THE JOURNAL OF
INVESTMENT CONSULTING

*A reprinted article from Volume 18, Number 1, 2017*

# Are Exchange-Traded Funds Harvesting Factor Premiums?

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INVESTMENTS & WEALTH INSTITUTE™
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## ABSTRACT

Some exchange-traded funds (ETFs) are specifically designed for harvesting factor premiums, such as the size, value, momentum, and low-volatility effects. Other ETFs, however, may implicitly go against these factors. This paper analyzes the factor exposures of U.S. equity ETFs and finds that, indeed, for each factor there are funds that offer a large positive exposure and also funds that offer a large negative exposure toward that factor. On aggregate, all factor exposures turn out to be close to zero, and plain market exposure is all that remains. This finding argues against the concern that factor premiums are being arbitraged away rapidly by investors in ETFs.

## INTRODUCTION

This paper investigates if factor premiums, such as the size, value, momentum, and low-volatility effects, are systematically being harvested by investors in exchange-traded funds (ETFs). Some ETFs are clearly designed to harvest factor premiums. For instance, the Powershares S&P Low Volatility Index ETF (SPLV) specifically targets the low-volatility premium. Many other ETFs, however, are not factor-based but based on a different philosophy. For example, a large number of ETFs target a specific sector. Implicitly this also tends to bring along factor exposures, although not necessarily in the right direction from a factor investing perspective. This raises the question of what kind of factor exposures ETFs exhibit individually as well as on aggregate.

The process of systematically harvesting the premiums offered by factors that have been thoroughly established in the academic literature is known as "factor investing," and it is advocated by studies such as Ang et al. (2009), Bender et al. (2010), Blitz (2012, 2015), and Ang (2014). In theory, long-short factor portfolios, which capture pure factor premiums and have a low correlation with asset class risk premiums, are most attractive for factor investing purposes; see, for example, Ilmanen and Kizer (2012). In practice, however, factor investing typically is implemented using long-only strategies, which offer a combination of market exposure and factor exposure. Smart beta indexes, which use mechanical rules to deviate from the capitalization-weighted market index, are a popular example. These mechanical rules tend to result, either explicitly or implicitly, in systematic tilts toward certain factors. Chow et al. (2011) find that the added value of popular smart beta indexes is entirely explained by exposures toward classic factor premiums. A fundamentally weighted index, for instance, is an implicit value strategy, and a minimum-variance index is essentially a low-volatility strategy. ETFs on a wide number of smart beta indexes are available nowadays.

Assets in ETFs have been growing strongly, and the end is not yet in sight. This growth gives rise to the concern that the practical implementation of factor strategies will become increasingly costly. Ang et al. (2016) examine this issue in detail and find that factor strategies remain profitable after costs even when applied on a huge scale, which suggests that smart beta ETFs have plenty of capacity left for further growth. Another concern, however, is that if too many investors start chasing the same factor premiums, the magnitude of these premiums will come down. If ETFs, on aggregate, are systematically harvesting factor premiums, then steadily rising assets in these ETFs require an increasing number of other investors who are willing to be on the other side of these factor trades. Such an imbalance between demand and supply may cause factor premiums to shrink or perhaps even disappear. In effect, ETF investors would be arbitraging away factor premiums.

This paper examines whether this concern is justified. Using a comprehensive sample of U.S. equity ETFs, it finds that many funds offer a large positive exposure to target factors such as size, value, momentum, and low volatility. At the same time, however, many funds also offer a large negative exposure toward these factors. On aggregate, the exposures toward the size, value, momentum, and low-volatility factors turn out to be very close to zero. The finding that ETFs are collectively neutral on factors argues against the concern that factor premiums are being arbitraged away rapidly by ETF investors.

## DATA AND METHODOLOGY

The sample consists of all ETFs that are listed in the United States and that invest in U.S. equities, and which have at least thirty-six months of return history as of December 31, 2015. This amounts to 415 distinct funds, with combined assets under management (AUM) of more than $1.2 trillion. As such, these funds "own" about 5 percent of the entire U.S. equity market. For each ETF, monthly AUM and total return data over the sixty-month period from January 2011 to December 2015 are obtained from Thomson Reuters Datastream. In case less than sixty months but at least thirty-six months of data is available, the maximum available history is used.

Monthly excess total returns for each ETF are calculated by subtracting monthly risk-free returns from the monthly total returns. For each fund, the time series of monthly excess total returns is regressed on the time series of market excess returns and the size (SMB), value (HML), momentum (MOM), and low-minus-high volatility (LV-HV) factor returns, as in equation (1).

$$R_{fund,t} - R_{f,t} = \alpha + \beta_{market} (R_{market,t} - R_{f,t}) + \beta_{SMB} R_{SMB,t} + \beta_{HML} R_{HML,t} + \beta_{MOM} R_{MOM,t} + \beta_{LV\text{-}HV} R_{LV\text{-}HV,t} + \varepsilon_t \quad (1)$$

Data for the risk-free return, market excess return, and the size, value, and momentum factor returns is obtained from the online data library of Kenneth French.[1] The LV-HV factor is self-constructed, using a methodology that resembles the one used by Fama and French to construct their HML and MOM factors. Specifically, every month all common stocks in the Center for Research in Security Prices database are first classified as either large or small, using the New York Stock Exchange (NYSE) median market capitalization as the breakpoint. Next, value-weighted portfolios consisting of the 30-percent lowest and 30-percent highest volatility stocks are created within each of these size groups. The LV-HV factor return is then calculated as the average return of the two low-volatility portfolios minus the average return of the two high-volatility portfolios over the subsequent month. Volatility is defined as the standard deviation of total returns over the past thirty-six months.

## MAIN RESULTS

Figures 1A and 1B depict the estimated market beta exposures, where each dot represents an individual fund. The market beta exposures are plotted on the horizontal axes, against AUM levels on the vertical axes. For the latter, a log-scale is used to improve readability of the graph. Figure 1A shows that the beta toward the market factor is close to 1 for many funds, but it also shows that quite a few funds have significantly higher or lower market betas. The clustering of betas around 2 and 3 comes from leveraged ETFs, and the clustering of betas around –1, –2, and –3 comes from inverse and leveraged inverse ETFs. Leveraged and inverse ETFs may use derivatives instead of investing directly in the underlying stocks, but they are relevant to the analysis because they also bring along factor exposures. In terms of AUM, leveraged and inverse ETFs make up less than 2 percent of the total sample, so the choice to include them does not critically influence the results. Figure 1B depicts market beta exposures excluding these funds.

Figure 1

### MARKET BETA EXPOSURE OF ETFs

(A) ALL FUNDS

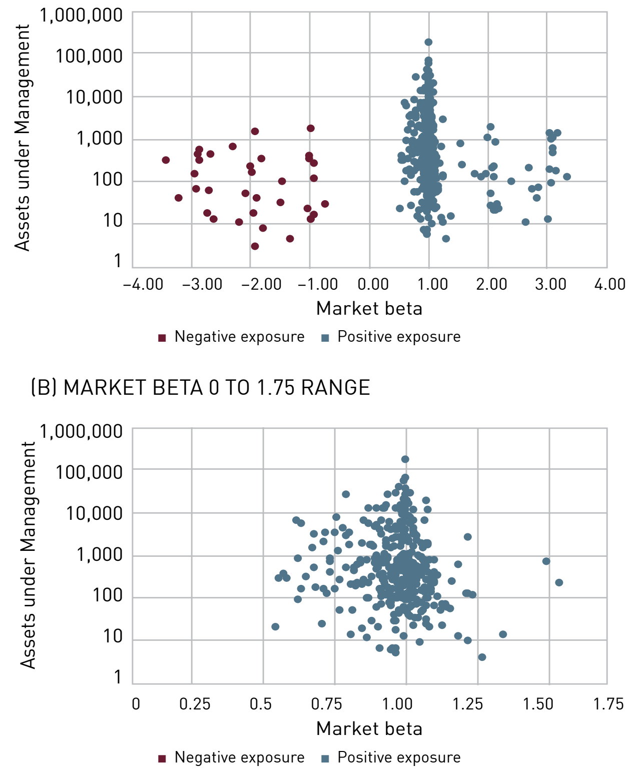
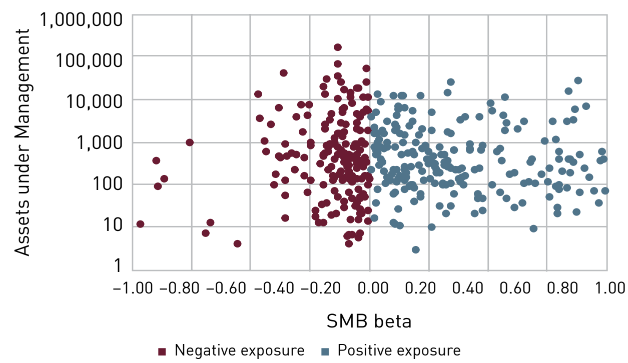



Figure 2

### SMB FACTOR EXPOSURE OF ETFs

(A) ALL FUNDS




Figures 2–5 show estimated exposures toward the other factors included in the regressions. Because the handful of leveraged and inverse ETFs give some extreme observations that diminish the readability of these graphs, only factor betas between –1 and +1 are depicted. The full graphs are available upon request. Figures 2–5 show that exposures toward the size, value, momentum, and low-minus-high volatility factors are centered around zero, but with a large dispersion in positive as well as in negative territory. In other words, there are many funds with positive factor betas, but also many funds with similar-sized negative factor betas.

Figure 3

## HML FACTOR EXPOSURE OF ETFs

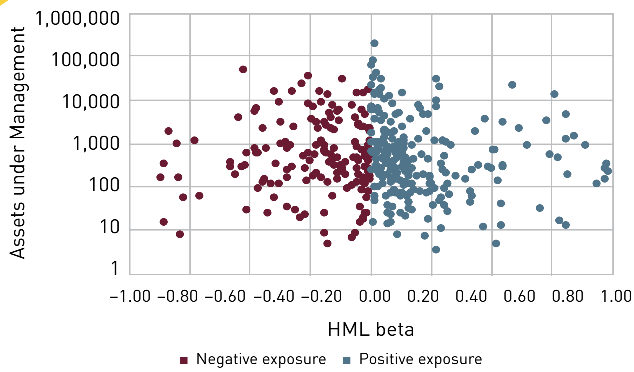



Figure 4

## MOM FACTOR EXPOSURE OF ETFs

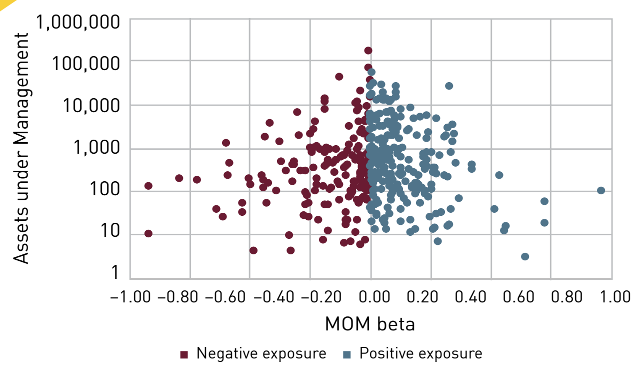



Figure 5

## LV–HV FACTOR EXPOSURE OF ETFs

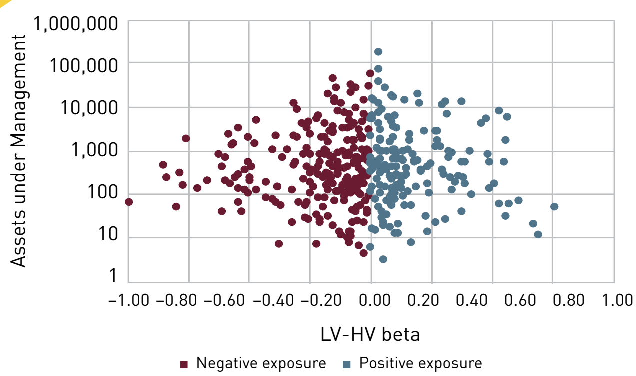



Table 1 reports on the aggregate factor exposures of ETFs. The first two rows in table 1A report the level and statistical significance of the AUM weighted average exposures, respectively. The AUM weighted average market beta of all the funds in the sample amounts to 0.97, which is remarkably close to 1 given the huge dispersion in market betas across funds observed before. Note that the small deviation from 1 does not imply a slight net bias toward low-beta or low-volatility stocks, because the LV-HV factor is specifically included in the regressions to account for such exposures. The dispersion in exposures toward the size, value, momentum, and low-volatility factors also was observed to be large, but the AUM weighted average exposures toward these factors all turn out to be very close to zero, ranging between −0.03 and 0.03. These aggregate factor exposures are economically small and also statistically insignificant in each of the four instances. The interpretation of this result is that the positive exposures toward a certain factor provided by some funds are offset almost perfectly by the negative exposures toward the same factor provided by other funds.

Table 1A also reports the percentage of funds with statistically significant positive and negative exposures toward a given factor. For the SMB factor, there are many more funds with a significant positive exposure (32.0 percent) than funds with a significant negative exposure (18.1 percent). This also is reflected in tables 2A and 2B, which shows that the distribution of SMB factor exposures is skewed to the right. This does not translate into a significant exposure toward the SMB factor on aggregate because many of these funds are small. Five out of the six very largest ETFs exhibit a statistically significant negative SMB exposure, because they track large-cap indexes such as the S&P 500, which do not include small-cap stocks.

For the HML value factor and for the MOM momentum factor there are slightly more funds with significant positive exposures than funds with significant negative exposures, but for the LV-HV low-minus-high volatility factor it is the other way around, i.e., there are slightly more funds with a negative exposure toward this factor (25.8 percent) than funds with a positive exposure toward this factor (19.5 percent). The finding that the weighted average exposure toward each of these factors is close to zero implies that, on aggregate, all these differences largely cancel out. The take-away from these results is that despite a large variation in factor exposures across funds, the only thing that remains when everything is added up is plain market beta exposure.

These findings do not support the concern that factor premiums are rapidly being arbitraged away by ETF investors. If ETFs would be systematically harvesting factor premiums, then continued flows into these funds would require an increasing number of investors willing to be on the other side of these factor trades, which might cause factor premiums to shrink. This fear turns out to be unwarranted though, because although some ETFs are systematically harvesting factor premiums, other ETFs are effectively doing the exact opposite. At the aggregate level, all these factor exposures cancel out, meaning that, collectively, ETF investors are just as much seeking exposure toward established factor premiums as taking a position against the very same factors.

This result also can be interpreted as an argument against the related concern that factor strategies may have become “overcrowded trades.” The concept of overcrowding is a bit

Table 1

## AGGREGATE FACTOR EXPOSURES OF ETFs

| | Alpha | Market | SMB | HML | MOM | LV-HV |
|---|---|---|---|---|---|---|
| **(A) All ETFs** | | | | | | |
| AUM weighted aggregate exposure | 0.02% | 0.97 | 0.03 | -0.03 | 0.01 | -0.00 |
| *t*-statistic | 0.48 | 64.31 | 1.40 | -1.30 | 0.97 | -0.29 |
| % funds significant positive exposure | 4.1% | 91.1% | 32.0% | 21.4% | 13.0% | 19.5% |
| % funds significant negative exposure | 6.7% | 8.2% | 18.1% | 17.3% | 10.6% | 25.8% |
| **(B) Smart-beta ETFs** | | | | | | |
| AUM weighted aggregate exposure | -0.03% | 0.97 | 0.25 | 0.08 | 0.03 | 0.06 |
| *t*-statistic | -0.44 | 43.42 | 7.89 | 2.29 | 1.28 | 2.42 |
| **(C) Conventional ETFs** | | | | | | |
| AUM weighted aggregate exposure | 0.04% | 0.97 | -0.06 | -0.08 | 0.01 | -0.03 |
| *t*-statistic | 0.90 | 62.04 | -2.62 | -3.07 | 0.57 | -1.78 |

ambiguous and lacks a clear definition, but many investors are concerned about it. The general idea behind factor overcrowding is that so many investors are chasing the same factors that the long-term premiums associated with these factors disappear, that valuations of the stocks in factor portfolios increase, and that correlations among the stocks in factor portfolios increase as well, which might result in elevated crash risk; see, for instance, Chincarini (2012). Because, from a factor investing perspective, there seems to be just as much ETF money chasing stocks with the wrong factor characteristics as ETF money chasing stocks with the right factor characteristics, the ETF market does not seem to justify the concern that factor strategies are massively overcrowded. However, overcrowding is a multi-faceted concept, and the results in this paper for instance do not rule out that ETFs might collectively develop highly concentrated positions in certain stocks at a certain point in time. This issue, however, is beyond the scope of this paper.

## SPLIT-SAMPLE RESULTS

The broad sample of ETFs can be split into smart-beta ETFs (i.e., ETFs that systematically target factor premiums, either explicitly or implicitly) versus all other ETFs (i.e., ETFs that are based on conventional indexes). All funds that explicitly target factor premiums, such as ETFs based on small-cap or value indexes, are assigned to the smart-beta category. Funds that use alternative weighting formulas, such as ETFs based on fundamentally weighted indexes and equally weighted indexes, also are included in the smart-beta category. High-dividend ETFs also are included, because high-dividend investing is essentially a form of value investing. Using these criteria to manually classify all 415 ETFs in the sample results in a smart-beta ETF subsample consisting of 103 funds with combined AUM of $345 billion. The remaining 312 ETFs, with combined AUM of $861 billion, are classified as conventional ETFs. This group contains many sector-based ETFs, but it also includes funds with a mix of desired and undesired factor exposures, such as ETFs on small-cap growth indexes.

Table 1B shows that, on aggregate, the smart-beta ETFs have positive exposures toward the size, value, momentum, and low-volatility factors. The largest and most significant exposure is toward the size factor, which is not surprising given that many ETFs are based on various small-cap indexes. From a factor investing perspective, however, the size factor might be one of the least interesting factors, because it has shown weak performance since it was first documented; see, for instance, van Dijk (2011) and Beck et al. (2016). The exposures of the smart-beta ETFs toward the value and low-volatility factors are considerably smaller but still statistically significant, and the exposure toward the momentum factor is not statistically significant.

Table 1C shows that the picture for the conventional ETFs is essentially a mirror image of the smart-beta ETFs. The conventional ETFs have statistically significant negative exposures toward the size and value factors, and a smaller, weakly significant negative exposure toward the low-volatility factor. These results imply that, from a factor investing perspective, smart-beta ETFs tend to provide the right factor exposures and conventional ETFs tend to be on the other side of the trade with the wrong factor exposures. Another take on these opposing factor exposures is that the liquidity needed by smart-beta ETFs to go long factor premiums is provided by conventional ETFs, which effectively short these factors.

## DETAILED RESULTS

Tables 2–5 show for each factor the ten funds with the largest positive exposures toward that factor and the ten funds with the largest negative exposures toward that factor, among the 100 largest funds in the broad sample. Table 2 shows that seven of the ten funds with the largest positive SMB size factor exposures are ETFs on small-cap indexes such as the Russell 2000 and S&P 600 Small-Cap indexes, which is fully in line with intuition. The ten funds with the most negative SMB exposures are a mixed bag.

Table 2

## LARGEST 100 ETFs SORTED ON SMB EXPOSURE

| Ticker | Name | AUM | SMB |
|---|---|---|---|
| **(A) Ten Largest Positive Exposures** | | | |
| XBI US | SPDR S&P Biotech | 2,295 | 1.45 |
| KRE US | SPDR S&P Regional Banking | 2,851 | 1.02 |
| IWO US | iShares Russell 2000 Growth | 7,177 | 0.91 |
| IWM US | iShares Russell 2000 | 29,239 | 0.88 |
| IWN US | iShares Russell 2000 Value | 6,047 | 0.87 |
| IJT US | iShares S&P Small-Cap 600 Growth | 3,551 | 0.86 |
| IJR US | iShares Core S&P Small-Cap | 17,421 | 0.84 |
| IJS US | iShares S&P Small-Cap 600 Value | 3,286 | 0.83 |
| FBT US | First Trust NYSE Arca Biotech | 3,388 | 0.78 |
| SCHA US | Schwab US Small-Cap | 3,153 | 0.65 |
| **(B) Ten Largest Negative Exposures** | | | |
| XLP US | SPDR Consumer Staples | 7,825 | -0.26 |
| OEF US | iShares S&P 100 | 4,570 | -0.26 |
| SSO US | ProShares Ultra S&P500 | 1,902 | -0.28 |
| VGT US | Vanguard Information Technology | 8,340 | -0.29 |
| HDV US | iShares Core High Dividend | 4,197 | -0.31 |
| QQQ US | PowerShares QQQ Trust Series | 43,059 | -0.36 |
| AMLP US | Alerian MLP ETF | 7,088 | -0.38 |
| IYW US | iShares US Technology | 2,740 | -0.42 |
| AMJ US | JP Morgan Alerain MLP | 3,726 | -0.46 |
| XLK US | SPDR Technology Select | 13,659 | -0.47 |

Table 3

## LARGEST 100 ETFs SORTED ON HML EXPOSURE

| Ticker | Name | AUM | HML |
|---|---|---|---|
| **(A) Ten Largest Positive Exposures** | | | |
| XOP US | SPDR S&P Oil & Gas Exploration and Production | 1,796 | 1.04 |
| VDE US | Vanguard Energy | 4,034 | 0.81 |
| XLE US | SPDR Energy Select | 12,290 | 0.76 |
| KBE US | SPDR S&P Bank | 2,971 | 0.73 |
| IGE US | iShares North America Natural Resources | 1,922 | 0.62 |
| XLF US | SPDR Financial Select | 19,257 | 0.59 |
| KRE US | SPDR S&P Regional Banking | 2,851 | 0.55 |
| VFH US | Vanguard Financials | 3,312 | 0.47 |
| VTV US | Vanguard Value | 18,693 | 0.29 |
| IVE US | iShares S&P 500 Value | 8,660 | 0.27 |
| **(B) Ten Largest Negative Exposures** | | | |
| XLV US | Health Care Select | 13,697 | -0.41 |
| IYH US | iShares US Healthcare | 1,941 | -0.45 |
| VHT US | Vanguard Healthcare | 5,718 | -0.47 |
| FDN US | First Trust DJ Internet Index | 4,811 | -0.48 |
| QQQ US | Powershares QQQ Trust Series | 43,059 | -0.53 |
| FXH US | First Trust Health Care Alpha | 3,467 | -0.55 |
| PJP US | Powershares Dyn Pharmaceuticals | 1,664 | -0.84 |
| IBB US | iShares Nasdaq Biotechnology | 8,393 | -1.32 |
| FBT US | First Trust NYSE Arca Biotech | 3,388 | -1.38 |
| XBI US | SPDR S&P Biotech | 2,295 | -1.88 |

Even though among the 100 largest funds there are ten ETFs tracking various value indexes, table 3 shows that only two of these make it to the top ten funds with the largest positive exposure toward the HML value factor. Instead, the top ten is dominated by energy and financials ETFs. This implies that certain sector indexes provide more value exposure than indexes that are specifically designed to provide value exposure. Eight of the ten funds with the most negative HML exposures are healthcare and biotechnology sector funds. These results reflect large differences in valuations across sectors. These valuation differences tend to be persistent over longer periods of time, so sector ETFs might be the preferred choice for investors who wish to harvest the value premium with ETFs. These results suggest, however, that there may be room for ETFs based on value indexes that provide more pronounced exposure toward the value premium. This finding is consistent with Blitz (2016), which also finds that popular smart-beta indexes fail to provide a large exposure toward the academic value factor.

Table 4 shows that maximum exposures toward the MOM momentum factor are much smaller than maximum exposures toward the SMB size and HML value factors. Among the funds with the largest positive and largest negative MOM exposures, no funds specifically target the momentum premium; but most again are sector funds. However, because momentum is a much more transitory stock characteristic than value, these results probably are heavily dependent on the sample period. Over this five-year period, half of the ten funds with the largest positive MOM factor exposure are real estate sector funds, and the ten funds with the largest negative MOM factor exposure consist mostly of energy and technology sector funds.

Table 5 shows the funds with the most extreme exposures toward the LV-HV factor. Not surprisingly the two large, dedicated low-volatility ETFs—the PowerShares S&P Low Volatility Index ETF (SPLV) and the iShares Edge MSCI Minimum Volatility US Index ETF (USMV)—are among the top ten funds with the largest positive LV-HV exposures. Other funds here include ETFs on typical low-volatility sectors such as utilities and consumer staples, and no fewer than five high-dividend ETFs. The latter result suggests that, over this sample period, low-volatility investing was highly correlated with

Table 4

## LARGEST 100 ETFS SORTED ON MOM EXPOSURE

| Ticker | Name | AUM | MOM |
|---|---|---|---|
| **(A) Ten Largest Positive Exposures** | | | |
| ITB US | iShares US Home Construction | 2,079 | 0.35 |
| ICF US | iShares Cohen & Steers REIT | 3,590 | 0.35 |
| VNQ US | Vanguard REIT | 26,986 | 0.33 |
| RWR US | SPDR Dow Jones REIT | 3,061 | 0.32 |
| XHB US | SPDR S&P Homebuilders | 1,935 | 0.32 |
| SCHH US | Schwab US REIT | 1,858 | 0.31 |
| IYR US | iShares US Real Estate | 4,737 | 0.28 |
| XBI US | SPDR S&P Biotech | 2,295 | 0.24 |
| XLU US | SPDR Utilities Select | 5,740 | 0.24 |
| VPU US | Vanguard Utilities | 1,657 | 0.24 |
| **(B) Ten Largest Negative Exposures** | | | |
| VGT US | Vanguard Information Technology | 8,340 | -0.18 |
| XLK US | SPDR Technology Select | 13,659 | -0.19 |
| XLE US | SPDR Energy Select | 12,290 | -0.19 |
| VDE US | Vanguard Energy | 4,034 | -0.23 |
| IYW US | iShares US Technology | 2,740 | -0.23 |
| XLB US | SPDR Materials Select | 2,237 | -0.25 |
| IGE US | iShares North American Natural Resources | 1,922 | -0.30 |
| AMLP US | Alerian MLP ETF | 7,088 | -0.30 |
| AMJ US | JP Morgan Alerian MLP INDEX | 3,726 | -0.42 |
| XOP US | SPDR S&P Oil & Gas Exploration and Production | 1,796 | -0.43 |

Table 5

## LARGEST 100 ETFS SORTED ON LV–HV EXPOSURE

| Ticker | Name | AUM | LV–HV |
|---|---|---|---|
| **(A) Ten Largest Positive Exposures** | | | |
| XLU US | SPDR Utilities Select | 5,740 | 0.57 |
| VPU US | Vanguard Utilities | 1,657 | 0.56 |
| XLP US | SPDR Consumer Staples | 7,825 | 0.53 |
| SPLV US | Powershares S&P 500 Low Volatility | 5,124 | 0.48 |
| HDV US | iShares Core High Dividend | 4,197 | 0.46 |
| DVY US | iShares Select Dividend | 13,520 | 0.38 |
| USMV US | iShares Edge MSCI Minimum Volatility US | 6,820 | 0.32 |
| SDY US | SPDR S&P Dividend | 13,073 | 0.31 |
| VYM US | Vanguard High Dividend Yield | 11,338 | 0.30 |
| SCHD US | Schwab US Dividend Equity | 2,837 | 0.28 |
| **(B) Ten Largest Negative Exposures** | | | |
| XHB US | SPDR S&P Homebuilders | 1,935 | -0.30 |
| IBB US | iShares Nasdaq Biotechnology | 8,393 | -0.30 |
| XLE US | SPDR Energy Select | 12,290 | -0.31 |
| ITB US | iShares US Home Construction | 2,079 | -0.31 |
| XLB US | SPDR Materials Select | 2,237 | -0.39 |
| FDN US | First Trust DJ Internet Index | 4,811 | -0.47 |
| IGE US | iShares North American Natural Resources | 1,922 | -0.50 |
| FBT US | First Trust NYSE Arca Biotech | 3,388 | -0.55 |
| XBI US | SPDR S&P Biotech | 2,295 | -0.58 |
| XOP US | SPDR S&P Oil & Gas Exploration and Production | 1,796 | -0.76 |

high-dividend investing. The ten funds with the most negative LV-HV factor exposure are a mixed bag of ETFs on sectors such as biotechnology, energy, and information technology.

## SUMMARY

ETFs exhibit a wide range in exposures toward established factors such as size, value, momentum, and low volatility. As such, they can be suitable instruments for investors who specifically aim to systematically harvest these premiums, except perhaps for the momentum premium. This gives rise to the question of whether ETF investments are causing factor premiums to be arbitraged away. The results in this study strongly suggest that these concerns are unjustified, because the exposures of ETFs that may be suitable for factor investors are almost perfectly offset by opposing exposures of other ETFs. Despite a large variation in factor exposures across funds, all that remains when everything is added up is plain market beta exposure. This seems to make factors a zero-sum game in the ETF space, where smart-beta ETFs tend to be on the long side and conventional ETFs tend to be on the short (opposite) side of factor trades.

As an example, consider investors interested in harvesting the low-volatility premium. The results in this study show that several ETFs provide targeted exposure toward low-volatility stocks. In addition, certain sector or high-dividend ETFs also might be suitable for capturing this premium. Investors looking only at the billions of dollars in these ETFs may be concerned about the sustainability of the low-volatility premium going forward. However, the funds in question represent only a small fraction of the total ETF market. Looking at the other end of the spectrum, it turns out that a similar number of funds provide the exact opposite factor exposure, i.e., they exhibit a large exposure toward high-volatility stocks. These funds are not identified easily as high-volatility funds by their names, because they tend to be sector funds. However, they effectively neutralize the exposures of low-volatility funds. Looking at the entire ETF market, the net exposure toward the low-versus-high volatility factor is indistinguishable from zero. These results imply that ETF investors, on aggregate, are not arbitraging away the low-volatility premium or turning low-volatility stocks into an overcrowded trade.

An interesting topic for follow-up research would be to examine the development of ETF factor exposures over time. This, however, would require a survivorship-bias-free historical database of ETFs, instead of the point-in-time analysis conducted in this paper. The findings for ETFs in this paper also raise the question of what aggregate factor exposures look like for other types of investment vehicles. Blitz (2017) examines the aggregate factor exposures of hedge funds and also finds little evidence that, as a group, these funds are harvesting factor premiums. In fact, hedge funds are found to be betting strongly against the low-volatility effect, and, as such, appear to be clearly on the opposite side of this trade.

## ACKNOWLEDGMENTS

The author thanks Matthias Hanauer, Jan Sytze Mosselaar, Laurens Swinkels, and Pim van Vliet for helpful comments and support.

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## ENDNOTE

1. See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

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