THE BETA ANOMALY IN RECESSIONS

REVISITING BETA'S ROLE IN THE BETA ANOMALY

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Bachelor Thesis

Stockholm School of Economics

2020

The Beta Anomaly in Recessions: Revisiting Beta's role in the Beta Anomaly

Abstract:

In this thesis, we extend upon existing research on the beta anomaly by investigating beta's role in the anomaly. This is done by studying the anomaly during recessions, where beta-driving variables such as leverage constraints likely are affected. Our empirical results are presented as portfolios based on a sorting of beta and mispricing and we explore explanatory variables such as beta by eliminating portions of the variable. Our results show that beta indeed plays a large role in explaining the beta anomaly and that low-beta stocks as well as high-beta stocks perform above average during recessions. A study by Frazzini, Pedersen (2014) of leverage constraints may be able to explain our findings, but further research is necessary to draw certain conclusions.

Keywords:

Beta anomaly, recessions, beta, idiosyncratic volatility, leverage constraints

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Acknowledgements:

We would like to thank our tutor, Adrien d'Avernas, for his guidance. We would also like to thank Niklas Mannerskog and Simon Enström for their invaluable help.

Bachelor Thesis

Bachelor Program in Finance

Stockholm School of Economics

Introduction

One of the most fundamental models within finance is the Capital Asset Pricing Model, developed by Sharpe (1964) and Lintner (1965). To explain expected market returns with a single factor, beta, was simple and intuitive. This made the CAPM an important ground stone for finance professionals and students alike. Despite its simple logic, CAPM was challenged empirically early on. Several papers pointed to the fact that stocks with low betas earned more than stocks with high betas over time. This phenomenon is known by many names, such as the low beta anomaly, the beta anomaly or the low volatility anomaly, and the reasons for its presence is still widely debated.

The arguably most important development was published by Fama, French (1993) in their paper *Common risk factors in the returns on stocks and bonds*. In this paper they present a three-factor model that has proven to explain significantly more of empirical returns, compared to CAPM. Most recent studies focus on beta-driven explanations of the beta anomaly, with leverage or margin constraints as prominent topics of discussion. These theories are challenged by Liu, Stambaugh & Yuan (2018) where they show that mispricing and idiosyncratic volatility are factors that have a significantly larger role than beta has in explaining the beta anomaly. However, the authors did not dismiss beta as an explanatory variable completely, as the underlying factors may exert return effects.

To extend upon Liu, Stambaugh & Yuan's research, we apply the same methodology on periods where the United States were in recession. We then compare our findings in a recession scenario with our base scenario, where we do not filter for recessions. The recession scenario is particularly interesting as these are periods with distinct characteristics such as tightened leverage constraints. Tightened leverage constraints in recessions are expected to lead to high beta stocks performing better than in base scenarios as levered investors would have to unlever and sell their low-beta stocks.

If beta is able to explain more of the anomaly than mispricing and idiosyncratic volatility in the recession scenario, we provide empirical evidence that beta still has an important role in explaining the anomaly. On the other hand, if mispricing and idiosyncratic volatility still explains more of the anomaly than beta, this would support the findings of Liu, Stambaugh & Yuan (2018) and provide further evidence against beta as a driving factor for the anomaly.

Our research question is therefore *"Is beta a driving factor of the beta anomaly during recessions?"*

When applying Liu, Stambaugh & Yuan's methodology only to periods with recession, we get results that are inconsistent with the *low beta anomaly*. Instead, we observe that stocks with very low betas or very high betas outperform other stocks significantly. We refer to this phenomenon as the *extreme beta anomaly*. One theory that could explain this observation is the importance of leverage constraints for the anomaly. If we assume tightened leverage constraints during recessions, levered investors would have to un-lever, sell their low-beta stocks and buy high-beta stocks to achieve similar returns as earlier.

When controlling for high idiosyncratic volatility, mispricing and beta, we come to the conclusion that beta plays a significant role in explaining the extreme beta anomaly in the recession scenario. This is in contrast to Liu, Stambaugh & Yuan's findings in a base scenario, where idiosyncratic volatility and mispricing plays a considerably larger role.

With our findings, we can conclude that beta indeed plays an important role in explaining the beta anomaly, as it is a driving factor during recessions. However, our study does not test the theory of leverage constraints, as it is merely a plausible explanation for our findings. Additionally, although our study serves as a stepping-stone for future research, our results suffer from inaccurate alphas and t-statistics which makes it difficult to accurately measure how significant our results are.

Relevant Literature

Beta-driven explanations

Historically, most studies have investigated different variables and explanations connected to beta and its effect on the beta anomaly. Theories regarding leverage constraints and margin constraints have been a prominent part of the discussion ever since empirical evidence against the Capital Asset Pricing Model was presented, perhaps most prominently by Black (1972) who developed a model which essentially worked as a CAPM with restricted borrowing. In *Betting Against Beta* (2014), Frazzini and Pedersen extend upon Black's research on leverage constraints in their quest to develop a more practical approach for how an unconstrained investor would exploit the anomaly.

Other important topics of discussion has been that professional investors strives to beat benchmarks and thus overweight their portfolio with high-beta stocks (Christoffersen, Simutin, 2017) and that unsophisticated investors are overly optimistic (Antoniou, Doukas & Subrahmanyam, 2015).

Mispricing and idiosyncratic volatility

Liu, Stambaugh & Yuan (2018) showed that beta was not the driving factor behind the beta anomaly in their paper *Absolving beta of volatility's effects.* The authors argued that beta suffered from guilt by association and showed that mispricing and idiosyncratic volatility played a significantly larger role than beta in explaining the beta anomaly. As the main argument against beta-driven theories, the authors meant there was little rationale why investors would prefer overpriced stocks to underpriced stocks, which their empirical results showed. While the argument is capable of showing the strength of mispricing as an important variable, it does not refute beta-driven theories. Indeed, the authors explained that beta-driving factors may still play an important, underlying role for the anomaly.

Our contribution

In our study, we extend upon Liu, Stambaugh & Yuan's research by examining the anomaly during recessions with the intention of revisiting the role of beta and its effect on the beta anomaly. We use the condition of recessions as they are assumed to have distinct characteristics such as tightened leverage constraints which according to Frazzini, Pedersen (2014) should lead to higher returns for high-beta stocks. Consequently, it should increase the explanatory power behind beta.

Our study will not be able to draw any conclusions on the theory of leverage constraints since a large number of variables may affect our results in recessions. However, we hope to expand upon existing research by vindicating or debunking beta as an explanatory variable for the beta anomaly.

Method

The primary method used in this thesis is to construct portfolios based on a sorting on one or more of the following measures: beta, idiosyncratic volatility and mispricing measure. This section aims to explain how these measures are estimated.

Sample and exclusions

Our sample is obtained from the Center for Research in Security Prices (CRSP) and our sample period is from July 1965 to December 2016. The sample with monthly stock prices includes common stocks from the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and Nasdaq with prices of at least five dollars. By eliminating stocks with a price of less than five dollars, we exclude typical penny stocks in which there may be little or no trading. Furthermore, we only include stocks where we are able to compute at least 6 of the 11 return anomaly variables necessary to compute a mispricing measure.

Mispricing measure

The estimation for mispricing is a score calculated as the average score of 11 different rankings. These rankings are based on 11 return anomalies as variables. A lower mispricing score would mean that the stock has a higher estimated alpha, while a higher mispricing score would represent a lower estimated alpha.

The 11 return anomalies are:

1. Net Stock Issues
2. Composite Equity Issues
3. Accruals
4. Net Operating Assets
5. Asset Growth
6. Investment-to-Assets
7. Distress
8. O-score
9. Momentum
10. Gross Profitability
11. Return on Assets

The mispricing measure for each stock and for each month would then be an average of its ranking percentile for the anomalies. According to Stambaugh, Yu & Yuan (2015) the score should be interpreted as a proxy for its potential to be mispriced, rather than historical mispricing. Furthermore, in order to be included as a return anomaly in the mispricing model, there must be at least 30 stocks with non-missing values for each month in our sample period. For our intentions, the mispricing measure is obtained from Robert Stambaugh's website (Stambaugh).

Idiosyncratic volatility

Idiosyncratic volatility is estimated as the standard deviation of the residual returns from the Fama-French three-factor model. The excess return, defined as the daily return excess of the one-month Treasury-bill rate, is regressed on Small-Minus-Big and High-Minus-Low from the Fama-French three-factor model.

$$r_t^i = a^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i \qquad (1)$$

Where idiosyncratic risk is defined as $\sqrt{var(\varepsilon_t^i)}$ in equation (1).
For our purposes, the idiosyncratic volatility is obtained from the Beta Suite by Wharton Research Data Services, based on the Center for Research in Security Prices (CRSP) database.

Beta

To compute beta, a regression is performed on each stock's monthly excess return on monthly market excess returns. As with idiosyncratic volatility above, the excess return is defined as the daily return excess of the one-month US Treasury-bill rate. The regression also includes lagged market return.

$$r_{i,t} = a_i + \beta\, r_{m,t} + \beta\, r_{m,t-1} + \varepsilon_{i,t} \qquad (2)$$

The time-series regression is run over a moving window of the most recent 60 months where no more than 24 months have missing data. The summed-slopes procedure of Dimson is then applied (Dimson, 1979):

$$\hat{\beta}_i^{ts} = \hat{\beta}_{i,0} + \hat{\beta}_{i,t} \qquad (3)$$

This is our estimated beta, computed according to the same procedure as Fama, French. There are a number of ways to compute beta and adjust it, but the procedure mentioned in equation (2) and equation (3) is frequently used. Liu, Stambaugh & Yuan (2018) applied a shrinkage developed by Vasicek, but historically many research papers on the beta anomaly has not applied shrinkage to their beta estimates. In our regressions for beta and alpha for our constructed portfolios, we have obtained the Three Fama French Factors from Kenneth R. French's website (French).

Recessions

Our intention with this study is to examine the beta anomaly during financial recessions, its behavior and what causes it. In order to do so, we have combined the data from the last six recessions in the U.S. These are:

December 1969 - November 1970, a mild recession caused by increased inflation rates and closing budget deficits on the Vietnam war.

November 1973 - March 1975, a consequence of an oil embargo from OPEC, increasing oil prices several hundred percent in combination with a stock market crash.

July 1981 - November 1982, mainly caused by sharply increased oil prices due to the Iranian Revolution, combined with tightened monetary policies in the United States.

July 1990 - March 1991, a brief recession caused by a combination of the 1990 oil price shock, the debt accumulation of the 1980s and growing consumer pessimism.

March 2001 - November 2001, primarily caused by the dot-com bubble. Despite other events, such as the 9/11 attacks, the recession was rather brief.

December 2007 - June 2009**,** the subprime mortgage crisis led to a housing bubble in the United States. Further, this led to a global financial crisis and several of the largest financial institutions of the United States collapsed. (The National Bureau of Economic Research)

We have defined a recession as two consecutive quarters of negative growth in Gross Domestic Product, which is widely considered to be the definition of a recession. The cause and the nature of the recession may differ vastly, but we do not investigate the underlying factors further. It should, however, be mentioned that in three of the six recessions during our sample period, oil prices have been an underlying factor.

Constructing portfolios

In our study, we rely heavily on the technique of constructing portfolios and examining the differences in alphas for the constructed portfolios, often after doing adjustments by controlling for variables.

We begin by sorting all stocks each month according to their estimated beta and divide these in ten into deciles. Independent of our decile construction, we then sort all stocks each month according to their mispricing score. We then divide these in five into quintiles.

By having our dataset divided into ten beta deciles and five mispricing quintiles, we can then construct portfolios based on the intersection of the beta deciles and mispricing quintiles, resulting in a total of 50 value-weighted portfolios.

The procedure described above is then performed for two different scenarios. The base scenario covers the entire sample period from July 1965 to December 2016 with no time-based restrictions. The recession scenario covers all time-periods between July 1965 to December 2016 where the United States' economy experienced a recession according to the above-mentioned definition. In our base scenario we have a total of 1565816 data points available. In our recession scenario, we have 175655 data points available.

Empirical results

In this section, we will present the results of our study. For every result we present in our base scenario, we present the corresponding result for a recession scenario so that we are able to examine differences easily.

We begin our study by examining the existence of the beta anomaly in Table 1-3. Afterwards, we compare whether mispricing and idiosyncratic volatility or beta is able to explain our findings, and the result of these are presented in Table 4 and 5.

When computing our alphas and t-scores in Table 3-5 and our appendix, we come across a problem we are unable to solve with the limited time allowed for this thesis. The alphas, and their t-statistics, are significantly higher than what can be considered to be accurate results. However, the general trend of the alphas corresponds accurately to the alphas computed in Liu, Stambaugh & Yuan (2018), and we encourage our readers to focus more on the general trend rather than the actual figure.

The existence of the beta anomaly

In order to examine the beta anomaly and its causes, we must first confirm its existence. We perform the procedure described in the method section above and create portfolios by dividing stocks into beta deciles and mispricing quintiles.

Table 1a: Average number of stocks in each portfolio – Base Scenario

	Beta Deciles									
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	29	47	56	63	66	67	64	58	49	31
2	29	46	55	60	62	61	62	60	54	38
3	30	50	53	56	57	55	58	57	55	43
4	31	47	49	51	53	52	53	57	57	50
5	31	38	42	44	43	44	46	52	59	62

Note: The table presents the average number of stocks in portfolios constructed by sorting independently on mispricing and betas. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks.

From Table 1a we can see that stocks are relatively evenly distributed across the 50 portfolios constructed from the beta sorting and mispricing sorting. We can also observe that stocks with high betas have a tendency to be overpriced, rather than underpriced. For example, the most overpriced stocks in the highest beta decile have an average stock frequency of 62, compared to the most underpriced stocks in the highest beta decile which only have an average stock frequency of 31. The same conclusion can be drawn by examining beta decile 9, although the difference is not as significant as in the highest beta decile.

Table 1b: Average number of stocks in each portfolio – Recession Scenario

	Beta Deciles									
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	34	48	55	57	58	59	53	45	34	18
2	32	41	52	55	54	54	50	48	38	26
3	30	40	46	50	50	46	51	49	45	34
4	26	34	40	43	44	44	48	52	52	45
5	24	26	32	31	32	35	39	47	60	63

Note: The table presents the average number of stocks in portfolios constructed by sorting independently on mispricing and betas. Only periods when the United States was in a recession is included in this sample. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks.

In the recession scenario stocks are still evenly distributed across all portfolios. Stocks with high betas are still more likely to be overpriced, rather than underpriced, and the spread between the highest and the lowest mispricing quintile within the highest beta decile is slightly larger in our recession scenario than in our base scenario. Nevertheless, the general trend is the same as in our base scenario.

Next, we investigate the relationship between the estimated betas for portfolios and their mispricing scores.

Table 2a: Estimated beta for each portfolio – Base Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	0,05	0,41	0,60	0,71	0,84	0,99	1,07	1,20	1,40	1,77	1,72
2	0,11	0,47	0,60	0,70	0,88	0,96	1,11	1,24	1,37	1,76	1,65
3	0,15	0,40	0,55	0,65	0,88	1,03	1,18	1,31	1,44	1,86	1,71
4	0,12	0,37	0,55	0,74	0,85	1,05	1,17	1,34	1,51	1,85	1,73
5	0,12	0,42	0,62	0,76	0,87	1,07	1,21	1,33	1,57	1,98	1,86

Note: The table presents the estimated beta for portfolios constructed by sorting independently on mispricing and betas. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks.

From table 2a, we can observe an increase in estimated beta for every increase in beta decile. By examining the different mispricing quintiles, we also see that overpriced stocks have a higher estimated beta than underpriced stocks. In fact, this trend is witnessable for every beta decile when comparing the most overpriced stocks to the most underpriced stocks.

This observation increases in significance particularly amongst high-beta stocks, as can be witnessed within beta decile 9 and 10. For example, the estimated beta for the portfolio with the highest beta decile and the most overpriced stocks have an estimated beta of 1,98, compared to 1,77, which is the estimated beta for the portfolio with the highest beta decile but the most underpriced stocks. This difference of 0,21 is significantly larger than in the lowest beta decile, where the difference is merely 0,07 between the fifth and the first quintile.

As a consequence, we can conclude two things. Firstly, overpriced stocks are estimated to have larger betas than underpriced stocks. Secondly, this difference increases amongst high-beta stocks, meaning we should control for high-beta stocks when examining its importance for the anomaly.

Table 2b: Estimated beta for each portfolio – Recession Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	0,03	0,37	0,60	0,66	0,77	0,99	1,08	1,25	1,45	1,98	1,95
2	0,17	0,56	0,58	0,65	0,90	0,93	1,14	1,29	1,42	1,80	1,63
3	0,11	0,48	0,52	0,77	0,99	1,07	1,31	1,34	1,42	2,19	2,08
4	0,07	0,39	0,53	0,79	0,98	1,19	1,34	1,46	1,59	2,19	2,12
5	-0,02	0,36	0,73	0,84	1,04	1,03	1,34	1,30	1,77	2,19	2,21

Note: The table presents the estimated beta for portfolios constructed by sorting independently on mispricing and betas. Only periods when the United States was in a recession is included in this sample. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks.

Similar to our base scenario, there is an increase in beta for each portfolio for every increase in beta decile. It is also reported that overpriced stocks have a higher estimated beta than underpriced stocks. This is also visible from our Highest-Lowest spread. The Highest-Lowest spread is also notably higher amongst high-beta stocks as visible in beta deciles 9 and 10. We can therefore conclude that the same conclusion can be drawn in our recession scenario as in our base scenario.

Next, we will present the results for each portfolio's returns based on alpha to finally examine the existence of the beta anomaly.

Table 3a: Estimated alpha for each portfolio – Base Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	1,93	0,91	0,70	0,84	0,71	0,53	0,64	0,58	0,62	1,21	**-0,72**
2	1,58	0,99	0,72	0,82	0,56	0,32	0,61	0,43	0,56	0,81	**-0,77**
3	1,97	0,97	0,50	0,66	0,44	0,49	0,45	0,32	0,48	0,98	**-0,99**
4	1,89	0,85	0,71	0,32	0,54	0,12	0,38	0,29	0,40	0,70	**-1,19**
5	1,65	0,74	0,53	0,41	0,34	0,15	0,06	0,05	-0,01	0,30	**-1,35**
Average	**1,80**	**0,89**	**0,63**	**0,61**	**0,52**	**0,32**	**0,43**	**0,33**	**0,41**	**0,80**	

Note: The table presents the estimated alphas for portfolios constructed by sorting independently on mispricing and betas. The estimated alphas are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks. Accompanying t-statistics can be found in Appendix A.

We notice clearly that the lowest beta stocks overperforms in contrast to the highest beta stocks. As our base scenario covers the entire sample period from July 1965 to December 2016, this confirms the observation that stocks with low betas perform better than stocks with high betas over time.

It is also apparent that the largest spread in estimated alphas in absolute terms is observed amongst the most overpriced stocks, where the difference in alpha is a substantial -1,35 compared to -0,72 for the most underpriced stocks. This confirms the observation of Liu, Stambaugh & Yuan (2018) that the beta anomaly is significant primarily amongst overpriced stocks, and that the mispricing measure has a significant role in explaining the beta anomaly in our base scenario.

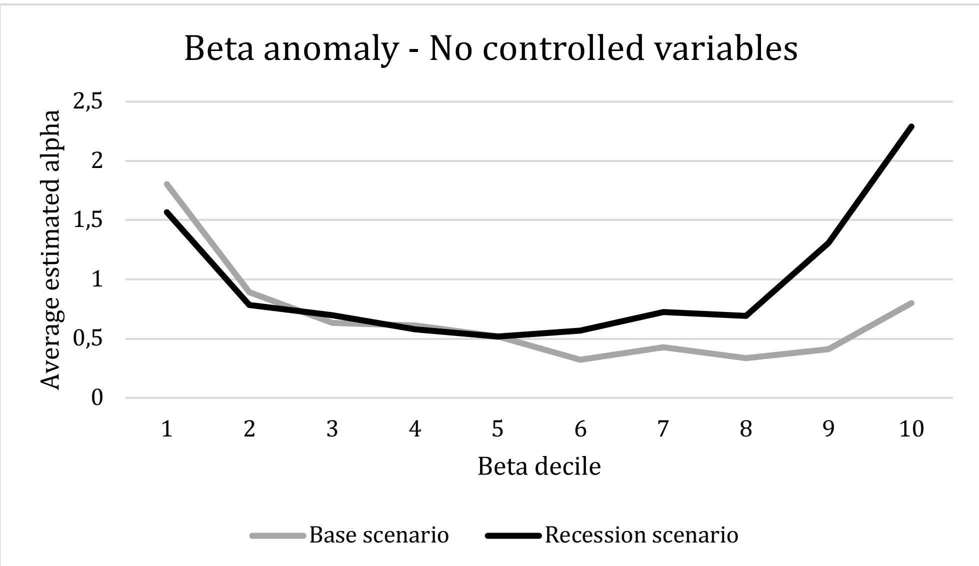
Table 3b: Estimated alpha for each portfolio – Recession Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	1,71	0,34	0,68	0,50	0,60	1,28	1,50	0,68	1,02	2,54	**0,83**
2	2,97	0,93	0,55	0,52	0,58	0,54	0,51	0,34	1,25	2,06	**-0,91**
3	2,05	0,60	0,17	0,85	0,65	0,63	0,72	0,60	0,73	2,38	**0,33**
4	0,51	0,33	1,18	0,26	0,03	0,97	0,66	1,30	2,63	3,02	**2,51**
5	0,59	1,71	0,91	0,76	0,73	-0,57	0,24	0,54	0,92	1,45	**0,86**
Average	**1,57**	**0,78**	**0,70**	**0,58**	**0,52**	**0,57**	**0,73**	**0,69**	**1,31**	**2,29**	

Note: The table presents the estimated alphas for portfolios constructed by sorting independently on mispricing and betas. Only periods when the United States was in a recession is included in this sample. The estimated alphas are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks. Accompanying t-statistics can be found in Appendix B.

In our recession scenario, we observe differences compared to our base scenario. Albeit the portfolios in the lowest beta decile still performs well, it is clear that they do not perform better than the stocks in the highest beta decile.

Our findings are graphically presented in Graph (1):



As can be observed, there is no low beta anomaly in our recession scenario as portfolios in the lowest beta decile do not perform better than stocks in our highest beta decile. However, we observe that stocks in either end of our beta decile sorting performs considerably better than stocks assigned to medium-level beta deciles.

This observation is a significant one, and an important observation for our study. There may be plenty of plausible explanations for this finding, but consistent with earlier research of Frazzini, Pedersen (2014) would be the theory of leverage constraints. In recessions, it is likely that leverage constraints would tighten. Levered investors would then sell their low-beta stocks as they unlever and instead buy high-beta stocks to reach similar yields.

While the low beta anomaly is proven for the base scenario, it would be more appropriate to find a different name for the anomaly present in our recession scenario. For the rest of this study, we will refer to this anomaly as the *extreme beta anomaly*. This refers to the observation that stocks in the extreme ends of our beta decile sorting performs better than stocks that are assigned to medium-level beta deciles.

Examining idiosyncratic volatility and mispricing

Liu, Stambaugh & Yuan (2018) showed that idiosyncratic volatility and mispricing has an important role in explaining the low beta anomaly. In this section, we will both re-examine this observation and apply the same procedure to our recession scenario. If idiosyncratic volatility and mispricing is able to explain a large part of the beta anomaly in both scenarios, this would strengthen Liu, Stambaugh & Yuan's argument that these factors indeed are more relevant in explaining the anomaly compared to beta.

In order to examine the role of idiosyncratic volatility and mispricing in the explanation for the beta anomaly, we control for these variables. We repeat much of the process from above where we confirmed the existence of the anomaly, but control for these variables through elimination. Consequently, we will put these results in further context by controlling for beta in our next section and comparing these results with each other. If beta is able to decrease the Highest-Lowest spreads even further, then beta can be regarded as a more important factor than mispricing and idiosyncratic volatility.

We sort our stocks according to both mispricing score and idiosyncratic volatility. The mispricing sorting is then divided into quintiles, while the idiosyncratic volatility is sorted into quartiles. We then eliminate all stocks that are assigned to both the top mispricing quintile and the top idiosyncratic volatility quartile. This eliminates about 7% of our stock universe. This method follows the procedure in Liu, Stambaugh & Yuan (2018).

Table 4a: Estimated alpha for each portfolio after deleting stocks that are overpriced and with high idiosyncratic volatility (about 7% of the stock universe) – Base Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	1,30	0,90	0,84	0,70	0,67	0,60	0,60	0,63	0,66	1,10	**-0,20**
2	1,11	0,74	0,96	0,49	0,54	0,45	0,57	0,52	0,47	0,94	**-0,17**
3	1,27	0,76	0,66	0,55	0,53	0,63	0,43	0,36	0,38	0,88	**-0,39**
4	1,36	0,68	0,43	0,48	0,56	0,38	0,39	0,28	0,19	0,49	**-0,87**
5	0,68	0,48	0,70	0,27	0,18	0,04	0,27	-0,04	-0,04	0,26	**-0,42**
Average	**1,14**	**0,71**	**0,72**	**0,50**	**0,50**	**0,42**	**0,45**	**0,35**	**0,33**	**0,73**	

Note: The table presents the estimated alphas for portfolios constructed by sorting independently on mispricing and betas, after deleting stocks with high mispricing scores and high idiosyncratic volatility (approximately 7% of our stock universe). The estimated alphas are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks. Accompanying t-statistics can be found in Appendix C.

Despite eliminating only 7% of our entire stock universe in Table 4a, we find important differences in our results compared to Table 3a. The highest-lowest spread across all mispricing quintiles has to a large extent decreased, rendering the low beta anomaly considerably less significant.
We also see that the difference between the highest and lowest beta decile still increases slightly for overpriced stocks, although this observation is much less clear than in Table 3a.

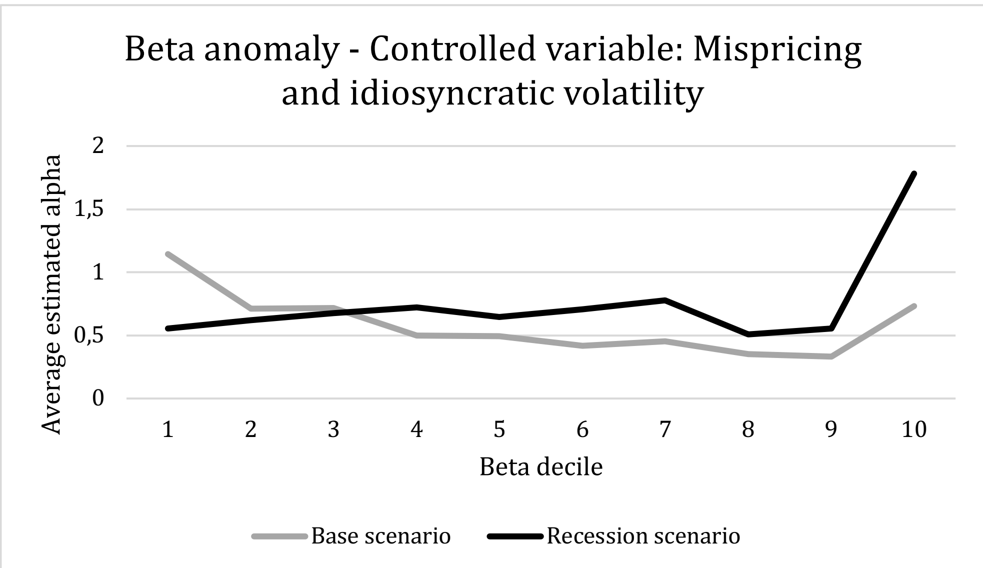
The observation that eliminating stocks with high idiosyncratic volatility and high mispricing scores renders the beta anomaly considerably less significant provides evidence that these variables play an important role in explaining the beta anomaly. This is accurate with the findings of Liu, Stambaugh & Yuan (2018).

Table 4b: Estimated alpha for each portfolio after deleting stocks that are overpriced and with high idiosyncratic volatility (about 7% of the stock universe) – Recession Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	0,66	0,50	0,74	0,58	0,90	1,40	1,28	0,81	1,13	2,02	**1,36**
2	0,64	0,48	0,59	0,89	0,49	1,00	0,67	0,68	0,51	1,98	**1,34**
3	0,71	0,43	0,69	0,45	1,01	0,93	0,44	0,14	0,75	2,15	**1,44**
4	0,76	1,43	0,21	0,94	0,60	0,20	0,85	0,68	-0,16	1,32	**0,56**
5	0,01	0,26	1,15	0,75	0,24	0,01	0,66	0,23	0,55	1,44	**1,43**
Average	**0,56**	**0,62**	**0,68**	**0,72**	**0,65**	**0,71**	**0,78**	**0,51**	**0,56**	**1,78**	

Note: The table presents the estimated alphas for portfolios constructed by sorting independently on mispricing and betas, after deleting stocks with high mispricing scores and high idiosyncratic volatility (approximately 7% of our stock universe). Only periods when the United States was in a recession is included in this sample. The estimated alphas are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks. Accompanying t-statistics can be found in Appendix D.

When applying the same procedure as above to our recession sample, we can report different results. The above-average performance amongst low-beta stock portfolios has decreased significantly after eliminating stocks with high idiosyncratic volatility and high mispricing scores. However, the procedure fails to explain the above-average performance amongst high-beta stock portfolios, which exists only in recessions according to our findings in our previous section. Our findings are also presented in Graph (2):



Examining beta

If beta is the driving factor behind the beta anomaly, eliminating approximately the same amount of stocks as in our previous section (approximately 7% of our stock universe) should lead to at least the same reduction in significance of the beta anomaly.

We test this by sorting stocks based on a variable, eliminating a sample of our controlled variable and then constructing portfolios similarly to the procedure mentioned earlier in our work. In this section, we sort our stocks based on beta. We then eliminate 7% of our entire stock universe, the 7% with the highest beta. This size of elimination is done to keep our eliminated sample approximately as large as in our procedure for Table 4a. After eliminating the high-beta stocks, we once again sort our stocks according to the mispricing measure and the estimated beta. The mispricing measure is divided into quintiles and beta is divided into deciles. Portfolios are constructed based on the intersection of these, as in previous sections.

Table 5a: Estimated alpha for each portfolio after deleting stocks with high betas (about 7% of the stock universe) – Base Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	1,36	0,82	0,74	0,78	0,64	0,69	0,62	0,53	0,69	0,46	**-0,90**
2	1,31	0,83	0,98	0,66	0,57	0,36	0,46	0,58	0,46	0,48	**-0,83**
3	1,33	0,62	0,78	0,50	0,53	0,38	0,52	0,38	0,52	0,29	**-1,04**
4	1,43	0,70	0,56	0,49	0,49	0,27	0,35	0,30	0,27	0,25	**-1,18**
5	1,18	0,64	0,71	0,40	0,32	0,30	0,21	0,11	0,03	0,15	**-1,03**
Average	**1,32**	**0,72**	**0,75**	**0,57**	**0,51**	**0,40**	**0,43**	**0,38**	**0,39**	**0,33**	

Note: The table presents the estimated alphas for portfolios constructed by sorting independently on mispricing and betas, after deleting stocks with high beta (approximately 7 % of our stock universe). The estimated alphas are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced. Accompanying t-statistics can be found in Appendix E.

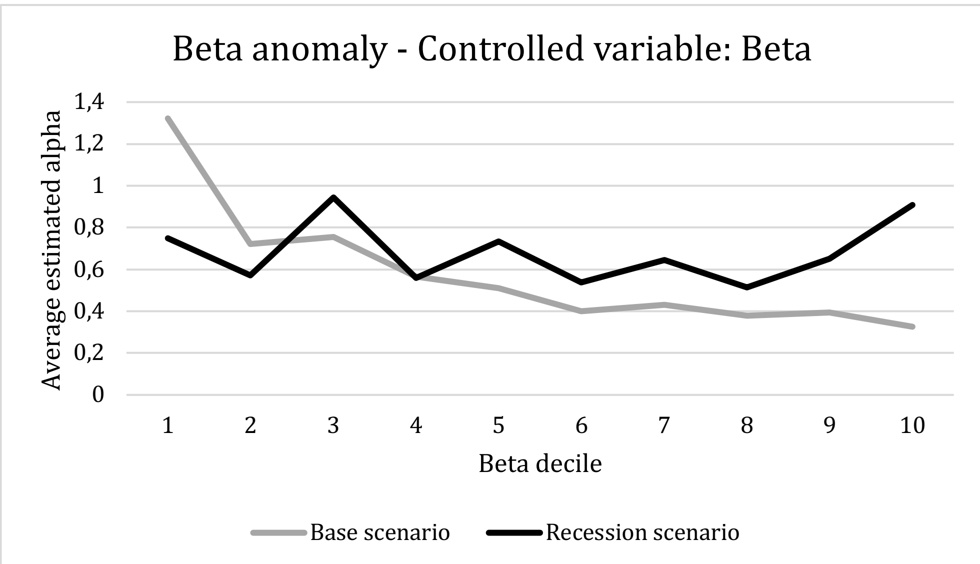
If beta indeed was the driving factor behind the beta anomaly, we would see even smaller Highest-Lowest spreads than in Table 4a. On the contrary, our results from Table 5a shows that not only are the spreads considerably bigger compared to Table 4a where stocks that are overpriced with high idiosyncratic volatility and mispricing, they are approximately just as large as in Table 3a, where no stocks were eliminated. As eliminating high-beta stocks had no, or very little, impact on the Highest-Lowest spread, it is unlikely that beta would be the driving factor behind the low beta anomaly. With these results, we confirm the findings of Liu, Stambaugh & Yuan (2018) that mispricing and idiosyncratic volatility drives the beta anomaly in a base scenario, rather than beta.

Table 5b: Estimated alpha for each portfolio after deleting stocks with high betas (about 7% of the stock universe) – Recession Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	0,76	0,25	0,65	0,65	0,44	1,71	1,09	1,07	0,74	0,55	**-0,21**
2	1,31	0,50	1,12	0,41	0,73	0,89	0,68	0,73	0,65	1,06	**-0,25**
3	1,09	0,32	1,03	-0,01	1,12	0,18	0,48	0,39	0,47	1,29	**0,20**
4	0,52	0,80	0,78	0,40	0,83	0,10	0,54	0,62	0,61	0,54	**0,02**
5	0,07	0,99	1,14	1,34	0,55	-0,19	0,43	-0,24	0,79	1,10	**1,03**
Average	**0,75**	**0,57**	**0,94**	**0,56**	**0,73**	**0,54**	**0,64**	**0,51**	**0,65**	**0,91**	

Note: The table presents the estimated alphas for portfolios constructed by sorting independently on mispricing and betas, after deleting stocks with high beta (approximately 7% of our stock universe). Only periods when the United States was in a recession is included in this sample. The estimated alphas are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced. Accompanying t-statistics can be found in Appendix F.

By applying the same procedure to our recession scenario, eliminating the top 7% of our stock universe with the highest beta, we get interesting observations. While stocks with high idiosyncratic volatility and high mispricing scores explains a large portion of the low beta anomaly in our base scenario, it failed to explain why high beta portfolios overperformed in recession scenarios where we have an extreme beta anomaly, rather than a low beta anomaly. Our findings are also presented in Graph (3):



By eliminating high-beta stocks, we managed to explain much of the beta anomaly, both in the lower ends as well as the higher ends of the beta deciles. Only amongst the most overpriced stocks can we find a notable result in our Highest-Lowest spread, but it is unlikely to be a significant observation considering the large difference between the first and second beta decile.

The highest estimated alphas can now, on average, be found in beta decile 3 and there is no overall trend to observe. These empirical results show that beta, while unable to explain the low beta anomaly in our base scenario, manages to explain a large part of the extreme beta anomaly observable in recession scenarios.

However, drawing definite conclusions from our thesis should be done with a large degree of cautiousness. Although we can reach a similar trend in our results as our replicated article, our alphas and t-statistics are inaccurate. This comes with certain problems, such as not being able to accurately measure the significance of our findings. Nevertheless, we believe our article serves as a stepping-stone for future research on the subject.

Conclusion

With our results in this thesis, we can confirm Liu, Stambaugh & Yuan's results from 2018 where they show that mispricing and idiosyncratic volatility play a significantly more important role than beta in explaining the beta anomaly over time. However, the authors argued that beta-driven factors such as leverage constraints or margin constraints could still play an underlying role and our findings support this.

With our results in the recession scenario, we are able to report two interesting discoveries. First of all, there is no low beta anomaly in recessions but rather an extreme beta anomaly. This reflects the observation that stocks within the lowest and the highest beta deciles both perform above average in recessions. Secondly, we examine the explanatory power behind different variables and come to the conclusion that beta is able to explain much more of the extreme beta anomaly compared to mispricing and idiosyncratic volatility.

Our observations are supported by Frazzini, Pedersen (2014), who explained that tightened leverage constraints should lead to higher returns for high-beta stocks as levered investors un-lever and sell their low-beta stocks. This is, assuming, that leverage constraints are tightened during recessions. As the leverage constraints theory is a beta-driven argument, our findings that beta is an explanatory factor is natural.

As plausible as the leverage constraints theory may sound, we must keep in mind that there may be a large number of factors contributing to the anomaly and that controlling for recessions by no means proves the validity of leverage constraints as a driving factor in the beta anomaly. Recessions, and the base scenario itself, is dependent on an enormous number of variables that may or may not play a part in it.

What we can conclude, however, is that beta indeed has an important role for the beta anomaly, and that it cannot be excluded from further research on the topic.

Further Research

Our finding that researchers should not close the door on beta as an explanatory variable for the beta anomaly may open up a number of questions marks for future study. For example, in order to understand how the phenomenon works in a recession scenario further research must be conducted on several different variables such as leverage constraints. To understand the anomaly further, one natural point of investigation is the underlying mechanisms of mispricing. Although our study shows that beta is still an important variable for the anomaly, the research by Liu, Stambaugh & Yuan (2018) still asks questions on why investors would prefer overpriced stocks over underpriced stocks.

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Appendix

Table A: T-statistics for estimated alpha for each portfolio – Base Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	8,83	7,17	5,59	7,38	7,12	5,64	6,93	5,02	4,83	5,85	-2,98
2	6,33	6,56	5,93	7,06	5,46	3,32	5,51	4,20	4,44	4,58	-1,75
3	7,03	6,69	4,16	5,25	4,35	4,47	4,18	2,89	3,75	5,58	-1,45
4	7,29	5,31	6,02	2,80	4,23	1,00	3,29	2,54	2,83	3,89	-3,40
5	5,96	4,35	3,68	3,05	2,38	1,13	0,45	0,34	-0,07	1,73	-4,23

Note: The table presents accompanying t-statistics for Table 3a. The t-statistics are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks.

Table B: T-scores for estimated alpha for each portfolio – Recession Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	2,47	1,10	1,78	1,45	1,82	4,38	5,37	1,72	2,21	3,25	0,78
2	2,68	1,93	1,33	1,36	1,97	1,84	1,56	0,87	2,18	3,15	0,47
3	2,72	1,08	0,44	2,28	2,18	1,98	2,00	1,51	1,28	4,03	1,31
4	0,75	0,57	2,71	0,72	0,64	0,07	2,54	1,95	1,96	3,78	3,03
5	0,66	2,28	1,58	1,59	1,23	-1,08	0,48	1,19	1,74	2,34	1,68

Note: The table presents accompanying t-statistics for Table 3b. Only periods when the United States was in a recession is included in this sample. The t-statistics are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks.

Table C: T-scores for estimated alpha for each portfolio after deleting stocks that are overpriced and with high idiosyncratic volatility (about 7% of the stock universe) – Base Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	8,46	6,98	6,78	6,31	6,61	5,73	5,83	5,58	4,76	5,96	-2,50
2	6,76	6,00	6,90	4,48	5,38	4,41	4,70	4,74	3,74	5,86	-0,90
3	6,77	5,70	6,21	4,72	4,68	5,63	4,14	3,38	3,01	5,58	-1,19
4	8,40	5,11	3,53	3,75	4,54	3,22	3,19	2,20	1,54	3,22	-5,18
5	4,48	3,21	5,60	2,06	1,42	0,29	2,07	-0,33	-0,31	1,63	-2,85

Note: The table presents accompanying t-statistics for Table 4a. The t-statistics are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks.

Table D: T-scores for estimated alpha for each portfolio after deleting stocks that are overpriced and with high idiosyncratic volatility (about 7% of the stock universe) – Recession Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	1,51	1,29	2,02	1,65	2,66	3,90	4,41	2,32	2,34	2,59	1,08
2	1,27	1,22	1,26	2,55	1,62	3,21	1,96	1,87	1,03	3,77	2,50
3	1,25	0,81	1,44	1,16	2,73	2,54	1,27	0,40	1,43	3,77	2,52
4	1,58	2,33	0,45	2,89	1,52	0,59	2,35	1,68	-0,44	2,64	1,06
5	0,02	0,60	2,54	1,39	0,43	0,03	1,25	0,55	1,15	2,59	2,57

Note: The table presents accompanying t-statistics for Table 4b. Only periods when the United States was in a recession is included in this sample. The t-statistics are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks.

Table E: T-scores for estimated alpha for each portfolio after deleting stocks with high betas (about 7% of the stock universe) – Base Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	8,43	6,23	6,26	6,49	6,11	6,64	6,05	4,76	5,50	2,90	-5,53
2	7,56	6,51	7,14	5,37	5,58	3,33	4,02	5,35	3,90	3,88	-3,68
3	7,03	4,82	5,19	4,32	4,35	3,34	4,85	2,69	2,37	4,33	-2,70
4	8,40	5,25	4,76	3,96	3,94	2,33	2,99	2,45	2,21	1,95	-6,45
5	6,07	4,17	5,29	2,94	3,32	2,14	1,61	0,83	0,23	1,00	-5,07

Note: The table presents accompanying t-statistics for Table 5a. The t-statistics are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks.

Table F: T-scores for estimated alpha for each portfolio after deleting stocks with high betas (about 7% of the stock universe) – Recession Scenario

	Beta Deciles										
Mispricing Quintile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**H-L**
1	1,65	0,64	1,95	1,70	1,37	5,12	2,96	3,02	1,78	0,91	-0,74
2	2,26	1,21	2,38	1,00	2,09	2,91	2,17	2,07	1,50	1,98	-0,28
3	1,88	0,58	2,01	-0,01	2,91	0,49	1,41	1,20	0,98	2,52	0,64
4	1,09	1,35	1,78	1,16	1,85	0,27	1,43	1,86	1,74	1,15	0,06
5	0,09	1,63	2,25	2,12	0,88	-0,46	0,92	-0,52	1,61	2,00	1,91

Note: The table presents accompanying t-statistics for Table 5b. Only periods when the United States was in a recession is included in this sample. The t-statistics are inaccurately calculated, but the general trend corresponds accurately to the replicated article by Liu, Stambaugh & Yuan. We suggest that the reader focuses on the general trends on which we draw our conclusions. Mispricing is based on Stambaugh, Yu & Yuan (2015) and is an average ranking on 11 return anomalies. Beta is based on a rolling 60-month window and is based on a regression on the stock's monthly return on market return plus lagged monthly return and summing slope coefficients according to Dimson. The highest beta decile represents the stocks with the highest estimated betas, while the lowest beta decile represents the stocks with the lowest estimated betas. The highest mispricing quintile represents the most overpriced stocks, while the lowest mispricing quintile represents the most underpriced stocks.