ERASMUS UNIVERSITY ROTTERDAM
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# Is smart beta investing reaching its limits? An analysis of capacities, factor exposures and performance of smart beta ETFs

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# Abstract

Using a sample of all ETFs listed in the United States and investing in U.S. stocks from January 1993 (launch of the first U.S. ETF) till May 2018, I investigate whether smart beta strategies are reaching their limits. I find that most smart beta strategies have lots of capacity left for further growth. Furthermore, on the aggregate level, ETFs have no positive bias toward certain factors. These findings argue against the concern that factor premiums are getting arbitraged away rapidly through ETF investing. Also, I investigate whether smart beta ETFs deliver on their promise of outperforming traditional passive cap-weighted indices. Performance analysis shows, that at the aggregate level, smart beta strategies do not generate outperformance, except for the multi-factor strategy. Studied at the individual level, only a small percentage of smart beta funds generates significant positive alphas. Overall, I find no conclusive evidence that smart beta ETFs earn superior risk-adjusted returns. This finding does not explain the rising popularity of smart beta instruments.

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# 1 Introduction

Throughout the years, hundreds of anomalies and hundreds of factors have been documented to explain the cross-section in stock returns. Some of them are well-known and have been included in popular asset pricing factor models. Examples of well-known factors are the market, size, value, momentum, low volatility and quality factor. Factor investing, or smart-beta investing, has become increasingly popular and has been implemented on a large scale. Factor investing tries to harvest risk premiums by taking on positive exposures toward these factors. A popular way to harvest these premiums is investing in smart beta Exchange Trading Funds (ETFs), which are designed to capture certain premiums. Smart beta ETFs seek to enhance returns or minimize risk relative to their passive market-cap weighted benchmark in order to outperform the market on a risk-adjusted basis. Assets under managements (AUM) of (smart beta) ETFs have experienced tremendous growth over the last years. BlackRock forecasts that AUM of smart beta ETFs might reach $2.4 trillion by 2025, with double the growth rate of the overall ETF market[1].

This explosive growth raises the concern that if too many assets flow into these smart beta ETFs, the profitability of factor investing will attenuate. If factors would get arbitraged away, this would have large consequences for future returns of smart-beta investing (and for investing itself). Ang, Miranda and Ratcliffe (2016) examine this concern by looking at the practical implication of factor strategies. They calculate AUM capacities for various smart beta strategies for which turnover transaction costs of the strategies offset the factor premiums. The profitability of factor investing could also decrease if factor premiums are caused to shrink, or perhaps even disappear, due to large fund inflows. Blitz (2017) tries to investigate this concern by looking at ETFs' aggregate factor exposures. He argues that if ETFs, on aggregate, are systematically harvesting factor premiums, the magnitude of these premiums may decrease. He finds a large dispersion in factor exposures but on aggregate these factor exposures cancel out. Another way to look at the concern of factor premiums getting arbitraged away is to look at the performance of smart beta investing. Some studies, e.g. Asness (2006), document outperformance of smart beta strategies. On the other hand, Glushkov (2016), for example, finds no conclusive empirical evidence that smart beta ETFs generate outperformance compared to the benchmark.

In this paper, I investigate whether smart beta strategies are reaching their capacities. Also, I investigate whether smart beta products deliver on their promise of outperforming

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[1] See: https://www.businesswire.com/news/home/20160512006061/en/

traditional passive market-cap weighted indices. I use a sample of all ETFs listed in the United States and investing in U.S. stocks from January 1993, when the first ETF was launched in the U.S., till May 2018. This study builds on the paper of Ang et al. (2017) by examining if AUM of smart beta strategies are already close to their capacities (as computed by Ang et al. 2017). Furthermore, I perform time-series regressions for each ETF on a multi-factor model to document their factor exposures. From these factor exposures, I calculate aggregate AUM weighted average factor exposures. This study extends the research of Blitz (2017) by also calculating aggregate factor exposures over time, using rolling regressions with a thirty-six months time-window. Moreover, smart beta ETF performance is measured at the aggregate level by forming AUM weighted strategy portfolios. This study contributes to existing literature by also measuring performance of a broad sample of ETFs at the individual level. Performance is measured using aggregate alphas, alphas from a one-factor model, alphas from a multi-factor model and Sharpe ratios. This analysis extends the study of Glushkov (2016) by using a longer sample period and by using a survivorship-bias free sample.

I find that most strategies have lots of capacity left for further growth; only the value strategy, and to a lesser extent the multi-factor strategy, are close to their capacities. The interpretation of this is that factor investing through ETFs generally does not get overcrowded, studied from a transaction cost perspective. Furthermore, results show that on the aggregate level, there is no positive bias toward certain factors, in line with the findings of Blitz (2017). The one aggregate factor that is significantly different from zero is that of the momentum factor and is negative. Dynamic aggregate factor exposures show that there are no clear trends visible of aggregate factor exposures growing over time. The interpretation of this is that factor investing through ETFs does not get overcrowded, studied from a transaction cost perspective and studied from a factor exposure perspective. Moreover, performance analysis shows that at the aggregate level, no significant outperformance of smart beta strategy portfolios is found, except for the multi-factor strategy. Also, at the individual ETF level, only a small percentage of smart beta ETFs generates statistically significant positive alphas. I find, similar to the findings of Glushkov (2016), no conclusive evidence that smart beta ETFs generate superior risk-adjusted returns. This finding challenges the growing popularity of smart beta ETFs.

The outline of this paper is as follows: in Section 2, I discuss relevant literature concerning smart beta investing. Section 3 and 4 report respectively the data and methodology involving this research. Section 5 presents the results and Section 6 discusses and concludes.

# 2 Literature review

This section presents literature on the factors involved in this study. Furthermore, it provides literature on (the capacities of) smart beta investing. Lastly, I discuss several papers that study smart beta performance.

## 2.1 Anomalies and factors

Fund managers and investors are always trying to analyze historical data to implement strategies that generate superior risk-adjusted returns. The Efficient Market Hypothesis (EMH) argues that no such strategies exist since markets are efficient and all available information is directly reflected into stock prices (see, e.g., Fama, 1970). On the other hand, Ross (1976) comes up with the Arbitrage Pricing Theory (APT), which is an alternative to the mean variance capital asset pricing model (CAPM), introduced by Sharpe, Lintner and Treynor. The APT model is based on the idea that an asset's returns can be predicted using the relation between that asset and many common risk factors.

Throughout the years many anomalies have been documented in the stock market that have had historically superior performance and higher Sharpe ratios with respect to the market (using the CAPM model). An anomaly is defined as a structural, replicable pattern, that cannot be explained in the framework of existing theory, but can (potentially) be explained economically.

Fama and French (1992) find that firms' size (measured by market-cap) and value characteristics (measured by book-to-market ratio) capture the cross-sectional variation in average stock returns. Small company stocks and high value stocks tend to generate higher returns than large company stocks and low value stocks, respectively. When double-sorted on market beta and size or value characteristics, the relation between market beta and average returns is flat. Fama and French (1993) create factors for the size and value anomaly in their first five-factor asset pricing model. Jegadeesh and Titman (1993) find that stocks that have performed well in the past (past winners) outperform stocks that have performed poorly in the past (past losers) over three- to twelve-month holding periods. This is known as the momentum anomaly. Ang, Hodrick, Xing and Zhang (2006) find that stocks with high idiosyncratic volatility have lower average returns. Blitz and Van Vliet (2007) further examine this (low) volatility anomaly and find that low-volatility stocks outperform high volatility stocks, adjusted for well-known risk factors. Frazzini and Pedersen (2014) create a betting against beta (BAB) factor, which longs low beta stocks and shorts high beta stocks, that produces significant positive risk-adjusted returns. Asness, Frazzini and Pedersen (2019) create a Quality Minus

Junk (QMJ) factor. The factor, that goes long in high-quality stocks (highly profitable, high profit growth and safe stocks) and short in low-quality stocks, earns significant positive risk-adjusted returns in the US and globally across twenty-four countries.

There has been a long ongoing debate whether these factors are rewards for additional (systematic) risk or that the mispricings can be explained from a behavioral viewpoint. The behavioral school of thought, of which for example Shiller is a proponent, challenges the EMH by assuming not all investors are rational and there are some behavioral biases in place (such as overconfidence, optimism, hindsight and overreaction) that could cause mispricings (anomalies) in the market.

## 2.2 Smart beta investing (capacities)

Factor investing, or smart beta investing, is the investment strategy of harvesting risk premiums offered by academic established factors. It is advocated by various studies, such as Bender, Briand, Nielsen and Stefek (2010); Blitz (2012) and Ang (2014). Harvesting premiums could be done through long-short factor portfolios, which capture pure factor premiums, or long-only factor portfolios, which also have exposure to the market factor. Smart-beta ETFs are examples of the latter category. Smart-beta ETFs tilt toward certain factors through alternative weighting schemes (to market-cap weighting) or screening securities on certain characteristics.

There are several papers that study the capacities of factor investing. Blitz (2017), for example, investigates the concern that factor premiums will attenuate or even disappear if too many investors are chasing the same risk premiums. He examines factor exposures of US ETFs from January 2011 till December 2015. He finds large dispersion in factor exposures. In general, smart-beta ETFs exhibit positive exposures toward factors where conventional ETFs are on the other side of these factor exposures. On aggregate, however, factor exposures cancel out and are on average close to zero. Blitz (2017) concludes that this finding argues against the concern that factor premiums are rapidly being arbitraged away through ETF investing. Blitz (2018) studies aggregate factor exposures of hedge funds and finds, also for this investment vehicle, little evidence that hedge funds are harvesting factor premiums. Toward the low volatility anomaly, hedge funds even tend to have aggregate negative exposure.

Various studies, such as Novy-Marx and Velikov (2016), and Frazzini, Israel and Moskowitz (2012) find smart beta capacities to be large. Novy-Marx and Velikov (2016) specifically find that low turnover strategies such as value and quality have capacities of hundreds of billions of dollars. Ang et al. (2017), in contrast to these previous studies, focus on smart beta strategies that are directly available to investors and that are not based on proprietary implementations. They study capacities of (the practical implementation of) factor investing from a transaction costs perspective, using a transaction cost model used by a large asset manager. They estimate for each strategy the capacity for which the smart beta premium is offset by the strategy's rebalancing costs, for a given trading horizon. Ang et al. (2017) also find that capacity in smart beta strategies is large, implying that there is plenty of capacity left for further growth.

## 2.3 Smart beta performance

Smart beta ETFs, according to their threads on Morningstar, seek to enhance returns or minimize risk relative to their passive market-cap weighted benchmark. Several papers study the performance of smart beta investing.

For instance, Asness (2006) finds that there is empirical evidence that the outperformance of smart beta strategies can be nearly entirely explained by tilts toward the size or value factor or a combination of both. Chow, Hsu, Kalesnik and Little (2011) find something similar: they find alternative betas do outperform their market-cap weighted counterparts, but the added value of these smart beta indexes is driven largely by exposures to the value and size factor.

On the other hand, Malkiel (2014) finds that many smart beta ETFs fail to generate reliable excess returns and only a few ETFs have managed to beat the market over their lifetime. Glushkov (2016) studies smart beta performance using a sample of 164 domestic equity smart beta ETFs over the sample period 2003-2014. Smart beta ETFs are categorized into thirteen smart beta category portfolios based on common factor theme. Glushkov (2016) finds no conclusive empirical evidence that smart beta ETFs generate superior risk-adjusted returns compared to the benchmark. Only two groups, value and volatility, significantly outperform their risk-adjusted benchmark. Furthermore, he finds that smart beta ETFs exhibit potentially unintended factor tilts that may offset the factor returns from intended factor exposures.

# 3 Data

I use a sample of all ETFs listed in the United States and investing in U.S. stocks. The sample period runs from January 1993 till May 2018. In January 1993, the first ETF, the SPDR S&P500 ETF Trust (SPY), was launched in the United States. Dead ETFs that did not survive till May 2018 are included in the sample for a survivorship-bias free sample. For each ETF, monthly total return data and AUM data are retrieved from Thomson Reuters Datastream.

Descriptive statistics of the ETF sample can be found in Table 1. Table 1A shows that the total sample consists of 897 ETFs of which 212 ETFs did not survive till May 2018. For the (aggregate) factor exposure analysis and the individual ETF performance analysis, only ETFs with a minimum of thirty-six months return history are included in the sample. These amount to a total of 562 ETFs of which 76 ETFs have not survived, as can be seen in Table 1B.

**Table 1: ETF sample statistics**

This table lists the number of ETFs for each (sub)sample. Panel A includes all ETFs that have return data and AUM data. Panel B includes all ETFs that have return data, AUM data and that have at least thirty-six months of return history.

| **Statistic** | **Amount** |
|---|---|
| **Panel A: All ETFs** | |
| Total ETFs | 897 |
| Smart beta ETFs | 243 |
| Leveraged ETFs | 69 |
| Short ETFs | 82 |
| Dead ETFs | 212 |
| % of dead ETFs that are smart beta ETFs | 6.13% |
| **Panel B: ETFs with min. 36 months return history** | |
| Total ETFs | 562 |
| Smart beta ETFs | 136 |
| Leveraged ETFs | 51 |
| Short ETFs | 58 |
| Dead ETFs | 76 |

I classify ETFs manually either as smart beta (i.e., ETFs systematically targeting a factor strategy) or conventional (i.e. all other ETFs). Within the smart beta subsample, ETFs are sorted into one of the following factor strategy categories: size (SMB), value (HML), momentum (MOM), low risk (BAB), quality (QMJ) or multi-factor (M-F), a combination of two or more factor strategies. The sorting is done using factor-specific criteria, partly following the MSCI Smart Beta Indices descriptions[2]. An ETF is sorted into the SMB category if it explicitly targets (a combination of) small- or mid-cap(s) (indices) or if it tracks equally weighted indices. ETFs that are based on large-cap indices that are equally weighted are not classified as size strategy. To be included in the HML category, ETFs must explicitly target stocks with one or more of the following characteristics: high book value to price, high 12-month forward earnings to price or high dividend yield. Indices that use value weighted formulas using one or more of above characteristics are also considered value strategies. ETFs targeting a momentum strategy or indices that are weighted by a momentum measure are sorted into the MOM subsample. The low risk strategy contains ETFs that follow a low beta and/or a low volatility strategy. All ETFs

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[2] Source: MSCI

that have exposure to the low risk factor by a volatility weighting or beta weighting scheme are also considered low risk ETFs. The QMJ subsample consists of ETFs that explicitly target stocks with one or more of the following characteristics: high return on equity, low earnings variability and low debt-to-equity. Indices weighted by one or more of above quality characteristics are also sorted into the QMJ strategy. ETFs that have exposure to multiple factors through multiple sorting or a combination of sorting and weighting (e.g. a small-cap index that is momentum weighted) are labeled as multi-factor strategies. ETFs that have a mix of positive and negative factor exposures (e.g. small-cap growth stocks) do not classify as multi-factor ETFs, but are considered conventional. An exception to this rule are ETFs that apply factor strategies based on large-cap indices (e.g. a large-cap value index ETF). All remaining ETFs are labeled conventional ETFs. These are mainly sector-based ETFs or conventional indices ETFs (such as the S&P500 Index ETF).

Table 2 shows that smart beta ETFs make up for almost one fourth ($471 billion) of total AUM of all ETFs ($~2 trillion). Total AUM of all ETFs make up for approximately 6 percent of the value of the total US equity market (~34 trillion). In the manually sorting process ETFs are also labeled leveraged if they apply leverage or short if they take short positions. Leveraged and short ETFs account for ~1.3 percent of total ETF AUM. Details of these ETFs and their exposures are given in Table 3.

**Table 2: AUM sample statistics**

This table lists total AUM values for each (sub)sample. AUM of ETFs is measured at May 2018.

| **Statistic** | **Amount** |
|---|---|
| Total AUM ETFs | $1,996 billion |
| Total AUM smart beta ETFs | $471 billion |
| Total AUM conventional ETFs | $1,524 billion |
| Total AUM leveraged ETFs | $20.064 billion |
| Total AUM short ETFs | $6.138 billion |

**Table 3: Leveraged/ short exposure sample statistics**

This table lists the number of ETFs that have leveraged or short exposures. The second column shows numbers for the sample described in Table 1A, whereas the third column shows numbers for the sample described in table 1B.

| **Leveraged/ short exposure** | **Number of ETFs (1A)** | **Number of ETFs (1B)** |
|---|---|---|
| 1.25x | 3 | 2 |
| 2x | 41 | 31 |
| 3x | 25 | 18 |
| -1x | 20 | 13 |
| -2x | 38 | 28 |
| -3x | 24 | 17 |

Data for the risk-free return, market excess return, size factor, value factor and momentum factor are retrieved from the Kenneth R. French online data library[3]. Data for the BAB factor and QMJ factor are obtained from the AQR online data library[4].

# 4 Methodology

In this section, I discuss the methodology for the three different parts of this research: factor capacities, (aggregate) factor exposures and performance measurement.

## 4.1 Factor capacities

The factor capacities, in terms of AUM, used for this research are taken from Ang et al. (2017). In their study, they measure the capacity of smart beta strategies from a transaction costs perspective, using the following formula:

$$[AUM_c * TO] * \ TC(AUM_c * TO, T) = SBP * AUM_c, \tag{1}$$

where

| | |
|---|---|
| $TC$ | is the transaction cost function, |
| $AUM_c$ | is the critical AUM level/ the estimate of capacity, |
| $TO$ | is the turnover of the strategy, |
| $T$ | is the trade time horizon, and |
| $SBP$ | is the estimated smart beta premium for a particular strategy |

Equation (1) computes the breakeven point where the smart beta premium is offset by the transaction costs of rebalancing the smart beta strategy. The smart beta premium is estimated using a regression of the particular MSCI factor index on the market, proxied by the MSCI USA Index. Since the MSCI smart beta indexes rebalance every six months, smart beta premiums over six months are used in the equation. To measure transactions costs Ang et al. (2017) use BlackRock's proprietary transaction cost (t cost) model. This model includes a fixed cost and market impact component. The t cost model estimates the transaction costs of each stock traded by BlackRock. The transaction costs in equation (1) are estimated as the weighted

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

[4] See: https://www.aqr.com/Insights/Datasets

sum of each constituent trade. Other important parameters to determine the smart beta strategy rebalancing costs are the turnover of the strategy and the trade time horizon.

In this research, total AUM at each date for each strategy is computed. Total AUM of each factor strategy at May 2018 is compared to the factor capacities calculated by Ang et al. (2017).

## 4.2 (Aggregate) factor exposures

For each ETF, monthly excess returns are calculated by subtracting monthly risk-free rates from monthly total returns. To estimate the factor exposures of each ETF, I regress the time-series of monthly excess total returns on the time-series of the monthly market excess returns, the size factor (SMB), the value factor (HML), the momentum factor (MOM) and the low-risk factor (BAB) using the following formula:

$$R_{fund,t} - R_{f,t} = \alpha + \beta_{MKT} \left(R_{MKT,t} - R_{f,t}\right) + \beta_{SMB} R_{SMB,t} + \beta_{HML} R_{HML,t} + \beta_{MOM} R_{MOM,t} + \beta_{BAB} R_{BAB,t} + \varepsilon_t \tag{2}$$

Following Blitz (2017), aggregate factor exposures are calculated as the AUM weighted average factor exposures. The statistical significance of these aggregate exposures is computed using a weighted regression of the factor exposures. For the calculation of aggregate factor exposures over time I use ETFs' factor exposures estimated by rolling regressions with a time-window of thirty-six months.

## 4.3 Performance measurement

ETF performance is measured at the aggregate level using AUM weighted returns. Different kinds of AUM weighted portfolios are formed (including portfolios for each strategy) and regressed on a one-factor model as well as a multi-factor model. The multi-factor model used includes the market, size, value, momentum, low risk and quality factor. In Appendix 1 (correlation matrix of factor returns), it can be seen that no correlation between factors causes a multicollinearity problem in this regression setting.

ETF performance is also measured at an individual fund level by the fund's alpha and Sharpe ratio. The fund's alpha is estimated using a time-series regression of the monthly excess total returns on the monthly market excess return, given the following equation:

$$R_{fund,t} - R_{f,t} = \alpha + \beta_{MKT} \left(R_{MKT,t} - R_{f,t}\right) + \varepsilon_t \tag{3}$$

The alphas are estimated using a one-factor model instead of a multiple-factor model, since the primary reason of a retail investor to invest in a smart beta ETF is to beat the market. Next to the market excess return from the Kenneth R. French online data library, the excess return of the SPDR S&P 500 ETF Trust (SPY) is also used as the benchmark. The SPY ETF tracks a market-cap-weighted index of US large- and midcap stocks selected by the S&P Committee. The reason for including the SPY ETF as a benchmark is that the SPY ETF is investable (in contrast to the Kenneth R. French market factor) and the return of the SPY ETF also includes costs (like all other ETFs).

Funds' Sharpe ratios are computed and compared to the Sharpe ratios of the benchmark (both the market portfolio as well as the SPY ETF) for the corresponding time-period. To test for the statistical significance of the difference between an ETF's Sharpe ratio and the Sharpe ratio of the benchmark, the following Jobson-Korkie (1981) z-test with the Memmel (2003) correction is applied, following Blitz and Van Vliet (2007):

$$z = \frac{SR_1 - SR_2}{\sqrt{\frac{1}{T}[2\left(1-\rho_{1,2}\right)+\frac{1}{2}\left(SR_1^2+SR_2^2-SR_1SR_2\left(1-\rho_{1,2}^2\right)\right)}} \qquad (4)$$

# 5 Results

In this section, I discuss the results of the different parts of this research.

## 5.1 Factor capacities

### 5.1.1 Total AUM smart beta strategies

Table 4 shows total AUM of each smart beta strategy versus corresponding AUM capacities of the smart beta strategies, as computed by Ang et al. (2017). Total AUM of the smart beta strategies are compared to the capacities, calculated using the 100% premium (the historical premium) as well as capacities calculated using the 50% premium (the smart beta premium going forward is 50% of the historical premium). As can be inferred from Table 4, only two smart beta strategies are (relatively) close to their capacities; the value strategy and multi-factor strategy. The value strategy (AUM: $175 billion) even exceeds capacity (AUM: $153 billion) if taken the 50% premium capacity. Also, the value strategy has the most ETFs targeting the smart beta premium (39). This could mean, with the assumptions that value ETFs generally target the same stocks and rebalance at the same time, that the value strategy is overcrowded and that the premium earned by investing in value ETFs is offset by rebalancing costs or that these ETFs even underperform relative to the market. The other strategy close to its capacity (AUM: $151 billion, 50% premium) is the multi-factor strategy (AUM: $102 billion). However, in this study all ETFs that target two or more factors are classified as multi-factor ETFs whereas Ang et al. (2017) calculate capacity for the MSCI Diversified Multiple Factor (a strategy that combines the momentum, quality, size and value factor). Therefore, the computed capacity of the multi-factor strategy does not fully resemble the capacity of the multi-factor strategy in this study, since parameters such as the smart beta premium and turnover assumptions could differ. The other smart beta strategies, and to a lesser extent the momentum strategy, have lots of capacity left, according to this table. The strategy that has the most capacity left before rebalancing costs get too high, is the low risk strategy (AUM: $24 billion, capacity AUM: $1,353 billion).

**Table 4: AUM smart beta strategies versus AUM smart beta capacities**

This table shows, for each smart beta strategy, total AUM and the number of ETFs at May 2018. Also, for each smart beta category, their capacities, computed by Ang et al. (2017), are displayed. Capacities computed using the 100% smart beta premium as well as capacities computed using the 50% smart beta premium are shown.

| ***Strategy*** | *Size* | *Value* | *Momentum* | *Low risk* | *Quality* | *Multi-factor* |
|---|---|---|---|---|---|---|
| **Capacity Ang et al. ($bn/ 100% premium)** | $5,086 | $353 | $65 | $1,353 | $287 | $316 |
| **Capacity Ang et al. ($bn/ 50% premium)** | $2,477 | $153 | $27 | $657 | $130 | $151 |
| **AUM ($bn)** | $153 | $175 | $11 | $24 | $8 | $102 |
| **Number of ETFs** | 37 | 39 | 11 | 14 | 8 | 90 |

In this study, factor strategies in the large-cap universe are considered smart beta strategies, since Ang et al. (2017) compute factor capacities for MSCI Factor Indices that target the more liquid large- and mid-cap stocks. Using an alternative criterion, following Blitz (2017), factor strategies in the large-cap universe are assigned to the conventional category, since these ETFs have a mix of desired and undesired factor exposures (e.g. a large-cap value index). Table 5 also shows total AUM of the smart beta strategies that are sorted using this alternative method. Logically, this does not change total AUM of the size strategy. For the other strategies, total AUM is lower. Total AUM of the value strategy reduces the most, indicating that $27 billion is invested in large-cap value ETFs.

**Table 5: AUM smart beta strategies versus AUM smart beta capacities (alternative sorting)**

This table shows, for each smart beta strategy, total AUM at May 2018 for two different kinds of methods of sorting ETFs into (smart beta) categories. Also, for each smart beta category, their capacities, computed by Ang et al. (2017), are displayed. Capacities computed using the 100% smart beta premium as well as capacities computed using the 50% smart beta premium are shown.

| ***Strategy*** | *Size* | *Value* | *Momentum* | *Low risk* | *Quality* | *Multi-factor* |
|---|---|---|---|---|---|---|
| **Capacity Ang et al. ($bn/ 100% premium)** | $5,086 | $353 | $65 | $1,353 | $287 | $316 |
| **Capacity Ang et al. ($bn/ 50% premium)** | $2,477 | $153 | $27 | $657 | $130 | $151 |
| **AUM ($bn)** | $153 | $175 | $11.0 | $23.5 | $7.8 | $102 |
| **AUM ($bn) (alternative sorting)** | $153 | $148 | $10.9 | $14.9 | $5.5 | $93.6 |

The results imply that factor investing through ETFs generally does not get overcrowded, studied from a transaction cost perspective. The value strategy, however, could be reaching its AUM limits. In the next section, AUM growth over time of smart beta strategies is shown to see whether past AUM growth can be extrapolated into the future.

### 5.1.2 AUM smart beta strategies over time

Figures 1-6 depict the development of total AUM of the different smart beta strategies over time. What stands out for all factor strategies is the explosive growth of total AUM. The difference across the factor strategies is the start of this explosive AUM growth. Figures 1 and 2 show that for the size and value strategy inflows start approximately around the same time (2004) and explosive AUM growth starts around 2009 (after the financial crisis). Figures 3-5 show that explosive growth for the momentum, low risk and quality factor start at a later date. For the momentum factor, explosive AUM growth begins around 2012. The first low risk ETF originates in end 2011. AUM of low risk ETFs begin to grow explosive since then. AUM of quality ETFs start to grow exponentially from around 2014 onwards. This is consistent with the documentation of the quality factor by Asness, Frazzini and Pedersen in 2014. In Figure 6 can be seen that AUM growth for the multi-factor strategy starts around 2004 (resembling the start of the value and size strategy) and explosive AUM growth starts around 2012.

**Figure 1: AUM of size ETFs over time**

This figure displays total AUM over time of the ETFs classified as SMB strategy. The sample period runs from the launch of the first size ETF till May 2018. Total AUM values are given in million dollars.

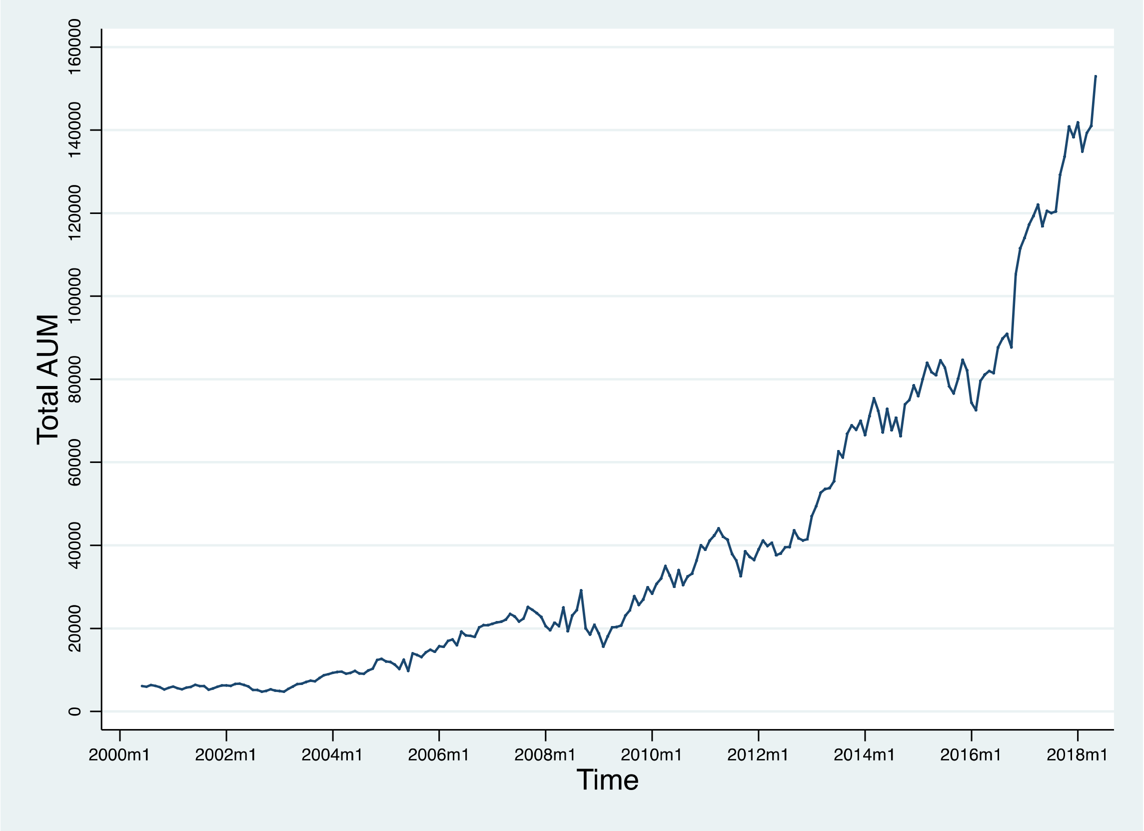


**Figure 2: AUM of value ETFs over time**

This figure displays total AUM over time of the ETFs classified as HML strategy. The sample period runs from the launch of the first value ETF till May 2018. Total AUM values are given in million dollars.

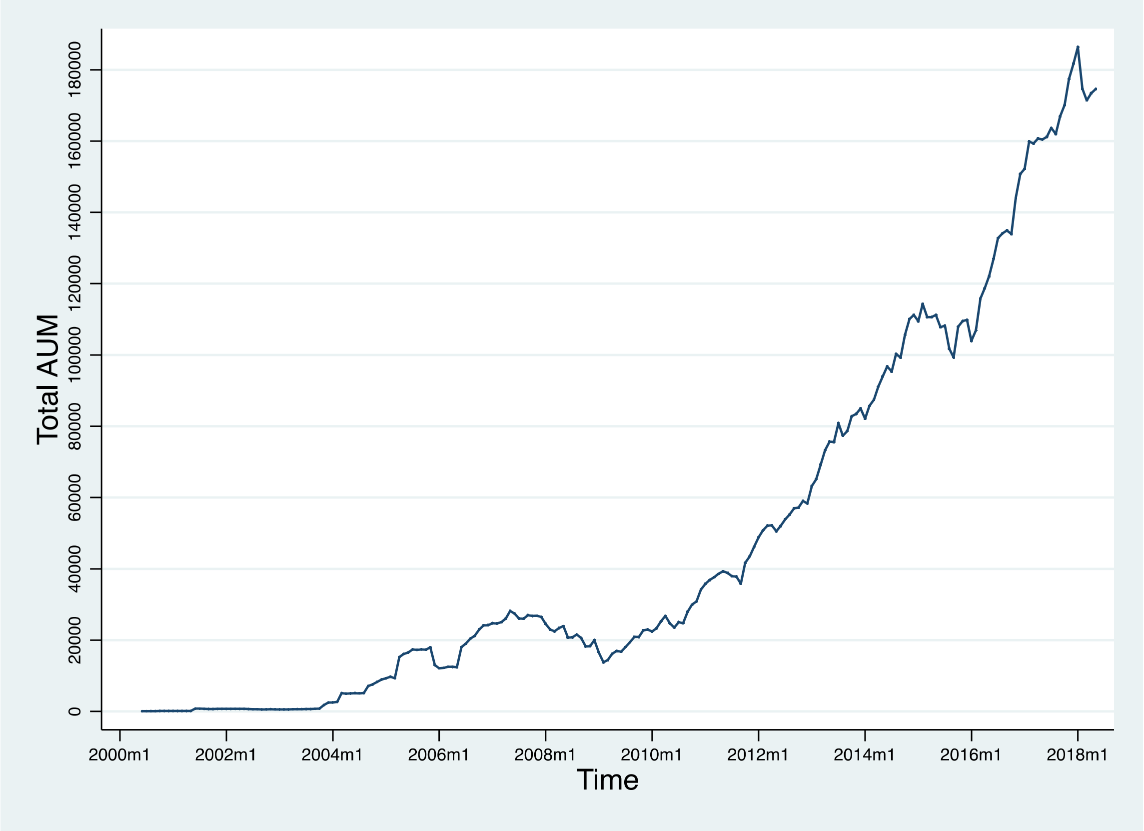


**Figure 3: AUM of momentum ETFs over time**

This figure displays total AUM over time of the ETFs classified as MOM strategy. The sample period runs from the launch of the first momentum ETF till May 2018. Total AUM values are given in million dollars.

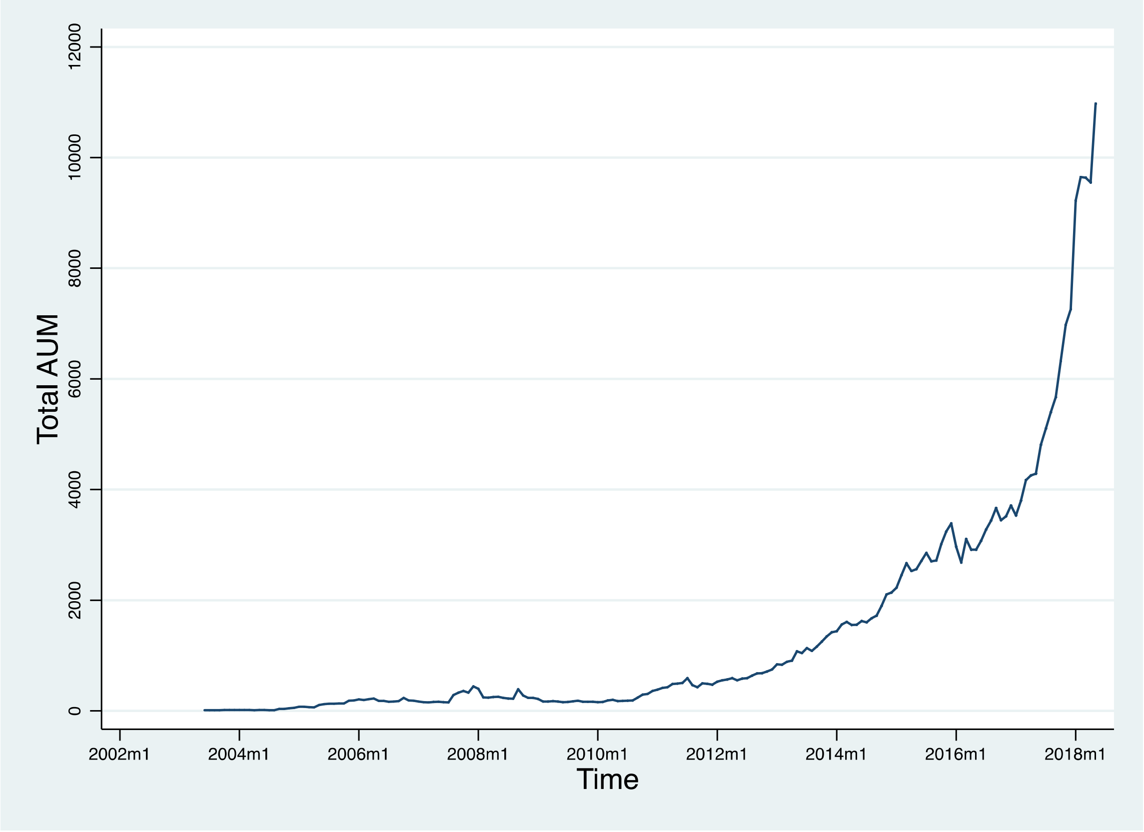


**Figure 4: AUM of low risk ETFs over time**

This figure displays total AUM over time of the ETFs classified as BAB strategy. The sample period runs from the launch of the first low risk ETF till May 2018. Total AUM values are given in million dollars.

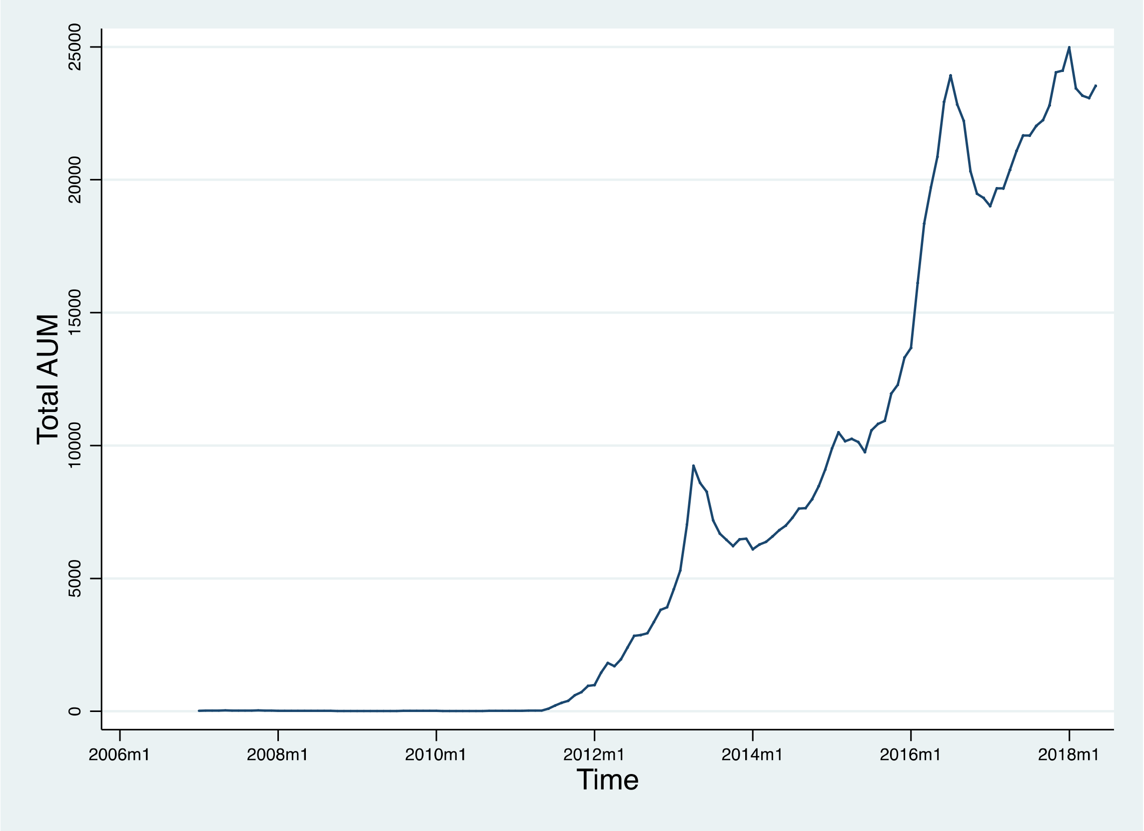


**Figure 5: AUM of quality ETFs over time**

This figure displays total AUM over time of the ETFs classified as QMJ strategy. The sample period runs from the launch of the first quality ETF till May 2018. Total AUM values are given in million dollars.

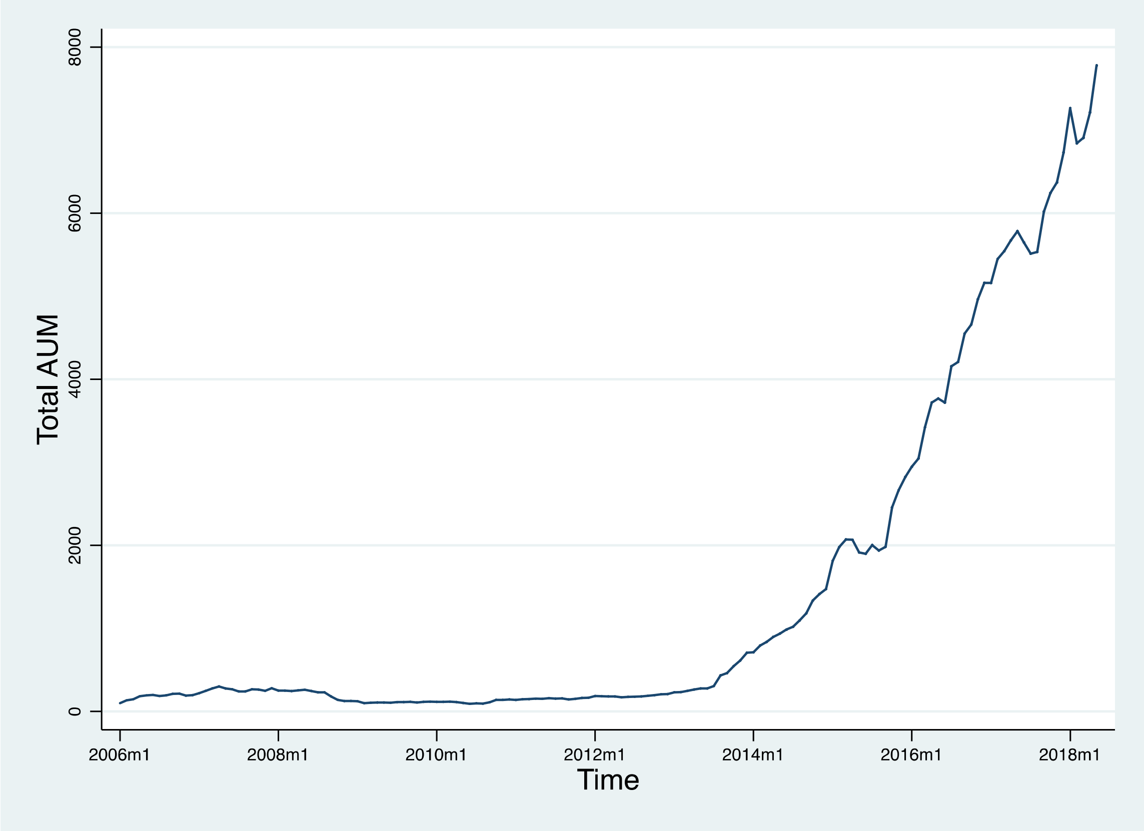


**Figure 6: AUM of multi-factor ETFs over time**

This figure displays total AUM over time of the ETFs classified as M-F strategy. The sample period runs from the launch of the first multi-factor ETF till May 2018. Total AUM values are given in million dollars.

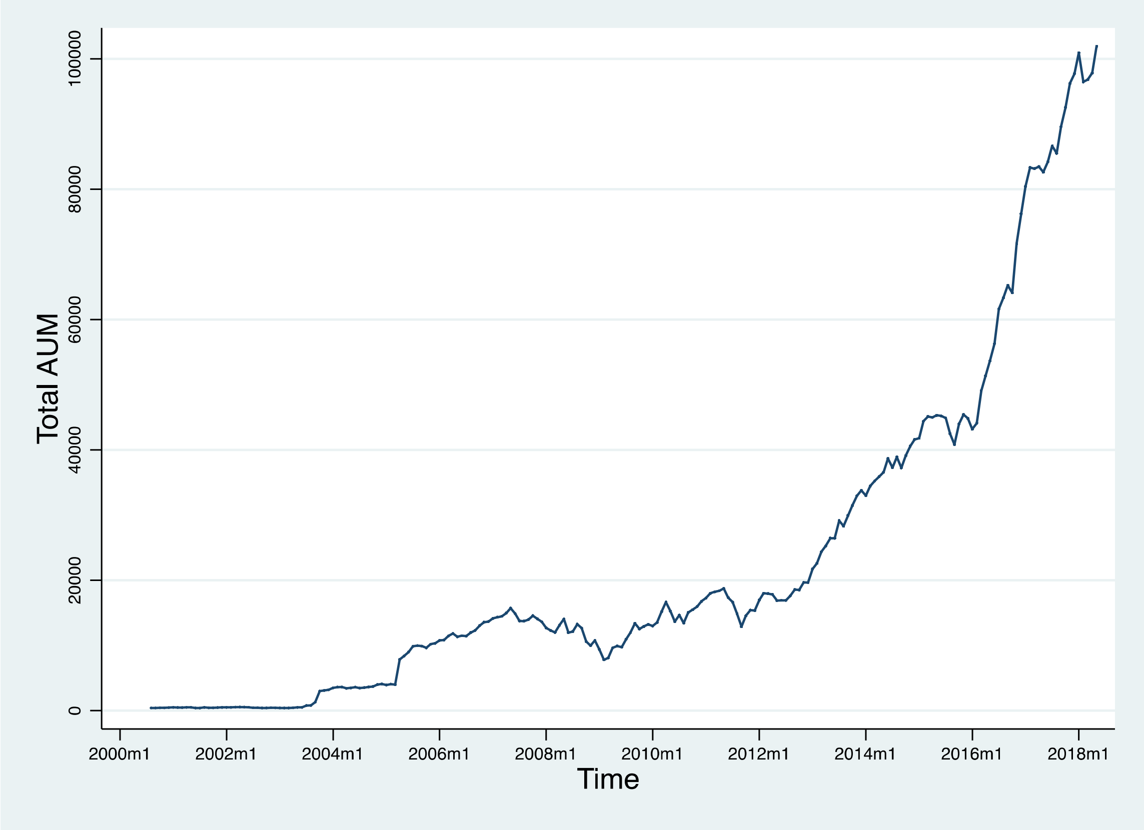
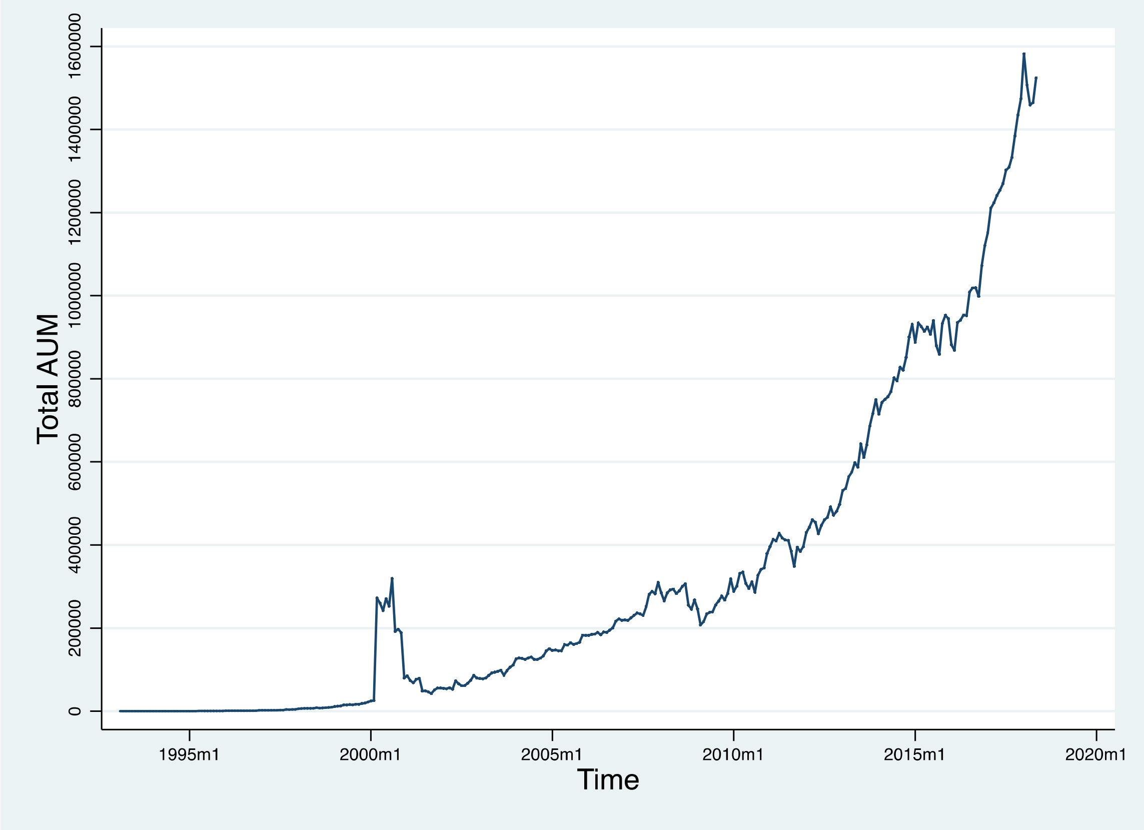


Figure 7 shows total AUM over time of conventional ETFs. AUM start to grow since the inception of the first ETF (SPY) in January 1993. The spike around 2000 shows massive AUM growth during the dot-com bubble and the crash afterwards. Explosive AUM growth starts after the financial crisis in 2009, similar to the size and value strategy.

**Figure 7: AUM of conventional ETFs over time**

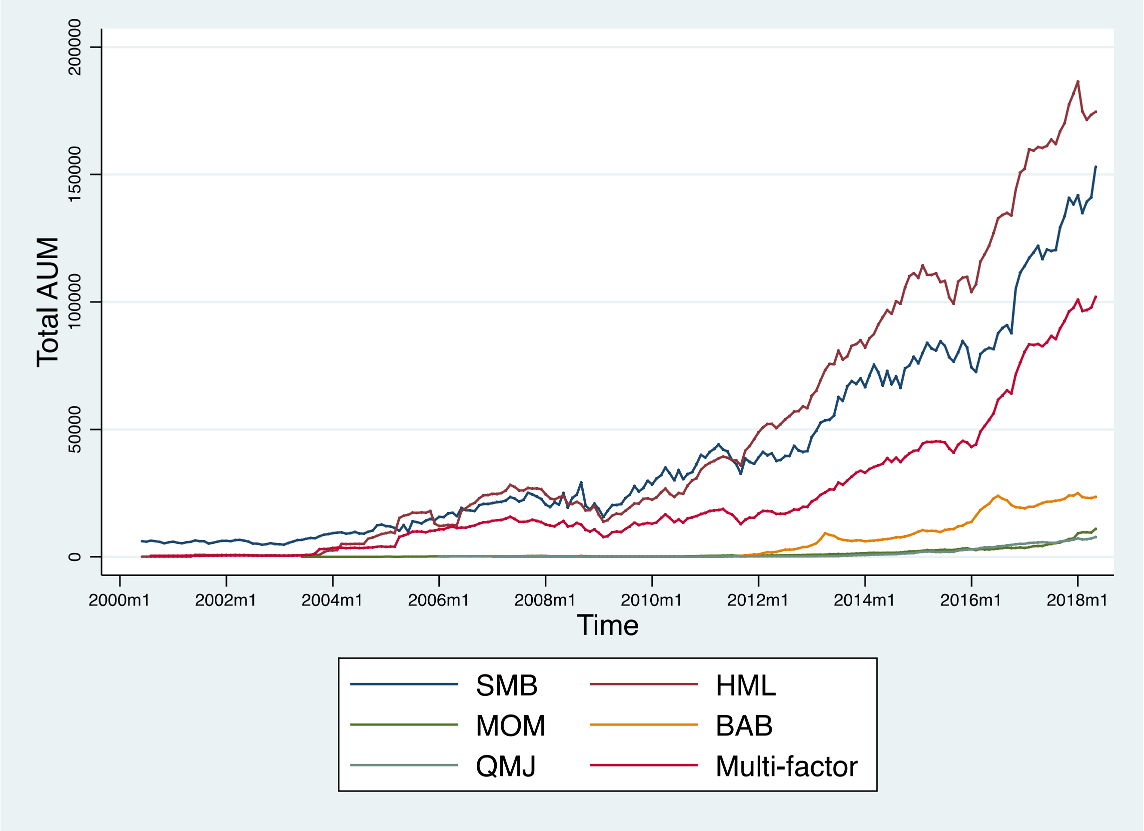
This figure displays total AUM over time of the ETFs classified as conventional. The sample period runs from the launch of the first conventional ETF till May 2018. Total AUM values are given in million dollars.



In Figure 8, AUM growth of all smart beta strategies is shown. Total AUM for the size, value and multi-factor strategy have grown much larger than AUM for the low risk, momentum and quality strategy.

**Figure 8: AUM of different smart beta strategy ETFs over time**

This figure displays total AUM over time for each smart beta strategy. The sample period runs from the launch of the first smart beta ETF till May 2018. Total AUM values are given in million dollars.



If these explosive growth rates of the smart beta strategies continue, other strategies might also reach capacities in the future. However, most strategies have lots of capacity left, as shown in table 4, so this is probably not the case in the very near future.

### 5.1.3 Detailed results

Table 6-11 report the top five largest ETFs for each different smart beta strategy. Table 6 shows that the largest SMB ETFs are small-cap indices and one mid-cap index, with the iShares Russell 2000 ETF being the largest ETF with AUM of $47 billion. The largest HML ETF is the Vanguard Value ETF with $37 billion AUM, as shown in Table 7. This ETF tracks an index with stocks from the top 85% of market capitalization based on multiple value factors. Tables 8-10 display that for the MOM, BAB and QMJ strategy the MSCI USA Factor ETF is the largest ETF, significantly larger than the other largest ETFs for these strategies. Table 11 shows that the four largest multi-factor ETFs invest in a combination of the size and value factor by tracking a small-cap value index or a mid-cap value index.

### Table 6: Largest 5 ETFs classified as size strategy (SMB)

This table lists the five largest ETFs, in terms of AUM, classified as SMB strategy.

| **Ticker** | **Name** | **AUM ($bn)** |
|---|---|---|
| IWM | iShares Russell 2000 ETF | 47.089 |
| IJR | iShares Core S&P Small-Cap ETF | 41.374 |
| VB | Vanguard Small-Cap ETF | 23.229 |
| IWR | iShares Russell Mid-Cap ETF | 17.303 |
| SCHA | Schwab US Small-Cap ETF | 7.781 |

### Table 7: Largest 5 ETFs classified as value strategy (HML)

This table lists the five largest ETFs, in terms of AUM, classified as HML strategy.

| **Ticker** | **Name** | **AUM ($bn)** |
|---|---|---|
| VTV | Vanguard Value ETF | 37.035 |
| IWD | iShares Russell 1000 Value ETF | 36.006 |
| VYM | Vanguard High Dividend Yield ETF | 20.940 |
| DVY | iShares Select Dividend ETF | 16.812 |
| IVE | iShares S&P 500 Value ETF | 15.880 |

### Table 8: Largest 5 ETFs classified as momentum strategy (MOM)

This table lists the five largest ETFs, in terms of AUM, classified as MOM strategy.

| **Ticker** | **Name** | **AUM ($bn)** |
|---|---|---|
| MTUM | iShares Edge MSCI USA Momentum Factor ETF | 8.997 |
| PDP | Invesco DWA Momentum ETF | 1.604 |
| FDMO | Fidelity Momentum Factor ETF | 0.086 |
| DWTR | Invesco DWA Tactical Sector Rotation ETF | 0.067 |
| DWAQ | Invesco DWA NASDAQ Momentum ETF | 0.056 |

### Table 9: Largest 5 ETFs classified as low risk strategy (BAB)

This table lists the five largest ETFs, in terms of AUM, classified as BAB strategy.

| **Ticker** | **Name** | **AUM ($bn)** |
|---|---|---|
| USMV | iShares Edge MSCI Min Vol USA | 14.491 |
| SPLV | Invesco S&P 500 Low Volatility | 6.939 |
| CFO | VictoryShares US 500 Enhanced Volatility Wtd Index ETF | 0.908 |
| CFA | VictoryShares US 500 Volatility Wtd ETF | 0.541 |
| DEF | Invesco Defensive Equity ETF | 0.171 |

### Table 10: Largest 5 ETFs classified as quality strategy (QMJ)

This table lists the five largest ETFs, in terms of AUM, classified as QMJ strategy.

| **Ticker** | **Name** | **AUM ($bn)** |
|---|---|---|
| QUAL | iShares Edge MSCI USA Quality Factor ETF | 5.130 |
| SPHQ | Invesco S&P 500 Quality ETF | 1.359 |
| FTCS | First Trust Capital Strength ETF | 0.900 |
| FNDB | Schwab Fundamental U.S. Broad Market Index ETF | 0.267 |
| FQAL | Fidelity Quality Factor ETF | 0.065 |

### Table 11: Largest 5 ETFs classified as multi-factor strategy (M-F)

This table lists the five largest ETFs, in terms of AUM, classified as M-F strategy.

| **Ticker** | **Name** | **AUM ($bn)** |
|---|---|---|
| VBR | Vanguard Small-Cap Value ETF | 13.440 |
| IWS | iShares Russell Mid-Cap Value ETF | 10.483 |
| IWN | iShares Russell 2000 Value ETF | 10.207 |
| VOE | Vanguard Mid-Cap Value ETF | 8.563 |
| SCHD | Schwab US Dividend Equity ETF | 7.407 |

## 5.2 (Aggregate) factor exposures

### 5.2.1 Plotted factor exposures

Figures 9 and 10 display estimated market factor exposures of ETFs. ETFs' market betas are plotted against their AUM levels. Figure 9 shows that the betas of the majority of ETFs are centered around one. The remainder of ETFs have betas clustering around -3, -2, -1, 2 and 3. These are leveraged (2, 3) and inverse (-3, -2, -1) ETFs, that apply leverage to their positions, through investing in derivatives for example. Following Blitz (2017), leveraged and inverse ETFs are included in this research, since they also bring along factor exposures. However, leveraged and short ETFs make up for less than 1.5 percent of total AUM, so the impact of including these ETFs is relatively small. The two outliers that catch the eye are the Direxion Daily S&P Biotech Bear 3x Shares with an estimated beta of -6.7 and the Direxion Daily S&P Biotech Bull 3x Shares with an estimated market beta of 5.3. Figure 10 shows estimated market betas within a 0-1.75 range, excluding leveraged and short positions.

**Figure 9: MKT factor exposure of ETFs**

This figure depicts market betas of all ETFs, where each dot represents an individual ETF. Market betas of ETFs are plotted on the horizontal axis against AUM values on the vertical axis. The market betas are estimated by regressing each ETF on the market, size, value, momentum and low risk factor. To improve readability of the figure, a logarithmic scale is used for the AUM values. AUM values are given in billion dollars.

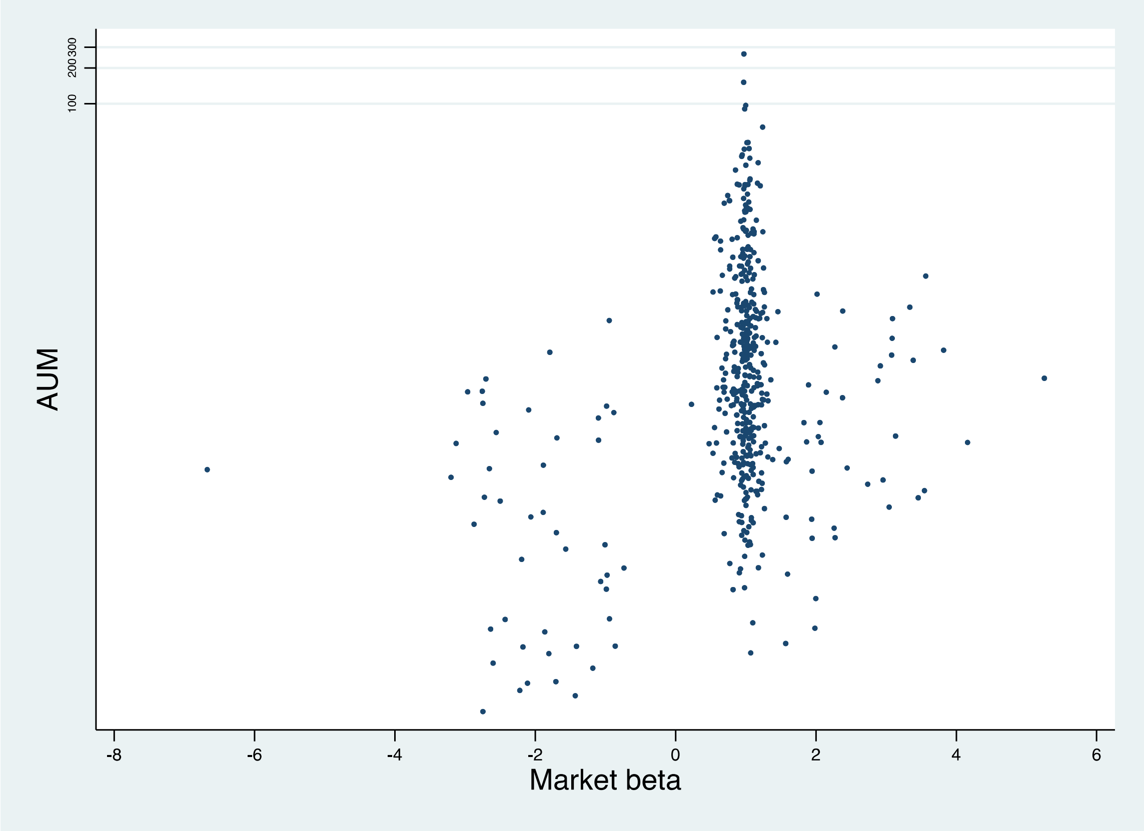
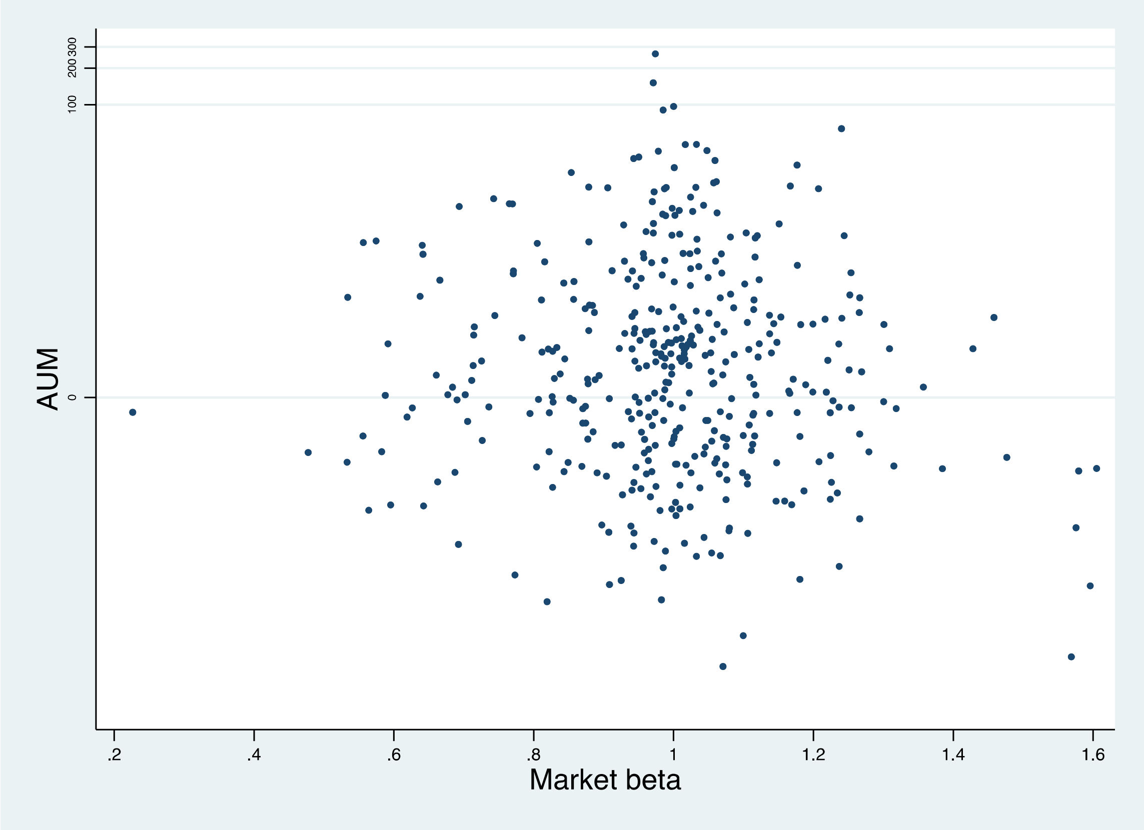


**Figure 10: MKT factor exposure of ETFs (0 to 1.75 range)**

This figure depicts market betas of all ETFs, where each dot represents an individual ETF. Market betas of ETFs are plotted on the horizontal axis against AUM values on the vertical axis. The market betas are estimated by regressing each ETF on the market, size, value, momentum and low risk factor. In this figure, only market betas between 0 and 1.75 are shown, removing ETFs with (extreme) leveraged and short positions. To improve readability of the figure, a logarithmic scale is used for the AUM values. AUM values are given in billion dollars.



Figures 11-14 depict figures of ETFs’ factor exposures toward the other factors (SMB, HML, MOM and BAB). Only factor exposures between the range of -1 to +1 are included to improve readability, removing some extreme leveraged and short positions. Estimated factor exposures toward the size, value and low risk factor are centered around zero, with a large dispersion in positive as well as negative exposures. The SMB factor exposures are positively skewed; there are more funds with positive SMB exposure than funds with negative SMB exposure. These findings are consistent with the findings of Blitz (2017). The estimated factor exposures toward the momentum factor, however, seem to be centered around -0.05 instead of zero. This finding differs from Blitz (2017), who finds momentum exposures to be centered around zero.

**Figure 11: SMB factor exposure of ETFs (-1 to 1 range)**

This figure depicts SMB exposures of all ETFs, where each dot represents an individual ETF. SMB betas of ETFs are plotted on the horizontal axis against AUM values on the vertical axis. The SMB betas are estimated by regressing each ETF on the market, size, value, momentum and low risk factor. Only SMB betas between -1 and

+1 are shown, removing ETFs with (extreme) leveraged and short positions. To improve readability of the figure, a logarithmic scale is used for the AUM values. AUM values are given in billion dollars.

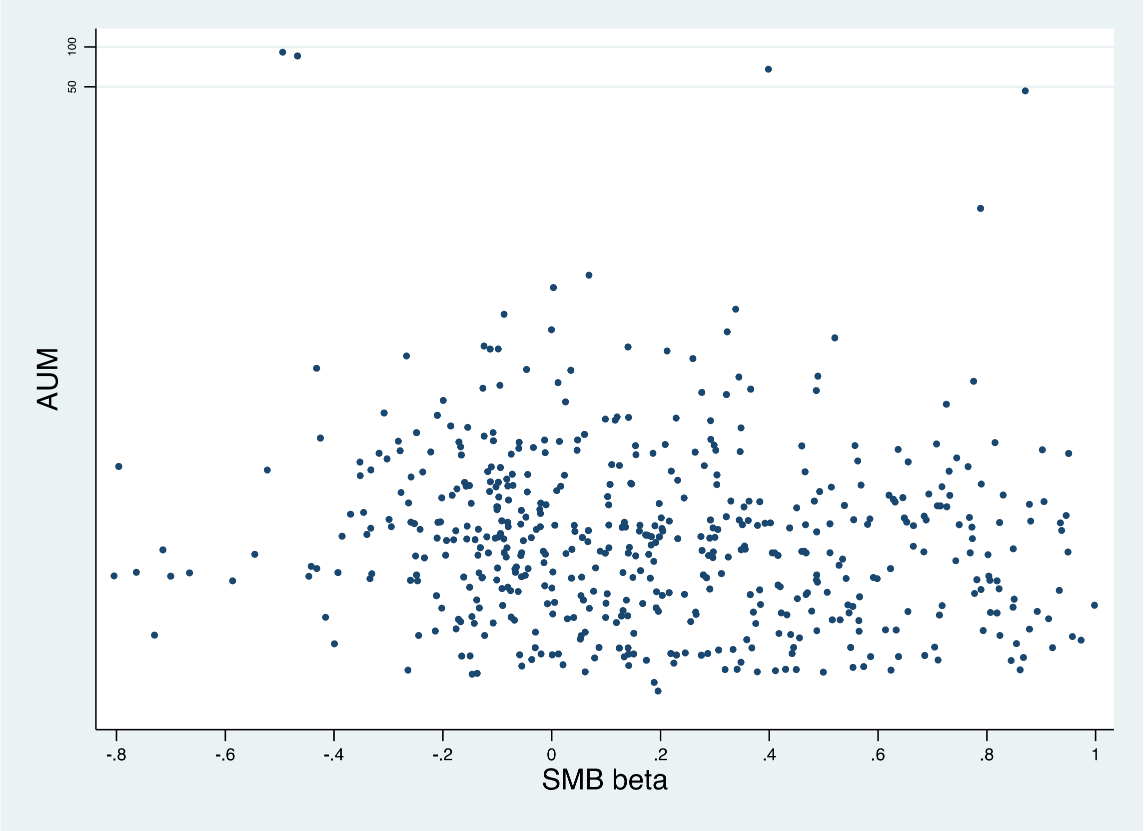


**Figure 12: HML factor exposure of ETFs (-1 to 1 range)**

This figure depicts HML exposures of all ETFs, where each dot represents an individual ETF. HML betas of ETFs are plotted on the horizontal axis against AUM values on the vertical axis. The HML betas are estimated by regressing each ETF on the market, size, value, momentum and low risk factor. Only HML betas between -1 and +1 are shown, removing ETFs with (extreme) leveraged and short positions. To improve readability of the figure, a logarithmic scale is used for the AUM values. AUM values are given in billion dollars.

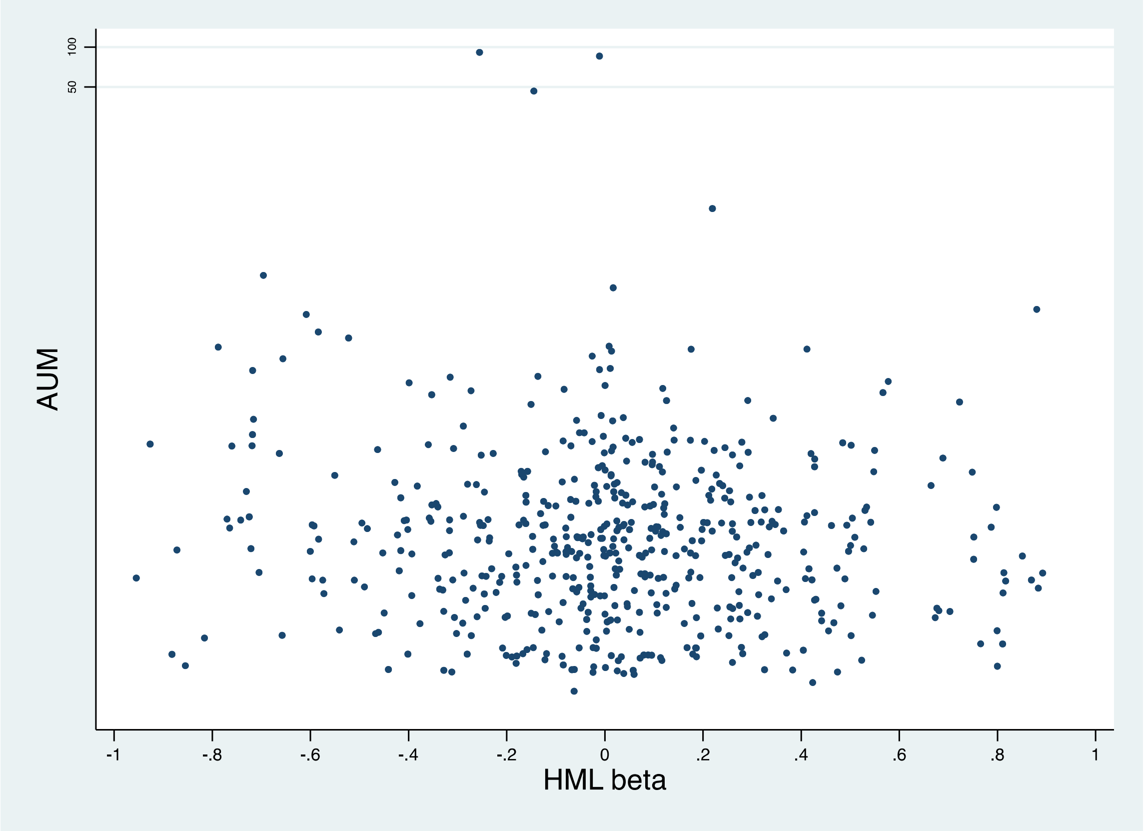


**Figure 13: MOM factor exposure of ETFs (-1 to 1 range)**

This figure depicts MOM exposures of all ETFs, where each dot represents an individual ETF. MOM betas of ETFs are plotted on the horizontal axis against AUM values on the vertical axis. The MOM betas are estimated by regressing each ETF on the market, size, value, momentum and low risk factor. Only MOM betas between -1 and +1 are shown, removing ETFs with (extreme) leveraged and short positions. To improve readability of the figure, a logarithmic scale is used for the AUM values. AUM values are given in billion dollars.

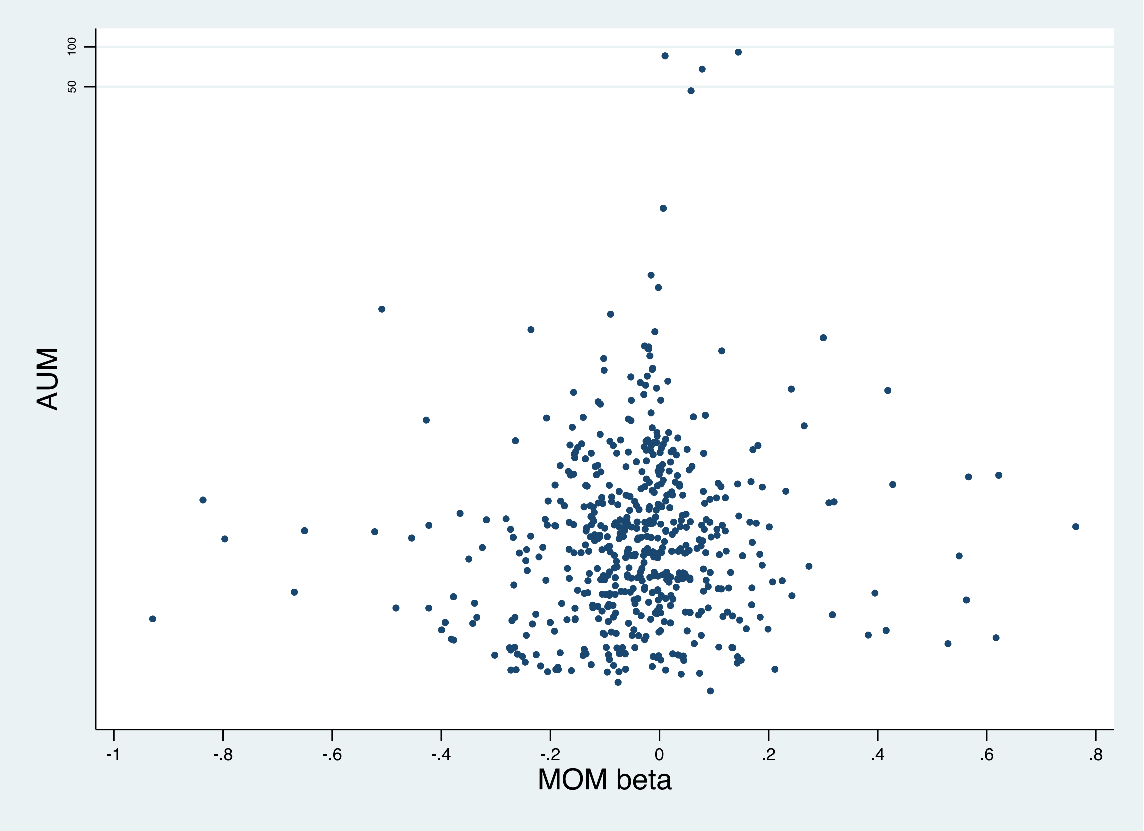
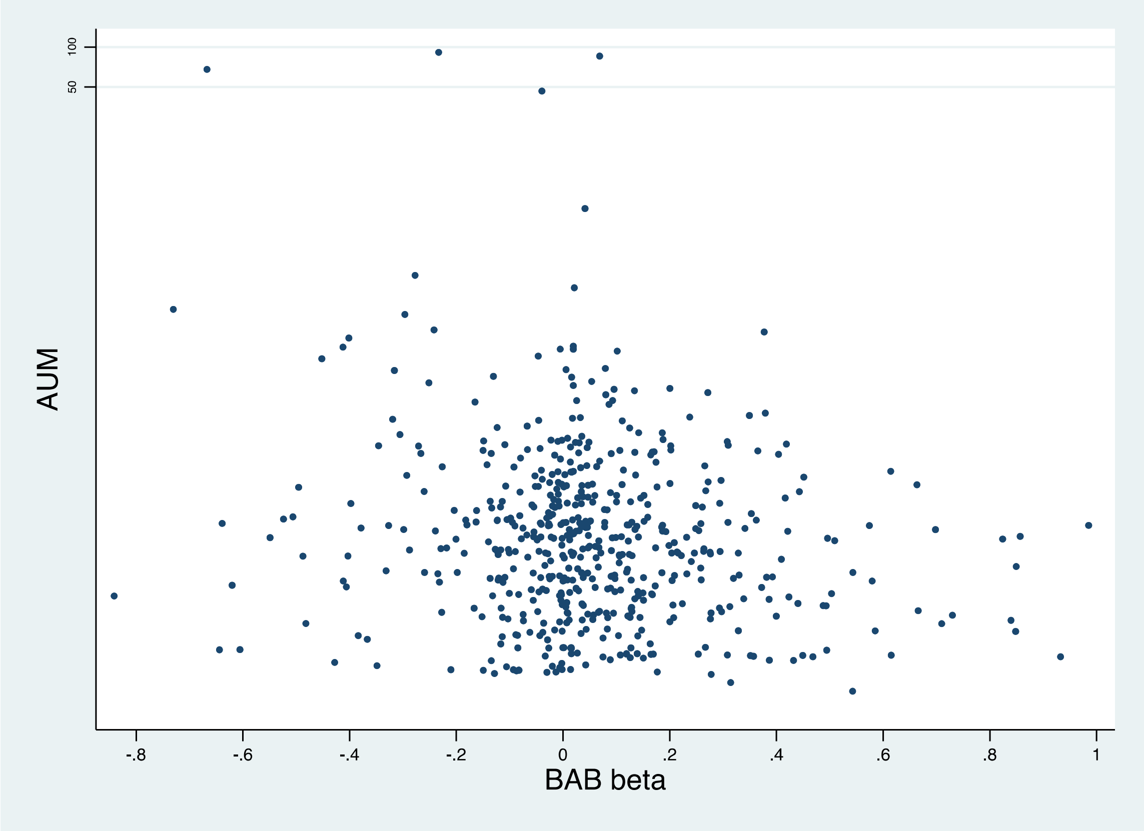


**Figure 14: BAB factor exposure of ETFs (-1 to 1 range)**

This figure depicts BAB exposures of all ETFs, where each dot represents an individual ETF. BAB betas of ETFs are plotted on the horizontal axis against AUM values on the vertical axis. The BAB betas are estimated by regressing each ETF on the market, size, value, momentum and low risk factor. Only BAB betas between -1 and +1 are shown, removing ETFs with (extreme) leveraged and short positions. To improve readability of the figure, a logarithmic scale is used for the AUM values. AUM values are given in billion dollars.



### 5.2.2 Aggregate factor exposures of ETFs

Table 12 reports on the aggregate factor exposures and their statistical significance for all ETFs and for the two subsamples (smart beta ETFs and conventional ETFs). Next to this, for each factor and (sub)sample, the percentage of funds with significant positive exposure as well as the percentage of funds with significant negative exposure is shown.

**Table 12: Aggregate factor exposures of ETFs**

This table shows aggregate factor exposures for each (sub)sample of ETFs. Aggregate exposures are calculated as the AUM weighted average factor exposures. These factor exposures are estimated, for each ETF, by regressing each ETF on the market, size, value, momentum and low risk factor. The *t*-statistics of the aggregate factor exposures are computed using a AUM weighted regression of the factor exposures. Furthermore, for each (sub)sample, the percentage of funds with significant positive exposure and the percentage of funds with significant negative exposure, on a 5% significance level, toward each factor is shown.

| **Panel A: All ETFs** | **Alpha** | **MKT** | **SMB** | **HML** | **MOM** | **BAB** |
|---|---|---|---|---|---|---|
| AUM weighted aggregate exposure | 0.01% | 1.00 | 0.05 | 0.03 | -0.03 | 0.02 |
| *t*-statistic | 0.35 | 73.29 | 1.22 | 0.74 | -5.65 | 1.56 |
| % funds significant positive exposure | 3.3% | 90.1% | 47.5% | 37.0% | 10.9% | 30.0% |
| % funds significant negative exposure | 17.5% | 9.3% | 23.0% | 24.9% | 30.7% | 12.1% |
| **Panel B: Smart Beta ETFs** | | | | | | |
| AUM weighted aggregate exposure | -0.03% | 0.93 | 0.24 | 0.22 | -0.02 | 0.07 |
| *t*-statistic | -1.53 | 46.76 | 2.50 | 8.66 | -2.33 | 4.21 |
| % funds significant positive exposure | 0.8% | 95.2% | 54.0% | 67.7% | 9.7% | 41.9% |
| % funds significant negative exposure | 25.8% | 4.8% | 26.6% | 11.3% | 41.9% | 4.8% |
| **Panel C: Conventional ETFs** | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| AUM weighted aggregate exposure | 0.02% | 1.03 | -0.00 | -0.04 | -0.03 | 0.00 |
| *t*-statistic | 0.85 | 56.02 | -0.04 | -0.86 | -5.13 | 0.27 |
| % funds significant positive exposure | 4.1% | 88.4% | 45.3% | 26.5% | 11.3% | 26.0% |
| % funds significant negative exposure | 14.6% | 10.8% | 21.8% | 29.6% | 26.8% | 14.6% |

Table 12A shows that the AUM weighted aggregate market factor exposure amounts to exactly 1.00 (the plain market beta). This implies that ETFs, on the aggregate level, have no bias toward high or low beta stocks. The aggregate BAB exposure confirms this inference, since the exposure is not significant. The aggregate factor exposures of the size and value factor and the alpha are positive, but not statistically significant. These results all correspond to the findings of Blitz (2017). The result that differs from his research, is the aggregate exposure of the momentum factor. The aggregate momentum exposure amounts to -0.03 and is highly statistically significant. The interpretation of this is that ETFs on aggregate have a slight bias toward ‘loser stocks’. Further on in this study, the aggregate factor exposures, including momentum, over time are discussed. It is interesting to see whether this negative aggregate exposure is present during the whole sample period.

For the size and value factor, there are more funds with significant positive exposure than there are funds with significant negative exposure. The size factor has the largest difference in funds, that is also reflected by the positive skewness of the factor exposures, reported in Figure 11. These results are consistent with the findings of Blitz (2017). In comparison with the findings of his research however, the percentage of funds that have significant positive exposure or significant negative exposure toward the size or value factor have grown, especially for funds that have significant positive exposure. Furthermore, Blitz (2017) finds that there are slightly more funds with significant positive exposure than negative exposure toward the momentum factor and for the low risk factor vice versa. In this research, it is the other way around: especially the percentage of funds with positive exposure to the low risk factor and the percentage of funds with negative exposure toward the momentum factor have grown. The growing percentage of negative momentum exposure funds is in accordance with the negative aggregate momentum exposure. Also, compared to Blitz (2017) the percentage of funds with a significant negative alpha exposure is larger.

Panel B and C of Table 12 report on (aggregate) factor exposures of the smart beta ETF subsample and the conventional subsample. In the smart beta subsample aggregate factor exposures toward the size, value and low risk factor are positive and statistically significant. Differences with the findings of Blitz (2017) are that the aggregate value exposure is much larger (0.22 versus 0.08) and the aggregate momentum exposure is significantly negative instead of insignificantly positive. So, also in the smart beta subsample, the aggregate factor exposure toward the momentum factor is negative.

Table 12C shows that none of the aggregate factor exposures toward the smart beta factors (except the momentum factor) is negative and statistically significant. This contrasts with the study of Blitz (2017). What stands out is that also in the conventional subsample the percentage of funds with significant positive exposure toward the size, value and low risk factor is high.

The results show that on the aggregate level there is no positive bias toward certain factors. On the contrary, the aggregate momentum exposure is found to be negative (-0.03). The interpretation of this is that the concern that factor premiums are being rapidly arbitraged away through ETF investing is not justified, studied from this perspective. However, the finding that aggregate factor exposures in the conventional subsample are not statistically significant negative is notable. The reason for conventional ETFs to cancel out the positive factor exposures of smart beta ETFs could be the relative small AUM total of smart beta ETFs in comparison to AUM of conventional ETFs. The question is if these factor exposures will cancel out going forth, given some studies (e.g. BlackRock) forecasts smart beta ETFs will have double the growth rate of conventional ETFs. In the following section, aggregate factor exposures over time are shown and discussed, to see whether some possible trends of aggregate factor exposures growing can be discovered.

### 5.2.3 Dynamic aggregate factor exposures of ETFs

Figures 15-18 depict aggregate factor exposures over time for the size, value, momentum and low risk factor, respectively. Aggregate factor exposures, for each date, are computed as the AUM weighted average exposures from rolling regressions with a time-window of thirty-six months

**Figure 15: Aggregate SMB factor exposure over time**

This figure displays the aggregate factor exposures of the SMB factor over time. For each date, aggregate exposures are calculated as the AUM weighted average factor exposures. These factor exposures are estimated, for each ETF, by rolling regressions of each ETF on the market, size, value, momentum and low risk factor with a time-window of thirty-six months.

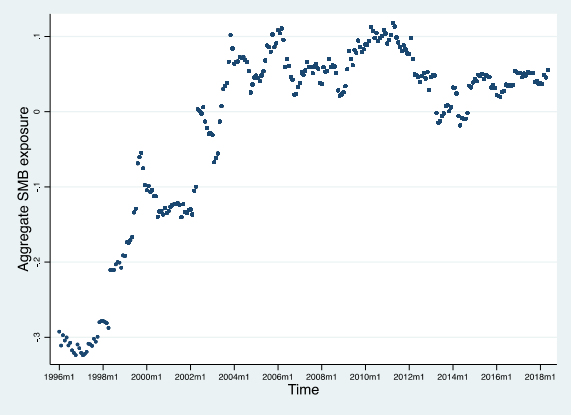


**Figure 16: Aggregate HML factor exposure over time**

This figure displays the aggregate factor exposures of the HML factor over time. For each date, aggregate exposures are calculated as the AUM weighted average factor exposures. These factor exposures are estimated, for each ETF, by rolling regressions of each ETF on the market, size, value, momentum and low risk factor with a time-window of thirty-six months.

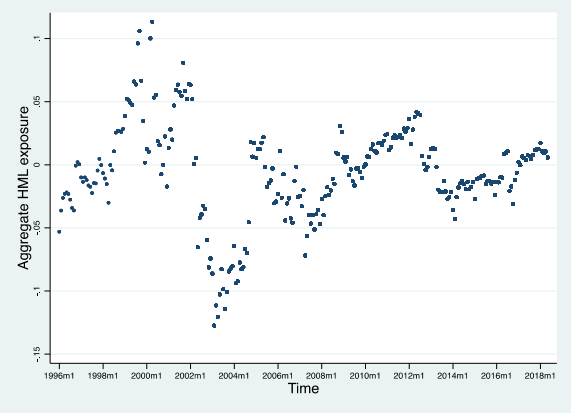


**Figure 17: Aggregate MOM factor exposure over time**

This figure displays the aggregate factor exposures of the MOM factor over time. For each date, aggregate exposures are calculated as the AUM weighted average factor exposures. These factor exposures are estimated, for each ETF, by rolling regressions of each ETF on the market, size, value, momentum and low risk factor with a time-window of thirty-six months.

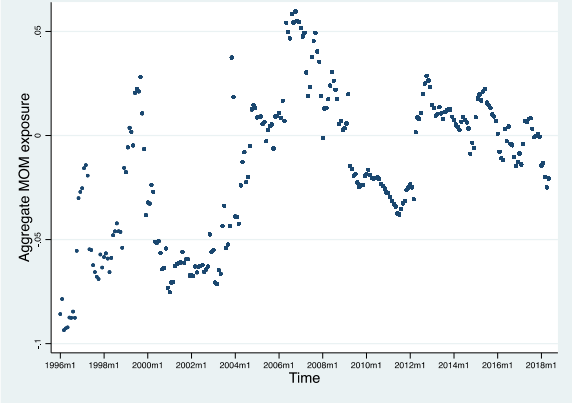


**Figure 18: Aggregate BAB factor exposure over time**

This figure displays the aggregate factor exposures of the BAB factor over time. For each date, aggregate exposures are calculated as the AUM weighted average factor exposures. These factor exposures are estimated, for each ETF, by rolling regressions of each ETF on the market, size, value, momentum and low risk factor with a time-window of thirty-six months.

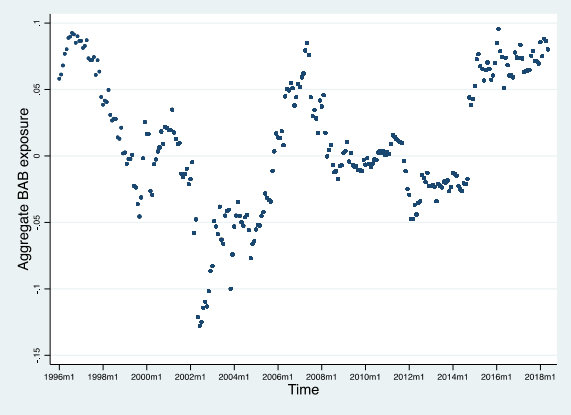


Figure 15 shows that the aggregate SMB factor exposures has been the most stable compared to the other factors. From 2004 onward, aggregate factor exposure tends to be positive. In Figure 16 can be seen that aggregate HML exposure moves volatile but averages around zero. Figure 17 shows that the aggregate MOM exposure moves even more volatile but seem to have a slight net negative bias over the whole sample period. Figure 18 shows that the BAB aggregate exposure has been volatile, but for the last years (2015-2018) it has been positive. The reason for this could be the fact that low risk ETFs started to launch around 2012.

Figures 15-18 show us that for the most recent years, aggregate SMB factor exposure is positive, MOM aggregate factor exposure has a slight negative bias over the whole sample period and BAB aggregate factor exposure has been rather positive for the most recent years. However, there are no real trends visible of aggregate factor exposures growing over time. This finding does not support the concern that smart beta premiums are rapidly arbitraged away through ETF investing.

### 5.2.4 Detailed results

Tables 13-16 show, among the largest 100 ETFs in terms of AUM, the five funds with the largest positive exposures and the five funds with the largest negative exposures toward each factor.

**Table 13: 5 largest ETFs sorted on SMB exposure**

This table lists the five ETFs with the largest positive SMB exposure and the five ETFs with the largest negative SMB exposure among the 100 largest ETFs, in terms of AUM. The SMB exposure is estimated by regressing each ETF on a multi-factor model, including the market, size, value, momentum and low risk factor.

| Ticker | Name | AUM ($bn) | SMB |
|---|---|---|---|
| **Panel A: Positive Exposures** | | | |
| XBI | SPDR S&P Biotech ETF | 5.136 | 1.06 |
| IWO | iShares Russell 2000 Growth ETF | 10.418 | 0.87 |
| IJS | iShares S&P Small-Cap 600 Value ETF | 5.460 | 0.81 |
| IWM | iShares Russell 2000 ETF | 47.089 | 0.79 |
| IWN | iShares Russell 2000 Value ETF | 10.207 | 0.78 |
| **Panel B: Negative exposures** | | | |
| TQQQ | ProShares UltraPro QQQ | 3.521 | -0.76 |
| XLP | Consumer Staples Select Sector SPDR Fund | 7.532 | -0.35 |
| VDC | Vanguard Consumer Staples ETF | 3.577 | -0.34 |
| HDV | iShares Core High Dividend ETF | 5.854 | -0.33 |
| XLU | Utilities Select Sector SPDR Fund | 7.300 | -0.28 |

**Table 14: 5 largest ETFs sorted on HML exposure**

This table lists the five ETFs with the largest positive HML exposure and the five ETFs with the largest negative HML exposure among the 100 largest ETFs, in terms of AUM. The HML exposure is estimated by regressing each ETF on a multi-factor model, including the market, size, value, momentum and low risk factor.

| Ticker | Name | AUM ($bn) | HML |
|---|---|---|---|
| **Panel A: Positive Exposures** | | | |
| KBE | SPDR S&P Bank ETF | 3.946 | 1.33 |
| KRE | SPDR S&P Regional Banking ETF | 5.074 | 1.10 |
| VFH | Vanguard Financials ETF | 8.327 | 0.75 |
| XLF | Financial Select Sector SPDR Fund | 31.796 | 0.75 |
| IWN | iShares Russell 2000 Value ETF | 10.207 | 0.58 |
| **Panel B: Negative exposures** | | | |
| TQQQ | ProShares UltraPro QQQ | 3.521 | -1.54 |
| IBB | iShares Nasdaq Biotechnology ETF | 8.763 | -0.76 |
| FDN | First Trust Dow Jones Internet Index Fund | 8.320 | -0.74 |
| XBI | SPDR S&P Biotech ETF | 5.136 | -0.73 |
| IYW | iShares US Technology ETF | 4.118 | -0.72 |

Table 13 reports that ETFs with the largest exposures toward the size factor, are ETFs tracking small-cap indices, which is in line with expectations. The fund with the largest SMB exposure is a biotechnology fund. Funds with the largest negative exposures are a mixed group, most of them being sector ETFs. These findings are consistent with Blitz (2017).

Table 14 shows that funds with the largest value exposure are not ETFs based on a value strategy, but are sector ETFs, such as bank and financial funds. Only the fifth largest exposure (0.58) is that of a multi-factor ETF (size and value). This finding is consistent with the finding of Blitz (2017) and that of Blitz (2016), who finds that popular smart beta ETFs fail to provide large exposures to the value factor. Funds with the largest negative HML exposure are sector funds (internet, biotech and technology).

**Table 15: 5 largest ETFs sorted on MOM exposure**

This table lists the five ETFs with the largest positive MOM exposure and the five ETFs with the largest negative MOM exposure among the 100 largest ETFs, in terms of AUM. The MOM exposure is estimated by regressing each ETF on a multi-factor model, including the market, size, value, momentum and low risk factor.

| Ticker | Name | AUM ($bn) | MOM |
|---|---|---|---|
| **Panel A: Positive Exposures** | | | |
| MTUM | iShares Edge MSCI USA Momentum Factor ETF | 8.997 | 0.27 |
| XBI | SPDR S&P Biotech ETF | 5.136 | 0.23 |
| KRE | SPDR S&P Regional Banking ETF | 5.074 | 0.19 |
| VPU | Vanguard Utilities ETF | 2.583 | 0.12 |
| IJT | iShares S&P Small-cap 600 Growth ETF | 5.914 | 0.11 |
| **Panel B: Negative exposures** | | | |
| SPHD | Invesco S&P 500 High Div Low Vol ETF | 2.634 | -0.28 |
| VNQ | Vanguard Real Estate ETF | 30.299 | -0.21 |
| IYR | iShares U.S. Real Estate ETF | 3.386 | -0.16 |
| ICF | iShares Cohen & Steers REIT ETF | 2.485 | -0.16 |
| PRF | Invesco FTSE RAFI US 1000 ETF | 5.201 | -0.15 |

**Table 16: 5 largest ETFs sorted on BAB exposure**

This table lists the five ETFs with the largest positive BAB exposure and the five ETFs with the largest negative BAB exposure among the 100 largest ETFs, in terms of AUM. The BAB exposure is estimated by regressing each ETF on a multi-factor model, including the market, size, value, momentum and low risk factor.

| Ticker | Name | AUM ($bn) | BAB |
|---|---|---|---|
| **Panel A: Positive Exposures** | | | |
| SPHD | Invesco S&P 500 High Div Low Vol ETF | 2.634 | 0.70 |
| SCHH | Schwab U.S. REIT ETF | 4.272 | 0.61 |
| SPLV | Invesco S&P 500 Low Volatility ETF | 6.939 | 0.44 |
| VPU | Vanguard Utilities ETF | 2.583 | 0.42 |
| XLU | Utilities Select Sector SPDR Fund | 7.300 | 0.37 |
| **Panel B: Negative exposures** | | | |
| KRE | SPDR S&P Regional Banking ETF | 5.074 | -0.50 |
| IYW | iShares US Technology ETF | 4.118 | -0.31 |
| XLK | Technology Select Sector SPDR Fund | 21.376 | -0.30 |
| QQQ | Invesco QQQ Trust | 63.445 | -0.28 |
| IBB | iShares Nasdaq Biotechnology ETF | 8.763 | -0.27 |

In Table 15 can be seen that momentum exposures (positive as well as negative) are much smaller than for the other factors. The fund with the largest positive MOM exposure is the MSCI USA Momentum Factor ETF, which is in line with intuition. Other funds with positive exposure are mainly sector funds. Most funds with the largest negative exposure toward the momentum factor are real estate ETFs. This is the opposite of Blitz (2017), who finds that real estate ETFs are among the funds with the largest positive exposure. In this study, however, the sample period differs from that of Blitz (2017). Since momentum is more like a price characteristic than a stock characteristic, the different sample periods could be the explanation for this difference in results.

Table 16 reports that among the funds with the largest BAB exposure, only one fund explicitly targets the low risk strategy (S&P 500 Low Volatility ETF). Funds with the largest negative exposures are sector funds with generally higher betas (technology, biotech).

## 5.3 Performance measurement

### 5.3.1. Aggregate ETF performance

Table 17 shows regression outputs from AUM weighted portfolios of the broad sample and two subsamples (smart beta ETFs and conventional ETFs) regressed on a multi-factor model. The portfolio formed from the total (survivorship-bias free) sample loads significantly positive on the SMB factor and significantly negative on the BAB factor. Furthermore, this portfolio earns an average statistically significant alpha of 0.14%. In line with the results from Table 12, the smart beta portfolio does not load statistically positive on the MOM factor and the conventional portfolio does not load statistically significant negative on the smart beta factors, except for the BAB factor. In contrast to the conventional portfolio, the smart beta portfolio does not earn a significant positive alpha.

**Table 17: Aggregate (sub)sample portfolio performance (multi-factor model)**

This table reports on factor exposures and their statistical significance for each (sub)sample. For each (sub)sample, portfolios are created by AUM weighting returns. These time-series returns are regressed on a multi-factor model (consisting of the market, size, value, momentum and low risk factor). For this analysis, a survivorship-bias free sample is used.

| **All ETFs** | **Alpha** | **MKT** | **SMB** | **HML** | **MOM** | **BAB** |
|---|---|---|---|---|---|---|
| Factor exposure | 0.14 | 0.98 | 0.06 | -0.00 | 0.00 | -0.05 |
| *t*-statistic | 2.14 | 61.59 | 3.19 | -0.07 | 0.09 | -2.81 |
| **Smart Beta ETFs** | | | | | | |
| Factor exposure | -0.03 | 0.94 | 0.44 | 0.20 | -0.02 | 0.02 |
| *t*-statistic | -0.45 | 59.09 | 18.99 | 9.32 | -1.11 | 1.13 |
| **Conventional ETFs** | | | | | | |
| Factor exposure | 0.14 | 0.98 | 0.03 | -0.04 | 0.00 | -0.05 |
| *t*-statistic | 2.15 | 59.95 | 1.39 | -1.56 | 0.09 | -2.68 |

Table 18 shows regression outputs from a multi-factor model for each AUM weighted strategy portfolio. Alphas of the strategy portfolios are not statistically significant, except for the quality portfolio, that has a relatively large negative alpha that is significant on the 10% significance level. An explanation for the absence of outperformance of smart beta ETFs could be that all potential outperformance is fully captured by the factors included in the regressions.

The table also shows the ability of each strategy to provide the intended factor exposure, also examined by Glushkov (2016). What stands out, is the fact that the quality portfolio is the only strategy that does not load significantly on its factor (QMJ). This finding is consistent with Glushkov (2016). Appendix 2 shows that this result is robust to regressions without the low risk factor and regressions without the low risk and value factor. Also, the multi-factor portfolio loads significantly on all the factors, except the quality factor. The value portfolio loads highly statistically significant on the value factor (0.32), in contrast to Glushkov (2016), who finds value funds not to provide the intended value exposure. Another finding of his research is that smart beta ETFs may load potentially on unintended factors which may work to offset capturing the risk-adjusted outperformance of intended factor exposures. This finding is also documented in this study. For example, the value portfolio loads negatively on the size and momentum factor, and the momentum portfolio loads negatively on the value and quality factor. These factor loadings are generally consistent with the factor correlation matrix, shown in Appendix 1 (e.g. a positive correlation between BAB and QMJ and a negative correlation between HML and MOM).

**Table 18: Aggregate smart beta strategy portfolio performance (multi-factor model)**

This table reports on the regression results of the different formed strategy portfolios. For each smart beta strategy, portfolios are created by AUM weighting returns. These time-series returns are regressed on a multi-factor model (consisting of the market, size, value, momentum and low risk factor). For this analysis, a survivorship-bias free sample is used.

| **Strategy** | **SMB** | **HML** | **MOM** | **BAB** | **QMJ** | **M-F** |
|---|---|---|---|---|---|---|
| $\alpha_i$ | -0.06 | -0.05 | 0.01 | -0.01 | -0.23* | -0.06 |
| Pr[$\alpha_i$] | 0.328 | 0.499 | 0.950 | 0.930 | 0.070 | 0.439 |
| $\beta_i^{MKT}$ | 0.94*** | 0.91*** | 1.06*** | 0.78*** | 1.02*** | 0.96*** |
| $\beta_i^{SMB}$ | 0.68*** | -0.11*** | 0.20*** | -0.07 | 0.10* | 0.53*** |
| $\beta_i^{HML}$ | 0.16*** | 0.32*** | -0.21*** | 0.02 | -0.11** | 0.43*** |
| $\beta_i^{BAB}$ | 0.05*** | 0.04** | -0.00 | 0.26*** | 0.16*** | 0.11*** |
| $\beta_i^{MOM}$ | 0.00 | -0.06*** | 0.21*** | -0.02 | 0.10*** | -0.03* |
| $\beta_i^{QMJ}$ | -0.05 | 0.02 | -0.15* | 0.16** | 0.05 | 0.06 |
| *# obs* | 216 | 216 | 180 | 137 | 149 | 214 |

*, ** and *** represent statistical significance on the 10%, 5% and 1% level, respectively.

Table 19 shows regression outputs from a one-factor market model for AUM weighted portfolios of the broad sample and two subsamples (smart beta ETFs and conventional ETFs). What stands out, is that the AUM weighted portfolio created from all smart beta ETFs in the sample does not earn a statistically positive alpha. In contrast to Table 17, the conventional portfolio does not earn a statistically significant alpha, either.

**Table 19: Aggregate (sub)sample portfolio performance (one-factor market model)**

This table reports on alphas and market exposures including their statistical significance for each (sub)sample. For each (sub)sample, portfolios are created by AUM weighting returns. These time-series returns are regressed on a one-factor market model. For this analysis, a survivorship-bias free sample is used.

| **All ETFs** | **Alpha** | **MKT** |
|---|---|---|
| Factor exposure | 0.08 | 1.00 |
| *t*-statistic | 1.33 | 67.15 |

| | | |
|---|---|---|
| **Smart Beta ETFs** | | |
| Factor exposure | 0.15 | 1.02 |
| *t*-statistic | 1.43 | 42.67 |
| **Conventional ETFs** | | |
| Factor exposure | 0.08 | 1.00 |
| *t*-statistic | 1.22 | 65.58 |

Table 20 shows regression outputs from a one-factor market model for each AUM weighted strategy portfolio. None of the individual strategy portfolio report a statistically significant alpha or a Sharpe ratio significantly higher than the market's. This is different from the results of Glushkov (2016), who finds for two smart beta categories (value and volatility) outperformance of the risk-adjusted benchmark. The explanation for this could be the difference in the benchmark. Glushkov (2016) uses the Vanguard Total Stock Market ETF (VTI) as benchmark, whereas in this regression the market factor of the Kenneth R. French online data library is used, which excludes costs. Another difference is the fact that Glushkov (2016) does not use a survivor-ship bias free data sample, which may improve performance.

The multi-factor portfolio, however, does report a large alpha (0.31) that is significant on the 5% level. Also, the Sharpe ratio of the portfolio is higher than the market's Sharpe ratio on a 5% significance level. Although Sharpe ratios of the momentum and low risk strategy portfolios are higher than the Sharpe ratio of the multi-factor portfolio, these are not significant higher than the Sharpe ratio of the market. The explanation for this is the difference in sample periods; the market performed better in a more recent time-period. Detailed results of the strategies' Sharpe ratios in comparison to the market are shown in Appendix 3. The reason for the outperformance of the multi-factor portfolio in comparison to the other portfolios could be that this portfolio loads positively on most factors (except for momentum) and thus does not have many unintended factor exposures.

**Table 20: Aggregate smart beta strategy portfolio performance (one-factor market model)**

This table reports on the regression results of the different formed strategy portfolios. Also, for each strategy portfolio, the Sharpe ratio and its z-statistic are reported. For each smart beta strategy, portfolios are created by AUM weighting returns. These time-series returns are regressed on a one-factor market model. For this analysis, a survivorship-bias free sample is used.

| **Strategy** | **SMB** | **HML** | **MOM** | **BAB** | **QMJ** | **M-F** |
|---|---|---|---|---|---|---|
| $E[r_i]$ | 0.686 | 0.478 | 0.840 | 0.706 | 0.623 | 0.787 |
| $\alpha_i$ | 0.17 | 0.05 | 0.02 | 0.20 | -0.07 | 0.31** |
| $Pr[\alpha_i]$ | 0.218 | 0.591 | 0.888 | 0.169 | 0.615 | 0.034 |
| $\beta_i^{MKT}$ | 1.08*** | 0.88*** | 1.06*** | 0.70*** | 0.95 | 1.00*** |
| Shrp | 0.136 | 0.118 | 0.182 | 0.204 | 0.145 | 0.164 |
| z-stat | 0.888 | 0.236 | -0.420 | 0.875 | -0.914 | 1.71** |

| | | | | | | |
|---|---|---|---|---|---|---|
| *# obs* | 216 | 216 | 180 | 137 | 149 | 214 |

*, ** and *** represent statistical significance on the 10%, 5% and 1% level, respectively.

## 5.3.2 Individual ETF performance

At the aggregate level, no significant outperformance of smart beta strategies is found, except for the multi-factor strategy portfolio. Most retail investors invest in one or a few ETFs, however, and not in a value-weighted portfolio of many smart beta ETFs. In this section, I measure performance of ETFs at an individual level by their alphas and Sharpe ratios.

### 5.3.1.1 Alpha

Tables 21 and 23 report on the aggregate alpha exposures and their statistical significance for the broad sample and for the two subsamples (smart beta ETFs and conventional ETFs). Next to this, in Tables 21-24, for each (sub)sample, the percentage of funds with a significant positive alpha as well as the percentage of funds with a significant negative alpha is shown. For Tables 21 and 22, the alpha is estimated using a one-factor market model, whereas for Tables 22 and 23, alpha is measured using a one-factor model containing the SPY ETF as a benchmark. Tables 22 and 24 report on alpha characteristics using a survivorship-bias free sample.

**Table 21: Individual ETF performance**

This table shows aggregate alphas and aggregate market exposures for each (sub)sample of ETFs. These are calculated as the AUM weighted average factor exposures. The factor exposures are estimated, for each ETF, by regressing each ETF on a one-factor market model. The *t*-statistics of the aggregate factor exposures are computed using a AUM weighted regression of the factor exposures. Furthermore, for each (sub)sample, the percentage of funds with significant positive exposure and the percentage of funds with significant negative exposure, on a 5% significance level, is shown.

| **All ETFs** | **Alpha** | **MKT** |
|---|---|---|
| AUM weighted aggregate exposure | 0.02% | 1.02 |
| *t*-statistic | 1.69 | 48.31 |
| % funds significant positive exposure | 4.7% | 90.1% |
| % funds significant negative exposure | 13.0% | 9.3% |
| **Smart Beta ETFs** | | |
| AUM weighted aggregate exposure | 0.09% | 0.99 |
| *t*-statistic | 3.12 | 31.27 |
| % funds significant positive exposure | 5.6% | 95.2% |
| % funds significant negative exposure | 8.1% | 4.8% |
| **Conventional ETFs** | | |
| AUM weighted aggregate exposure | 0.00% | 1.03 |
| *t*-statistic | 0.26 | 38.20 |
| % funds significant positive exposure | 4.4% | 88.4% |
| % funds significant negative exposure | 14.6% | 10.8% |

**Table 22: Individual ETF performance (survivorship-bias free sample)**

This table shows, for each (sub)sample, the percentage of funds with significant positive exposure and the percentage of funds with significant negative exposure, on a 5% significance level These factor exposures are estimated, for each ETF, by regressing each ETF on a one-factor market model. For this analysis, a survivorship-bias free sample is used.

| All ETFs | Alpha | MKT |
|---|---|---|
| % funds significant positive exposure | 4.1% | 89.3% |
| % funds significant negative exposure | 14.2% | 10.1% |
| **Smart Beta ETFs** | | |
| % funds significant positive exposure | 5.1% | 93.4% |
| % funds significant negative exposure | 11.8% | 6.6% |
| **Conventional ETFs** | | |
| % funds significant positive exposure | 3.8% | 88.0% |
| % funds significant negative exposure | 15.0% | 11.3% |

**Table 23: Individual ETF performance (SPY market)**

This table shows aggregate alphas and aggregate SPY exposures for each (sub)sample of ETFs. These are calculated as the AUM weighted average factor exposures. The factor exposures are estimated, for each ETF, by regressing each ETF on a one-factor model containing the SPY ETF as a benchmark. The *t*-statistics of the aggregate factor exposures are computed using a AUM weighted regression of the factor exposures. Furthermore, for each (sub)sample, the percentage of funds with significant positive exposure and the percentage of funds with significant negative exposure, on a 5% significance level, is shown.

| All ETFs | Alpha | SPY |
|---|---|---|
| AUM weighted aggregate exposure | 0.06% | 1.05 |
| *t*-statistic | 3.32 | 56.87 |
| % funds significant positive exposure | 5.8% | 89.9% |
| % funds significant negative exposure | 11.1% | 9.3% |
| **Smart Beta ETFs** | | |
| AUM weighted aggregate exposure | 0.13% | 1.01 |
| *t*-statistic | 3.93 | 36.13 |
| % funds significant positive exposure | 7.3% | 95.2% |
| % funds significant negative exposure | 5.6% | 4.8% |
| **Conventional ETFs** | | |
| AUM weighted aggregate exposure | 0.03% | 1.07 |
| *t*-statistic | 2.07 | 44.63 |
| % funds significant positive exposure | 5.2% | 88.1% |
| % funds significant negative exposure | 13.0% | 10.8% |

**Table 24: Individual ETF performance (SPY market, survivorship-bias free sample)**

This table shows, for each (sub)sample, the percentage of funds with significant positive exposure and the percentage of funds with significant negative exposure, on a 5% significance level These factor exposures are estimated, for each ETF, by regressing each ETF on a one-factor model containing the SPY ETF as a benchmark. For this analysis, a survivorship-bias free sample is used.

| All ETFs | Alpha | SPY |
|---|---|---|
| % funds significant positive exposure | 5.2% | 89.1% |
| % funds significant negative exposure | 12.1% | 10.1% |
| **Smart Beta ETFs** | | |
| % funds significant positive exposure | 6.6% | 93.4% |
| % funds significant negative exposure | 8.1% | 6.6% |
| **Conventional ETFs** | | |
| % funds significant positive exposure | 4.7% | 87.8% |
| % funds significant negative exposure | 13.4% | 11.3% |

Table 21 shows that aggregate alpha exposure in the broad sample is positive and weakly statistically significant. However, there are more than twice as much funds with significant negative alphas (13.0%) than funds with significant positive alphas (4.7%). The aggregate alpha of smart beta ETFs is positive (0.09%) and statistically significant. Despite that, the percentage funds with significant positive alphas is small (5.6%) and less than funds with significant negative alphas (8.1%). Aggregate alpha exposure of conventional ETFs is zero and statistically insignificant. The percentage of funds with significant positive alphas is less than the smart beta subsample and the percentage funds with significant negative alphas is greater than that of the smart beta subsample. It seems that the smart beta subsample performs slightly better than the conventional subsample in terms of alpha characteristics; however, differences are small. Detailed results of ETFs with the largest (significant) positive and negative alphas for each strategy are shown in Appendix 4-7.

Table 22 shows that in all (sub)samples the percentage of funds with significant positive alphas decreases and the percentage of funds with significant negative alphas increases by adding dead ETFs to the sample. This is in line with intuition, since ETFs generally stop existing because of bad performance or too few inflows (because of bad performance).

In Table 23 can be seen that all alpha characteristics (aggregate exposures and positive/ negative exposures) have improved compared to Table 21, using the SPY ETF as a benchmark. The reason for this could be that costs (e.g. an expense ratio of 0.09%) are included in the benchmark's returns. Aggregate alpha exposure in the smart beta sample amounts to 0.13% and is highly statistically significant. The percentage of funds with significant positive alphas in this subsample, however, is still low (7.3%).

Table 24 shows the same result as shown by Table 22; performance measured by alpha weakens by adding dead ETFs to the sample.

#### 5.3.1.2 Sharpe ratio

Tables 25 and 26 report on the percentage of funds with a higher Sharpe ratio than the specific benchmark and its statistical significance, for each (sub)sample.

**Table 25: Individual ETF performance measured by Sharpe ratio**

This table reports, for each (sub)sample, the percentage of funds with a higher Sharpe ratio than the market and the percentage of funds with a higher Sharpe ratio than the SPY benchmark, for the corresponding time-period. The z-statistic reports on the percentage of funds that have a higher Sharpe ratio that are statistically significant on a 5% significance level.

| **All ETFs** | **Sharpe ratio** | **z-statistic** |
|---|---|---|
| % funds Sharpe ratio higher than MKT | 19.5% | 3.2% |
| % funds Sharpe ratio higher than SPY | 26.7% | 6.9% |
| **Smart Beta ETFs** | | |
| % funds Sharpe ratio higher than MKT | 20.2% | 4.0% |
| % funds Sharpe ratio higher than SPY | 23.4% | 10.3% |
| **Conventional ETFs** | | |
| % funds Sharpe ratio higher than MKT | 19.3% | 2.9% |
| % funds Sharpe ratio higher than SPY | 27.9% | 5.9% |

**Table 26: Individual ETF performance measured by Sharpe ratio (survivorship-bias free sample)**

This table reports, for each (sub)sample, the percentage of funds with a higher Sharpe ratio than the market and the percentage of funds with a higher Sharpe ratio than the SPY benchmark, for the corresponding time-period. The z-statistic reports on the percentage of funds that have a higher Sharpe ratio that are statistically significant on a 5% significance level. For this analysis, a survivorship-bias free sample is used.

| **All ETFs** | **Sharpe ratio** | **z-statistic** |
|---|---|---|
| % funds Sharpe ratio higher than MKT | 19.4% | 3.7% |
| % funds Sharpe ratio higher than SPY | 26.0% | 7.5% |
| **Smart Beta ETFs** | | |
| % funds Sharpe ratio higher than MKT | 19.1% | 3.8% |
| % funds Sharpe ratio higher than SPY | 22.1% | 10.0% |
| **Conventional ETFs** | | |
| % funds Sharpe ratio higher than MKT | 19.5% | 3.6% |
| % funds Sharpe ratio higher than SPY | 27.2% | 6.9% |

Table 25 shows that approximately one fifth of smart beta ETFs have higher Sharpe ratios than the market and approximately one fourth of smart beta ETFs have higher Sharpe ratios than the SPY ETF. However, the percentage of these funds that are statistically significant is low (4.0% and 10.3%, respectively). The smart beta subsample is not performing significantly better than the conventional subsample, according to this table.

Table 26 reports that percentages of funds with higher Sharpe ratios than the benchmark decrease by adding dead ETFs to the sample. Only the percentage of conventional funds with significant higher Sharpe ratios than the market increases, which implies that a few funds that had a significant higher Sharpe ratio than the market did not survive till the end of the sample period.

At the individual ETF level, I find no conclusive empirical evidence that smart beta ETFs generate risk-adjusted outperformance. Although aggregate alphas of the smart beta subsamples are positive, the percentage of smart beta funds that have statistically significant positive alphas is small. Also, the percentage of smart beta funds that have a significantly higher Sharpe ratio than the market is very small. The conclusion of this is that the rising popularity of smart beta ETFs is not supported by significant outperformance in the historical data.

# 6 Discussion and conclusion

Factor investing, or smart beta investing is the investment strategy of harvesting risk premiums offered by academically established factors. Historically, smart beta strategies generally have shown to outperform the market on a risk-adjusted basis. With the invention of ETFs, investors are now able to directly capture these risk premiums by investing in smart beta strategies. The popularity of smart beta ETFs rises with yearly double digit growth rates. This raises the concern that if too many investors are chasing the same risk premiums, factors could be arbitraged away and smart beta performance could attenuate. This study aims to provide empirical evidence on the question whether smart beta strategies are reaching their limits. Also, it aims to answer the question whether smart beta ETFs deliver on their promise to generate outperformance.

I find that most smart beta strategies have lots of capacity left for further growth. Only the value strategy, and to a lesser extent the multi-factor strategy, approach AUM capacity where rebalancing costs could offset risk premiums. Furthermore, I show that aggregate exposures toward the various factors are not significantly positive. The momentum factor is even significantly negative at the aggregate level. Aggregate factor exposures do not show visible trends of growing over time. These findings argue against the concern that these factors are rapidly being arbitraged away by ETF investors. Moreover, this study provides empirical evidence that at the aggregate level, smart beta strategy portfolios do not generate significant outperformance, except for the multi-factor strategy portfolio. Studied at the individual ETF level, only a small percentage of smart beta funds generates excess returns. A possible explanation for this could be that performance of smart beta funds is weakened by unintended factor exposures. Overall, no conclusive evidence is found that smart beta investing earns superior risk-adjusted returns. This finding is not in line with the growing popularity of smart beta ETFs.

There are several limitations to this research. First of all, the sorting process of ETFs into (smart beta) categories is done manually using particular criteria. These criteria could differ from other studies. For example, I have not classified high dividend ETFs as smart beta ETFs, since this is not one of the value characteristics specified by MSCI, whereas other studies regard these ETFs to be smart beta ETFs. These differences could have an effect on total AUM computation of the strategies. Furthermore, there is criticism on the paper of Ang et al. (2017) that the transaction cost model for computing factor capacities does not work with such large trade amounts. Critics argue that especially the market impact of transaction costs cannot be predicted by the model for such trade amounts. Moreover, in this research, strategies targeting low (idiosyncratic) volatility stocks and strategies targeting low beta stocks are both sorted into the low risk strategy. The BAB factor, low beta stocks minus high beta stocks, is used in the regressions to capture these factor exposures. In existing literature however, a separate factor is created for strategies based on low (idiosyncratic) volatility stocks (LH-HV factor). Since both factors cannot be included in the same regression because of multicollinearity problems, it could be that the BAB factor does not fully explain part of the low risk ETFs' returns.

For further research, it would be interesting to include other investment vehicles in the research. Blitz (2018), for instance, has already examined what aggregate factor exposures of hedge funds look like. This research could be extended by looking at aggregate factor exposures of mutual funds. Also, extending the performance analysis of ETFs by studying performance over time would be a fruitful venue for further research. The concern that due to the rising popularity of smart beta ETFs performance weakens over time could be examined by a time-series performance study.

# 7 Appendix

### A1: Correlation matrix factors

This table shows the correlation matrix for the different kinds of factors used in this study for the sample period January 1990 till May 2018. Data for the factor returns are retrieved from the Kenneth R. French online data library and the AQR online data library, respectively.

| | MKT | SMB | HML | MOM | BAB | QMJ |
|---|---|---|---|---|---|---|
| MKT | 1 | | | | | |
| SMB | 0.22 | 1 | | | | |
| HML | -0.17 | -0.26 | 1 | | | |
| MOM | -0.25 | 0.05 | -0.19 | 1 | | |
| BAB | -0.32 | -0.21 | 0.43 | 0.26 | 1 | |
| QMJ | -0.63 | -0.46 | 0.06 | 0.33 | 0.33 | 1 |

### A2: Detailed results quality strategy portfolio performance

This table reports on the regression results of the formed quality strategy portfolio. For the quality strategy, a portfolio is created by AUM weighting returns. These time-series returns are regressed on a multi-factor model. In the first column, the multi-factor model consists of the market, size, value, momentum and low risk factor. For the second column, the low risk factor is removed from the regression. In the third column, regression results are shown from a regression without the value and low risk factor. For this analysis, a survivorship-bias free sample is used.

| **Strategy** | **QMJ** | **QMJ** | **QMJ** |
|---|---|---|---|
| $\alpha_i$ | -0.23* | -0.17 | -0.17 |
| $Pr[\alpha_i]$ | 0.070 | 0.204 | 0.213 |
| $\beta_i^{MKT}$ | 1.02*** | 1.03*** | 1.03*** |
| $\beta_i^{SMB}$ | 0.10* | 0.08 | 0.07 |
| $\beta_i^{HML}$ | -0.11** | -0.16*** | |
| $\beta_i^{BAB}$ | 0.16*** | | |
| $\beta_i^{MOM}$ | 0.10*** | 0.12*** | 0.15*** |
| $\beta_i^{QMJ}$ | 0.05 | 0.03 | 0.07 |
| *# obs* | 149 | 149 | 149 |

*, ** and *** represent statistical significance on the 10%, 5% and 1%, respectively.

### A3: Detailed results Sharpe ratios smart beta strategies

This table reports on the Sharpe ratio details of the different formed strategy portfolios and on the Sharpe ratio details of the market for the corresponding time-period. Also, the z-statistic for the test of the difference in Sharpe ratios between the portfolio and the market is shown. For each smart beta strategy, portfolios are created by AUM weighting returns. For this analysis, a survivorship-bias free sample is used.

| **Strategy** | **SMB** | **HML** | **MOM** | **BAB** | **QMJ** | **M-F** |
|---|---|---|---|---|---|---|
| $E[r_i]$ | 0.686 | 0.478 | 0.840 | 0.706 | 0.623 | 0.787 |
| $\sigma_i$ | 5.050 | 4.055 | 4.606 | 3.465 | 4.298 | 4.817 |
| Shrp | 0.136 | 0.118 | 0.182 | 0.204 | 0.145 | 0.164 |
| $E[r_{market}]$ | 0.481 | 0.481 | 0.770 | 0.718 | 0.727 | 0.476 |
| $\sigma_{market}$ | 4.308 | 4.308 | 3.919 | 4.310 | 4.164 | 4.314 |
| $Shrp_{market}$ | 0.112 | 0.112 | 0.196 | 0.167 | 0.175 | 0.110 |
| z-stat | 0.888 | 0.236 | -0.420 | 0.875 | -0.914 | 1.71** |
| *# obs* | 216 | 216 | 180 | 137 | 149 | 214 |

*, ** and *** represent statistical significance on the 10%, 5% and 1% level, respectively.

### A4: 5 largest SMB ETFs sorted on alpha

This table lists the five ETFs with the largest positive alphas and the five ETFs with the largest negative alphas in the SMB subsample. The alphas are estimated by regressing each ETF on a one-factor market model. ETFs with leveraged and short positions are excluded from the sample.

| **Ticker** | **Name** | **AUM (bn)** | **Alpha** |
|---|---|---|---|
| **Panel A: Positive Exposures** | | | |
| IJR | iShares Core S&P Small-Cap ETF | 41.374 | 0.33** |
| IWM | iShares Russell 2000 ETF | 47.089 | 0.15 |
| IWR | iShares Russell Mid-Cap ETF | 17.303 | 0.10 |
| VXF | Vanguard Extended Market ETF | 6.215 | 0.09 |
| EUSA | iShares MSCI USA Equal Weighted ETF | 0.157 | 0.04 |
| **Panel B: Negative exposures** | | | |
| SMCP | Alphamark Actively Managed Small Cap ETF | 0.027 | -0.98*** |
| EWSC | Invesco S&P SmallCap 600 Equal Weight ETF | 0.032 | -0.54** |
| PZI | Invesco Zacks Micro Cap ETF | 0.020 | -0.53*** |
| WMCR | Invesco Wilshire Micro-Cap ETF | 0.029 | -0.33* |
| IWC | iShares Micro-Cap ETF | 1.013 | -0.25 |

*, ** and *** represent statistical significance on the 10%, 5% and 1% level, respectively.

### A5: 5 largest HML ETFs sorted on alpha

This table lists the five ETFs with the largest positive alphas and the five ETFs with the largest negative alphas in the HML subsample. The alphas are estimated by regressing each ETF on a one-factor market model. ETFs with leveraged and short positions are excluded from the sample.

| **Ticker** | **Name** | **AUM (bn)** | **Alpha** |
|---|---|---|---|
| **Panel A: Positive Exposures** | | | |
| HDV | iShares Core High Dividend ETF | 5.854 | 0.31* |
| RDIV | Oppenheimer S&P Ultra Div Revenue ETF | 0.534 | 0.26 |
| IUSV | iShares Core S&P U.S. Value ETF | 3.702 | 0.10 |
| SDY | SPDR S&P Dividend ETF | 15.282 | 0.09 |
| IWD | iShares Russell 1000 Value ETF | 36.006 | 0.07 |
| **Panel B: Negative exposures** | | | |
| PEY | Invesco High Yield Equity Div Achievers ETF | 0.772 | -0.18 |
| VOOV | Vanguard S&P 500 Value ETF | 0.813 | -0.16* |
| IWX | iShares Russell Top 200 Value ETF | 0.295 | -0.15* |
| MGV | Vanguard Mega Cap Value ETF | 1.934 | -0.13 |
| RPV | Invesco S&P 500 Pure Value ETF | 0.873 | -0.13 |

*, ** and *** represent statistical significance on the 10%, 5% and 1% level, respectively.

### A6: 2 largest MOM ETFs sorted on alpha

This table lists the two ETFs with the largest positive alphas and the two ETFs with the largest negative alphas in the MOM subsample. The alphas are estimated by regressing each ETF on a one-factor market model. ETFs with leveraged and short positions are excluded from the sample.

| **Ticker** | **Name** | **AUM (bn)** | **Alpha** |
|---|---|---|---|
| **Panel A: Positive Exposures** | | | |
| MTUM | iShares Edge MSCI USA Momentum Factor ETF | 8.997 | 0.41** |
| MMTM | SPDR S&P 1500 Momentum Tilt ETF | 0.030 | 0.13 |
| **Panel B: Negative exposures** | | | |
| DWAQ | Invesco DWA NASDAQ Momentum ETF | 0.056 | -0.08 |
| PDP | Invesco DWA Momentum ETF | 1.604 | -0.05 |

*, ** and *** represent statistical significance on the 10%, 5% and 1% level, respectively.

### A7: 5 largest BAB ETFs sorted on alpha

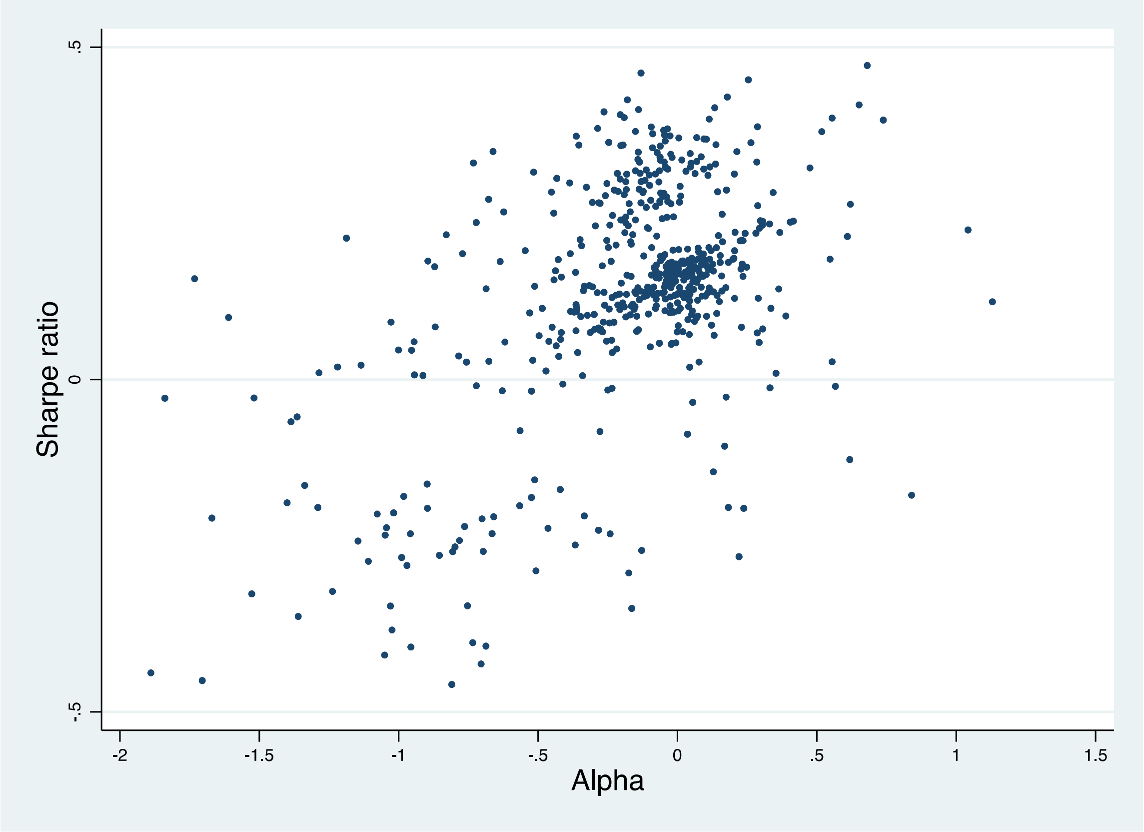
This table lists the five ETFs with the largest positive alphas in the BAB subsample. The alphas are estimated by regressing each ETF on a one-factor market model. ETFs with leveraged and short positions are excluded from the sample.

| Ticker | Name | AUM (bn) | Alpha |
|---|---|---|---|
| **Panel A: Positive Exposures** | | | |
| SPLV | Invesco S&P 500 Low Volatility ETF | 6.939 | 0.39** |
| USMV | iShares Edge MSCI Min Vol USA ETF | 14.491 | 0.31** |
| DEF | Invesco Defensive Equity ETF | 0.171 | 0.12 |
| LGLV | SPDR SSGA US Large Cap Low Vol Index ETF | 0.103 | 0.09 |
| CFA | VictoryShares US 500 Volatility Wtd ETF | 0.541 | 0.07 |

*, ** and *** represent statistical significance on the 10%, 5% and 1% level, respectively.

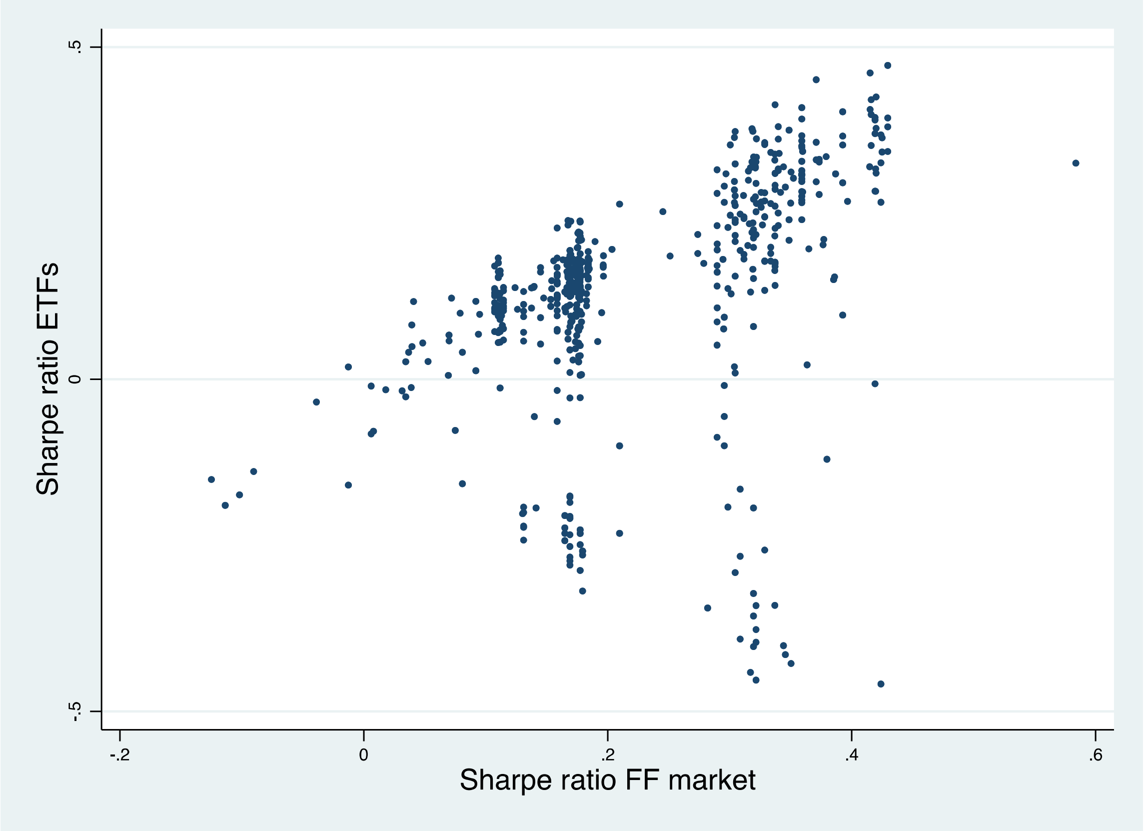
### A8: ETF Sharpe ratios plotted against ETF alphas

This figure depicts alphas and corresponding Sharpe ratios of all ETFs, where each dot represents an individual ETF. Alphas of ETFs are plotted on the horizontal axis against Sharpe ratios on the vertical axis. The alphas are estimated by regressing each ETF on a one-factor market model. For this analysis, a survivorship-bias free sample is used.



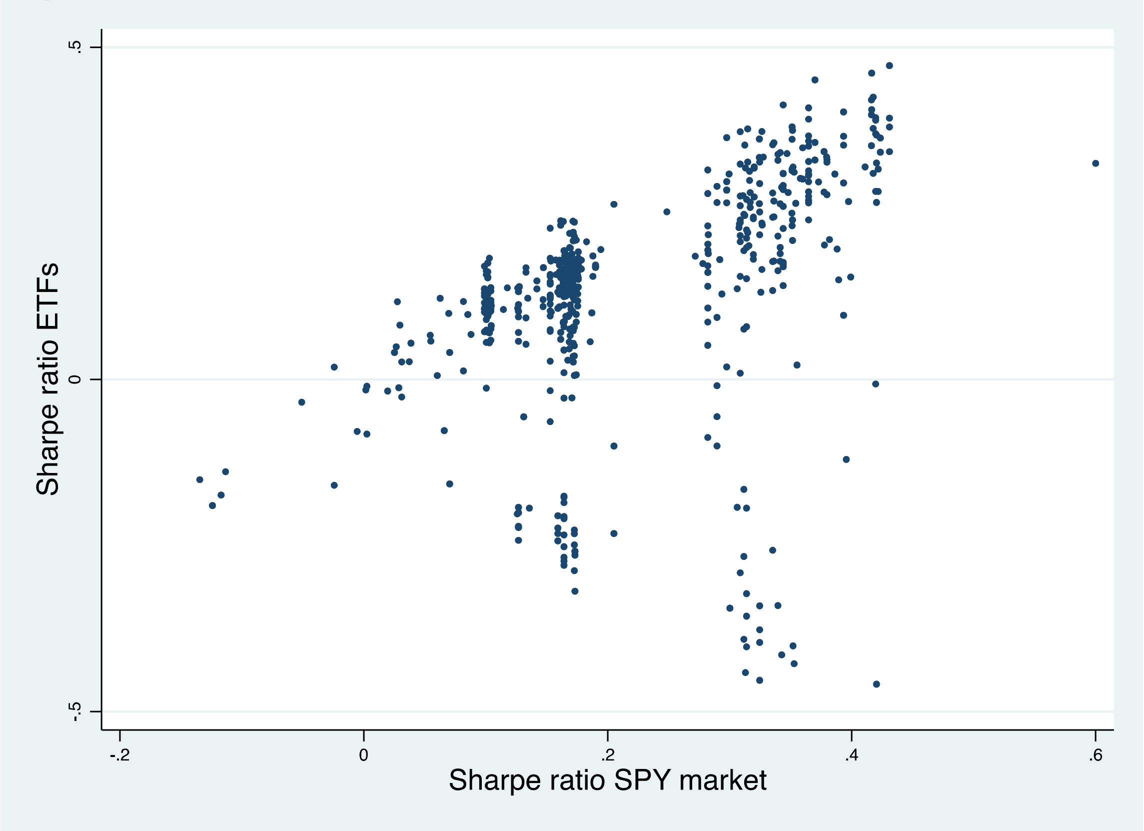
### A9: Sharpe ratios ETFs plotted against Sharpe ratios market

This figure depicts Sharpe ratios of ETFs and Sharpe ratios of the market for the corresponding time-period, where each dot represents an individual ETF. Sharpe ratios of the market are plotted on the horizontal axis against Sharpe ratios of the funds on the vertical axis. For this analysis, a survivorship-bias free sample is used.



**A10: Sharpe ratios ETFs plotted against Sharpe ratios SPY ETF**

This figure depicts Sharpe ratios of ETFs and Sharpe ratios of the SPY benchmark for the corresponding time-period, where each dot represents an individual ETF. Sharpe ratios of the SPY benchmark are plotted on the horizontal axis against Sharpe ratios of the funds on the vertical axis. For this analysis, a survivorship-bias free sample is used.



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