.51	-0.68	-1.16	0.96	0.23
	(-0.64)	(-0.68)	(-0.96)	(-1.15)	(-1.53)	(1.55)	(0.39)

Panel A: Exponential trend

	B1	B2	B3	B4	B5	B15UL	B15L
Up	0.80	0.94	1.01	1.00	0.96	-0.16	**0.63***
						(-0.35)	(1.65)
Down	1.46	1.57	1.70	1.72	1.93	-0.46	**1.50*****
						(-1.09)	(3.49)
Up - Down	**-0.66****	-0.63	-0.69	-0.72	-0.97	0.31	-0.87
	(-2.14)	(-1.44)	(-1.31)	(-1.22)	(-1.28)	(0.50)	(-1.50)

However, the similar average returns alone do not mean that investor sentiment does not influence betting against beta above and over the level of the market. Most importantly, investor sentiment influences the betting against beta cross-sectionally. Panels A and B show that the return differences for B15UL and B15L strategies following up and down market are not statistically significant. The results in **Table 7** showed clearly that following high sentiment low-beta stocks clearly outperformed their high-beta counterparts whereas following high market levels there are no differences between average returns of the quintile portfolios. Furthermore, the returns following low investor sentiment were more strongly upward sloping in the quintile portfolios than following low market level, measured either by deviations from linear or exponential trend.

Lastly, the "flight-to-quality" phenomenon has disappeared. In effect, all the quintile portfolios including the lowest beta portfolio earn higher returns following down market. Uniquely, the lowest beta portfolio produced lower returns following low sentiment supporting the hypothesis that investors shift from speculative to safe stocks. These findings together with the results of the multifactor regressions in **Table 8** support the hypothesis that investor sentiment influences the betting against beta phenomenon in the stock market and is distinct from the market effect.

Table 13
Average returns of the quintile and zero-cost portfolios during up and down market.

Table shows the performance of the quintile and zero-cost portfolios during up and down market from July 1984 to June 2011. There are 324 monthly observations in the sample. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months. B15UL is the return on the lowest beta portfolio minus the return on the highest beta portfolio. B15L is the return on return on the lowest beta portfolio minus the return on the highest beta portfolio, where both portfolios are levered or de-levered to have a beta of one. BAB factor is from Frazzini and Pedersen (2014).

Up (down) is defined as a positive (negative) return on value-weighted market index from Kenneth French's website. Up – Down is the difference between up and down market return.

I report t-statistic in the parenthesis when appropriate. Furthermore, statistically significant values are bolded. Statistical significance is also highlighted using asterisks (*** = 1 %; ** = 5 %; * = 10 %).

All values are monthly values or calculated from monthly values. For example, the average return on B1 portfolio during up market is 2.22 % per month.

	B1	B2	B3	B4	B5	B15UL	B15L	BAB
Up	2.22	3.10	3.63	3.96	4.83	**-2.61*** **	**1.17*** **	**0.40***
						(-8.83)	(3.63)	(1.67)
Down	-1.07	-2.49	-3.27	-3.92	-5.44	**4.36*** **	0.86	**1.72*** **
						(9.86)	(1.47)	(4.75)
Up - Down	3.30	5.59	6.91	7.88	10.27	**-6.97*** **	0.31	**-1.32*** **
	(10.51)	(13.80)	(14.82)	(15.88)	(17.30)	(-13.11)	(0.46)	(2.94)

Table 13 shows the quintile portfolio and zero-cost strategy returns during both up and down market. Up includes all the months when the value-weighted market returns is above zero, and down all the months it is below zero. Interestingly, it shows that while low-beta stocks provide much better returns in down market, high-beta stocks perform better in up markets. The return on B15UL strategy is 4.36 % per month in down markets and -2.61 % in up markets. Also,

while there is no statistically significant difference in the returns on B15L strategy during up and down market, BAB factor performs much better during down markets.

Importantly, these results provide support for an important limits-to-arbitrage argument, time horizon. As discussed in Section 2.3.2, a hedge fund investing in the low-beta stocks might have to report lower than average returns for some time and justify the losses to investors. If the underperformance lasts long, investors might get uncomfortable and redeem their funds, forcing the hedge fund to realize its long-run profitable positions in the short-run with losses (Shleifer and Vishny, 1997).

7 Conclusions

My study shows that the betting against beta is robust in the U.S. stock market. Despite the conservative empirical setting of the study, the results support empirical finding of the previous studies that low-beta stocks earn better than expected returns and high-beta stocks earn worse than expected returns. On absolute return basis I do not find significant differences in the returns of beta-sorted portfolios. The return on a simple lowest minus highest beta quintile portfolio is also statistically indistinguishable from zero.

Furthermore, the low-beta stocks outperform high-beta stocks on risk-adjusted basis. Sharpe ratios and CAPM regression alphas are declining in beta, the empirical security market line is too flat, and a long-short portfolio conceptually similar to BAB factor (Frazzini and Pedersen, 2014) produces positive and statistically significant returns during the sample period. Finally, the betting against beta is robust after controlling with variables known to explain cross-sectional stock returns (e.g. size, value, and momentum).

My study also shows that high-beta stocks have the characteristics of speculative stocks that individual investors prefer. Therefore investor sentiment should influence the performance of the betting against beta. I show that during high-sentiment retail investors bid up the prices of high-beta stocks and during low-sentiment they fly to quality. Consequently, following high sentiment the low-beta stocks outperform high-beta stocks. Moreover, following low sentiment the high-beta stocks outperform low-beta stocks. Importantly, empirical patterns and multifactor regressions verify that the effect of sentiment is distinct from the market effect as well as from the most popular empirical style factors. Lastly, I show that the results are not specific to the chosen time period or alternative measures of sentiment.

The results are consistent with a behavioral finance framework in which non-fundamental demand and limits of arbitrage affect stock prices. Particularly, investor sentiment acts as a non-fundamental demand shock. I followed the discussion in Baker and Wurgler (2007) to show that high-beta stocks have the characteristics of hard-to-value stocks that individual investors demand. Fortunately, or unfortunately depending on one's view, the same stocks that are affected by investor sentiment are also hard-to-arbitrage Furthermore, I discussed comprehensively about other potential limits of arbitrage in the case of betting against beta. This paper also showed that during up markets the betting against beta is weaker and discussed why this could be an important limit to arbitrage for many fund managers.

The results also shed light on the dynamics of the betting against beta by providing support for other behaviorally motivated explanations such as overconfidence, representativeness, and lottery demand. More broadly, the results further support the role of investor sentiment in the study of financial markets.

While my study supports the role of investor sentiment as an explanation of the betting against beta, it does not clearly distinguish between the different explanations (e.g. investor sentiment and benchmarking). And although I do believe that most of the explanations are important in complete understanding of the betting against beta, trying to distinguish between them provides an interesting avenue for future research.

Furthermore, the index of investor sentiment from Baker and Wurgler (2006) used in this study is a piece-of-art but still a very rough measure of the average bullishness of individual investors. It was also assumed based on the previous literature that individuals demand certain characteristics in stocks. However, future research could discover more specific ways how the "irrational demand" contributes to the time-variation in the betting against beta and try to distinguish between them. The lottery demand explanation (Bali et al., 2014) seems most promising at the moment.

The application of the results beyond stock markets should be done cautiously. The betting against beta phenomenon exists also within other markets (e.g. Frazzini and Pedersen, 2014) but other markets have different structures and dynamics. At the moment, there are multiple explanations for the betting against beta, and while they can all have a role to play, their importance can vary across different markets. Thus, an obvious extension of my study is to investigate whether investor sentiment influences the betting against beta in other markets.

To distinguish between different explanations it could be fertile to provide more evidence on issues such as the distribution of different agents in different markets, both by number and capitalization. For example, if the retail investors are more abundant in the stock than bond market, investor sentiment could be less important in the bond market. Furthermore, the better understanding of preferences and mandates of different investors can be helpful in understanding how the clientele effect (Barberis, Shleifer, and Wurgler, 2005) works in practice.

Appendix A

A.1.

Yearly number of stocks in the quintile portfolios.

This table shows the number of stocks in each quintile portfolio for each year. The years are not calendar years. Year 1984 corresponds to a period from July 1984 to June 1985, etc. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months.

	B1	B2	B3	B4	B5
1984	188	187	188	185	187
1985	184	183	182	181	182
1986	178	178	180	175	177
1987	179	176	178	177	177
1988	201	199	200	199	198
1989	218	217	214	215	215
1990	230	229	228	231	227
1991	241	241	239	238	239
1992	250	248	254	260	261
1993	293	257	273	258	277
1994	326	264	277	269	293
1995	305	305	302	304	304
1996	334	334	333	332	333
1997	370	368	370	368	368
1998	385	382	384	388	377
1999	392	392	388	391	388
2000	385	385	384	384	384
2001	395	395	393	396	392
2002	395	398	393	394	390
2003	425	422	428	421	421
2004	445	439	440	441	440
2005	461	456	456	457	457
2006	474	474	471	472	472
2007	466	465	464	463	464
2008	435	434	435	433	432
2009	466	463	463	465	461
2010	485	486	483	481	483

A.2.

Average betas of the stocks in the quintile portfolios.

This table shows the average beta of a quintile portfolio. B1-B5 are beta-sorted portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months. The average betas of the quintile portfolios show larger variation that the actual betas of the portfolios. This result is familiar from Blume (1975) who show that betas regress toward mean even after controlling for the “order bias”.

	B1	B2	B3	B4	B5
1984	0.42	0.81	1.04	1.29	1.73
1985	0.34	0.77	1.02	1.26	1.75
1986	0.49	0.81	1.05	1.25	1.67
1987	0.47	0.78	1.02	1.24	1.63
1988	0.45	0.87	1.06	1.25	1.56
1989	0.47	0.86	1.06	1.23	1.54
1990	0.49	0.83	1.02	1.19	1.48
1991	0.46	0.85	1.06	1.24	1.59
1992	0.41	0.81	1.05	1.25	1.61
1993	0.34	0.75	1.02	1.28	1.77
1994	0.37	0.77	1.03	1.28	1.78
1995	0.32	0.71	1.01	1.30	1.87
1996	0.24	0.59	0.88	1.18	1.85
1997	0.27	0.58	0.84	1.12	1.78
1998	0.24	0.55	0.80	1.06	1.61
1999	0.16	0.57	0.85	1.11	1.65
2000	0.08	0.47	0.77	1.03	1.63
2001	0.05	0.34	0.61	0.89	1.63
2002	0.02	0.31	0.57	0.88	1.65
2003	0.03	0.33	0.59	0.94	1.78
2004	-0.03	0.24	0.51	0.90	1.83
2005	0.03	0.34	0.63	1.00	1.92
2006	0.07	0.48	0.80	1.13	1.93
2007	0.10	0.55	0.85	1.17	1.91
2008	0.25	0.73	1.02	1.31	1.93
2009	0.31	0.73	1.04	1.33	1.89
2010	0.33	0.73	1.01	1.29	1.82
Average	0.27	0.64	0.90	1.16	1.73

Appendix B

B.1.

The results of the multifactor regressions, zero-cost portfolios.

Table shows the results of the multifactor regression from July 1984 to June 2011. The factor models are CAPM, Fama and French (1993) three-factor model, four-factor model of Carhart (1997), and six-factor model including additional factors for liquidity (Pastor and Stambaugh, 2003) and profitability (Novy-Marx, 2013).

The dependent variables are zero-cost portfolios. Each year at the end of June all sample stocks are sorted into ascending order based on previous 60 month betas with a value-weighted market index. Secondly, the stocks are assigned to five portfolios so that each portfolio contains equal number of stocks. Lastly, an equally weighted average return is calculated for the next 12 months. B15UL is the return on the lowest beta portfolio minus the return on the highest beta portfolio. B15L is the return on the lowest beta portfolio minus the return on the highest beta portfolio, where both portfolios are levered or de-levered to have a beta of one.

I report t-statistic in the parenthesis. Furthermore, statistically significant values are bolded and highlighted using asterisks when deemed important (***, **, and * denote statistical significance at the 1 %, 5%, and 10 % levels).

All the figures are monthly values or calculated from monthly values. For example, the alpha of B15L portfolio using CAPM is 1.07 % per month. Adjusted R^2 is reported in the last column.

Panel A: Levered B15L portfolio

	alpha	MRKT	SMB	HML	MOM	LIQ	PMU	Adj. R^2
CAPM	1.07	0.00						0 %
	(3.65)	(0.00)						
Three factor	0.81	0.18	-0.29	0.64				19 %
	(3.06)	(2.97)	(-3.32)	(6.99)				
Four factor	0.64	0.23	-0.29	0.70	0.20			22 %
	(2.42)	(3.78)	(-3.48)	(7.66)	(3.56)			
Six factor	0.69	0.23	-0.30	0.65	0.20	0.16	-0.27	25 %
	(2.54)	(3.89)	(-3.63)	(6.93)	(3.61)	(2.34)	(-2.28)	

Panel B: Unlevered B15UL portfolio

	alpha	MRKT	SMB	HML	MOM	LIQ	PMU	Adj. R^2
CAPM	0.28	-0.95						62 %
	(1.50)	(-23.18)						
Three factor	0.18	-0.82	-0.52	0.26				76 %
	(1.18)	(-23.29)	(-10.33)	(4.88)				
Four factor	-0.02	-0.76	-0.53	0.33	0.23			79 %
	(-0.11)	(-22.71)	(-11.41)	(6.60)	(7.53)			
Six factor	0.02	-0.76	-0.53	0.30	0.23	0.07	-0.14	80 %
	(0.16)	(-22.92)	(-11.57)	(5.86)	(7.61)	(1.75)	(-2.20)	

B.2.

Correlations of the sentiment and market measures

Table shows the correlations of the sentiment measure and market measures used in the study. SENT(t-1) is the beginning of period value of investor sentiment index (Baker and Wurgler, 2007). MRKT(t) is the value-weighted excess market return from Kenneth French's website. Linear(t-1) is the deviation of the level of the market from the linear trend line. Exponential(t-1) is the deviation of the level of the market from the exponential trend line. MRKT(t) gets values from August 1984 to January 2011. SENT(t-1), Linear(t-1), and Exponential(t-1) get values from July 1984 to December 2011. Table shows that the level of sentiment and the level of market are positively correlated. Furthermore, all the three level measures are negatively correlated to the next month's stock returns.

	SENT(t-1)	MRKT(t)	Linear(t-1)	Exponential(t-1)
SENT(t-1)	1.00			
MRKT(t)	-0.09	1.00		
Linear(t-1)	0.49	-0.12	1.00	
Exponential(t-1)	0.34	-0.07	0.76	1.00

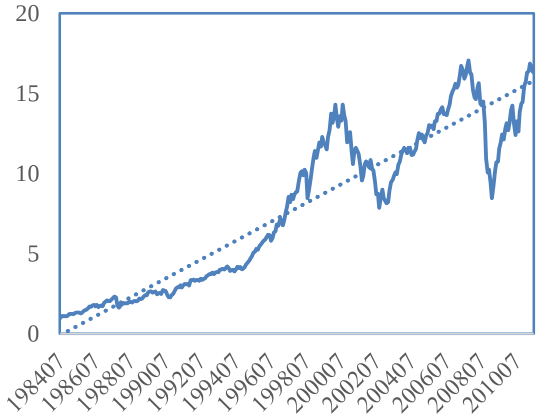
B.3.

Development of investor sentiment and market

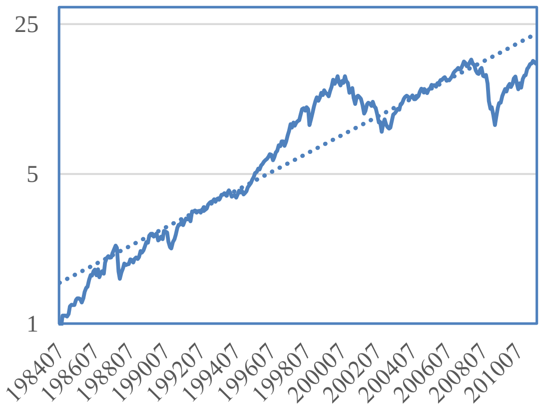
Panel A shows the development of the investor sentiment index (Baker and Wurgler, 2007) graphically during the sample period from July 1984 to January 2011. Sentiment values are beginning of period. Panel B shows the development of market level around linear trend line. Panel C shows the development of market level around exponential trend line. The development of market index is calculated using the value-weighted market return from Kenneth French's website.

Panel A: Investor sentiment index

Panel B: Linear market trend



Panel C: Exponential market trend



B.4.

Factor-model regression alphas following low and high sentiment.

Table shows factor-model alphas from the multifactor-model regressions following low and high sentiment. The factor models are CAPM, Fama and French (1993) three-factor model, four-factor model of Carhart (1997), and six-factor model including additional factors for liquidity (Pastor and Stambaugh, 2003) and profitability (Novy-Marx, 2013). The dependent variables are monthly returns on zero-cost strategies going long the lowest quintile of beta-sorted stocks while shorting the highest quintile of beta-sorted stocks following either high or low level of investor sentiment. B15UL is the return on the lowest beta portfolio minus the return on the highest beta portfolio. B15L is the return on the lowest beta portfolio minus the return on the highest beta portfolio, where both portfolios are levered or de-levered to have a beta of one.

The sample period from July 1984 to January 2011 is divided to two based on average level of investor sentiment. High (low) contains the months when the previous month's level of investor sentiment index is above (below) average. In total there are 319 observations. Details about the index of investor sentiment are in Baker and Wurgler (2006).

I report t-statistic in the parenthesis. Furthermore, statistically significant values are bolded and highlighted using asterisks when deemed important from the point of view of the discussion (***, **, and * denote statistical significance at the 1 %, 5%, and 10 % levels).

All the figures are monthly values or calculated from monthly values. For example, the alpha of B15L strategy following high sentiment is 1.85 %.

	Sentiment	CAPM	Three factor	Four factor	Six factor
Panel A: Levered B15L portfolio					
	High	**1.85*** **	**1.26*** **	**0.92***	**1.05** **
		(3.25)	(2.58)	(1.95)	(2.00)
	Low	**0.68** **	**0.59***	**0.55***	**0.55***
		(2.04)	(1.90)	(1.74)	(1.78)
	High - Low	**1.16***	0.67	0.37	0.49
		(1.78)	(1.19)	(0.69)	(0.94)
Panel B: Unlevered B15UL portfolio					
	High	**0.69***	0.41	0.07	0.04
		(1.83)	(1.32)	(0.26)	(0.12)
	Low	0.08	0.05	-0.05	-0.02
		(0.39)	(0.31)	(-0.28)	(-0.15)
	High - Low	0.61	0.35	0.12	0.06
		(1.43)	(1.04)	(0.39)	(0.21)

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