Do Smart Beta ETFs Capture Factor Premiums? A Bayesian Perspective

Abstract

We investigate which factors matter to explain the returns of smart beta and conventional ETFs using a Bayesian approach. We find that smart beta ETFs are well explained by the market, size and the betting-against-beta factor, whereas conventional ETFs are explained by the market, the quality-minus-junk factor, and a value factor. Smart beta ETFs benefit from their exposure to the betting-against-beta factor, but still underperform on a risk-adjusted basis, while the factor exposure of conventional ETFs is purely detrimental. Our results suggest investors should be skeptical about the ability of smart beta ETFs to capture factor premiums.

Keywords: Smart Beta, strategic beta, factor investing, factor selection, Bayesian variable selection.

JEL Classifications: G11, G12, C3

The popularity of factor investing among institutional investors has spawned a range of financial products, most notably Exchange Traded Funds (ETFs), that aim to provide factor exposure in a cheap and transparent way.[1] "Smart" or "strategic" beta ETFs, which explicitly target one or more factors or employ alternative weighting schemes using fundamental variables (i.e. *fundamental indexation*), have become a significant portion in the ETF market. A recent study published by MorningStar (Johnson, 2017) shows that, as of June 2017, there were 1,320 "strategic beta" exchange traded products, with global assets under management of over $700 billion worldwide, the majority of which comprises U.S. equity ETFs.

The factor exposure of smart beta ETFs is an important issue for investors, but is not straightforward for various reasons, such as differences in the ways these products attempt to capture factor returns, potential time variation in factor loadings (Ang et al., 2017), differences with respect to factor definitions in the asset pricing literature, and the inherent uncertainty regarding which factors are priced or robust sources of return (Baker et al., 2017; Beck et al., 2016). For example, even fundamental indexation strategies could create unanticipated (typically value) factor tilts (Asness, 2006; Blitz and Swinkels, 2008). Additionally, smart beta ETFs implement long-only strategies, hindering their ability to capture full factor premiums, as suggested by Blitz (2016). Therefore, it is important not only to understand the factor exposures of these products to intentional factor bets, but also to detect exposures to other factors not directly targeted by them.[2]

In this study, we apply a Bayesian factor selection method to investigate which factors matter to explain the returns of smart beta as well as conventional ETFs. The returns of all ETFs in each category are analyzed using an extensive set of candidate factors, and the posterior probabilities of the best factor models are calculated for the two ETF groups. We then

[1] A recent survey on factor investing among investment professionals (Amen et al., 2017) report that 73% make use of a multi-factor framework, with another 18% planning to implement one. See Ang (2014) for a review of the factor investing approach. See also Angelidis and Tessaroma (2017) for an application of factor investing in a global equity country allocation context.
[2] See, for example, Amenc et al. (2018) and Shirbini (2018).

investigate the differences in factor exposure between smart beta and conventional ETFs by comparing the contribution of these factors to the two ETF groups.

We explore all U.S. equity ETFs which are active as of December 2017 and have return data over the period from January 2013 to December 2017, comprising 200 smart beta ETFs and 168 conventional ETFs, totalling over $1.5 trillion in assets under management. We create automatic rules to classify ETFs as smart beta or conventional based on keyword searches in the ETFs names and descriptions obtained from Thomson Reuters DataStream, and then manually check the resulting classification to ensure that it conforms to our definition of smart beta ETFs.

Due to the uncertainties regarding the (intended or unintended) factor exposures of smart beta ETFs, we consider a comprehensive set of candidate factors. This set includes the factors popular in asset pricing such as those proposed by Fama and French (2015), Chen and Zhang (2010), and Hou et al. (2015), which comprise the market factor and factors related to the size, value, investment and profitability effects. Additionally, we consider factors related to momentum (Jegadeesh and Titman, 1993), volatility (Ang et al., 2006), betting-against-beta (Frazzini and Pedersen, 2014), quality (Asness et al., 2017), illiquidity (Amihud, 2002), and the alternative value factor of Asness and Frazzini (2013).

We compare the performance of the best models selected using our methodology with that of a benchmark model that includes the largest number of factors that do not cause severe multicollinearity.[3] The benchmark model includes eight factors. The first four factors comprise the market excess return, value (HML), profitability (RMW), and investment (CMA) factors from the Fama and French (2015) model. The other factors are the momentum (MOM),

[3]Some of these factors are highly correlated. For example, the correlation of the profitability factors based on ROE (return on equity) (Hou et al., 2015) and ROA (return on assets) (Chen and Zhang, 2010) is close to 0.95, and the correlation between the Fama and French (2015) size factor and the Amihud (2002) illiquidity factor is 0.92. Other related factors such as the Fama and French (2015) HML (High Minus Low) value factor and the Asness and Frazzini (2013) HMLd (High Minus Low "Devil") factor have correlations close to 0.80.

quality-minus-junk (QMJ), and illiquidity (ILL) factors, and the Chen and Zhang (2010) investment factor (INV).[4] We note that multicollinearity is not an issue in our framework, as the variable selection methodology will focus on the most parsimonious sets of factors, and thus models which include highly correlated or redundant factors will naturally have low posterior probability.

Our main results from applying the Bayesian factor selection procedure to smart beta and conventional ETFs show that (i) parsimonious models with up to three factors are selected with high posterior probability for both groups of ETFs; (ii) the selected factors for smart beta ETFs are different from those for conventional ETFs; (iii) the performance of the highest posterior probability models to explain the two groups of ETFs is similar to the performance of the benchmark model with eight factors.

For smart beta ETFs, a two-factor model with the market and the size (small-minus-big, SMB) factors is selected with high posterior probability (0.67). The second best model includes the Frazzini and Pedersen (2014) betting-against-beta (BAB) factor, with a posterior probability of 0.29. The average R^2 of this three-factor model (the excess market return, SMB, and BAB) identified by our procedure is 0.84, compared to 0.89 using the benchmark model and 0.74 for the single-factor market model. The average absolute alpha across all smart beta ETFs from this three-factor model is 0.16% per month, whereas it is 0.14% for the benchmark model and 0.24% for the market model. Therefore, adding the two factors (SMB and BAB) to the market factor produces a parsimonious model that explains almost as much variability and average returns as the full benchmark model for smart beta ETFs. This result raises an important question about the ability of smart beta ETFs to capture premiums related to other factors such as value, momentum, profitability, and investment, especially as the BAB factor is not significantly correlated to these factors.

[4] The Chen and Zhang (2010) investment factor (INV) is based on a different definition of investment from the one proposed by Fama and French (2015) and has a low correlation with that factor.

For conventional ETFs, the model with the highest posterior probability (with a posterior probability of 0.70) includes the market factor, the Asness and Frazzini (2013) HMLd factor, and the Quality-Minus-Junk (QMJ) factor of Asness et al. (2017). The average R^2 of this three factor model is 0.66, compared to 0.72 for the benchmark model, and 0.56 for the market model. These results reveal that conventional ETFs have significant factor exposures, but to different factors compared with smart beta ETFs.

We find that, although smart beta ETFs, on average, benefit from their exposure to the BAB factor, they still underperform the market on a risk-adjusted basis, as evidenced by their negative alphas. The factor exposures of conventional ETFs to non-market factors such as QMJ, CMA and HMLd, on the other hand, are purely detrimental, reducing the average ETF return by -0.14% per month. These results suggest that investors should be skeptical about the possibility of obtaining factor exposure through smart beta ETFs, and should also be mindful of potentially undesired factor exposure in conventional ETFs.

Methodology

We start by considering a linear factor model with N assets and K predictor variables (factors) over T periods:

$$\mathbf{r}_i = \mathbf{X}\boldsymbol{\beta}_i + \mathbf{e}_i, \qquad i = 1, \dots, N, \tag{1}$$

where, for each asset i (in this study, an ETF), $\mathbf{r}_i$ is the $T \times 1$ vector of excess returns, $\mathbf{X}$ is the $T \times K$ matrix of factors, $\boldsymbol{\beta}_i = (\beta_{i,1}, \dots, \beta_{i,K})'$ is the vector of unknown regression coefficients (factor sensitivities), and $\mathbf{e}_i$ is the $T \times 1$ vector of disturbances or specific returns. The system can be stacked in a single equation $\tilde{\mathbf{r}} = \widetilde{\mathbf{X}}\widetilde{\boldsymbol{\beta}} + \tilde{\mathbf{e}}$ in the following way:[5]

[5] If the error terms are contemporaneously cross-correlated, the system of regressions is a special case of the Seemingly Unrelated Regressions (SUR) model, where the predictor variables are the same for all equations. The SUR model, introduced by Zellner (1962), consists of N

$$\underbrace{\begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_2 \\ \vdots \\ \mathbf{r}_N \end{bmatrix}}_{\tilde{\mathbf{r}}} = \underbrace{\begin{bmatrix} \mathbf{X} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{X} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{X} \end{bmatrix}}_{\tilde{\mathbf{X}}} \underbrace{\begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \vdots \\ \boldsymbol{\beta}_N \end{bmatrix}}_{\tilde{\boldsymbol{\beta}}} + \underbrace{\begin{bmatrix} \mathbf{e}_1 \\ \mathbf{e}_2 \\ \vdots \\ \mathbf{e}_N \end{bmatrix}}_{\tilde{\mathbf{e}}}. \tag{2}$$

This formulation assumes that we know, in advance, the K factors that shoud be included in the model, which in practice is not the case. In order to carry out factor selection in model (2), we introduce a vector $\boldsymbol{\gamma} = (\gamma_1, \dots, \gamma_K)'$ of dummy variables, where $\gamma_j = 1$ if the $j-th$ factor is included in the model, and zero otherwise. Given a set of K candidate factors, each value of $\boldsymbol{\gamma}$ represents a distinct factor model.

We focus on the identification of the binary vector $\boldsymbol{\gamma}$ in this study, which determines the combination of factors (or the linear factor model) that matters for the explanation of ETFs. Comparison of all possible models becomes computationally infeasible as the number of candidate factors (K) grows, since the number of possible models increases at the rate of 2^K. In this study, we apply the Bayesian variable selection method introduced by Hwang and Rubesam (2018), which provides consistent estimates of model probabilities with large panels of data using Markov Chain Monte Carlo (MCMC) methods. The posterior distribution of the binary vector $\boldsymbol{\gamma}$ indicates which models are supported by the data, i.e. have high posterior probability to explain the returns on the N assets.

Let $\mathbf{X}_\gamma$ represent the matrix $\mathbf{X}$ where each column is multiplied by the corresponding element of $\boldsymbol{\gamma}$. Then we can write the model with variable selection as $\mathbf{r}_i = \mathbf{X}_\gamma \boldsymbol{\beta}_i + \mathbf{e}_i,\ i = 1, \dots, N$, or stacking the N equations as before:

$$\tilde{\mathbf{r}} = \tilde{\mathbf{X}}_\gamma \tilde{\boldsymbol{\beta}} + \tilde{\mathbf{e}} \tag{3}$$

where $\tilde{\mathbf{X}}_\gamma$ is defined analogously. For the estimation of model (3), we need to specify the prior distributions of $\tilde{\boldsymbol{\beta}}$, $\boldsymbol{\Sigma}$ and $\boldsymbol{\gamma}$, which reflect our prior beliefs about the distributions of factor

regression equations, each with T observations, which are linked solely through the covariance structure of error terms at each observation, i.e. errors are contemporaneously correlated but not autocorrelated. Bayesian inference in the SUR model can be carried out in a relatively straightforward manner, see for example Giles (2003).

sensitivities, the cross-correlation of specific returns, and the probability that each candidate factor should be included in the model, respectively. Under standard prior distributions for $\widetilde{\boldsymbol{\beta}}$, $\boldsymbol{\Sigma}$ and $\boldsymbol{\gamma}$, we can iteratively generate values from the conditional posterior distributions of each parameter.[6] The simulated values of $\boldsymbol{\gamma}$ can then be tabulated to make inference on posterior distribution of individual models and factors.

Prior Distributions

We assume Gaussian priors for $\widetilde{\boldsymbol{\beta}}$, which leads to Gaussian conditional posterior distributions. Two alternative priors have been considered in this study. The first option is to use an empirical Bayes prior, by centering the prior distribution of the factor sensitivities of each ETF around their Ordinary Least Squares (OLS) estimates: $\boldsymbol{\beta}_i \sim N\left(\widehat{\boldsymbol{\beta}}_i, cVar(\widehat{\boldsymbol{\beta}}_i)\right)$. The second option is to use a prior centered on a vector of zeros: $\widetilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$. This choice reflects a complete lack of knowledge about the factors, both in terms of which predictors should enter the model as well as regarding the dependence structure of the regression coefficients. The parameter c in both cases controls how informative the prior is: the prior becomes less informative as c increases. Note that the first component of each $\boldsymbol{\beta}_i$ is the intercept (alpha) of each regression. The intercept is included as a factor because there is no guarantee that the factors we test in this study can fully explain individual ETF returns.

Data

ETFs

We obtain all U.S. equity ETFs that are active as of the end of 2017 from Thomson

[6] We apply the methodology for variable selection in the SUR model introduced by Hwang and Rubesam (2018). The method uses standard prior distributions for the parameters of the model, and assumes independence between the factor sensitivities and the dummy variables. The prior distributions for $\widetilde{\boldsymbol{\beta}}$, $\boldsymbol{\Sigma}$ and $\boldsymbol{\gamma}$ are Gaussian, inverse-Whishart, and binomial, respectively. A summary of the model estimation procedure is provided in the Appendix, and we refer the readers to the original paper for a detailed derivation of the conditional posterior distributions.

Reuters. These 799 ETFs have approximately $1.6 trillion of assets under management (AUM). Since we are interested in equity factor exposure, we remove leveraged and inverse ETFs, as well as ETFs which make use of derivatives. We further require 60 months of available returns, which leads to a sample of 368 ETFs, with aggregate AUM of $1.54 trillion.[7]

Classification of ETFs

There is no universally accepted definition of smart beta ETFs. In this study, we employ an automatic procedure to identify smart beta ETFs from each ETF's name and description using certain keywords. We then manually review the list and the descriptions of smart beta and conventional ETFs to ensure the classification is consistent, consulting the fact sheet or other ETF documentation in case of doubt.[8] The ETFs that do not have any of the characteristics of smart beta ETFs are classified as "conventional ETFs". This includes all passive ETFs which track common indices, as well as sector-specific ETFs.

Smart beta ETFs in this study are those that have at least one of the following characteristics:

- Attempt to increase returns relative to a market capitalization-weighted index by providing exposure to one or more factors thought to be sources of return (e.g. ETFs focused on value, size, quality, or momentum factors);
- Attempt to reduce risk or increase diversification (e.g. low volatility and minimum variance ETFs);
- Alternative weighting schemes (e.g. ETFs weighted by fundamentals; equally-weighted ETFs);
- Deviation from market capitalization-weighted schemes in a systematic, rules-based way

[7] Most ETFs excluded from our sample are due to their shorter history. If we were to require a longer history, the number of smart beta ETFs would decrease significantly.
[8] The details from this procedure are available upon request.

(e.g. ETFs based on dividend or shareholder yield screens).

Using the procedure outlined above, we classify 200 ETFs in the smart beta category, and 168 ETFs in the conventional category. Smart beta ETFs as a group manage $515 billion in assets, while the combined AUM of conventional ETFs is over $1 trillion.

Factors

We use a total of 14 factors in this study. We start with the five Fama and French (2015) factors, as well as the momentum (MOM) factor, from Professor Kenneth French's data library.[9] The five Fama and French (2015) factors are the market (MKT), size or Small-Minus-Big (SMB), value or High-Minus-Low (HML), profitability or Robust-Minus-Weak (RMW), and Investment or Conservative-Minus-Aggressive (CMA). We also include the Quality-Minus-Junk (QMJ) factor of Asness et al. (2017), the Betting-Against-Beta (BAB) factor of Frazzini and Pedersen (2014), and the alternative value factor HML "devil" (HMLd) of Asness and Frazzini (2013), which we download from the AQR data library[10]. Finally, we add five factors related to illiquidity (ILL, Amihud, 2002), volatility (VOL, Ang et al., 2006), and investment (INV) and profitability based on return on assets (ROA, Chen and Zhang, 2010) and return on equity (ROE, Hou et al., 2015).[11]

Table 1 reports descriptive statistics on the 14 factors for the period from January 2013 to December 2017. The average returns on most factors (Panel A) are relatively small during this period, with the exception of QMJ (0.95% per month) and BAB (1.25% per month). In

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[10] https://www.aqr.com/Insights/Datasets
[11] These factors are value-weighted hedge portfolio returns based on double sorts on all available U.S. common stocks from the CRSP and Compustat databases, excluding micro-cap stocks, defined as those with market capitalization lower than the 20th percentile of all NYSE stocks. The illiquidity factor is based on a two-by-three sort on volatility and illiquidity as in Amihud et al. (2015) because of the high correlation between illiquidity and volatility. For each month, we calculate the median return volatility using the NYSE breakpoint, and use it to assign all stocks into low or high volatility groups. We then calculate the Amihud (2002) illiquidity measure for all stocks, and use the NYSE low 30%, middle 40% and high 30% breakpoints to assign stocks into three illiquidity groups. The illiquidity factor is calculated as the difference between the average return on the two high illiquidity portfolios and the average return on the two low illiquidity portfolios. The volatility, investment, and profitability factors based on ROE and ROA are constructed using two-by-three sorts on size (using the median NYSE market capitalization) and the variables in question. The volatility factor is the difference between the average return on the two low and high volatility portfolios. The investment factor is constructed following Chen and Zhang (2010), i.e. the difference between the average return on the two low and high investment portfolios. Finally, the ROA (ROE) profitability factors are the differences between the average return on the two high and low ROA (ROE) portfolios.

fact, the returns on the Fama and French (2015) size (SMB), value (HML), and investment (CMA) factors are all negative. Interestingly, the average return on the Chen and Zhang (2010) investment factor is positive at 0.30% per month, which could reflect differences in the definition of investment, and highlights the importance of considering alternative factors when studying the factor exposure of products which may differ significantly in terms of implementation.[12] The only factors with t-statistics above 2 during the sample period are MKT (t-stat of 3.44), BAB (t-stat of 4.94) and INV (t-stat of 2.03).

Many of these factors are highly correlated. Panel B reports the ten largest correlations (in absolute value). The most extreme correlations are between ROE and ROA (0.95), SMB and ILL (0.92), VOL and ROA (0.86), QMJ and ROA (0.84), and VOL and ROE (0.82). As mentioned, this is not an issue for our variable selection methodology, but multicollinearity may be problematic in the conventional regression if all these factors were included as explanatory variables. Therefore, we build a benchmark model by including the largest number of factors that do not cause severe multicollinearity. Using variance inflation factors (VIFs), we remove the factors with the highest VIFs one at a time, and recalculate the VIFs each time. This procedure eliminates ROA, SMB, HMLd, VOL, BAB, and ROE. We consider all 14 factors when applying the Bayesian variable selection methodology. The eight-factor benchmark model is used for comparison purposes.[13]

[Table 1 about here.]

[12] Fama and French (2015) define investment as "the change in total assets from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by t-2 total assets", while Chen and Zhang (2010) definition is "annual change in gross property, plant, and equipment plus annual change in inventories divided by lagged book assets ".

[13] The resulting benchmark model has eight factors, the highest VIF (corresponding to CMA) is 2.78, and the highest correlation is 0.64, between CMA and HML.We also considered models with more than eight factors. In this case, individual factors had VIFs as high as 7. In any case, the results were not qualitatively different and do not change our conclusions.

Empirical Results

Exploratory Analysis of ETF Factor Exposure

We start by conducting an exploratory analysis of ETFs using OLS regressions for individual ETFs. Panel A of Table 2 reports OLS estimates of factor sensitivities for three groups of ETFs: all ETFs (Panel A.1), smart beta ETFs (Panel A.2) and conventional ETFs (Panel A.3). We report the average aggregate sensitivity to each factor, the corresponding t-statistic, the 5th and 95th percentiles of factor sensitivities, and the percentage of ETFs for which the factor is significant, either with a positive or negative sign at the 95% confidence level.

Panel A.1 shows that the aggregate factor sensitivities across all ETFs is significant for the excess market return, CMA, QMJ, and ILL factors, as evidenced by their t-statistics. Aggregate sensitivities are close to zero and not statistically significant for the other factors (HML, RMW, MOM, and INV). However, all factors are significant for many individual ETFs. For example, the HML factor is significantly positive (negative) for 18% (23%) of the ETFs. It is also evident that factor exposure is skewed; the 5th and 95th percentiles do not appear equidistant from their means, although the aggregate exposure to most factors is not different from zero.[14]

Panels A.2 and A.3 of Table 2 reveal similarities as well as differences between the factor sensitivities of smart beta and conventional ETFs. Both groups of ETFs have, on average, a positive sensitivity to CMA (tilt towards "conservative" firms in terms of investment), and a negative sensitivity to QMJ (tilt towards "junk" or unprofitable companies), although the latter is more pronounced for conventional ETFs. Smart beta ETFs also have, on average, positive and significant sensitivities to the momentum and illiquidity factors, revealing a tilt towards

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[14] We confirm the significant differences in factor sensitivities between conventional and smart beta ETFs by estimating the distribution of factor sensitivities with a nonparametric method (not reported). In general, despite the fact that both groups of ETFs have similar mean factor sensitivities for many factors, conventional ETFs have a much wider range of factor sensitivities compared to smart beta ETFs, i.e. the estimated densities for conventional ETFs have much longer tails. This may reflect other characteristics such as sector returns, which we have not considered in this study.

past winners and less liquid (typically smaller) stocks. In contrast, conventional ETFs are, in aggregate, tilted towards growth stocks, as evidenced by the negative and significant sensitivity to HML, while smart beta ETFs have zero sensitivity to that factor on average. We also note that smart beta ETFs have, on average, a slightly lower market beta than conventional ETFs, which is not surprising considering that there are many low volatility ETFs in the smart beta category.

Panel B of Table 2 reports, for each group of ETFs, the average return and its decomposition in terms of the return due to market exposure, the return due to exposure to other factors, and the intercept. Smart Beta ETFs in our sample appear to perform slightly better than conventional ETFs by 0.05% per month, although neither group performs particularly well and both underperform the market portfolio. Based on the benchmark model, smart beta ETFs do not appear to benefit from their non-market factor exposures, which contribute -0.05% per month. They also show a negative (although insignificant) alpha of -0.01% per month. The factor exposure of conventional ETFs appears even more detrimental, reducing the average conventional ETF return by -0.21% per month.

Panel B also reports the average R^2 when only the market factor is considered and with the benchmark model, the number of ETFs, total AUM, and the average (AUM-weighted) expense ratio for each group of ETFs.[15] Across all ETFs, the average R^2 of the benchmark model is 0.79, compared to 0.64 of the market model. Interestingly, a higher proportion of the variance of the returns of smart beta ETFs is explained by the market factor: i.e. 0.74 compared to 0.56 of conventional ETFs. Also, the increase in R^2 from adding the additional seven factors is more pronounced for conventional ETFs (from 0.56 to 0.72, increase of 27%) compared to smart beta ETFs (0.74 to 0.89, increase of 20%). We also note that the annual expense ratio of smart beta ETFs is slightly higher than that of conventional ETFs (0.21%

[15] All R^2 values used in this study are adjusted R^2.

compared with 0.17%).

Summarizing, smart beta and conventional ETFs have significant sensitivities to different factors. In aggregate, smart beta ETFs have slightly lower market betas compared to conventional ETFs, and are tilted towards less liquid stocks and stocks with strong recent performance, while conventional ETFs are more tilted towards growth stocks. Therefore, the trading strategies of smart beta ETFs may satisfy investors who pursue the overall market performance but, at the same time, seek for higher returns or lower risk by attempting to exploit various trading strategies, in particular, the size, low volatility and momentum effects. However, smart beta ETFs do not seem to reap any benefits from their factor exposure.

[Table 2 about here.]

Bayesian Factor Selection

The main results of applying our Bayesian factor selection method to the groups of conventional and smart beta ETFs are obtained using an empirical Bayes prior for the factor sensitivities that are centered around their OLS estimate. All factors are assumed to have the same prior probability of being selected, and thus the prior probability for the inclusion of each factor is set equal to 0.5. We then estimate the model using 50,000 iterations of the MCMC algorithm.[16]

We focus on the posterior distribution of $\boldsymbol{\gamma}$, which reveals which factors best explain each group of ETFs. Panels A and B of Table 3 report models with the largest posterior probabilities for smart beta and conventional ETFs, respectively. With 14 factors plus the intercept, there are $2^{15} = 32{,}768$ possible models. Nevertheless, the results reveal that only a handful of models have meaningful posterior probabilities. The highest posterior probability

[16] Later we investigate the robustness of our results with respect to the form of the prior and its variance scaling parameter, c.

model for the group of smart beta ETFs includes the market (MKT) and size (SMB) factors (posterior probability = 0.67). The second best model (posterior probability = 0.29) also adds the betting-against-beta (BAB) factor. Other models have negligible posterior probabilities. For conventional ETFs, different factors appear to be significant. The best model (posterior probability = 0.70) includes the market factor (MKT), the quality-minus-junk (QMJ) and the alternative value factor HMLd. The second best model (posterior probability = 0.30) also adds the Fama and French (2015) investment factor (CMA). Interestingly, the set of factors selected for the group of conventional ETFs includes many factors typically targeted by smart beta ETFs. We note that, in all cases, the intercept is not selected, which means that the selected factors are enough to explain the returns of ETFs.

[Table 3 about here.]

The results obtained with smart beta ETFs are somewhat surprising, considering that many of these products explicitly attempt to capture premiums related to other factors such as value, momentum and volatility. In order to better understand these results and assess to what degree smart beta ETFs capture any factor premiums, we estimate (using OLS) the three-factor model suggested by our Bayesian procedure, which includes the MKT, SMB and BAB factors. The results are reported on Panel A of Table 4.

As expected, we find that the SMB and BAB factors are significant for many smart beta ETFs, as evidenced by the large t-statistics and the percentage of significant factor sensitivities. Although smart beta ETFs seem to benefit from their positive exposure to the BAB factor, which generates a monthly premium of 1.25% during our sample period, they underperform on a risk-adjusted basis, with an alpha of -0.08% per month. Moreover, their positive average exposure to SMB produces a small negative return of -0.04% per month (not reported). Panel

B of Table 4 shows that the average excess return of smart beta ETFs is 1.20% per month, of which 1.21% per month on average is due to their market exposure, and 0.08% is due to their exposure to the SMB and BAB factors.

In order to gauge how the three-factor model for smart beta ETFs obtained using the Bayesian approach performs relative to the eight-factor benchmark model, we compare the average absolute alpha and R^2 across all smart beta ETFs using the three factors (MKT, SMB and BAB factors).[17] The results are reported in Panel B of Table 4. The average absolute alpha from the three-factor model for the group of smart beta ETFs is 0.16% per month, and the average R^2 is 0.84. For the eight-factor benchmark model, the numbers are 0.14% and 0.90, respectively. The difference between the average absolute alphas using the two models, 0.02% per month, is economically insignificant, and thus it is unlikely that these smart beta ETFs exploit profit opportunities related to the other factors. This result raises serious questions about the ability of smart beta ETFs to capture factor premiums, which may be related to their long-only restriction, or to other differences related to how factors are constructed in the asset pricing literature.

We repeat this exercise for conventional ETFs, estimating a four-factor model with the MKT, CMA, QMJ, and HMLd factors identified by our Bayesian procedure. The results are shown in Panel A.2 of Table 4. We find that, on average, the only factor other than the market return which has a significant sensitivity is the QMJ factor, although CMA and HMLd sensitivities are significant for many ETFs. Contrary to the results of smart beta ETFs, the non-market factor exposure of conventional ETFs during this sample period is purely detrimental because it reduces the average ETF return by -0.14% per month (Panel B). These ETFs show, on average, positive exposures to CMA and HMLd whose returns are negative, and a negative exposure to QMJ, which shows a high positive return of 0.95%.

[17] The average absolute alpha should be close to zero if the model explains the returns on the ETFs well.

The average absolute alpha and average R^2 for the model identified with the Bayesian method for conventional ETFs are 0.31% and 0.66, respectively, while for the benchmark model the numbers are 0.29% and 0.72, respectively. Again, we find that the Bayesian method finds a parsimonious model which performs quite well compared to the benchmark model.

[Table 4 about here.]

Robustness Analysis

Our main results were obtained using an empirical Bayes prior, centering each $\boldsymbol{\beta}_i$ around their OLS estimate by setting $\boldsymbol{\beta}_i \sim N\left(\widehat{\boldsymbol{\beta}}_i, cVar\left(\widehat{\boldsymbol{\beta}}_i\right)\right)$, with $c = 1$. In this subsection we analyze the robustness of our results relative to this choice, by varying both the type of prior and the value of c. For a different type of prior, we try $\widetilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$, which does not make use of the data and reflects a complete lack of knowledge about the predictors. We also vary the value of c and obtain results using $c = 1, 2, 5$. A larger c represents a less informative prior regarding the range of possible values for the regression coefficients (i.e. factor sensitivities).

The results using the empirical Bayes prior with $c = 2$ are reported in Panel A of Table 5, and are essentially similar to our main results with $c = 1$. The best models remain the same for both smart beta ETFs (Panel A.1) and conventional ETFs (Panel A.2). This is also the case with $c = 5$, and we omit the results.

Panel B of Table 5 reports results using the prior centered on a vector of zeros with $c = 1$. The only difference compared to our previous results is that the QMJ factor is not selected in the best model for conventional ETFs, although both the QMJ and CMA factors are present in the second and third best models, as before. The results with $c = 2$ do not differ significantly and are omitted. The results with $c = 5$ (also omitted) show that the best model for both smart beta ETFs (posterior probability=0.90) and conventional ETFs (posterior probability = 0.80) is the model with only the MKT factor. Thus, for an investor with an uninformed view about the factor sensitivities of both groups of ETFs, i.e. when coefficient priors are centered on zero and the prior variance is large, the model selection procedure can only find posterior evidence for the market beta for either group of ETFs. In this case, the selected models suggest that smart beta ETFs are not different from ETFs that just follow the market. This did not occur when the empirical prior was used, as the point of departure is in the neighborhood where factor sensitivities are more likely to be different from zero.

Overall, we interpret that our results are robust to the prior specification for the regression coefficients, except in cases when the prior variance is too large and the prior is centered on zeros.

[Table 5 about here.]

Conclusion

Smart beta ETFs have grown enormously in popularity and assets over the last years. These products are intended to increase returns or lower risk relative to market capitalization-weighted indices by attempting to capture premiums on well-known factors such as size, value, quality, momentum and volatility.

In this paper, we employ a Bayesian variable selection methodology to investigate the factor exposure of smart beta and conventional ETFs. Our results reveal that the market and the Fama and French (2015) size (SMB) factors are relevant to explain the returns of smart beta ETFs, with weaker evidence for the inclusion of the Frazzini and Pedersen (2014) betting-against-beta (BAB) factor. For conventional ETFs, the best model includes the quality-minus-junk (QMJ) factor of Asness et al. (2017) and the alternative value factor (HML “devil”) of Asness and Frazzini (2013), with weaker evidence for the inclusion of the Fama and French (2015) investment (CMA) factor.

Although, on average, smart beta ETFs benefit from their exposure to the BAB factor, they still underperform the market on a risk-adjusted basis, as suggested by their negative alphas. The factor exposures of conventional ETFs to non-market factors such as QMJ, CMA and HMLd, on the other hand, are purely detrimental, reducing the average ETF return by -0.14% per month.

The best models selected by the Bayesian method perform very similarly to a benchmark eight-factor model in terms of their ability to explain the average returns and the return variation on each set of ETFs, as measured by the average absolute alpha and the average R^2. Therefore, it is unlikely that smart beta ETFs are exploiting other factors. Overall, our results suggest investors should be skeptical about the ability of smart beta ETFs to capture factor premiums. This may be related to their long-only restriction, as mentioned by Blitz (2016), or to differences in how ETFs implement factor exposure compared to asset pricing studies.

References

Amen, Noël, Goltz, Felix, and Le Sourd, Véronique. 2017. *EDHEC Survey on Equity Factor Investing*. Tech. rept. EDHEC-Risk Institute.

Amenc, Noël, Goltz, Felix, and Lodh, Ashish. 2018. Mind the Gap: On the Importance of Understanding and Controlling Market Risk in Smart Beta Strategies. *The Journal of Portfolio Management*, **44**(03), 60–70.

Amihud, Yakov. 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, **5**(1), 31–56.

Amihud, Yakov, Hameed, Allaudeen, Kang, Wenjin, and Zhang, Huiping. 2015. The illiquidity premium: International evidence. *Journal of Financial Economics*, **117**(2), 350–368.

Ando, Tomohiro. 2011. Bayesian Variable Selection for the Seemingly Unrelated Regression Model with a Large Number of Predictors. *J. Japan Statist. Soc.*, **41**(2), 187–203.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. 2006. The cross-section of volatility and expected returns. *Journal of Finance*, **61**, 259–299.

Ang, Andrew. 2014. *Asset management: A systematic approach to factor investing*. Oxford University Press.

Ang, Andrew, Madhavan, Ananth, and Sobczyk, Aleksander. 2017. Estimating Time-Varying Factor Exposures. *Financial Analysts Journal*, **73**(4).

Angelidis, Timotheos, and Nikolaos Tessaromatis. 2017. Global Equity Country Allocation: An Application of Factor Investing. *Financial Analysts Journal,* **73** (4).

Asness, Clifford. 2006. The value of Fundamental Indexing. *Institutional Investor*, **40**, 94–99.

Asness, Clifford, and Frazzini, Andrea. 2013. The devil in HML's details. *The Journal of Portfolio Management*, **39**(4), 49–68.

Asness, Clifford S, Frazzini, Andrea, and Pedersen, Lasse Heje. 2017. *Quality minus junk.*

Baker, M., Taliaferro, R. and Burnham, T., 2017. Optimal Tilts: Combining Persistent Characteristic Portfolios. *Financial Analysts Journal*, **73**(4).75-89.

Beck, Noah, Hsu, Jason, Kalesnik, Vitali, and Kostka, Helge. 2016. Will Your Factor Deliver? An Examination of Factor Robustness and Implementation Costs. *Financial Analysts Journal*, **72**(5), 58–82.

Blitz, David. 2016. *Factor Investing with Smart Beta Indices*.

Blitz, David, and Swinkels, Laurens. 2008. Fundamental Indexation: An Active Value Strategy in Disguise. *Journal of Asset Management*, **9**, 264–269.

Brown, P J, Vannucci, M, and Fearn, T. 1998. Multivariate Bayesian variable selection and prediction. *J. R. Statist. Soc. B*, **60**(3), 627–641.

Chen, Long, and Zhang, Lu. 2010. A better three-factor model that explains more anomalies. *Journal of Finance*, **65**(2), 563–595.

Fama, Eugene F, and French, Kenneth R. 2015. A Five-Factor Asset Pricing Model. *Journal of Financial Economics*, **116**, 1–22.

Frazzini, Andrea, and Pedersen, Lasse Heje. 2014. Betting against beta. *Journal of Financial Economics*, **111**(1), 1–25.

George, E I, and McCulloch, Robert E. 1993. Variable Selection Via Gibbs Sampling. *Journal of the American Statistical Association*, **88**(423), 881–889.

George, E I, and McCulloch, Robert E. 1997. Approaches for Bayesian Variable Selection. *Statistica Sinica*, **7**, 339–373.

Giles, David E A. 2003. *Computer-Aided Econometrics*. New York, N.Y.: Marcel Dekker, Inc.

Hall, Anthony, Hwang, Soosung, and Satchell, Stephen E. 2002. Using Bayesian variable selection methods to choose style factors in global stock return models. *Journal of Banking and Finance*, **26**(12), 2301–2325.

Hou, Kewei, Xue, Chen, and Zhang, Lu. 2015. Digesting Anomalies: An Investment Approach.

The Review of Financial Studies, **28**(3), 650–705.

Hwang, Soosung, and Rubesam, Alexandre. 2018. *Searching the Factor Zoo*. Working Paper Series 2018-ACF-03. IÉSEG School of Management.

Jegadeesh, Narasimhan, and Titman, Sheridan. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, **48**(1), 65–91.

Johnson, Ben. 2017. *A Global Guide to Strategic-Beta Exchange-Traded Products*. Tech. rept. Morning Star.

Kuo, Lynn, and Mallick, Bani. 1998. Variable selection for regression models. *Sankhya*, **60**(1).

O'Hara, R B, and Sillanpää, M J. 2009 A Review of Bayesian Variable Selection Methods: What, How and Which. *Bayesian Analysis*, **4**(1), 85-118.

Puelz, David, Hahn, P Richard, Carvalho, Carlos M, 2017. Variable selection in seemingly unrelated regressions with random predictors. *Bayesian Analysis*.

Shirbini, Eric. 2018. *Misconceptions and Mis-selling in Smart Beta: Improving the Risk Conversation in the Smart Beta Space*. Tech. rept. ERI Scientific Beta.

Smith, Michael, and Kohn, Robert. 2000. Nonparametric seemingly unrelated regression. *Journal of Econometrics*, **98**(2), 257–281.

Wang, Hao. 2010. Sparse seemingly unrelated regression modelling: Applications in finance and econometrics. *Computational Statistics and Data Analysis*, 2866–2877.

Zellner, A. 1962. An efficient method of estimating seemingly unrelated regressions and tests of aggregation bias. *Journal of American Statistical Association*, 500–509.

Appendix

Bayesian Variable Selection in the SUR Model

We briefly review the estimation of the model using the Gibbs sampler and refer the reader to Rubesam and Hwang (2018) for the details. The main advantage of the method is that it can be used with large panels of returns (large N) and with a large number of candidate factors (large K). Since in model (2) specific returns are potentially cross-correlated at each point in time, if we let $\mathbf{e}_t = (e_{t,1}, \dots, e_{t,N})'$ represent the specific returns of all assets at time t, we have $\mathrm{Cov}(\mathbf{e}_t) = \mathbf{\Sigma}$. Thus the main assumption of the model can be written as $\tilde{\mathbf{e}} \sim N(\mathbf{0}, \mathbf{\Sigma} \otimes \mathbf{I_T})$. Let $\tilde{\boldsymbol{\beta}}_{-i}$ denote the full vector $\tilde{\boldsymbol{\beta}}$ omitting $\boldsymbol{\beta}_i$ and assume the following prior distributions for $\boldsymbol{\beta}_i$, $\mathbf{\Sigma}$ and $\boldsymbol{\gamma}$:

$$\boldsymbol{\beta}_i | \tilde{\boldsymbol{\beta}}_{-i} \sim N(\mathbf{b}_{0,i}, \mathbf{B}_{0,i}), \quad i = 1, \dots, N$$

$$\mathbf{\Sigma} \sim IW(\nu_0, \mathbf{\Phi}_0)$$

$$\gamma_j \sim B(1, \pi_j), \quad j = 1, \dots, K$$

where $IW(\nu_0, \mathbf{\Phi}_0)$ denotes the inverted-Wishart distribution (a generalization of the inverse gamma distribution often used to model covariance matrices in the Bayesian framework) with ν_0 degrees of freedom and parameter matrix $\mathbf{\Phi}_0$, and $B(1, \pi_j)$ denotes the Bernoulli distribution with probability of success π_j. The standard choice for the prior of $\mathbf{\Sigma}$ is to set $\nu_0 = N$ and $\mathbf{\Phi}_0 = \mathbf{I}$. In the above, each γ_j is independent of the remaining ones, therefore the prior for $\boldsymbol{\gamma}$ is given by $f(\boldsymbol{\gamma}) = \prod_{j=1}^{K} \pi_j^{\gamma_j} (1 - \pi_j)^{1-\gamma_j}$.

With the priors above and given initial values for the variables, the estimation procedure using the Gibbs sampler is as follows:

1. Generate $\boldsymbol{\beta}_i | \tilde{\boldsymbol{\beta}}_{-i}, \boldsymbol{\gamma}, \mathbf{\Sigma}, \tilde{\mathbf{r}} \sim N(\mathbf{b}_{1,i}, \mathbf{B}_{1,i})$, where

$$\mathbf{b}_{1,i} = (\mathbf{B}_{0,i}^{-1} + \sigma^{ii} \mathbf{X}_\gamma{}' \mathbf{X}_\gamma)^{-1} (\mathbf{B}_{0,i} \mathbf{b}_{0,i} + \sigma^{ii} \mathbf{X}_\gamma{}' \mathbf{r}_i^*)$$

$$\mathbf{B}_{1,i} = (\mathbf{B}_{0,i}^{-1} + \sigma^{ii}\mathbf{X}_\gamma{}'\mathbf{X}_\gamma)^{-1},$$

$$\mathbf{r}_i^* = \mathbf{r}_i - (\sigma^{ii})^{-1}\mathbf{A}_{-i}(\tilde{\mathbf{r}}_{-i} - \widetilde{\boldsymbol{X}}_{\gamma,-i}\widetilde{\boldsymbol{\beta}}_{-i}),$$

where σ^{ii} is the (i,i) element of $\boldsymbol{\Sigma}^{-1}$ and $\mathbf{A}_{-i}$ is a $T \times (N-1)T$ partition of $\boldsymbol{\Omega}^{-1}$

with the terms corresponding to the $i-th$ equation removed.

2. Generate $\boldsymbol{\Sigma}|\widetilde{\boldsymbol{\beta}}, \mathbf{r} \sim IW(\nu_1, \boldsymbol{\Phi}_1)$, with $\nu_1 = \nu_0 + T$ and $\boldsymbol{\Phi}_1 = \boldsymbol{\Phi}_0 + \mathbf{S}$, where $\mathbf{S}$ is the matrix of cross-products of the residuals, that is, if $\mathbf{E} = [\mathbf{e}_1 \dots \mathbf{e}_N]$, then $\mathbf{S} = \mathbf{E}'\mathbf{E}$.
3. Generate (in random order) γ_j conditional on the remaining $\gamma_k, k \neq j$, from the following conditional distribution:

$$P(\gamma_j = 1|\boldsymbol{\gamma}_{-j}, \widetilde{\boldsymbol{\beta}}, \boldsymbol{\Sigma}, \tilde{\mathbf{r}}) = \left(1 + \frac{1-\pi_j}{\pi_j}\exp(-0.5Tr(\boldsymbol{\Sigma}^{-1}(\mathbf{S}_\gamma^1 - \mathbf{S}_\gamma^0))\right)^{-1}, \tag{4}$$

where $\mathbf{S}_\gamma^1$ and $\mathbf{S}_\gamma^0$ represent the matrices of residuals when $\gamma_j = 1$ and $\gamma_j = 0$, respectively.

The estimation process iterates these steps in sequence a large number of times. The posterior distribution of $\boldsymbol{\gamma}$ can then be inferred from the values generated using equation (4).

Table 1. Descriptive statistics of factors, Jan/2013-Dec/2017

Panel A: Statistics of individual factor returns

	Average monthly return	Standard error	t-statistic
MKT	1.27%	0.37%	3.44**
SMB	-0.04%	0.31%	-0.12
HML	-0.04%	0.30%	-0.13
RMW	0.11%	0.20%	0.56
CMA	-0.18%	0.18%	-1.00
MOM	0.23%	0.39%	0.59
QMJ	0.95%	0.58%	1.63
BAB	1.25%	0.25%	4.94**
HMLd	-0.23%	0.35%	-0.68
ILL	0.04%	0.34%	0.11
VOL	0.18%	0.41%	0.43
INV	0.30%	0.15%	2.03*
ROE	0.23%	0.23%	1.00
ROA	0.20%	0.27%	0.76

Panel B: 10 largest absolute correlations

Factor pair	Correlation
ROE, ROA	0.95
SMB, ILL	0.92
VOL, ROA	0.86
QMJ ,ROA	0.84
VOL ,ROE	0.82
QMJ ,VOL	0.81
HML, HMLd	0.77
MOM, HMLd	-0.77
QMJ, ROE	0.77
RMW, ROA	0.70

* Significant at the 5% level.
** Significant at the 1% level.

Table 2: Ordinary Least Square Analysis of ETFs, Jan/2013-Dec/2017

Panel A.1 - Statistics of factor sensitivities for all ETFs

	Average sensitivity	t-stat	5^{th} percentile	95^{th} percentile	% significantly positive	% significantly negative
Intercept	0.01%	0.17	-0.44%	0.56%	2%	2%
MKT	1.03	51.51^{**}	0.73	1.43	99%	0%
HML	-0.04	-1.41	-0.71	0.80	18%	23%
RMW	0.05	1.07	-0.73	0.68	18%	4%
CMA	0.16	2.88^{**}	-1.14	1.71	24%	17%
MOM	0.00	0.11	-0.48	0.41	24%	15%
QMJ	-0.10	-6.71^{**}	-0.60	0.16	13%	33%
ILL	0.11	4.72^{**}	-0.30	0.75	30%	14%
INV	-0.07	-1.20	-1.97	1.02	20%	16%

Panel A.2 - Statistics of factor sensitivities for smart beta ETFs

	Average sensitivity	t-stat	5^{th} percentile	95^{th} percentile	% significantly positive	% significantly negative
Intercept	-0.01%	-0.17	-0.31%	0.39%	3%	1%
MKT	1.00	48.26^{**}	0.86	1.14	100%	0%
HML	0.00	0.07	-0.38	0.45	20%	25%
RMW	0.10	1.93	-0.25	0.45	26%	2%
CMA	0.17	2.92^{**}	-0.44	1.12	32%	14%
MOM	0.06	2.71^{**}	-0.19	0.33	33%	11%
QMJ	-0.06	-3.79^{**}	-0.26	0.13	14%	39%
ILL	0.22	9.52^{**}	-0.17	0.84	43%	14%
INV	0.01	0.08	-0.73	0.66	20%	16%

Panel A.3 - Statistics of factor sensitivities for conventional ETFs

	Average sensitivity	t-stat	5^{th} percentile	95^{th} percentile	% significantly positive	% significantly negative
Intercept	0.03%	0.40	-0.52%	0.64%	2%	1%
MKT	1.05	45.55^{**}	0.68	2.04	98%	0%
HML	-0.08	-2.28^{*}	-0.85	0.99	17%	21%
RMW	0.01	0.25	-0.90	0.92	12%	2%
CMA	0.15	2.39^{*}	-1.29	1.94	17%	12%
MOM	-0.04	-1.86	-0.62	0.48	17%	9%
QMJ	-0.14	-7.81^{**}	-0.69	0.21	12%	33%
ILL	0.01	0.35	-0.43	0.54	19%	12%
INV	-0.14	-1.97	-2.18	1.17	20%	14%

*Significant at the 5% level.
**Significant at the 1% level.

Panel B - Summary by type of ETF

	All ETFs	Smart beta ETFs	Conventional ETFs
Average return	1.17%	1.20%	1.15%
Average return due to market factor	1.30%	1.26%	1.33%
Average return due to other factors	-0.14%	-0.05%	-0.21%
Average non-factor return (intercept)	0.01%	-0.01%	0.03%
Average R^2 (market model)	0.64	0.74	0.56
Average R^2 (benchmark model)	0.79	0.89	0.72
# ETFs	368	168	200
AUM ($ Billions)	1542	515	1027
Average (AUM-weighted) expense ratio	0.18%	0.21%	0.17%

Note: This panel presents a decomposition of the average returns of each category of ETFs based on an eight-factor. The return components due to the market factor, due to other factors, and the non-factor return sum up to the average return of the ETFs in each category.

Table 3: Posterior model probabilities, Jan/2013-Dec/2017

Panel A: Smart Beta ETFs

Model	Number of Factors	Probability
MKT, SMB	2	0.67
MKT, SMB, BAB	3	0.29
MKT, SMB, HML	3	0.03
MKT, SMB, BAB, HMLd	4	0.01

Panel B: Conventional ETFs

Model	Number of Factors	Probability
MKT, QMJ, HMLd	3	0.70
MKT, CMA, QMJ, HMLd	4	0.30

Note: The table shows the posterior probabilities of models using all smart beta ETFs (Panel A) and all conventional ETFs (Panel B). An empirical Bayes prior is used for the factor sensitivities.

Table 4: Ordinary Least Square Analysis of High Posterior Probability Models

Panel A.1 - Statistics of factor sensitivities for smart beta ETFs

	Average sensitivity	t-stat	5th percentile	95th percentile	% significantly positive	% significantly negative
Intercept	-0.08%	-1.48	-0.43%	0.21%	0%	4%
MKT	0.95	42.28**	0.44	1.33	98%	0%
SMB	0.29	14.33**	-0.28	1.08	53%	20%
BAB	0.07	2.11*	-0.40	0.76	30%	9%

Panel A.2 - Statistics of factor sensitivities for conventional ETFs

	Average sensitivity	t-stat	5th percentile	95th percentile	% significantly positive	% significantly negative
Intercept	-0.03%	-0.39	-0.77%	0.73%	2%	3%
MKT	1.04	47.41**	0.46	2.06	96%	0%
CMA	0.02	0.42	-0.99	0.74	11%	9%
QMJ	-0.13	-8.55**	-0.58	0.22	16%	36%
HMLd	0.04	1.41	-0.70	1.47	19%	23%

*Significant at the 5% level.
**Significant at the 1% level.

Panel B - Summary by type of ETF

	Smart beta ETFs	Conventional ETFs
Average excess return	1.20%	1.15%
Average return due to market factor	1.21%	1.32%
Average return not due to market factor	0.08%	-0.14%
Average non-factor return (intercept)	-0.08%	-0.03%
Average absolute alpha (Bayesian model)	0.16%	0.31%
Average absolute alpha (Benchmark model)	0.14%	0.29%
Average R^2 (Bayesian model)	0.84	0.66
Average R^2 (Benchmark model)	0.89	0.72

Table 5: Posterior factor and model probabilities under alternative priors for the factor coefficients

Panel A: Empirical Bayes prior, c=2

Panel A.1: Smart Beta ETFs

Model	#Factors	Probability
MKT, SMB	2	0.90
MKT, SMB, BAB	3	0.09
MKT, SMB, BAB, HMLd	4	0.01

Panel A.2: Conventional ETFs

Model	#Factors	Probability
MKT, QMJ, HMLd	3	0.98
MKT, CMA, QMJ, HMLd	4	0.02

Panel B: Uninformative prior, c=1

Panel B.1: Smart Beta ETFs

Model	#Factors	Probability
MKT, SMB	2	0.90
MKT, SMB, BAB	3	0.08
MKT, SMB, HML, BAB, HMLd	5	0.02

Panel B.2: Conventional ETFs

Model	#Factors	Probability
MKT, HMLd	2	0.80
MKT, QMJ, HMLd	3	0.19
MKT, CMA, QMJ, HMLd	4	0.01

Note: The table shows the posterior probabilities of models using all smart beta ETFs under different specifications for the prior distributions of factor sensitivities. Panel A reports results using an empirical Bayes prior with a less informative parameter ($c = 2$), and Panel B reports results using a prior centered on zeros with $c = 1$.