Aalto University
School of Business

Smart Beta, Foolish Alpha

The twisted relationship between crowdedness and Smart Beta ETF returns

Bachelor’s Thesis
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Finance
Spring 2021

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Abstract of bachelor's thesis

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Title of thesis Smart Beta, Foolish Alpha – The twisted relationship between crowdedness and Smart Beta ETF returns

Degree Bachelor's degree

Degree programme Finance

Thesis advisor Juha Joenväärä

Year of approval 2021 **Number of pages** 23 **Language** English

Abstract

This thesis examines how the performance of Smart Beta ETFs corresponds to crowdedness as a measure of accumulated fund flow. I begin with providing empirical evidence on the negative and statistically significant relationship between Smart Beta ETF returns and crowdedness by constructing two separate models. I find that Smart Beta ETFs are currently generating -0.4% CAPM Alpha on average to investors and that different Smart Beta strategies exhibit varying sensitivities against crowdedness. My findings suggest that Smart Beta ETFs are inferior investment vehicles, and they provide no additional value to investors as a whole, other than their exceptional diversification benefits. Furthermore, the variation of sensitivities against crowdedness across strategies implies, that strategies are not universally affected by capacity constraints.

Keywords Smart Beta ETFs, Crowdedness, Alpha, ARP, Capacity constraints

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1 INTRODUCTION

In the midst of the growing relevance of Exchange Traded Funds (ETFs), one can observe a pervasiveness of “Smart Beta” products. Smart Beta refers to strategies exposing capital against systematic risk factors that affect the covariance structure of random financial assets. With the objective to harvest the associated return premia, also known as alternative risk premia (ARP), these risk factors function as alternatives to the traditional market index – hence the name ‘alternative’. The prevalence of ARP has heavily increased throughout the past two decades. The above is true both in the world of investing as well as in academia, and experts expect the demand for ARP to further increase. In a survey completed by J.P. Morgan in 2019, 36% of global institutional investors reported to having invested or planning to invest in alternative risk premia. The period of Covid-19 will remain an outlier in the observations of ARP performance and it is still unclear what its impact will be on the demand for ARP. Moreover, ARP failed miserably in the first half of 2020, but in contrast exhibited more moderate losses compared to equities (Clark & Sommers, 2020).

An investor can capture the premia implied by the risk factor exposure through a careful diversification of assets that entail a certain sensitivity against a given systematic component (the factor). In most factor strategies, investors are required to conduct dynamic adjustment of their portfolio in order to maintain the exposure against the systematic component. In practice, this adjustment can be very expensive and time consuming, and beyond the reach of small investors. Smart Beta ETFs provide a solution to the aforementioned problem.

Smart Beta ETFs are exchange traded funds which are by nature both active and passive. We can consider them active in the sense that the fund’s constituents are continuously readjusted in order to accurately track a given strategy. However, they are passive in the sense that the strategies are based on given sets of principles and rules, making the strategies transparent and replicable. When we take into consideration the transaction costs and required resources associated with these strategies, replication often becomes fruitless. Smart Beta ETFs replicate these strategies on behalf of investors and in essence function as convenient vehicles that provide investors with exposure to systematic components.

It is no secret, that the performance of Smart Beta has not been able to meet investor expectations since its inception (Arnott et al., 2020). However, in addition to the disappointing initial performance of newly listed Smart Beta ETFs, research has observed a continued deterioration of CAPM Alpha offered by factor strategies (McLean & Pontiff, 2015; Jones & Pomorski, 2016; Baltas, 2019; Huang, Liu & Zhu, 2020; Pénasse, 2020). This phenomenon is often referred to as Alpha Decay.

The forces behind Alpha Decay are not entirely understood due to the randomness that it exhibits (Jones & Pomorski, 2016). Some research claims that Alpha Decay is attributable to structural uncertainty and investor irrationality (Brav & Heaton, 2002), whereas some associate it with capacity constraints of strategies being exhausted by crowdedness (Arnott et al., 2019; Baltas, 2019). This paper will examine the suitableness of the latter in the context of Smart Beta ETFs. Along with the growing demand for Smart Beta ETFs, increasingly greater volumes of funds are channeled into approximately the same strategies and trades. With the hypothesis that this fund flow causes price pressure on the constituent components of factor strategies, I will explore the impact of crowdedness on the return that Smart Beta ETFs are able to generate. That said, I pose the following research question: *"What is the impact of crowdedness on the excess returns provided by Smart Beta ETFs?"*

I delineate the aggregate returns generated by an AUM-weighted portfolio of all available Smart Beta ETFs. I call this portfolio the Smart Beta Index (hereafter SBI). By running a regression on the CAPM Alpha (hereafter Alpha) of the SBI against the measure of crowdedness, I find a statistically significant result that indicates a negative relationship between SBI Alpha and crowdedness. The SBI considers all asset classes. In this paper, crowdedness is measured as the net value of all accumulated funds channeled into the SBI from $t = 0$ to $t = n$. Furthermore, I control for two other independent variables with a proven impact on systematic risk premia: quantitative easing and the Great Financial Crisis. My results show that the current level of crowdedness has exhausted the SBI's ability to generate positive Alpha. Hence Smart Beta strategies are implied to exhibit capacity constraints.

To thoroughly address the aforementioned research question, I further examine whether the impact of crowdedness is universal across the four factor strategies with the highest AUM by applying the same methodology for each strategy as I do for the SBI. I compare the behavior of the four strategies with respect to crowdedness and find that they correspond to crowdedness with varying sensitivities. These findings are consistent with previous literature associated to ARP.

The Smart Beta segment in the ETF marketplace is expected to grow considerably in the near future. BlackRock has projected that AUM within the segment will reach $2.4Tn by the year 2025 (Business Wire, 2016). Comparing this projection with the $1.4Tn AUM at the time of writing, the growth can be considered substantial. This expected growth highlights the relevance of my research. If crowdedness and the subsequent price pressure exhausts factor strategies' capacity to generate return, investors should approach Smart Beta products with caution.

2 THEORETICAL BACKGROUND

My research examines the relationship between fund flow as a measure of crowdedness and the CAPM Alpha of Smart Beta ETFs. To the extent of my awareness, this is the first paper to examine this relationship. I identify two relevant implications of the results of my research: 1) they help to determine whether Smart Beta ETFs are currently able to provide any additional value to investors; 2) they provide support to prior research surrounding capacity constraints and studies claiming that crowdedness exhibits predictability over Alpha Decay. That said, this paper is mainly related to two sections of literature.

2.1 Smart Beta Exchange Traded Funds and Factor Investing

The popularity of Smart Beta ETFs can largely be explained by two features. Firstly, some factor strategies have exhibited exceptionally attractive backtesting results. For example, when the momentum strategy was first documented, Jegadeesh and Titman (1993) observed the six-month momentum strategy generating an average monthly Alpha of about 1% in the period of 1965 and 1989. Secondly, Smart Beta ETFs provide favorable diversification opportunities in portfolio construction. The Capital Asset Pricing Model (CAPM) quantifies an investment's exposure (Beta) against the market and determines the expected equity risk premium associated with it. A similar logic can be applied to other deterministic factors associated with return premia. The accessibility of exposure to discovered factors has provided investors the opportunity to freely choose which systematic components they wish to have an effect on the covariance structure of their portfolios.

Conventional examples of popular factor strategies associated with return premia are Value and Momentum strategy. Beyond these two, the selection of discovered factors associated with return premia is very wide. Harvey and Liu (2019) document over 400 different factors that have been published in prestigious scientific journals. They expect the number to further increase in the future. Many of the identified factors are unquestionably false, as a fraction of statistically significant results are observed by chance. Literature typically claims results significant with p-values at the 5% level, and we end up observing a considerable number of Type 1 errors (rejection of a true null hypothesis). The frequent observation of Type 1 errors is especially true considering the incentive for data mining among academic researchers (Arnott et al., 2016). Significant results are cited more often by academic journals, and as factor strategies are evaluated according to their backtesting results, researchers tend to experiment with data until they attain the desired outcome (Harvey and Liu, 2019). When fund managers adopt these strategies with seemingly favorable historical performance, they attract substantial volumes of funds from investors. Exaggerated investor expectations often cause disappointment as the published factor strategies are applied in practice.

My research directly contributes to the literature surrounding Smart Beta, especially that in which it is applied to ETFs. Prior research suggests that the factor index Alphas turn negative quickly after Smart Beta ETF listings (Huang, Song, and Xiang, 2020). My findings support the results of Huang, Song, and Xiang in that the market-adjusted return on Smart Beta indexes are currently in negative territory. Arnott et al. (2016) provide a theory according to which Smart Beta ETFs have failed to meet investor expectation as a consequence of inflated valuation ratios in the factor strategies' constituent assets. My paper examines the effect of crowdedness on the performance of Smart Beta strategies and supports the hypothesis of Arnott et al. in that demand for Smart Beta and the subsequent price pressure deteriorates available returns. I contribute to this section of literature by deciphering the precise sensitivity of crowdedness on the excess return of Smart Beta strategies.

2.2 Capacity Constraints

As return generating strategies and assets are able to provide only a given stream of returns to investors, they entail a limited capacity at which they can do so. Capacity constraints curb the extent to which investors can benefit from investment opportunities. Berk & Green (2004) recognize that accumulated funds function as a benchmark with which to estimate performance of mutual funds. They observe a strong relationship between the two and imply the occurrence of deteriorating return as a consequence of investor demand. Under the Efficient Market Hypothesis, an investment's capacity would only be exhausted so far as its risk-adjusted excess return approximates zero.

McLean and Pontiff (2015) suggest that the publication of variables exhibiting return-predictability informs investors of mispricing, causing these variables to be overexploited and to lose their ability to predict return. This phenomenon corresponds to Berk and Green's (2004) model in which managers attract investor funds based on published anomalies and subsequently arbitrage favorable strategies away. The deterioration of the excess return is often referred to as Alpha Decay. The logic behind Alpha Decay is very intuitive, as it is consistent with the core principles of the Efficient Market Hypothesis (Lo, 2007). However, the performances of factor strategies have continuously challenged the scientific consensus over efficient markets. For example, the Momentum strategy assumes the role of anecdotal evidence against market efficiency. Despite the discovery and the increased demand for the superior performance of Momentum, its Alpha did not subside until a Momentum crash much later on (Kent & Moskowitz, 2016). Therefore, the research associated to factor investing has attracted academics and been vigorous due to the observed irregularities of different factor strategies' capacity constraints.

This paper implements multiple aspects of literature surrounding capacity constraints and contributes to it by supporting prior findings. Similar to Pénasse (2020), my results provide a model of predictability over Alpha Decay, although it is applied in the narrow context of Smart Beta ETFs. I have derived particular inspiration from Baltas' (2019) paper in which he studies the response of ARP to crowded periods. He applies a price-based valuation method to measure the level of crowdedness and finds variation in the behavior of different factors strategies. My results on the variability of crowdedness sensitivity across factor strategies is consistent with Baltas' findings. I chose to apply fund flow as a measure of crowdedness, as I believe it exhibits a more accurate estimate on the exhaustive effect of increased investor demand.

3 DATA AND METHODOLOGY

3.1 Data sources and the Smart Beta Index

The purpose of this study is to clarify the impact of crowdedness on the excess return of Smart Beta ETFs. I form a model in which I use the measure of crowdedness to predict the expected Alpha of a dollar invested in any given Smart Beta ETF. I attain more accurate estimates as I control the model for two components which have been proven to have an impact on systematic risk premia: quantitative easing (Balatti et al., 2016) and the Great Financial Crisis (Sullivan, 2020). To form comprehensive observations of Smart Beta strategy performance, I construct an AUM-weighted portfolio of all listed Smart Beta ETFs globally, including obsolete funds in historical data. I call this portfolio the *Smart Beta Index* (SBI). The SBI tracks the value-weighted average return that Smart Beta ETFs have generated to investors at large. I obtain the monthly Alpha of the SBI over a 20-year period from January 2001 to December 2020. 'Alpha' in this study refers to that obtained with the Capital Asset Pricing Model (CAPM).

The data used in this study has been retrieved from multiple sources. The complete set of data related to Smart Beta ETFs has been obtained from *Morningstar Direct* (2.3.2021). The data qualities included are the *monthly return* and the *net value of assets under management* (AUM) in the beginning of each month within the timeframe of January 2000 to December 2020 of all active and obsolete Smart Beta ETFs. The data has not been trimmed or edited in any way. The first year (January 2000 to December 2000) is not included in the actual regression model and is only used to configure an accurate market Beta for the Smart Beta Index (SBI). With an appropriate market Beta, I use the standard Capital Asset Pricing formula to calculate the monthly Alpha observations of the SBI:

$$\alpha_{SBI,t} = R_{SBI,t} - \beta_{SBI,t}\left(R_{m,t} - R_{rf,t}\right) - R_{rf,t}$$

$$\beta_{SBI,t} = \frac{cov\left(R_{SBI,t=0:n}, R_{m,t=0:n}\right)}{var(R_{m,t=0:n})}$$

in which…

$R_{SBI,t}$ is the return on the SBI index during month *t*,

$\beta_{SBI,t}$ is the market Beta of the SBI with data from $t = 0$ to the measured month $t = n$,

$R_{m,t}$ is the market return during month *t*,

$R_{rf,t}$ is the risk-free return during month *t*.

The observations for market return and risk-free return have been obtained from the *Kenneth R. French data library* (2.3.2021).

3.2 Crowdedness

In this study, I measure the level of crowdedness as the accumulated net flow of funds channeled into Smart Beta from month $t = 0$ to month $t = n$. I have computed the net fund flow, $Flow_t$, of all months from January 2001 to December 2020 followingly:

$$Flow_{SBI,t} = AUM_{SBI,t+1} - AUM_{SBI,t}(1 + R_{SBI,t})$$

in which…

$AUM_{SBI,t+1}$ is the total value assets under management within the Smart Beta Index in the beginning of month $t + 1$,

$AUM_{SBI,t}$ is the total value of assets under management within the Smart Beta Index in the beginning of month t,

$R_{SBI,t}$ is the return on the Smart Beta Index during month t.

When I obtained the monthly net fund flow, I calculated the level of crowdedness, $C_{SBI,t}$, for each month, which can be expressed followingly:

$$C_{SBI,t=n} = \frac{\sum_{t=0}^{n} Flow_{SBI,t}}{1000^4}$$

I divide the aggregate net fund flow with 1000^4 (1Tn). The division does not affect the results in any way and serves no other purpose than to support the comprehensibility of coefficients.

It is important to differentiate the concepts of crowdedness and AUM: the changes in AUM are to a large extent attributable to the performance of the index and thus do not exhibit an exhaustive effect on available returns; net inflow of funds, however, causes additional pressure on the fund to generate return, thus providing more suitable properties as a measure of crowdedness.

3.3 Model

The basic idea of my model is to regress the observed Alpha, $\alpha_{SBI,t}$, against the measure of crowdedness, $C_{SBI,t}$, at time *t*. The first regression model can be expressed followingly:

$$\alpha_{SBI,t} = \alpha_0 + \beta_C C_{SBI,t} + \varepsilon_{SBI,t} \tag{1.1}$$

in which…
α_0 is the initial Alpha provided by the SBI (when $C_{SBI,t} = 0$),
β_C is the impact of the independent variable $C_{SBI,t}$ on the dependent variable $\alpha_{SBI,t}$,
$\varepsilon_{SBI,t}$ is the noise term of the ordinary least square (OLS) regression.

I further include the effect of the Great Financial Crisis, GFC, and the independent variable of quantitative easing, QE_t, in the regression. I measure the level of quantitative easing according to the size of the Federal Reserve's balance sheet at time *t*, divided by 1000^4 (applying the same reasoning as in $C_{SBI,t}$). The data on the Federal Reserve's balance sheet has been retrieved from *Fred Economic Data, St. Louis* (2.3.2021). Because the aforementioned data set only includes observations from January 2003 forward, all regressions including the QE_t variable are regressed with data from January 2003 forward. For the purposes of this study, I do not consider it necessary to include variables associated with quantitative easing by central banks in other regions, as the majority of Smart Beta ETFs are mainly exposed to the US equity markets. Furthermore, as quantitative easing across central banks globally is highly correlated with each other, the omitted variable bias is minimal. GFC is added as a dummy variable, with $GFC = 0$ representing the period before January 2009 (January 2000-December 2008), and $GFC = 1$ representing the period after (January 2009-December 2020). The logic behind the severance-point is to clearly distinguish the two periods. When the above variables are in turn included, the model take the following forms:

$$\alpha_{SBI,t} = \alpha_0 + \beta_C C_{SBI,t} + \beta_{GFC} GFC + \varepsilon_{SBI,t} \tag{1.2}$$

$$\alpha_{SBI,t} = \alpha_0 + \beta_C C_{SBI,t} + \beta_{GFC} GFC + \beta_{QE} QE_t + \varepsilon_{SBI,t} \tag{1.3}$$

It is important to inspect regressions 1.2 and 1.3 separately, as the high correlation (0.91) of the independent variables QE_t and $C_{SBI,t}$ causes multicollinearity in the model, thus resulting in less precise estimates of the coefficients β_C and β_{QE}. I do not examine the estimate of β_{QE} in the absence of $C_{SBI,t}$, because QE_t is not the focus of this study.

As the Alpha observations are very noisy, I smooth the data by reconfiguring Alpha at time *t* as the 24-month forward average during $[t + 1; t + 24]$. Model 2 regresses the 24-month average against the relevant variables. The benefits of reconfiguration are two-fold: it leaves room for the delayed effect of changes in crowdedness and quantitative easing at time *t* and reduces the effect of the dependent variable's deviation from the trend. The objective of Model 2 is to model the predictability of return deterioration. The Model 2 regressions can be expressed followingly:

$$\alpha_{SBI,t+1:t+24} = \alpha_0 + \beta_C C_{SBI,t} + \varepsilon_{SBI,t} \tag{2.1}$$

$$\alpha_{SBI,t+1:t+24} = \alpha_0 + \beta_C C_{SBI,t} + \beta_{GFC} GFC + \varepsilon_{SBI,t} \tag{2.2}$$

$$\alpha_{SBI,t+1:t+24} = \alpha_0 + \beta_C C_{SBI,t} + \beta_{GFC} GFC + \beta_{QE} QE_t + \varepsilon_{SBI,t} \tag{2.3}$$

3.4 Subcategorization

The listing company reports the strategy which the Smart Beta ETF attempts to track. I used this information to categorize all the listed ETFs globally into seven categories: Value, Growth, Quality, Momentum, Dividend-oriented, Risk-oriented, and Other. In this study, I further examine whether the decay of Alpha is universal across the four strategies with the highest AUM: Growth, Value, Momentum, and Quality. Dividend- and Risk-oriented strategies could be further divided into a wide variety of sub-categories. As the aforementioned subcategorization would have turned out to be very laborious, I decided not to examine the two characteristic-related strategies separately. I applied precisely the same methodology on the four strategies as for the SBI. First, I formed AUM-weighted portfolios of all available ETFs under each factor strategy, thus attaining four different indexes: Growth Index, Value Index, Quality Index, and Momentum Index. Upon attaining the monthly Alpha for each index within the 20-year period, I calculated the monthly levels of crowdedness attributable to each strategy in the same way as for the SBI. I then proceeded to apply the same models (1.1-1.3 & 2.1-2.3) previously introduced in chapter 3.3 for each index.

4 RESULTS

The research question of this paper is: *"What is the impact of crowdedness on the excess returns provided by Smart Beta ETFs?"* My hypothesis states that crowdedness measured as the net value of accumulated fund flow causes price pressure on the constituent components of factor strategies, thus deteriorating their available returns. The results of my research fully support this hypothesis. I have divided my regression analysis into two models: one that attempts to estimate the SBI Alpha at time *t* as a function of the independent variables $C_{SBI,t}$, GFC, and QE_t at time *t*; another that attempts to estimate the expected SBI Alpha within the period of $t+1$ until $t+24$ as a function of the same independent variables as in the first model. The reasoning behind this division is the following: the first model deciphers the extent to which SBI Alpha corresponds to crowdedness; the second model projects the expected decay of SBI returns by taking into consideration the delayed effect of the relevant independent variables. The results of these separate models have differing implications, both supporting a clear resolution to the research question. Therefore, in this chapter, I examine the results of the two models separately.

4.1 Model 1

The regression of $\alpha_{SBI,t}$ against $C_{SBI,t}$ provides insight on how SBI's excess return corresponds with the level of crowdedness. I report all relevant findings from models 1 in Table I. Model 1.1 exhibits a crowdedness Beta of $\beta_C = -0.59\%$, with a statistically significant p-value of 0.1%. The Beta implies that for every \$1Tn of funds channeled into the SBI, approximately 0.59 percentage points of available returns are wiped out. The aforementioned implication may not stand in the future, as the Beta could theoretically flatten over time. However, the available data to make any such inferences about the flattening of the crowdedness Beta is insufficient. The regression asserts the equation coefficient, α_0, a statistically insignificant value of 0.05%. Even within the 95% confidence interval (0.16% upper and -0.06% lower) the coefficient is virtually zero. Models 1.1-1.3 all imply, that Smart Beta ETFs are not able to generate CAPM Alpha even when the level of crowdedness approaches zero. As of 2.3.2021, the level of crowdedness was 0.67 (\$670Bn). Chart 1 demonstrates that $\alpha_{SBI,t}$ has fallen into negative territory and the SBI is capable of generating -0.40% risk-adjusted excess return at the time of writing.

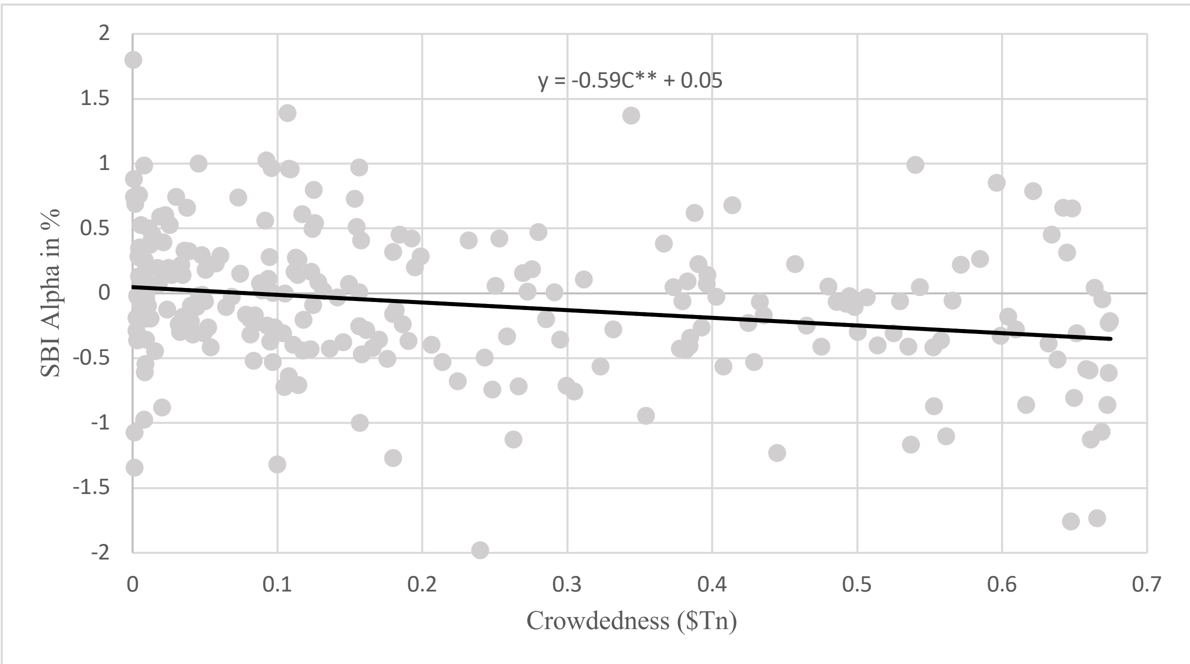


Chart1. The chart illustrates the SBI Alpha observations at the corresponding levels of crowdedness, as well as the associated OLS linear regression. Let *, **, and *** denote statistical significance at 5%, 1%, and 0.1% level, respectively.

The Beta for GFC is negative in model 1.2 as well as 1.3, but it turns statistically insignificant when QE_t is included in the model. The same applies for the level crowdedness, $C_{SBI,t}$. In model 1.3, QE_t explains most of the variation in $\alpha_{SBI,t}$. Balatti et al. (2016) provide empirical evidence from UK and US, which prove the inflationary effect of quantitative easing on the stock market. This could explain the negative relationship between quantitative easing and SBI Alpha in model 1: when the market return increases, the SBI Alpha decreases if we assume $R_m > R_{SBI}$.

There appears to be a direct linear relationship between the historical level of crowdedness and SBI returns. Some of the return deterioration is implied to be attributable to quantitative easing and the effect of the Great Financial Crisis. Although the SBI was never able to consistently generate positive CAPM Alpha, Smart Beta ETFs nonetheless attracted substantial volumes of funds – even when Alpha plunged below zero. I apply the findings of Huang, Song, and Xiang (2020) to explain this phenomenon. They claim that favorable factor strategy performance exists only in backtesting results and cannot be harvested in practice. The favorable historical performance lures more investor capital into these strategies – which do not outperform the market index in practice to begin with – causing returns to deteriorate even further. Kozak, Nagel and Santosh (2017) also provide a suitable exposition to my findings, attributing some of the decay to investor sentiment and the manifestation of mispricing as inflated valuations.

Table I

Smart Beta Index Alpha regressed against Crowdedness

Models 1 regress the SBI Alpha at month *t* against the relevant variables at month *t*. Models 1.1 and 1.2 include the complete 20-year set of data. Model 1.3 excludes data from before January 2003, as that is when the available Fed Balance Sheet data begins. Let *, **, and *** denote statistical significance at 5%, 1%, and 0.1% level, respectively.

Model	α_0	β_C	β_{GFC}	β_{QE}	R^2	Observations
1.1	0.05	-0.59**	-	-	0.04	252
	(0.83)	(-3.21)				
1.2	0.06***	-0.54***	-0.04*	-	0.66	252
	(6.23)	(-13.38)	(-2.07)			
1.3	0.11***	-0.04	-0.003	-0.063***	0.70	216
	(7.88)	(-0.46)	(-0.12)	(-4.01)		

4.2 Model 2

All relevant findings from models 2 are reported in Table II. The t-statistic for β_C remains very high throughout the models, supporting the validity of my original hypothesis. The p-values of β_C in models 2.1, 2.2, and 2.3 are all < 0.00001 (≈ 0). Significant t-statistics can be observed for β_{GFC} as well. The significance of QE reduces radically, as we regress the expected Alpha over the next 24-months instead of the observed Alpha during month *t*.

I find the accuracy of models 2 staggering. The coefficients are consistently statistically significant, and the models exhibit relatively fitting R^2 values. Chart 2 illustrates some of the development of $\alpha_{SBI,t+1:t+24}$ and the relevant variables $C_{SBI,t}$ and QE_t through time. One can clearly observe $\alpha_{SBI,t+1:t+24}$ falling into negative territory in the beginning of 2010. When controlling for QE, the negative relationship between crowdedness and SBI Alpha becomes evident. β_C in models 2.1 and 2.2 is comparable with that in models 1.1 and 1.2, respectively.

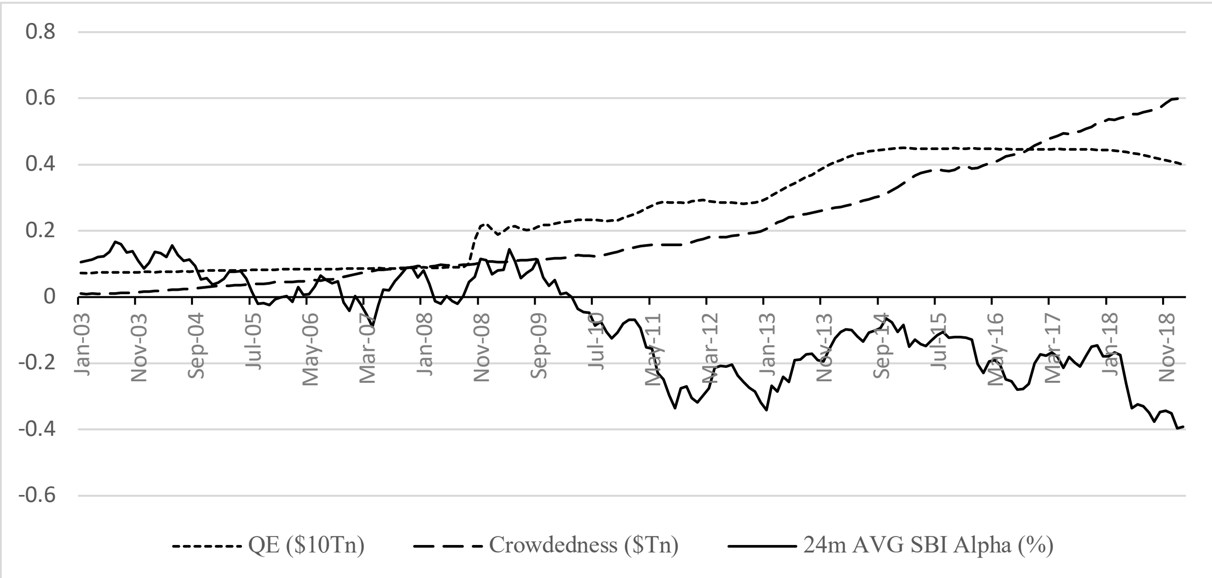


Chart 2. The chart illustrates the development of SBI Alpha (in units of %), the size of the Federal Reserve's Balance Sheet (in units of $10Tn), and the level of SBI crowdedness (in units of $1Tn) through time.

The results of models 2 imply a certain predictability of Alpha Decay and provide a measurement for the approximate trading capacity of the Smart Beta Index. The level of crowdedness has been increasing with an average of 46% annually within the past 20 years. Even if we apply the average annual growth within the past five years (11%) to project the level of crowdedness in 2025, we will observe a total decay of Alpha of -0.60%, according to model 2.3.

The cumulative value of assets under management within Smart Beta has been increasing with an annual average of 25% since January 2000, making it the fastest growing segment in the ETF marketplace. Of course, some of this increase can be attributed to the return that Smart Beta ETFs have generated over time. Currently, the SBI entails a total of $1.4Tn of AUM. Along with this trend, the number of listed Smart Beta ETFs started to fall in November 2019. These two trends conjoined imply a greater concentration of invested capital in approximately the same trades. Chart 3 illustrates the development of the number of listed Smart Beta ETFs and the total value of AUM within the SBI distributed according to designated strategy. A greater concentration would in turn intensify the deterioration of returns as a consequence of increased fund flow, if we assume my original hypothesis is correct. The growing demand for Smart Beta vehicles will only further deteriorate the returns that have already been below the market benchmark for almost a decade. My results all indicate towards the inferiority of Smart Beta ETFs and their failure to provide any additional value to investors.

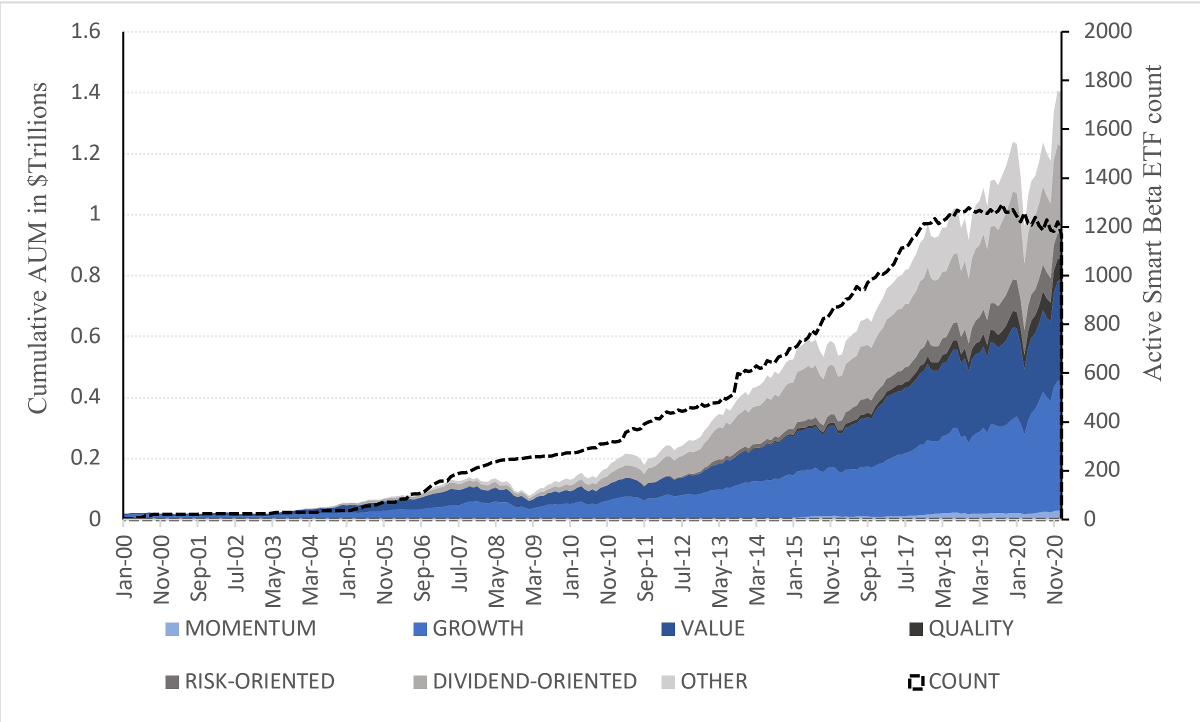


Chart 3. The chart illustrates the development of AUM within the SBI distributed according to designated strategy and the count of total active Smart Beta ETFs through time.

Table II

Smart Beta Index 24-Month Average Alpha regressed against Crowdedness

Models 2 regress the 24-month average SBI Alpha [t+1:t+24] against the relevant variables at month *t*. They exclude observations after January 2019, as the complete set of data ends in December 2020. Model 2.3 excludes data from before January 2003, as that is when the available Fed Balance Sheet data begins. Let *, **, and *** denote statistical significance at 5%, 1%, and 0.1% level, respectively.

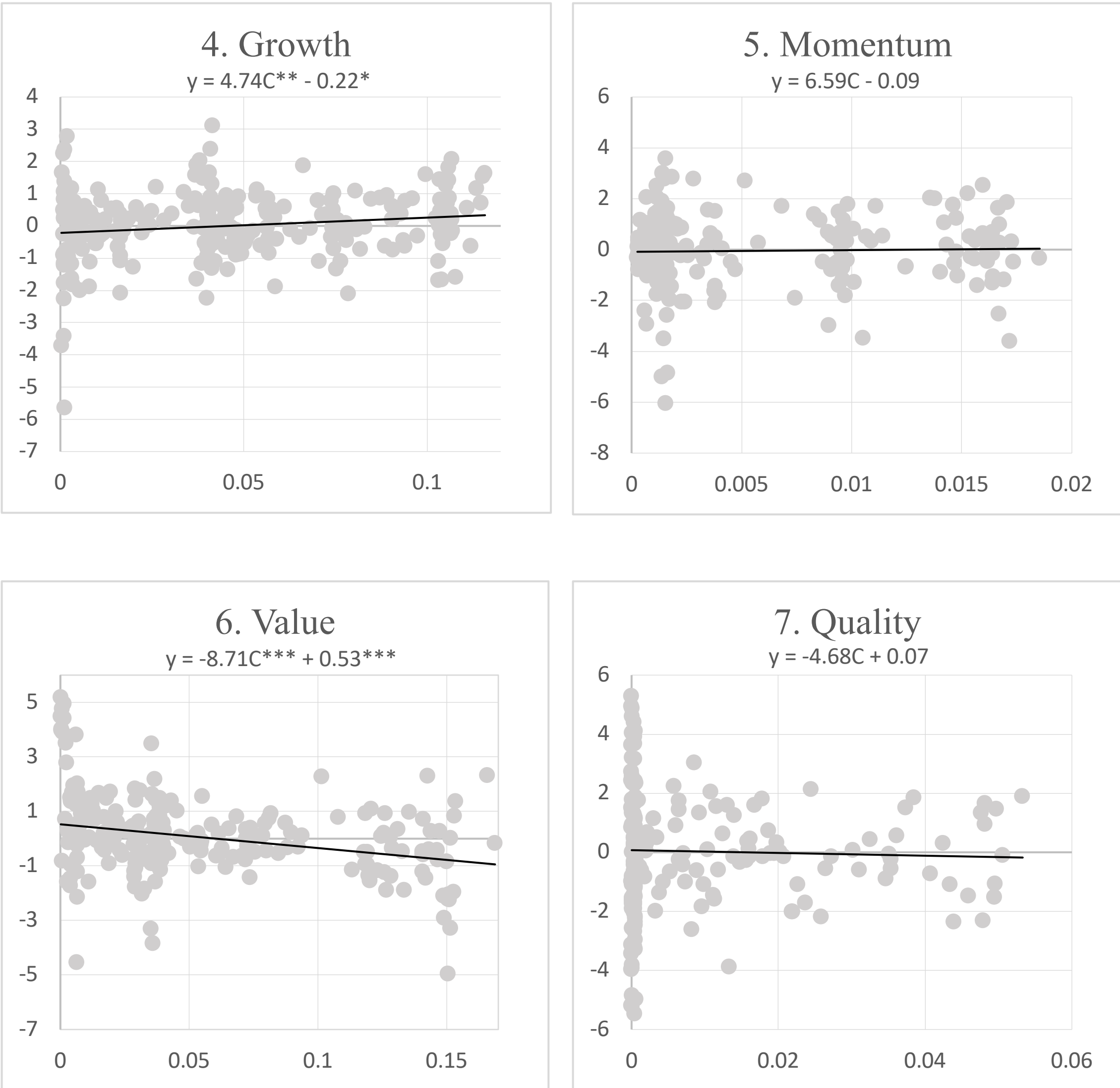
Model	α_0	β_C	β_{GFC}	β_{QE}	R^2	Observations
2.1	0.04***	-0.62***	-	-	0.62	228
	(4.06)	(-20.07)				
2.2	0.05***	-0.49***	-0.08***	-	0.64	228
	(5.43)	(-11.10)	(-4.04)			
2.3	0.06***	-0.53***	-0.14***	0.023	0.65	194
	(4.20)	(-5.52)	(-5.07)	(1.46)		

4.3 Growth, Value, Momentum, and Quality

My results from conducting model 1 and 2 regressions on the four different strategies are interesting. Their returns exhibit varying sensitivities against crowdedness. Whereas the Value and Quality strategy conveyed a negative tilt against crowdedness, Momentum and Growth were tilted positively. The model 2.3 crowdedness Betas for Growth, Momentum, Value, and Quality were 11.67%, 21.10%, -10.07%, -11.46%, respectively. Only Quality did not exhibit a 0.1% significance-level. Its insignificance can be explained by the fact that most of its observations correspond with a very low crowdedness, as its rise in popularity is rather recent. This leads to the majority of all observations being clustered very near the intercept. The result of factor strategies conveying varying sensitivities against crowdedness is in contradiction with my original hypothesis but is consistent with the findings of Baltas (2019).

The performance of Momentum strategy appears to be very periodic and is subject to sudden ‘momentum crashes’. Momentum crashes tend to be predictable (Kent and Moskowitz, 2016) and thus long position strategies exhibit depressed levels of crowdedness during periods close to Momentum crashes. Furthermore, indications of favorable performance are followed by periods of elevated levels of crowdedness. One can observe the clustering of Momentum

Alpha observations in three separate ranges of crowdedness in Chart 5. Perhaps this positive tilt is explained by the habit of investors channeling funds into the Momentum strategy during bullish periods and withdrawing funds during bearish periods, thus synthetically causing the relationship between crowdedness and Alpha to appear positive.



Charts 4, 5, 6, and 7. The charts illustrate model 1.1 applied to Growth, Momentum, Value, and Quality strategy and show the corresponding level of crowdedness for each observation of Alpha. Let *, **, and *** denote statistical significance at 5%, 1%, and 0.1% level, respectively.

The positive relationship between crowdedness and the Alpha of Growth strategy is surprising. It does not exhibit any other divergence of behavior compared to Value. Bollen et al. (2021) find that differentiation of fund strategy has historically indicated superior performance, as their returns exhibit investor sentimentality and are harvested as a consequence of continued mispricing. Perhaps Bollen et al. provide an explanation to the eccentric behavior of the Growth index in my analysis. Value and Quality appear to be consistent with my hypothesis, however. I found exceptionally significant and consistent estimates of crowdedness Beta associated to Value, with models 2 all conveying p-values of < 0.00001 (≈ 0). I have reported all relevant results associated with the four strategies in tables III, IV, V and VI in the Appendix.

5 DISCUSSION AND CONCLUSION

The results in this paper are fascinating. They break new ground in research related to Smart Beta ETFs, a relatively novel investment medium in the global marketplace that is expected to experience a substantial growth in the near future. As stated in chapter 2, the thesis has implications on two relevant branches of literature: Smart Beta exchange traded funds and factor investing, and capacity constraints. My results support previous research conducted on Smart Beta and factor investing and contribute to the literature by providing evidence on the relationship between ARP's excess return and crowdedness. I contribute to the literature surrounding capacity constraints by providing a model that illustrates the linear relationship between crowdedness and strategy performance.

The limitations of my study are few. Most limitations are related to the applied methodology in my paper. For example, I could have included more variables in my regression model. However, I did not consider ancillary variables necessary, as other recognized variables, such as Time and Inflation, were either insignificant or did not entail any theoretical substance. However, failure to recognize significant and relevant variables could cause the presence of unknown omitted variable bias.

The timeframe of the data set is only 20 years and it covers no more than a few market cycles. For more accurate results, one would have to examine a longer period. However, whereas the examined timeframe is finite, the examined population is comprehensive. The statistical tools used in this research could emanate minor inaccuracies in the computation of standard errors of estimators. Inaccuracies in standard errors would in turn affect the designated p-values. Even so, the precise values of estimates are correct, and I emphasize the economic significance of my results. To gain a higher level of reliability, I suggest the use of Newey-West estimators in potential replication of methodology.

All my findings imply that despite popular conception, the Smart Beta ETF segment was never capable of delivering any market-adjusted excess returns to investors to begin with. The favorable performance of factor strategies only exists in backtesting results but disappears immediately after the listing of ETFs associated to them (Huang, Song, and Xiang, 2020). The Efficient Market Hypothesis would assume that investors only involve themselves so far as the CAPM Alpha appears to hover near zero. Despite the nonexistent Alpha, investors have continued to plow more capital into Smart Beta strategies, thus causing excessive crowdedness in their constituents. My findings show with statistical significance that this crowdedness produces pressure on the available returns of factor strategies and causes deterioration of their performance. The growth of crowdedness has turned these strategies unprofitable and they generate a -0.40% Alpha to investors on average at the time of writing. As the segment is expected to grow substantially, my findings suggest that returns will deteriorate even further. Although it is no surprise that investors have been disappointed with the performance of Smart Beta ETFs, my findings validate their concern. This thesis encourages investors that are chasing returns to approach Smart Beta ETFs with caution. Although the premia are being washed away, investors could still gain value from these vehicles by utilizing their unparalleled diversification benefits (Asness, 2015).

The results of this thesis are consistent with theory relating to the phenomenon referred to as Alpha Decay. My models indicate that there appears to be a delayed effect of liquidity caused by quantitative easing and crowdedness on the returns of factor strategies. This delay in turn suggests the predictability of Alpha Decay, which could theoretically be utilized as a coefficient in the pricing of assets affected by it. The empirical consistency of Alpha Decay in the SBI could perhaps imply trading capacities related to other investment vehicles and strategies. Further research could explore the applicability of this decay beyond the scope of Smart Beta.

I further find that strategies within the SBI correspond to crowdedness with varying sensitivities. Momentum and Growth strategy are positively related to crowdedness, whereas Value and Quality were negatively so. This is surprising, as a positive tilt contradicts my original hypothesis. However, the variability of crowdedness Beta across strategies is consistent with prior research related ARP (Baltas, 2019). This result could imply that Alpha Decay and capacity constraints do not affect all strategies universally. I suspect that the slightly positive tilt of Momentum is synthetically manufactured by investor behavior in light of predictability. The eccentricity of Growth could be explained by continued mispricing as a consequence of fund differentiation. Perhaps the variability of sensitivities against crowdedness bears fruit for future research.

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7 APPENDIX

Table III

Growth Index absolute and 24-month average Alpha regressed against Crowdedness

Models 1 regress the Growth Index Alpha at month *t* against the relevant variables at month *t*. Models 2 regress the 24-month average Growth Index Alpha [t+1:t+24] against the relevant variables at month *t*. They exclude observations after January 2019, as the complete set of data ends in December 2020. Model 2.3 excludes data from before January 2003, as that is when the available Fed Balance Sheet data begins. Let *, **, and *** denote statistical significance at 5%, 1%, and 0.1% level, respectively.

Model	α_0	β_C	β_{GFC}	β_{QE}	R^2	Observations
1.1	-0.22*	4.74**	-	-	0.03	250
	(-2.01)	(2.53)				
1.2	-0.22*	4.79	-0.005	-	0.03	250
	(-1.99)	(1.51)	(-0.02)			
1.3	-0.10	8.17	0.11	-0.012	0.03	215
	(-0.89)	(1.91)	(0.50)	(-1.27)		
2.1	-0.10***	3.10***	-	-	0.22	226
	(-5.39)	(8.01)				
2.2	-0.10***	6.30***	-0.24***	-	0.33	226
	(-5.76)	(9.97)	(-6.15)			
2.3	-0.01	11.67***	-0.02	-0.018***	0.51	226
	(-0.63)	(13.79)	(-0.55)	(-8.95)		

Table IV

Momentum Index absolute and 24-month average Alpha regressed against Crowdedness

Models 1 regress the Momentum Index Alpha at month *t* against the relevant variables at month *t*. Models 2 regress the 24-month average Momentum Index Alpha [t+1:t+24] against the relevant variables at month *t*. They exclude observations after January 2019, as the complete set of data ends in December 2020. Model 2.3 excludes data from before January 2003, as that is when the available Fed Balance Sheet data begins. Let *, **, and *** denote statistical significance at 5%, 1%, and 0.1% level, respectively.

Model	α_0	β_C	β_{GFC}	β_{QE}	R^2	Observations
1.1	-0.08	6.11	-	-	0.000	210
	(-0.65)	(0.36)				
1.2	-0.19	-4.00	0.23	-	0.005	210
	(-1.12)	(-0.20)	(0.95)			
1.3	-0.20	-5.69	0.21	0.001	0.005	210
	(-0.98)	(-0.20)	(0.56)	(0.08)		
2.1	-0.10***	9.13**	-	-	0.04	188
	(-4.69)	(2.63)				
2.2	-0.15***	2.77	0.12**	-	0.08	188
	(-5.70)	(0.70)	(3.14)			
2.3	-0.05	21.10***	0.38***	-0.0132***	0.17	188
	(-1.46)	(3.79)	(5.54)	(-4.47)		

Table V
Value Index absolute and 24-month average Alpha regressed against Crowdedness

Models 1 regress the Value Index Alpha at month *t* against the relevant variables at month *t*. Models 2 regress the 24-month average Value Index Alpha [t+1:t+24] against the relevant variables at month *t*. They exclude observations after January 2019, as the complete set of data ends in December 2020. Model 2.3 excludes data from before January 2003, as that is when the available Fed Balance Sheet data begins. Let *, **, and *** denote statistical significance at 5%, 1%, and 0.1% level, respectively.

Model	α_0	β_C	β_{GFC}	β_{QE}	R^2	Observations
1.1	0.53***	-8.88***	-	-	0.07	250
	(3.77)	(-4.42)				
1.2	0.55***	-8.05**	-0.11	-	0.07	250
	(3.70)	(-2.85)	(-0.42)			
1.3	0.26	-7.40*	-0.008	0.004	0.07	215
	(1.84)	(-2.36)	(-0.03)	(0.31)		
2.1	0.32***	-7.29***	-	-	0.04	228
	(13.19)	(-17.03)				
2.2	0.31***	-8.15***	0.09	-	0.08	228
	(12.55)	(-13.34)	(1.96)			
2.3	0.17***	-10.07***	-0.09	0.013***	0.17	194
	(6.77)	(-14.69)	(-1.65)	(5.08)		

Table VI
Quality Index absolute and 24-month average Alpha regressed against Crowdedness

Models 1 regress the Quality Index Alpha at month *t* against the relevant variables at month *t*. Models 2 regress the 24-month average Quality Index Alpha [t+1:t+24] against the relevant variables at month *t*. They exclude observations after January 2019, as the complete set of data ends in December 2020. Model 2.3 excludes data from before January 2003, as that is when the available Fed Balance Sheet data begins. Let *, **, and *** denote statistical significance at 5%, 1%, and 0.1% level, respectively.

Model	α_0	β_C	β_{GFC}	β_{QE}	R^2	Observations
1.1	0.07	-4.76	-	-	0.001	228
	(0.35)	(-0.35)				
1.2	0.15	-2.36	-0.15	-	0.001	228
	(0.51)	(-0.16)	(-0.38)			
1.3	0.36	-0.92	-0.28	-0.028	0.005	215
	(0.98)	(-0.05)	(-0.40)	(-0.11)		
2.1	0.14***	-16.94**	-	-	0.05	208
	(3.45)	(-3.28)				
2.2	0.24***	-10.11	-0.21**	-	0.08	208
	(4.37)	(-1.77)	(-2.64)			
2.3	0.13	-11.46	-0.16	0.02	0.05	194
	(1.63)	(-1.52)	(-1.02)	(0.31)		