Unmasking Sin Stocks: Resolving the Anomaly and Evaluating Its Impact on Smart-Beta Performance

Paul Hänel

Dissertation written under the supervision of professor Zoë Venter

Dissertation submitted in partial fulfilment of requirements for the MSc in Economics, at the Universidade Católica Portuguesa, 17.12.2023.

Abstract

I examine the effect of excluding sin stocks on portfolio returns in the context of smart-beta strategies. Furthermore, this research tries to resolve the sin stock anomaly. My results add to the literature that does not find significant outperformance of smart-beta strategies. I propose a method to extend smart-beta strategies by loading on a set of factors. In this way, investors decrease the risk associated with smart-beta strategies and capture more factor returns. I find smart-beta strategies to have negative spillovers on the loadings of disregarded factors. Next, I show that there is no sin stock anomaly in smart-beta environments. The strategies internalize the anomaly. Finally, I explain the sin stock anomaly with an extension of the Fama-French five factor model. The anomaly is fully captured by loadings on the Fama-French five factor model factors and a betting-against-beta, momentum, and volatility factor. The volatility factor plays a crucial role in explaining the anomaly. Lastly, my study opens avenues for further research in extending the set of factors to further specify the factor loadings. Additionally, future research could aim to extend smart-beta or other trading strategies to capture more of each's factor returns.

Title: Unmasking Sin Stocks: Resolving the Anomaly and Evaluating Its Impact on Smart-Beta Performance

Author: Paul Hänel

Keywords: Sin stocks, Anomaly, Smart-beta, Portfolios, Trading strategies

Resumo

Eu examino o efeito da exclusão das acções ”pecado” na rendibilidade das carteiras no contexto das estratégias ”smart-beta”. Além disso, este estudo tenta resolver a anomalia das acções ”pecado”. Os meus resultados contribuem para a literatura, que não encontra um desempenho superior significativo das estratégias smart-beta. Proponho um método para alargar as estratégias smart-beta através da inclusão de um conjunto de factores. Desta forma, os investidores diminuem o risco associado às estratégias smart-beta e captam mais rendimentos de factores. Verifico que as estratégias smart-beta têm repercussões negativas nas inclusões de factores não considerados. Em seguida, demonstro que não existe uma anomalia nas acções “pecado” em ambientes “smart-beta”. As estratégias internalizam a anomalia. Por último, explico a anomalia das ações “pecado” com uma extensão do modelo de cinco factores Fama-French. A anomalia é totalmente captada pela inclusão dos factores do modelo de cinco factores de Fama-French e por um fator de aposta contra beta, momentum e volatilidade. O fator volatilidade desempenha um papel crucial na explicação da anomalia. Por último, o meu estudo abre caminhos para investigação futura, alargando o conjunto de factores para especificar melhor as cargas factoriais. Além disso, a investigação futura poderia ter como objetivo alargar as estratégias de negociação “smart-beta” ou outras para captar mais dos retornos de cada fator.

Título: Desmascarar as acções do pecado: Resolvendo a anomalia e avaliando o seu impacto no desempenho do Smart-Beta

Autor: Paul Hänel

Palavras-chave: Acções Sin, Anomalia, Smart-beta, Carteiras, Estratégias de negociação

Contents

List of Tables

List of Figures

Acknowledgements

I would like to express my heartfelt gratitude to my parents. Their unwavering support has made every opportunity possible, from studying abroad to the entirety of my life's journey. Their love and encouragement have been my driving force, and I am forever thankful for their sacrifices and devotion.
I extend my deepest appreciation to professor Zoë Venter Teixiera for her outstanding guidance and invaluable advice throughout my thesis. Her mentorship has played a pivotal role in my academic journey, and I am truly grateful for her expertise.
To all those who have taken the time to read and engage with this thesis, I offer my sincere thanks. Your interest and consideration are greatly appreciated.
Furthermore, I want to acknowledge my friends and the rest of my family. Their unwavering support, whether through words of encouragement or their simple presence in my life, has meant more to me than words can express. Their belief in me has been a constant source of motivation.
I want to thank Catolica for the opportunity of studying at this university.
Last but certainly not least, special thanks to my grandma. Her unshakeable faith in me has always given me the strength I needed. You will always be a part of me.

1 Introduction

In the past, stocks of firms that earn their money from human vice generated significant positive abnormal returns. However, there is an increasing trend of investors excluding stocks from their portfolios based on non-financial considerations [Blitz and Swinkels, 2021]. They do not want to be associated with the activities of firms engaging in ”sin” industries. Considering climate change, this is often related to carbon-intense firms. Another typical target of exclusion are firms with morally questionable business models, such as the alcohol, tobacco, or gambling industries. In the literature, these stocks are known as ”sin stocks”. On the other hand, there are specific investment vehicles that target sin stocks.

What explanation is there for the significant abnormal returns of sin stocks? One theory states that because many investors avoid sin stocks, they are systematically underpriced. Going against the social norm and investing in sin stocks might generate a ”reputation” risk premium [Fabozzi et al., 2008]. Additional hypotheses that have been put forth include that sin stocks might benefit from monopolistic returns or that investors receive a premium for increased litigation risk [Hong and Kacperczyk, 2009, Statman and Glushkov, 2009].

Regarding the exclusion of sin stocks it is important to realize that exclusion of sin stocks is simply transferring ownership rights to other investors. Alternatively, investors could choose to remain invested and adopt an active ownership policy, and thus, improving the company’s behaviour. The question of which approach is more efficient remains a hotly debated topic. Blitz and Swinkels [Blitz and Swinkels, 2020] discuss this issue. They find that exclusion translates to a transfer of ownership from sustainability-minded investors to other investors. The authors argue that exclusion policies are inefficient and active voting of sustainability-minded investors would have a positive societal impact.

But what are the financial implications of the exclusion of sin stocks? Sustainable investors argue that excluding sin stocks might increase returns - or at least decrease risk. My results suggest that there are no significant effects of excluding sin stocks in smart-beta environments. The outperformance of sin stocks does not seem to persist in smart-beta strategies. Thus, exclusion seems to be neither beneficial nor harmful.

I choose to use smart-beta strategies, because it provides a mixture of active and passive investing, and thus, allows to examine the effect of sin stocks on both. However, I acknowledge that smart-beta strategies are controversial. There is literature that does not find significant outperformance of smart-beta strategies. Such strategies might even increase risk [Malkiel, 2014, Jacobs and Levy, 2019]. Literature also proposes different extensions to smart-beta strategies [Amenc and Goltz, 2013]. However, these extensions are not relevant for the purpose of this thesis. Thus, I use basic smart-beta strategies as explained in the Methodology section. This is in line with Aleasandrini and Jondeau [Alessandrini and Jondeau, 2020].

How can we explain this lack of effect of sin stocks in a mix of active and passive trading strategies? As I do not find significant effects of excluding sin stocks, I propose a method to resolve the sin stock anomaly. My findings suggests that the anomaly is solved by an extension of the Fama-French five factor model. The anomaly is explained by different factor loadings. I will elaborate on this in the Methodology and Results section.

This thesis is structured as follows. In the following section I elaborate on the literature foundation of my thesis. Next, I present the data used and explain my methodology - namely, the construction of portfolios, the regressions used, and the method used to make the portfolios comparable. In section four I present the results. First, I elaborate on the impact of sin stocks in smart-beta environments. Second, I resolve the anomaly. Finally, I get to a conclusion and propose avenues for further research.

2 Literature Review

In this section I will elaborate on the literature that builds the foundation of my thesis.

Blitz and Swinkels [Blitz and Swinkels, 2021] find that excluding sin stocks is harmful for portfolio returns and goes against rewarded factors such as value and profitability. An exclusion of sin stocks increases the tracking error drastically, and thus, creates underdiversification problems. The authors suppose that sin might be a relevant factor by itself. However, this is not supported by data.

I use that framework and apply it to smart-beta portfolios. Additionally, I orientate myself on their approach in explaining excess returns. The authors create a volatility factor to capture excess returns. I will use a volatility factor to extend the Fama-French five factor model as well.

Alessandrini and Jondeau [Alessandrini and Jondeau, 2020] examine the effect of ESG investing on smart-beta strategies. Initially, socially responsible investment focused on sin stocks. As data availability increased and social norms have shifted, nowadays, socially responsible investment covers environmental, social, and governance (ESG) criteria. The authors examine the effect of ESG-score based exclusion of stocks from the MSCI World universe. They find that exclusion has significant positive effects on risk and return. This effect is even more pronounced in smart-beta environments.

In line with this paper, I explore the effect of the exclusion of sin stocks in smart-beta environments. The authors focus on more than just traditional sin industries, such as alcohol, tobacco, and gambling. However, I focus on these traditional sin stocks and use the definition of sin stocks from Hong and Kacperczyk [Hong and Kacperczyk, 2009] because this is the most straightforward approach to identify sin stocks. An exclusion based on ESG-scores is not universally applicable, because it depends on certain assumptions. By focusing on the basic sin industries, my approach is universally applicable.

Malkiel [Malkiel, 2014] questions the profitability of smart-beta strategies. He does not find significant outperformance of smart-beta strategies. Second, the author finds higher risk loadings in smart-beta strategies. Amenc and Goltz [Amenc and Goltz, 2013] elaborate on the unnecessary high risk of smart-beta strategies. The authors propose a new method to implement smart-beta strategies to tackle the risk issue. My study adds to the literature by examining the risk-adjusted profitability of smart-beta strategies in the context of sin stocks.

In their paper [Hong and Kacperczyk, 2009], Hong and Kacperczyk provide evidence for the outperformance of sin stocks. They explore the effects of social norms on markets. The authors hypothesize that there is a societal norm against funding companies that promote vice. Some investors, especially institutions subject to norms, pay a financial cost in abstaining from these stocks. Additionally, they add on the discussion whether abstaining from sin stocks is beneficial or not. They find that the exclusion of sin stocks significantly affected the cost of capital of sin firms. Thus, they find positive effects besides feeling good, which contradicts Blitz and Swinkels [Blitz and Swinkels, 2020]. This adds to the literature that builds the basis for my research. Hong and Kacperczyk document the premium on sin stocks. Furthermore, they use the Fama-French three factor model in their regressions. I extend this model in my own regressions.

Arnott, Li, and Linnainmaa [Arnott et al., 2023] build the basis for the rebalancing strategy in my portfolios. The authors examine which rebalancing strategies capture most of the factor premia while minimising turnover and trading costs. Transaction costs are crucial to estimate the profitability of trading strategies [Li et al., 2019]. Similar to my approach, Arnott et al. use a smart-beta setting. They find that in smart-beta momentum strategies monthly rebalancing works best. On the other hand, yearly rebalancing works best for smart-beta size and value strategies. I provide further insights on my rebalancing strategies in the Methodology section.

Blitz and Fabozzi [Blitz and Fabozzi, 2017] have already made the first effort on resolving the sin stock anomaly. They extend the Fama-French five factor model with a betting-against beta and a momentum factor. I closely follow this framework. However, as seen in other studies, I add a volatility factor. This allows me to further specify, which factor loadings explain the anomaly.

The authors find similar results to mine and resolve the anomaly. However, I find differences in factor loadings. I am going to comment on this in the Results section.

There are several studies that aim to answer the following question: Do sin stocks consistently outperform the market? Fabozzi et al. [Fabozzi et al., 2008] find a significant beta adjusted outperformance by more than 3% per annum and almost 6% per annum. Hong and Kacperczyk, and Statman and Glushkov [Hong and Kacperczyk, 2009, Statman and Glushkov, 2009] find similar results. Salaber [Salaber, 2007] finds significant outperformance depending on the religious and legal environments in different countries. On the other hand, a more recent study from Lobe and Walkshäusl [Lobe and Walkshäusl, 2016] finds no evidence that sin stocks out- or underperform. However, this study includes nuclear power as a sin stock. This is unique and seems to drive their results.

These studies underline the importance of further examining the sin stock anomaly. This paper aims to provide further insight in resolving the anomaly and to evaluate the performance of sin stocks and smart-beta investments.

3 Data and Methodology

3.1 Data

Using Datastream, I collect daily return index data for all current constituents of the S&P 500 and STOXX Europe 600 from January 2000 to June 2023.

I get data on the risk free rate, market risk premium (MRP), size factor (SMB), value factor (HML), operating profitability factor (RMW), investment strategy factor (CMA), and momentum factor from the Kenneth French online data library [1]. I download each variable with daily

[1] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

frequency. The Kenneth French data set has some missing days. Regarding the risk free rate, this is not a major issue. As the risk free rate does not change a lot between days, I use the value of the previous day. However, the daily changes in the factors are more pronounced. Thus, I calculate the standard deviation of each factor. For the missing days, I construct new values by generating a random number in the range of a positive and a negative standard deviation around the previous day value.

I calculate excess returns for each stock using the return index data from Datastream and substracting the risk free rate from the Kennth French online library.

Additionally, I construct the volatility factor (VOL). I use my whole sample of stock excess returns and calculate each stock's volatility. In the next step, I assign the stocks to percentiles according to their volatility. Finally, I go long on a low- and short on a high-volatility portfolio. The returns of this trading strategy yield the volatility factor.

Next, I download market capitalization and book-to-market data for all current constituents of the S&P 500 and STOXX Europe 600 from January 2000 to June 2023 using Datastream. I need these fundamentals to construct smart-beta portfolios. I will explain the portfolios in more detail in the Methodology section.

Lastly, I get data on the betting-against-beta factor (BAB) obtained by Frazzini and Pedersen [Frazzini and Pedersen, 2014] from AQR online library [2]. In betting-against-beta strategies, investors go long on low beta stocks and short on high-beta stocks.

3.1.1 Defining sin stocks

Different studies have shown different ways of classifying industries and sectors into sin and non-sin. The classification of sin stocks has critical implications on the results as seen in Lobe and Walkshäusl [Lobe and Walkshäusl, 2016], in which the nuclear industry drives the findings. In the literature there is no consensus on a general definition of sin stocks. The three major categories are alcohol sin stocks, tobacco sin stocks, and gambling sin stocks. An emerging industry that can be included as a sin industry is the marijuana industry. Other studies include the weapons, nuclear, and sex industries. Additionally, companies change over time. Heineken - a company involved in the alcohol industry - announced plans to aggressively market their non-alcoholic beer. Furthermore, there are many who argue that, in light of climate change, corporations with high carbon footprints may be viewed as sin stocks since investors are avoiding them. Finally,

[2] AQR online library: https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Daily

companies such as Mc Donald's could be seen as sin stocks as their association with sugar and fat boosts the obesity epidemic in large parts of the western world.

I follow the conservative procedure of Hong and Kacperczyk [Hong and Kacperczyk, 2009] using stocks from alcohol, tobacco, and the gambling industry. They identify sin stocks through their SIC and NAICS codes. Finally, I come up with twelve sin stocks from the S&P 500 and twelve sin stocks from STOXX Europe 600 (see Table 1).

Table 1: Sin Stocks

S&P 500	STOXX Europe 600
Coca-Cola Co	LVMH Moet Hennessy Louis Vuitton SE
PepsiCo Inc	Anheuser-Busch Inbev SA
Philip Morris International Inc	Diageo PLC
Altria Group Inc	British American Tobacco PLC
Constellation Brands Inc	Heineken NV
Keurig Dr Pepper Inc	Pernod Ricard SA
Las Vegas Sands Corp	Carlsberg A/S
Brown-Forman Corp	Imperial Brands PLC
MGM Resorts International	Davide Campari Milano NV
Caesars Entertainment Inc	Coca-Cola Europacific Partners PLC
Molson Coors Beverage Co	Remy Cointreau SA
WYNN Resorts Ltd	Royal Unibrew A/S

3.2 Methodology

In the following section, I present the methodology. The section is structured as follows. First, I elaborate on the portfolio construction and the summary statistics of the portfolios. Next, I explain the regressions. Finally, I comment on testing the significance of differences between Sharpe ratios.

3.2.1 Portfolios

First, I calculate excess returns for all stocks using the return index data from Datastream and the risk free data from the Kennth French online library. The excess returns build the basis of the portfolios. You can find a detailed overview of all portfolios in the following tables.

Table 2: Portfolios I

Portfolio	Weight Restrictions	Description
Portfolio 1	none	Equally-weighted portfolios consisting of all sin stocks from S&P 500 and STOXX Europe 600
Portfolio 2	none	Smart-Beta Momentum portfolio consisting of all sin stocks from S&P 500 and STOXX Europe 600
Portfolio 3	none	Smart-Beta Size portfolio consisting of all sin stocks from S&P 500 and STOXX Europe 600
Portfolio 4	none	Smart-Beta Value portfolio consisting of all sin stocks from S&P 500 and STOXX Europe 600
Portfolio 5	$\in [0, 1]$	Smart-Beta Momentum portfolio consisting of all stocks from S&P 500
Portfolio 6	$\in [0, 1]$	Smart-Beta Momentum portfolio consisting of all stocks from S&P 500, excluding sin stocks
Portfolio 7	$\in [0, 1]$	Smart-Beta Momentum portfolio consisting of all stocks from STOXX Europe 600
Portfolio 8	$\in [0, 1]$	Smart-Beta Momentum portfolio consisting of all stocks from STOXX Europe 600, excluding sin stocks
Portfolio 9	$\in [-0.5, 1.5]$	Smart-Beta Momentum portfolio consisting of all stocks from S&P 500
Portfolio 10	$\in [-0.5, 1.5]$	Smart-Beta Momentum portfolio consisting of all stocks from S&P 500, excluding sin stocks
Portfolio 11	$\in [-0.5, 1.5]$	Smart-Beta Momentum portfolio consisting of all stocks from STOXX Europe 600
Portfolio 12	$\in [-0.5, 1.5]$	Smart-Beta Momentum portfolio consisting of all stocks from STOXX Europe 600, excluding sin stocks

As explained in the Methodology section, I did not add restricted Size and Value Smart-Beta portfolios. By the way of construction, the weights of these portfolios are automatically between zero and one.

Table 3: Portfolios II

Portfolio	Weight Restrictions	Description
Portfolio 13	none	Smart-Beta Momentum portfolio consisting of all stocks from S&P 500
Portfolio 14	none	Smart-Beta Momentum portfolio consisting of all stocks from S&P 500, excluding sin stocks
Portfolio 15	none	Smart-Beta Size portfolio consisting of all stocks from S&P 500
Portfolio 16	none	Smart-Beta Size portfolio consisting of all stocks from S&P 500, excluding sin stocks
Portfolio 17	none	Smart-Beta Value portfolio consisting of all stocks from S&P 500
Portfolio 18	none	Smart-Beta Value portfolio consisting of all stocks from S&P 500, excluding sin stocks
Portfolio 19	none	Smart-Beta Momentum portfolio consisting of all stocks from STOXX Europe 600
Portfolio 20	none	Smart-Beta Momentum portfolio consisting of all stocks from STOXX Europe 600, excluding sin stocks
Portfolio 21	none	Smart-Beta Size portfolio consisting of all stocks from STOXX Europe 600
Portfolio 22	none	Smart-Beta Size portfolio consisting of all stocks from STOXX Europe 600, excluding sin stocks
Portfolio 23	none	Smart-Beta Value portfolio consisting of all stocks from STOXX Europe 600
Portfolio 24	none	Smart-Beta Value portfolio consisting of all stocks from STOXX Europe 600, excluding sin stocks

Pure Sin Portfolio. The pure sin portfolio consists of all 24 sin stocks in my sample. I assign equal weight to all stocks. Thus, I do not need to rebalance in Portfolio 1. I calculate the portfolio return by multiplying each stock's weight with its excess return.

In the other portfolios I either use all stocks of the given index or exclude the sin stocks. This allows me to see whether sin stocks boost or worsen the performance of the given portfolio.

Smart-Beta Momentum Portfolios. To construct momentum portfolios, I calculate a measure for the momentum score. Momentum score is equal to the sum of the excess returns in the previous twelve months excluding the last. Given each's stock momentum score, I calculate the sum of all individual momentum scores per period. Finally, I calculate weights for each individual stock by dividing its score by the sum of all momentum scores in each period. As daily rebalancing would be too costly and time-consuming, I follow Arnott et al. [Arnott et al., 2023]. The authors find that monthly rebalancing seems to be most profitable in momentum portfolios. Thus, I calculate weights every 20 days - assuming 240 trading days - and rebalance monthly. More concretely, I calculate weights in the above-described manner every 20 days. Finally, I multiply each stock's weight for the given month with its daily excess returns.

As the momentum score could be highly negative or positive, I add different weight restrictions. To do that, I calculate weights in the previously described manner. Next, I bind the weights to match the restrictions and calculate the sum of these weights. Finally, I normalize the weights given the sum of weights to make sure the total weight equals one. I build unrestricted portfolios, portfolios that do not allow for short selling (weights $\in [0, 1]$), and portfolios that allow for limited borrowing ($\in [-0.5, 1.5]$).
In Table 2 and 3 you find an overview of the momentum portfolios. Portfolio 2 is the pure sin momentum portfolio. Portfolios 5, 6, 9, 10, 13, and 14 are the momentum portfolios for the US. Lastly, Portfolios 7, 8, 11, 12, 19, and 20 are the momentum portfolios for Europe.

Smart-Beta Size Portfolios. To construct size portfolios, I use market capitalization data. Following Arnott et al. [Arnott et al., 2023], I rebalance yearly. The authors find yearly rebalancing to be optimal in size portfolios. To calculate weights, I build the sum of market capitalization of all stocks per period. Next, I divide each stock's market capitalization by the sum of all stocks market capitalization every year - again assuming 240 trading days. As market capitalization is not negative, the weights are automatically $\in [0, 1]$. Thus, I do not impose restrictions on the portfolios. Finally, I multiply each stock's weight for the given year with its daily excess returns.
Portfolio 3 is the pure sin size portfolio. Portfolio 15 and 16 are the size portfolios for the US, and Portfolio 21 and 22 are the size portfolios for Europe.

Smart-Beta Value Portfolios. To construct value portfolios, I use book-to-market data. Following Arnott et al. [Arnott et al., 2023], I rebalance yearly. The authors find yearly rebalancing to be optimal in value portfolios. To calculate weights, I build the sum of book-to-market values of all stocks per period. Next, I divide each stocks book-to-market value by the sum of all stocks book-to-market values every year assuming 240 trading days. As book-to-market is not negative, the weights are automatically $\in [0, 1]$. Thus, I do not impose restrictions on the portfolios. Finally, I multiply each stocks weight for the given year with its daily excess returns.
Portfolio 4 is the pure sin value portfolio. Portfolio 17 and 18 are the value portfolios for the US, and Portfolio 23 and 24 are the value portfolios for Europe.

Summary Statistics. I find Portfolios 10 and 14 to have surprisingly high average excess returns. These are momentum portfolios that allow for short selling and exclude sin stocks. However, these portfolios have by far the highest standard deviation. Thus, their Sharpe ratios are close to the Sharpe ratios of other portfolios. The Sharpe ratios are rather small. I find some Sharpe ratios to be negative in the momentum environment. Portfolio 4 builds an exemption as we have a negative Sharpe ratio in a value environment.

In many of the portfolios, the skewness is relatively close to zero. Thus, I can assume an approximately normal distribution of returns. However, some momentum portfolios deviate. They either have a positive skewness, indicating a shift to the right, and thus, more positive results, or a negative skewness, indicating a shift to the left, and thus, more negative results.

All portfolios have a leptokurtic excess kurtosis. The higher likelihood of extreme results is expected and makes sense in this sample. Fat tails are common in stock returns. The minimum and maximum values of the excess returns of the portfolios further support this. I find a rather low correlation of excess returns with its one period lagged value over all portfolios.

Table 4: Summary Statistics

	Mean (%)	Std. Dev. (%)	Sharpe Ratio	Skew.	Exc. Kurt.	Min. (%)	Median (%)	Max. (%)	AR(1)
S&P 500	0.03	1.22	0.02	-0.15	10.45	-11.99	0.03	11.58	-0.10
STOXX Europe 600	0.02	1.33	0.02	-0.17	8.51	-13.00	0.05	11.28	0.00
Portfolio 1	0.05	1.01	0.05	-0.49	14.57	-12.85	0.07	9.15	0.10
Portfolio 2	0.12	41.43	0.00	3.73	486.91	-1255.69	0.07	1182.66	-0.19
Portfolio 3	0.04	1.02	0.04	-0.32	10.06	-11.33	0.06	10.46	0.04
Portfolio 4	-0.02	3.92	-0.01	0.05	33.36	-44.70	0.03	56-12	-0.04
Portfolio 5	0.06	1.42	0.04	-0.22	12.12	-13.22	0.05	16.17	-0.04
Portfolio 6	0.06	1.42	0.04	-0.19	12.17	-13.16	0.05	16.17	-0,05
Portfolio 7	0.05	1.41	0.03	-0.18	10.54	-14.18	0.08	15.44	0.06
Portfolio 8	0.05	1.42	0.03	-0.17	10.42	-14.20	0.08	15.44	0.06
Portfolio 9	-0.22	11.23	-0.02	-5.29	288.03	-306.22	0.02	301.58	0.20
Portfolio 10	7.23	849.97	0.01	10.78	874.90	-28639.72	0.02	33784.54	0.18
Portfolio 11	-0.06	6.12	-0.01	-6.88	319.96	-180.42	0.08	121.64	0.10
Portfolio 12	0.64	39.01	0.02	9.73	544.80	-881.01	0.09	1325.81	0.10
Portfolio 13	-0.22	11.24	-0.02	-5.29	287.84	-306.22	0.02	301.58	0.20
Portfolio 14	7.23	849.97	0.01	10.78	874.90	-28639.72	0.02	33784.54	0.18
Portfolio 15	0.03	1.24	0.03	-0.07	11.49	-12.12	0.03	12.23	-0.10
Portfolio 16	0.03	1.26	0.03	-0.05	11.28	-12.18	0.03	12.28	-0.10
Portfolio 17	0.10	2.72	0.04	1.43	97.45	-37.72	0.04	67.88	-0.05
Portfolio 18	0.09	3.30	0.03	-4.25	121.69	-75.09	0.03	45.05	-0.14
Portfolio 19	-0.03	7.91	-0.00	-2.98	140.81	-200.64	0.07	122.48	0.06
Portfolio 20	0.63	39.01	0.02	9.73	544.76	-881.01	0.09	1325.81	0,10
Portfolio 21	0.04	1.24	0.03	-0.12	9.42	-12.96	0.07	11.11	0.03
Portfolio 22	0.04	1.24	0.03	-0.12	9.40	-13.04	0.07	11.18	0.04
Portfolio 23	0.03	1.50	0.02	-0.45	14.17	-14.98	0.05	14.80	0.04
Portfolio 24	0.04	1.49	0.03	-0.09	13.75	-14.44	0.06	15.02	0.03

3.2.2 Sharpe Ratio Differences

To compare the portfolios, I use the Sharpe ratio as a performance indicator. The Sharpe ratio gives a measure of the risk-adjusted return and despite its downsides it is widely used in research and the industry [Sharpe, 1998, Muralidhar, 2015]. The Sharpe ratio allows me to assess both - a potential out- or underperformance of sin stocks and the effects of an exclusion of sin stocks on risk. Therefore, I am able to assess risk and return.

To check for significance in the differences between the Sharpe ratios of the portfolios, I follow the procedure of [Ledoit and Wolf, 2008] and use a circular bootstrap method [Benhamou et al., 2019] to construct the testing parameter. The authors propose a method to test exactly the difference between portfolios, and thus, Sharpe ratios as a portfolio performance measure. They developed the R package "Peer Performance" [3] based on their research [Ardia and Boudt, 2018, Ardia and Boudt, 2015, Ardia and Boudt, 2013]. The aim of their test is to assess, whether hedge funds outperform their peers. This is easily transferred to the comparison of portfolios and their Sharpe ratios. More precisely, the authors propose a pairwise test of equal performance. The null hypothesis states that the performance - Sharpe ratio - of two portfolios is the same.

$$H_0 : SR_{PFx} - SR_{PFy} = \Delta_{x-y} = 0 \quad \text{(Sharpe ratios are equal)} \tag{1}$$

$$H_1 : SR_{PFx} - SR_{PFy} = \Delta_{x-y} \neq 0 \quad \text{(Sharpe ratios are not equal)} \tag{2}$$

Their method uses a studentized test statistic to account for the finite sample properties of the return distribution and the potential autocorrelation, heteroskedasticity and cross-dependence of returns. The test statistic is the ratio between the Sharpe ratio difference and its standard error.

$$teststat = \frac{\Delta_{x-y}}{s.e.\Delta_{x-y}} \tag{3}$$

3.2.3 Regressions

My regressions aim to explain the sin stock anomaly. Thus, I try to explain alpha. I regress the excess returns of the pure sin portfolios (Portfolios 1, 2, 3, and 4) on different factors to check for factor loadings that might explain the anomaly. My methodology follows Blitz and Fabozzi [Blitz and Fabozzi, 2017]. However, I add the volatility factor, because the anomaly might be explained by a premium paid for higher risk in sin stocks. This is in line with Blitz and Swinkes [Blitz and Swinkels, 2021].

[3] Peer Performance: `https://CRAN.R-project.org/package=PeerPerformance`

Sin stocks are less liquid as some investors are shunning them. Additionally, investors impose a higher risk premium on sin stocks because of stricter regulation and greater litigation risk.

I try to resolve the anomaly by running the following specifications:

$$ExcessReturns_t = \alpha + \beta_1 MRP_t + \varepsilon \tag{4}$$

This specification tests if the excess returns of a portfolio are fully explained by the simple CAPM model. The CAPM model is not likely to capture the entire alpha. However, it is still widely used in academia, and even more in industry.

$$ExcessReturns_t = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \varepsilon \tag{5}$$

As I suppose that the simple CAPM model does not fully capture excess returns [Jagannathan et al., 1995], I try to explain the remaining alpha by the Fama-French five factor model. By extending the CAPM framework I should be able to capture more of the anomaly's alpha. Previous research has shown that even the Fama-French five factor model does not fully capture the sin stock anomaly.

$$\begin{aligned} ExcessReturns_t = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t \\ + \beta_6 BAB_t + \beta_7 MOM_t + \beta_8 VOL_t + \varepsilon \end{aligned} \tag{6}$$

As explained, alpha remains positive and significant in the Fama-French five factor model providing evidence for the anomaly to persist. Thus, I add an extension of the model [Blitz and Swinkels, 2021, Blitz and Fabozzi, 2017]. The third specification fully captures alpha. It resolves the anomaly by different factor loadings. I am going to elaborate on that in the next section.

4 Results

This section is structured as follows. First, I explore the impact of sin stocks in smart-beta environments. Next, I will resolve the sin stock anomaly in a simple equal-weighted pure sin portfolio (Portfolio 1). Third, I explore the factor loadings explaining the anomaly in the context of smart-beta investments (Portfolio 2, 3, and 4). Lastly, I discuss remarkable results arising from resolving the anomaly.

4.1 Impact of Sin Stocks on Smart-Beta Investment

In the following section, I evaluate the effect of excluding/including sin stocks in investment strategies. As predicted by the anomaly, Table 5 shows that a pure sin portfolio offers a significantly higher Sharpe ratio than the indices the sin stocks are drawn from in this study. They generate significantly higher risk-adjusted returns.

Table 5: Sharpe Ratio Differences Pure Sin Portfolio & Indices

	Pure Sin Portfolio
S&P 500	0.029^{***} (0.004)
STOXX Europe 600	0.032^{***} (0.004)

Note: p-value in brackets; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

The difference between a pure sin portfolio and the indices is 0.03 and significant at 1% level. This indicates that in my sample period sin stocks outperformed the market considering their risk and return. These results add to the literature observing the sin stock anomaly.

However, I do not find similar results in smart-beta strategies. The differences in Sharpe ratios between portfolios are low and insignificant for all comparable portfolios.

Table 6: Sharpe Ratio Differences Momentum Portfolios

	Portfolio 5	Portfolio 7	Portfolio 9	Portfolio 11	Portfolio 13	Portfolio 19
Portfolio 6	-0.001					
	(0.482)					
Portfolio 8		0.000				
		(0.602)				
Portfolio 10			-0.028			
			(0.303)			
Portfolio 12				-0.026		
				(0.339)		
Portfolio 14					-0.028	
					(0.303)	
Portfolio 20						-0.020
						(0.307)

Note: p-value in brackets; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Looking at momentum (Table 6), I find the difference between Sharpe ratios to be close to zero and insignificant if I restrict the weights $\in [0, 1]$ in the US (Portfolio 5 and Portfolio 6) and Europe (Portfolio 7 and Portfolio 8). If the weights are restricted to be $\in [-0.5, 1.5]$ an exclusion slightly increases the Sharpe ratio (Portfolio 9, Portfolio 10, Portfolio 11, and Portfolio 12). However, this increase is insignificant as well. The same is observed for unrestricted portfolios. The Sharpe ratios for portfolios that exclude sin stocks is slightly higher, but the difference is insignificant (Portfolio 13, Portfolio 14, Portfolio 19, and Portfolio 20). Thus, I can conclude that in smart-beta momentum investments the sin stock anomaly does not play a role. An exclusion of sin stocks does not significantly impact the trading strategy. There are neither beneficial nor harmful implications.

Table 7: Sharpe Ratio Differences Size Portfolios

	Portfolio 15	Portfolio 21
Portfolio 16	0.000	
	(0.239)	
Portfolio 22		0.001
		(0.120)

Note: p-value in brackets; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Next, I take a closer look at size strategies (Table 7). By the way of construction of the portfolios, weights are automatically $\in [0, 1]$. The results show a similar pattern to momentum strategies. The differences between Sharpe ratios are close to zero and insignificant in US (Portfolio 15 and Portfolio 16) and Europe (Portfolio 21 and Portfolio 22). Again, I do not find any significant impact of the exclusion of sin stocks in smart-beta investments. In smart-beta size strategies there is no evidence for implications arising from the sin stock anomaly.

Table 8: Sharpe Ratio Differences Value Portfolios

	Portfolio 17	Portfolio 23
Portfolio 18	0.010	
	(0.367)	
Portfolio 24		-0.008
		(0.303)

Note: p-value in brackets; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Lastly, I want to dicuss smart-beta value strategies (Table 8). Again, weights are automatically $\in [0, 1]$. The differences between the Sharpe ratios are higher than in smart-beta size strategies but still close to zero and insignificant in the US (Portfolio 17 and Portfolio 18) and Europe (Portfolio 23 and Portfolio 24). This provides further evidence that the sin stock anomaly does not play a role in smart-beta investments. An exclusion of sin stocks has no effect on the performance of the portfolio.

Wrapping up, I find that an exclusion of sin stocks from smart-beta portfolios has no impact on their risk-adjusted performance. In the context of such investments, I do not find evidence for an impact arising from the sin stock anomaly. This contrasts the findings for simple passive investments. I suppose that factor loadings explain the anomaly. Smart-beta strategies aim to exploit factor loadings, thus, I presume them to internalize the anomaly. In the next section, I will explore this.

4.2 Resolving the Anomaly

My previous results suggest that the sin stock anomaly can be explained by different factor loadings. This is in line with the findings of Blitz and Fabozzi [Blitz and Fabozzi, 2017]. In the following regressions, I use the framework from the paper of Blitz and Fabozzi. However, I added a volatility factor that seems to play a crucial role in explaining the abnormal returns generated by sin stocks [Blitz and Swinkels, 2021]. To add robustness, I run different specifications with different combination of factors. As the results do not change, I present the three main models of this research.

4.2.1 Pure Sin Portfolio

First, I will look at the pure sin portfolio (Portfolio 1) consisting of all sin stocks in my sample.

Figure 1: Returns Indices & Pure Sin Portfolio

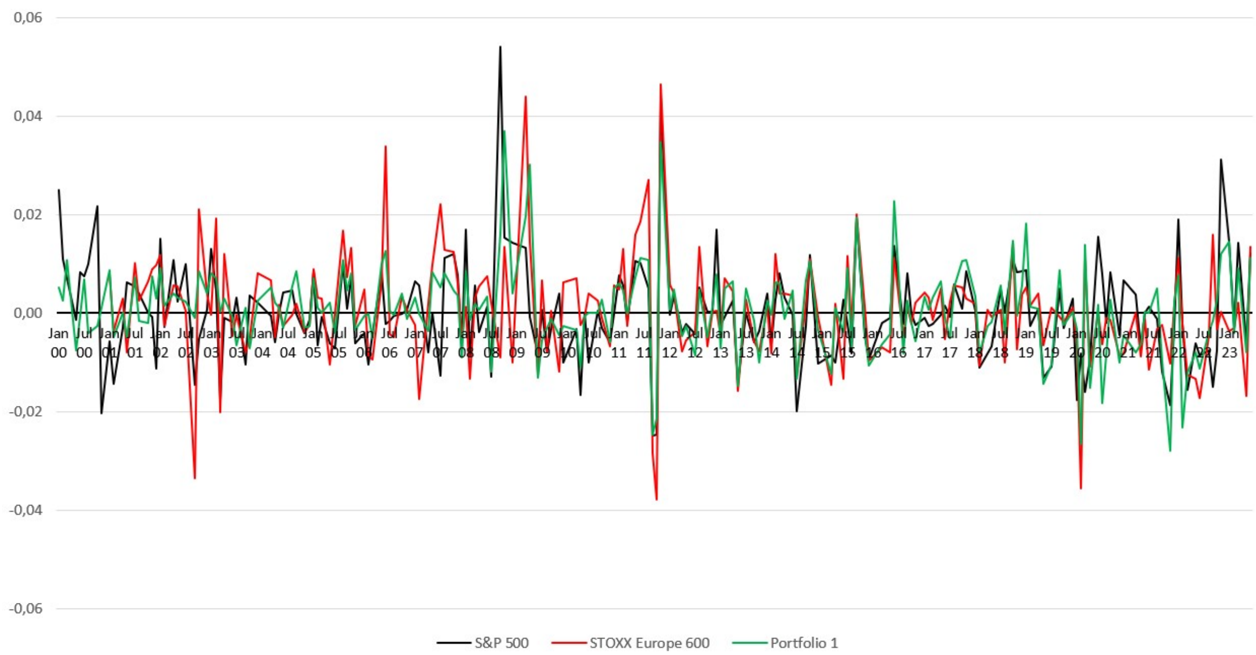

Figure 1 shows the evolution of excess returns for the two indices and the pure sin portfolio. We see that the pure sin portfolio has fewer extreme returns. Furthermore, the graph shows that the pure sin portfolio visibly outperforms the indices during the late 2010s.

In the following I will discuss the results (Table 9) in detail.

Table 9: Pure Sin Portfolio

	Dependent variable:		
	Excess Returns		
	(1)	(2)	(3)
MRP	0.005***	0.006***	0.005***
	p = 0.000	p = 0.000	p = 0.000
SMB		0.001***	0.0004**
		p = 0.000	p = 0.012
HML		0.001***	0.0005***
		p = 0.000	p = 0.001
RMW		0.003***	0.004***
		p = 0.000	p = 0.000
CMA		0.001***	0.002***
		p = 0.001	p = 0.000
BAB			0.369***
			p = 0.000
MOM			−0.001***
			p = 0.000
VOL			−0.532***
			p = 0.000
Alpha	**0.0003*****	**0.0002****	−**0.00001**
	p = 0.001	p = 0.015	p = 0.884
Observations	6,130	6,130	6,130
R^2	0.462	0.513	0.568
Adjusted R^2	0.462	0.513	0.568
Residual Std. Error	0.007	0.007	0.007
F Statistic	5,258.808***	1,291.303***	1,006.643***

Note: **p<0.1; **p<0.05; ***p<0.01*

I find a significant alpha in sin stock portfolios in the simple CAPM model of 0.03%. This supports my hypothesis that the simple CAPM model cannot fully capture the anomaly. I want to note that the regression already has a high R^2. To further investigate the positive alpha, I add the

Fama-French five factor model factors to the regression.

Alpha remains significant when using the Fama-French five factor model. However, it is slightly reduced to 0.02%. Furthermore, alpha's significance drops from 1% to 5% level. All factors are highly significant (at 1% level) in explaining excess returns. The second specification has a R^2 of 51.30%. As alpha remains significant, the model still does not fully explain the anomaly. Thus, I add another specification adding a betting-against-beta, a momentum, and a volatility factor [Blitz and Swinkels, 2021, Blitz and Fabozzi, 2017].

In my final specification, I find alpha to be highly insignificant and slightly negative. The inclusion of the momentum, volatility, and betting-against-beta factor resolves the anomaly by capturing all its alpha. R^2 is as expected even higher with a value of 56.80%.

To further explore, which of the variables contributes most significantly to the explanation of the anomaly, I run regressions using only one additional factor. I find the volatility factor to have the highest impact on alpha. However, only adding momentum and betting-against-beta factors fully captures alpha. This indicates that loadings on all factors play a crucial role in resolving the anomaly. All other factors from the Fama-French five factor model remain at similar magnitude and significant at 1% level. The only exception is the size factor. Its significance drops to a 5% level and slightly reduces.

In the pure sin portfolio, the anomaly is fully captured by my last specification. I am able to show that the volatility factor has the highest explanatory power in explaining the anomaly. However, only when including betting-against-beta and momentum I fully capture the anomaly. The strong effect of volatility makes sense. We can think of volatility as a proxy for risk. Sin stocks face several risks, such as regulation risk or specific taxation. Thus, it is likely that investors demand a higher risk premium. The dependence on the volatility factor reflects the riskiness of sin stocks. The dependence on the momentum factor might be explained by the stable business models and the inelastic demand of several sin industries. The tobacco industry, for example, is less sensitive to economic downturns and pays steady dividends. Together, this might create momentum. Lastly, the dependence on the betting-against-beta factor might be explained by investor preferences. Sin stocks, while belonging to controversial industries, might exhibit lower systematic risk for the previously mentioned reasons, making them attractive to risk-averse investors.

4.2.2 Smart-Beta Portfolios

I find different results in smart-beta environments. In momentum and value strategies there is no significant alpha indicating that sin stocks do not add value to smart-beta strategies. The strategies seem to exploit the anomaly by the nature of its strategy - namely loading on factors. This is in line with the results of the previous section. Sin stocks do not seem to have an impact on smart-beta strategies.

On the other hand, I do find a significant alpha for size strategies in the simple CAPM model. This is at least slightly surprising, as we find the size factor to be the only factor that decreases in significance in the pure sin portfolio.

Alpha already diminishes by the inclusion of the Fama-French five factor model. This further adds to the previous results that sin stocks do not seem to have an impact on smart-beta strategies.

Table 10: Pure Sin Smart-Beta Portfolios

	Momentum			*Size*			*Value*		
	Excess Returns								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MRP	0.013***	0.008	0.005	0.005***	0.006***	0.006***	0.006***	0.006***	0.006***
	p = 0.002	p = 0.108	p = 0.401	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
SMB		−0.020**	−0.024***		−0.001***	−0.001***		0.003***	0.002**
		p = 0.022	p = 0.008		p = 0.00000	p = 0.00000		p = 0.000	p = 0.016
HML		−0.005	−0.002		0.0003**	−0.0001		0.001	0.002**
		p = 0.553	p = 0.864		p = 0.023	p = 0.437		p = 0.384	p = 0.023
RMW		−0.026**	−0.021*		0.004***	0.004***		−0.001	0.000
		p = 0.021	p = 0.067		p = 0.000	p = 0.000		p = 0.638	p = 0.934
CMA		−0.033**	−0.035**		0.003***	0.004***		−0.003**	0.002
		p = 0.023	p = 0.022		p = 0.000	p = 0.000		p = 0.031	p = 0.178
BAB			−0.589			0.334***			0.248*
			p = 0.671			p = 0.000			p = 0.053
MOM			0.011*			−0.001***			−0.003***
			p = 0.074			p = 0.000			p = 0.000
VOL			−1.502			−0.217***			−0.519***
			p = 0.233			p = 0.000			p = 0.000
Alpha	**0.001**	**0.002**	**0.002**	**0.0002****	**0.0001**	**−0.0001**	**0.0001**	**−0.00001**	**−0.001**
	p = 0.885	p = 0.687	p = 0.688	p = 0.031	p = 0.463	p = 0.253	p = 0.646	p = 0.944	p = 0.191
Observations	6,118	6,118	6,118	6,130	6,130	6,130	6,130	6,130	6,130
R^2	0.002	0.006	0.006	0.413	0.493	0.512	0.040	0.044	0.053
Adjusted R^2	0.001	0.005	0.005	0.412	0.493	0.511	0.039	0.043	0.051
Residual Std. Error	0.414	0.413	0.413	0.008	0.007	0.007	0.038	0.038	0.038
F Statistic	9.705***	6.839***	4.859***	4,302.645***	1,192.843***	802.816***	252.702***	56.503***	42.528***

Note: *p<0.1; **p<0.05; ***p<0.01

Momentum. In the momentum environment, I do not find a significant alpha. Consequently, the factor loadings and their significance change drastically compared to the results for Portfolio 1. R^2 is low for all specifications.

In the first specification, I find the market risk premium to be significant at 1% level. In the other specifications its effect lowers and is insignificant. In contrast to the non-smart-beta regressions, the Fama-French five factor model factors are negative. The value factor is insignificant in all specifications. The operating profitability and investment strategy factor are significant at 5%, respectively 10%, level. Size factor increases in significance from model two to model three.

The betting-against-beta factor changes its sign and is negative now. However, the factor is highly insignificant. Momentum changes its sign as well. It is positive and significant at 10% level. Finally, volatility factor remains negative but insignificant.

As I do not find a significant alpha in smart-beta momentum strategies, there is no evidence for an effect of sin stocks in this environment. I do not find evidence for the anomaly. However, it is surprising that in momentum strategies the size factor is the only highly significant independent variable. One would expect momentum strategies to depend on the momentum factor, which the strategy tries to exploit. My results add to the literature that questions the profitability of smart-beta strategies [Malkiel, 2014].

Size. In smart-beta size strategies, I find a significant alpha. However, alpha disappears when including the Fama-French five factor model. In contrast to momentum smart-beta strategies I find different factor loadings with higher significance. R^2 is much higher for smart-beta size strategies.

I find the market risk premium factor to be positive and significant at 1% level in all specifications. With the exception of size, all Fama-French five factor model factors are positive. They are significant at 1% level. The value factor is significant at 5% level in the second specification. In the last specification the factor is slightly negative and insignificant.

The betting-against-beta, momentum, and volatility factor are significant at 1% level. They have the same signs as the non-smart-beta regressions.

The results from smart-beta size strategies are in line with the non-smart-beta regression. There is a significant alpha indicating an effect of sin stocks or profitability of smart-beta size strategies. As this effect is explained by the Fama-French five factor model, I expect alpha to depend on exploiting the size factor and not the sin stock anomaly. Thus, I find evidence for the profitability of smart-beta size strategies.

Value. In the value environment, I do not find a significant alpha. Consequently, the factor loadings and their significance change drastically. R^2 is low for all specifications.

I find the effect of the market risk premium to be positive significant at 1% level in all specifications. The size factor is positive in all specifications. Its significance decreases from 1% to 5% from the second to third specification. The value factor is positive and insignificant in model two. However, in the last specification the value factor is significant at 5% level. The operating profitability factor is insignificant. I find the investment strategy factor to be negative and significant at 5% level in the second specification, but insignificant in the last model.

Betting-against-beta factor is negative and significant at 10% level. Momentum and volatility factors are negative and significant at 1% level.

Again, I do not find evidence for an effect of sin stocks. Furthermore, there is no evidence for a remarkable profitability of smart-beta value strategies. Lastly, it is surprising that the value factor does not have a huge impact on excess returns compared to other factors. This is surprising as the trading strategy tries to exploit the value factor, and thus, should load on it.

My results suggest that there is no evidence for the sin stock anomaly in smart-beta strategies. By loading on factors, the strategies internalize the anomaly. However, my results suggest that there is no consistent outperformance of smart-beta strategies. The only smart-beta strategy that shows positive abnormal returns in my sample, is the smart-beta size strategy. This effect is rather small and might be explained by other factors I did not include, as I find a negative effect of the size factor in this environment. The negative effect is surprising as the size strategy tries to positively load on the size factor. Overall, the study provides evidence against the profitability of smart-beta strategies. In section 5, I present an extension of the simple smart-beta models that aims to combine different smart-beta strategies to exploit more than just one factor.

4.2.3 Sign Switch

In this section, I want to highlight the sin switches in the different models. I focus on the last specification and significant factors.

In the smart-beta setting, I find the size factor to be negative for momentum and size strategies, but positive for value strategies. In the non-smart-beta regression the factor is positive. One would expect the size factor to have a positive impact on smart-beta size strategies. This indicates that the smart-beta size strategy does not work as intended. Thus, my results suggest that the smart-beta strategies I use in this study do not outperform. Next, the operating profitability factor and the investment strategy factor are negative in momentum strategies, but positive for size strategies and the non-smart-beta portfolio. The momentum factor is positive in smart-beta momentum strategies, but negative for all other models. This is what one would expect from momentum strategies. The strategy loads on the momentum factor to exploit it.

Concluding, the results suggest that loading on one factor, e.g., momentum, influences each's stock weight in a way that it generates negative effects from other factors. More precisely, by simply focusing on one factor, smart-beta strategies generate weights that - should - exploit this factor. However, the weights might damage the performance by ”misloading” on other factors. For example, a loading on momentum could generate weights that load on ”big” stocks, which ultimately hurts the performance of the size factor (small minus big). Smart-beta imposes negative spillovers on disregarded factors.

4.2.4 Limitations

In this section, I want to summarise the major limitations I see in this study. This gives rise to various possibilities for further research.

First, my study has a strong regional focus. I center my results around the industrialized western world. However, I suppose social norms to play a crucial role in explaining my results in the context of sin stocks. Thus, I suggest further research to extend this study to other markets.

Second, my study is based on a small set of factors that should be extended. Using the whole universe of factors could provide further insights in explaining the anomaly, and the factor loadings explaining it. Future research could aim to further specify the factors that significantly influence excess returns.

Third, I explore the sin stock anomaly. I suppose that the approach I followed could be extended to other anomalies. This might resolve existing anomalies and explain them through different factor loadings. Extending the study to other anomalies might provide further insights in constructing a trading strategy that efficiently exploits factor loadings.

Lastly, I do not incorporate behavioral factors. Sin stocks are likely to be subject to behavioral biases. Investors that have a strong aversion against sin industries might shun them excessively. Personal preferences might influence investors, and thus, the performance of the stock. It would be interesting to examine if and how extensively behavioral factors play a role in sin stocks.

5 Multifactorial Smart-Beta

Resulting from the negative spillovers on other factor loadings, I construct a new smart-beta strategy. The aim of the strategy is to load on several factors instead of one, and thus, decreasing the risk resulting from misloading.

I construct a portfolio that combines smart-beta momentum and size strategies. First, I calculate weights for both factors as before. Next, I build the average weight for each stock. Finally, I calculate the portfolio returns using the average weights. In this case, I only used two factors. However, I suppose that investors should include more. Another drawback in my portfolio is the daily rebalancing. It is difficult to examine, which rebalancing strategy works best in a mixed factor portfolio. For simplicity, I assume absence of trading costs.

In my mixed portfolio, I use all stocks from the S&P 500. I do not impose any weight restriction. The mixed portfolio generates a Sharpe ratio of 0.02. Portfolio 13 (Momentum) and 15 (Size) serve as comparable portfolios as they are constructed using all stocks from the S&P 500 without any weight restriction as well. However, these portfolios are constructed using specific rebalancing strategies to account for trading costs. Thus, I build a second version assuming absence of trading costs. Consequently, I rebalance daily. The comparable portfolios generate a Sharpe ratio of -0.01, and 0.05 respectively. The differences between the Sharpe ratio of the combined and the comparable portfolios is insignificant.

Nonetheless, there is the clear tendency that a multifactorial smart-beta strategy reduces the risk arising from the loading of solely loading on one factor. The strategy balances the strategies. By adding more factors, this effect could be amplified. On the other hand, the Sharpe ratio of the combined portfolio does not outperform the market. Again, this questions the overall profitability of smart-beta strategies.

The strategy requires further research. My portfolio is unrealistic as it assumes the absence of trading costs. This is not plausible and should be further examined. Future research could aim to find optimal rebalancing strategies in a multifactorial smart-beta environment. Another drawback is the focus on the S&P 500. My results might be biased by its strong regional focus. Thus, I see avenues for further research applying the method to other geographic areas.

6 Conclusion

My results provide further evidence that simple smart-beta strategies do not work as intended, because they generate performance hurting loadings on disregarded factors. Additionally, I can show that there is no significant effect of sin stocks in a mix of active and passive trading strategies - namely smart-beta.

Moving on, my results show that the sin stock anomaly can be explained by a simple extension of the Fama-French five factor model. The study shows that the sin stock anomaly depends on different factor loadings - the Fama-French five factor model factors, a betting-against-beta factor, a momentum factor, and a volatility factor. The strongest effect arises from the volatility factor. I suppose that this could be further specified. Using the paper of Blitz et al. [Swade et al., 2023] one could check the whole universe of factors [Hsu and Kalesnik, 2014]. This could also be done for other anomalies.

In a next step, I started to work on trading strategies that might arise from the opportunity of exploiting the factor zoo. With a further specification of relevant factors from the factor zoo, I see a lot of potential for further research. As shown, smart-beta strategies that focus on one factor do not work in my sample. They have negative spillovers on the loadings on other factors. I propose that research could aim to construct multi factor smart-beta models. In this way, I see potential to capture abnormal returns from more than just one factor, or at least prevent hurtful loading on not intended factors. Such strategies could aim to reduce the risk of smart-beta strategies and conceptually follow Amenc and Goltz [Amenc and Goltz, 2013]. Considering my work, such strategies could assign scores to each stock for all factors. In the next step, I would aggregate all scores to a total score and calculate weights based on this total. The selection of factors is crucial and an important challenge is to find an optimal rebalancing strategy. E.g., momentum requires monthly rebalancing, whereas size requires yearly rebalancing.

Additionally, I see avenues for further research by changing the geographical focus. My study looks at the US and Europe. However, there might be differences within European countries. Furthermore, it would be interesting to look at Asia or developing countries. In this way research could capture regions with different cultural norms. I did not add a total for the world (e.g., MSCI World) because I would assume that it closely follows my results for the US. However, it would be interesting to verify this.

7 Appendix

Table 11: Variables

Variable Name	Variable Type	Variable Description	Variable Source	Reference
Excess Returns	Dependent	Excess Returns of the constructed portfolios	Self-constructed	[Blitz and Fabozzi, 2017]
MRP	Explanatory	Market Risk Premium	Kenneth French (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)	[Blitz and Fabozzi, 2017]
SMB	Explanatory	Small minus Big: The factor is constructed by going long on "small" stock portfolios and short on "big" stock portfolios. Size is measured by Market Capitalization.	Kenneth French (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)	[Blitz and Fabozzi, 2017]
HML	Explanatory	High minus Low: The factor is constructed by going long on value portfolios and short on growth portfolios. Value is measured by the book-to-market ratio.	Kenneth French (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)	[Blitz and Fabozzi, 2017]
RMW	Explanatory	Robust minus Weak: The factor is constructed by going long on robust operating profitability portfolios and short on weak operating profitability portfolios. Operating profit is calculated as Gross Profit minus Operating Expenses minus Depreciation minus Amortization.	Kenneth French (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)	[Blitz and Fabozzi, 2017]
CMA	Explanatory	Conservative Minus Aggressive: The factor is constructed by going long on conservative investment portfolios and short on aggressive investment portfolios.	Kenneth French (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)	[Blitz and Fabozzi, 2017]
BAB	Explanatory	Betting against Beta: The factor is constructed by going long on low beta stocks and short on high beta stocks.	https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Daily	[Frazzini and Pedersen, 2014, Blitz and Fabozzi, 2017]
MOM	Explanatory	Momentum: The factor is constructed by going long on prior higher earning stocks and low on prior lower earning stocks.	Kenneth French (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)	[Tai, 2003]
VOL	Explanatory	Volatility: The factor is constructed by going long on a prior low volatility portfolio and short on a prior high volatility portfolio.	Self-constructed	[Racicot and Théoret, 2009]

References

[Alessandrini and Jondeau, 2020] Alessandrini, F. and Jondeau, E. (2020). Esg investing: From sin stocks to smart beta. *The Journal of Portfolio Management*, 46(3):75–94.

[Amenc and Goltz, 2013] Amenc, N. and Goltz, F. (2013). Smart beta 2.0. *The Journal of Index Investing*, 4(3):15–23.

[Ardia and Boudt, 2013] Ardia, D. and Boudt, K. (2013). The peer performance of hedge funds. *Cahier de recherche/Working Paper*, 13:29.

[Ardia and Boudt, 2015] Ardia, D. and Boudt, K. (2015). Testing equality of modified sharpe ratios. *Finance Research Letters*, 13:97–104.

[Ardia and Boudt, 2018] Ardia, D. and Boudt, K. (2018). The peer performance ratios of hedge funds. *Journal of Banking & Finance*, 87:351–368.

[Arnott et al., 2023] Arnott, R. D., Li, F., and Linnainmaa, J. T. (2023). Smart rebalancing. *Available at SSRN*.

[Benhamou et al., 2019] Benhamou, E., Saltiel, D., Guez, B., and Paris, N. (2019). Testing sharpe ratio: luck or skill? *arXiv preprint arXiv:1905.08042*.

[Blitz and Fabozzi, 2017] Blitz, D. and Fabozzi, F. J. (2017). Sin stocks revisited: Resolving the sin stock anomaly. *The Journal of Portfolio Management*, 44(1):105–111.

[Blitz and Swinkels, 2020] Blitz, D. and Swinkels, L. (2020). Is exclusion effective? *The Journal of Portfolio Management*, 46(3):42–48.

[Blitz and Swinkels, 2021] Blitz, D. and Swinkels, L. (2021). Does excluding sin stocks cost performance? *Journal of Sustainable Finance & Investment*, pages 1–18.

[Fabozzi et al., 2008] Fabozzi, F. J., Ma, K., and Oliphant, B. J. (2008). Sin stock returns. *The Journal of Portfolio Management*, 35(1):82–94.

[Frazzini and Pedersen, 2014] Frazzini, A. and Pedersen, L. H. (2014). Betting against beta. *Journal of financial economics*, 111(1):1–25.

[Hong and Kacperczyk, 2009] Hong, H. and Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of financial economics*, 93(1):15–36.

[Hsu and Kalesnik, 2014] Hsu, J. and Kalesnik, V. (2014). Finding smart beta in the factor zoo. *Research Affiliates (July)*.

[Jacobs and Levy, 2019] Jacobs, P. D. and Levy, K. N. (2019). *Smart beta versus smart alpha*. SSRN.

[Jagannathan et al., 1995] Jagannathan, R., McGrattan, E. R., et al. (1995). The capm debate. *Federal Reserve Bank of Minneapolis Quarterly Review*, 19(4):2–17.

[Ledoit and Wolf, 2008] Ledoit, O. and Wolf, M. (2008). Robust performance hypothesis testing with the sharpe ratio. *Journal of Empirical Finance*, 15(5):850–859.

[Li et al., 2019] Li, F., Chow, T.-M., Pickard, A., and Garg, Y. (2019). Transaction costs of factor-investing strategies. *Financial Analysts Journal*, 75(2):62–78.

[Lobe and Walkshäusl, 2016] Lobe, S. and Walkshäusl, C. (2016). Vice versus virtue investing around the world. *Review of Managerial Science*, 10:303–344.

[Malkiel, 2014] Malkiel, B. G. (2014). Is smart beta really smart? *The Journal of Portfolio Management*, 40(5):127–134.

[Muralidhar, 2015] Muralidhar, A. (2015). The sharpe ratio revisited: what it really tells us. *Journal of Performance Measurement*, 19(3).

[Racicot and Théoret, 2009] Racicot, F.-E. and Théoret, R. (2009). Integrating volatility factors in the analysis of the hedge fund alpha puzzle. *Journal of Asset Management*, 10:37–62.

[Salaber, 2007] Salaber, J. M. (2007). The determinants of sin stock returns: Evidence on the european market. In *Paris December 2007 Finance International Meeting AFFI-EUROFIDAI Paper*.

[Sharpe, 1998] Sharpe, W. F. (1998). The sharpe ratio. *Streetwise–the Best of the Journal of Portfolio Management*, 3:169–85.

[Statman and Glushkov, 2009] Statman, M. and Glushkov, D. (2009). The wages of social responsibility. *Financial Analysts Journal*, 65(4):33–46.

[Swade et al., 2023] Swade, A., Hanauer, M. X., Lohre, H., and Blitz, D. (2023). Factor zoo (. zip). *Available at SSRN*.

[Tai, 2003] Tai, C.-S. (2003). Are fama–french and momentum factors really priced? *Journal of Multinational Financial Management*, 13(4-5):359–384.