Multifactor Funds vs. Homemade Factor Diversification Strategies

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KEY FINDINGS

- Multifactor funds seem to be a convenient way of obtaining exposure to several factors, all neatly packaged in one product, but their record is disappointing.
- Multifactor funds have underperformed two homemade strategies, considered in this article, that simply combine single-factor funds in a portfolio.
- This underperformance applies both on average and to most funds, and is observed in terms of return, risk-adjusted return, and downside protection.

ABSTRACT

Multifactor funds, which offer factor diversification neatly packaged in one product, have a rather short but poor track record; these funds have largely underperformed widely available broad market funds. This article evaluates the performance of multifactor funds relative to two homemade factor diversification strategies that simply combine single-factor funds in a portfolio. The results here, which reinforce previously reported poor results, show that multifactor funds largely underperformed both homemade strategies in terms of return, risk, risk-adjusted return, and downside protection.

Investing in factors expected to outperform, such as in value (rather than growth) stocks and in small-cap (rather than large-cap) stocks, has long been studied in academia and put into practice by investors. Investing in a single product that provides a diversified exposure to several factors, in turn, is a much more recent development. Assessing the performance of these products, usually referred to as multifactor funds, is the ultimate goal of this article.

The current evidence on the performance of multifactor funds is scarce, and the little evidence available suggests that the implementation of this seemingly good idea has been disappointing. Estrada (2023) shows that multifactor funds targeting the US, global, international, and emerging markets largely underperformed broad market indexes, as well as the widely available ETFs that track them, in terms of return, risk-adjusted return, and downside protection. Put differently, neatly packaged factor diversification largely underperformed traditional diversification.

This article evaluates multifactor funds from a different perspective. Instead of assessing their performance relative to traditional diversification, it does so relative to homemade factor diversification strategies; that is, an investor's combination of single-factor funds in a portfolio. Two variations of this approach are explored; one equally weighs the specific factors targeted by a given fund, and the other equally weighs the five factors most widely used by asset management companies in their products, namely, size, style, quality, volatility, and momentum.

The results here reinforce the current evidence on the poor performance of multifactor funds. In fact, these funds largely underperformed the two very simple homemade factor diversification strategies considered in terms of return, risk, risk-adjusted return, and downside protection. And they did so not only on average, but by and large individually as well, with the proportion of outperforming funds never being larger than one third across all the evaluations performed.

The rest of the article is organized as follows. The next section provides a brief history of factor investing and a brief introduction to multifactor funds; the section after discusses the evidence, followed by a section that provides an assessment. An appendix concludes the article.

THE ISSUE

A Very Brief History of Factors[1]

A factor can be defined as the spread between the return on one set of securities, systematically and clearly defined, versus another (Asness, 2016). Sharpe (1964), Lintner (1965), Mossin (1966), and Treynor (1962) introduced the capital asset pricing model, hence the market factor, which was followed by the introduction of many other factors. Ross (1976) advanced the arbitrage pricing theory, which argues that stock returns are determined not by one but by many factors, although the theory does not specify how many or which ones.

Haugen and Heins (1972, 1975) first reported that low-volatility stocks tend to outperform high-volatility stocks, a pattern that become known as the *volatility factor*. Blitz and van Vliet (2007) later reported that portfolios of low-volatility (high-volatility) stocks outperform (underperform) the market in terms or risk-adjusted return. Although not very widely discussed in academia, the volatility factor was enthusiastically embraced by asset management companies.

Basu (1977) and Banz (1981) are widely credited with being the seminal articles on the outperformance of value stocks over growth stocks (the *style factor*) and small-caps over large-caps (the *size factor*).[2] Fama and French (1993) added the style and size factors to the CAPM, ignoring the volatility factor, thus advancing the three-factor model. Asness et al. (2015) provide a good literature review on the style factor and Alquist et al. (2018) do the same for the size factor.

Jegadeesh and Titman (1993) showed that buying stocks that performed well in the recent past (winners) and selling stocks that performed poorly in the recent past (losers) leads to significant abnormal returns, a pattern that became known as the *momentum factor*. Carhart (1997) added the momentum factor to the Fama-French three-factor model, thus giving birth to the four-factor model.

Titman et al. (2004) showed that there is a negative relationship between capital investment and returns, with companies that substantially increase capital investments obtaining lower returns over the subsequent five years; this pattern eventually became known as the *investment factor*. Novy-Marx (2013) showed that profitability, measured by the ratio of a company's gross profit to assets, is positively related to stock returns; this pattern eventually became known as the *quality factor*. Fama and French (2015) added the investment and quality factors to their three-factor model (albeit ignoring the volatility and momentum factors), thus giving birth to the five-factor model.

[1] This section borrows heavily from Estrada (2023).

[2] The outperformance of value stocks over growth stocks is typically referred to as the "value" factor or the "style" factor. The latter, which is used throughout this article, is Morningstar's choice for their Factor Profile Methodology; see Johnson (2020).

The proliferation of empirical regularities uncovered in multiple studies led Cochrane (2011) to refer to them as a “zoo” of factors.[3] The explanatory power of factors, on the other hand, led researchers to ask whether the standard way of diversifying portfolios, across asset classes, could be improved upon by diversifying portfolios across factors. Page and Taborsky (2011) show that correlations across factors are lower than those across asset classes and argue that risk factor diversification is superior to asset class diversification.[4]

Finally, the popularity of factors led Morningstar to think beyond their style box, introduced in the early 1990s, which splits funds based on their valuation (growth/core/value) and market capitalization (large/medium/small cap). Acknowledging the importance of other factors, the company rather recently introduced the Morningstar Factor Profile, which adds five additional variables to the style box, so that funds are evaluated on the basis of their exposure to the size, style, quality, volatility, momentum, liquidity, and yield factors (Johnson 2020).

Multifactor Funds

Academics and practitioners, by and large, currently accept that stock returns are driven by factors, that some factors have been more thoroughly tested (hence are more reliable) than others, and that exposure to those factors is expected to enhance long-term risk-adjusted returns. Perhaps for these reasons, smart beta funds have been getting increasingly popular.[5]

Multifactor funds are generally considered smart beta products. As such, they aim to provide investors with rules-based active management, charging lower fees than actively managed funds, albeit substantially higher fees than passively managed index funds or ETFs. They also aim to provide investors with a neatly packaged, diversified exposure to well-known factors—such as size, style, quality, volatility, and momentum, which are the five most widely used by asset management companies in their products.

Importantly, because many products provide direct or indirect access to the size and style factors, the focus here is on those that provide broader diversification, with exposure to *at least three* factors. Additionally, the focus is on products that are *explicitly* marketed as multifactor funds, either by their labeling or by clearly highlighting a diversified exposure to factors in the product information.[6]

EVIDENCE

Data and Methodology

The sample consists of 30 multifactor funds that resulted from filtering the products available in this category. The screens applied selected products domiciled in

[3] Asness (2016) argues that not all factors are the result of data mining, and the excess return of those that are not should be expected to persist in the future; among them he includes the size, style, quality, and momentum factors.

[4] However, Idzorek and Kowara (2013) argue that the presumed superiority of risk factor diversification typically follows from an apples-to-oranges comparison. In fact, they formally show that, if properly evaluated, neither approach can be inherently superior to (that is, outperform) the other.

[5] Although there is no consensus definition of smart beta, Arnott (2014) argues that a smart beta strategy needs to break the link between the price of an asset and its weight in the portfolio; seeks to earn excess returns over a cap-weighted benchmark; and retains most of the positive attributes of passive indexing.

[6] An example of the former is the iShares MSCI USA Multifactor ETF (LRGF); an example of the latter is the Goldman Sachs ActiveBeta U.S. Large Cap Equity ETF (GSLC), which “aims to acquire stocks based on four well-established attributes of performance: good value, strong momentum, high quality and low volatility.”

the US and available to US investors; providing exposure to the US market; with at least three years of monthly data through March, 2023; with at least $10 million of net assets as of March, 2023; and, as already mentioned, that offer exposure to at least three factors and are explicitly marketed as multifactor funds.

Exhibit A1 in the appendix lists (alphabetically by ticker) all the funds in the sample, including their name, net assets, expense ratio, inception date, number of observations, and number of stocks in each fund. The average fund in the sample has net assets of $846 million (biased upward by GSLC's assets of $10.8 billion, by far the largest in the sample) and an expense ratio of 29 basis points, both as of the end of March, 2023. ROUS and DYNF are the funds with the oldest (February 25, 2015) and newest (March 19, 2019) inception dates, hence those with the largest (97) and smallest (48) number of observations (returns) in the sample. All returns are monthly, from the end of each fund's inception month and through the end of March, 2023.

Five single-factor funds are used to implement the two homemade factor diversification strategies considered here, all of which are BlackRock ETFs (iShares). Some information about the specific funds used for exposure to the size (IJR), style (IUSV), quality (QUAL), volatility (USMV), and momentum (MTUM) factors is shown in Exhibit A1. The broad market is also represented by a BlackRock ETF (IVV), which tracks the performance of the S&P 500.

Two homemade factor diversification strategies are considered here. The first equally weighs the specific factors targeted by each fund, and the second equally weighs the five factors already mentioned as being the most widely used by asset management companies in their products (size, style, quality, volatility, and momentum). Both strategies are implemented with annual rebalancing to equal weights at the end of each calendar year.[7]

The first homemade factor diversification strategy assumes that investors have decided the specific factors to which they want to be exposed; their choice, then, is between a multifactor fund that diversifies across those specific factors or an equally weighted portfolio of those factors implemented with single-factor funds. The second homemade factor diversification strategy assumes that an investor has no particular preference for specific factors; the choice, then, is between a multifactor fund or an equally weighted portfolio of the five most popular factors implemented with single-factor funds.

To elaborate, the first homemade strategy implicitly asks whether a multifactor fund with exposure to some specific factors provides anything beyond diversification across those factors. (Does the fund implement a strategy to optimally determine the exposure to each factor over time? Does it offer factor diversification at a particularly low cost?) The second homemade strategy, in turn, implicitly asks whether investors should carefully analyze which factors they should be exposed to and then select a multifactor fund, or they should just get exposure to the five most popular factors by "naively" combining five single-factor funds.

Multifactor Funds vs. Target Factors Portfolios

The evaluation of multifactor funds relative to the two homemade factor diversification strategies considered here is made along several dimensions. Compounding

[7] Equal weights are used in both strategies and not just for their simplicity. Recent research by Khang et al. (2023) shows that the 1/N strategy for factor investing outperforms all the other optimization strategies they consider. In their words, "1/N allocation appears a sensible strategic allocation for most factor investors without an edge in predicting factor premium."

power is evaluated with two variables, the terminal value (TV) on Mar/2023 of $100 invested at the end of each fund's inception month, and the annualized return (AR) over each fund's full sample period.[8] Risk, in turn, is assessed with annualized volatility (SD) over each fund's full sample period.

Risk-adjusted returns are evaluated using Modigliani and Modigliani's (1997) risk-adjusted performance metric, which (unlike the Sharpe ratio) is intuitively expressed in percent. Formally, the risk-adjusted performance of strategy *i* (RAP_i) is given by

$$RAP_i = (AM_i/SD_i) \cdot SD_B$$

where AM_i and SD_i are a strategy's arithmetic mean return and volatility, and SD_B is the volatility of the benchmark (the market).

Finally, although it is not entirely obvious from their marketing information, it is conceivable that multifactor funds aim to provide factor diversification with the ultimate goal of mitigating the downside, particularly during severe downturns. This downside protection is assessed with the maximum drawdown (MD), which is the maximum loss from peak to trough before a new peak is attained.

Exhibit 1 reports the results of the evaluation of multifactor funds relative to the first homemade factor diversification strategy considered here; that is, relative to equally weighted portfolios of single-factor funds that combine the specific factors featured in each multifactor fund. These homemade strategies are referred to here as target factors portfolios (TFP).[9]

The second and third columns of the exhibit show the terminal values of all multifactor funds and their respective TFPs. The third row from the bottom (Avg) shows that, on average, multifactor funds underperformed TFPs by 4.6% (= $181.9/173.8–1). Of the 30 multifactor funds considered, only 9 outperformed TFPs in terms of TV and 21 underperformed them. The next-to-last row (Avg-O) shows that the 9 funds that outperformed did so, on average, by 5.8% (= $182.5/172.4–1); the last row (Avg-U), in turn, shows that the 21 funds that underperformed did so, on average, by 9.3% (= $185.9/170.1–1). Hence the few multifactor funds that outperformed did so by a smaller margin than the many more that underperformed.

The fourth and fifth columns, which show annualized returns, provide similar information, but from a slightly different perspective. On average, multifactor funds underperformed their respective TFPs by 0.7% (= 9.7%–9.0%) a year; the 9 funds that outperformed in terms of AR did so by 1.1% (= 10.5%–9.4%), and the 21 that underperformed did so by 1.5% (= 9.8%–8.3%).

In terms of risk, the sixth and seventh columns show that, on average, multifactor funds were 1.9% (= 18.7%–16.8%) more volatile than TFPs. Only 5 multifactor funds outperformed (that is, they were *less* volatile than) their respective TFPs, and they did so by 0.6% (= 16.2%–16.8%); the 25 funds that underperformed did so by 2.3% (= 16.9%–19.2%). As with returns, many more multifactor funds underperformed than outperformed, and the margin of underperformance was larger than that of outperformance.

The eighth and ninth columns report risk-adjusted performance. As expected, given their lower average returns and higher average volatility, multifactor funds underperformed their respective TFPs in terms of risk-adjusted performance, and did so by 1.3% (= 11.5%–10.2%) a year. The 6 multifactor funds that outperformed in terms

[8] The annualized return is the mean annual compound (or geometric mean) return.

[9] To illustrate, the FlexShares US Quality Large Cap Index Fund (QLC) offers exposure to the style, quality, and momentum factors; hence the TFP equally weights the IUSV, QUAL, and MTUM funds.

EXHIBIT 1

Multifactor Funds vs. Target Factors Portfolios

	TV		AR		SD		RAP		MD	
Ticker	**Fund**	**TFP**	**Fund**	**TFP**	**Fund**	**TFP**	**Fund**	**TFP**	**Fund**	**TFP**
AUSF	140.0	138.2	7.6	7.3	19.9	17.2	9.5	10.0	–31.6	–20.3
DEUS	196.1	204.3	9.6	10.2	16.8	15.6	10.7	11.9	–27.3	–22.4
DYNF	143.0	139.6	9.4	8.7	18.9	18.5	11.5	11.0	–25.9	–22.4
FCTR	142.9	146.1	7.9	8.5	21.8	17.6	9.1	11.0	–26.7	–22.2
FLQL	182.3	179.5	10.7	10.4	16.2	16.9	13.0	12.3	–21.1	–23.8
FLQM	183.6	176.8	10.8	10.1	18.3	16.0	12.0	12.5	–25.1	–22.2
FLQS	145.5	171.5	6.5	9.5	19.4	16.8	7.6	11.5	–31.7	–22.4
FSMD	137.9	141.0	8.2	8.8	21.3	18.3	9.5	11.0	–29.3	–22.4
GSLC	232.7	224.5	11.9	11.4	15.7	14.8	13.6	13.8	–24.5	–22.2
GSSC	147.6	167.7	7.0	9.4	19.8	17.0	8.0	11.4	–26.5	–22.4
JHMM	210.3	218.8	10.4	11.0	18.2	17.3	10.8	11.7	–27.5	–26.1
JHSC	129.8	151.5	5.0	8.1	22.0	19.4	6.3	9.5	–32.0	–26.1
JPME	189.7	206.7	9.8	11.2	17.6	15.9	10.6	12.9	–29.1	–23.8
JPSE	169.2	186.7	8.7	10.4	21.1	17.2	8.8	11.7	–33.6	–23.6
JPUS	216.3	228.3	10.8	11.6	16.1	15.7	12.3	13.4	–26.0	–23.8
LRGF	192.9	210.2	8.7	9.8	15.9	16.3	10.1	11.1	–22.9	–23.6
MFUS	165.3	159.7	9.6	8.9	17.2	17.4	11.7	10.9	–23.9	–22.4
OMFL	196.6	151.0	13.5	8.0	19.2	17.6	14.6	10.1	–22.1	–22.4
OMFS	143.5	151.0	7.0	8.0	23.3	17.6	7.7	10.1	–33.3	–22.4
OUSM	160.1	177.8	7.8	9.6	18.7	16.6	8.7	11.4	–28.7	–23.1
PSC	174.7	191.6	9.0	10.5	22.4	17.1	8.6	11.8	–38.4	–23.6
QLC	205.7	228.3	10.1	11.6	16.5	15.7	11.3	13.4	–23.3	–23.8
QUS	224.2	210.3	10.7	9.8	15.0	14.7	12.8	12.0	–21.7	–20.9
ROSC	173.4	208.8	7.1	9.6	18.3	16.2	7.7	10.8	–34.0	–23.6
ROUS	185.1	214.0	7.9	9.9	15.6	15.4	9.4	11.5	–22.1	–23.8
SMLF	193.0	210.2	8.7	9.8	19.3	16.3	8.8	11.1	–31.9	–23.6
SQLV	151.9	164.9	7.7	9.2	24.8	19.0	7.7	10.4	–40.5	–26.1
USMF	164.6	174.4	9.1	10.2	16.7	17.2	11.2	12.1	–22.9	–23.8
VFMF	141.8	151.0	7.1	8.5	20.5	17.9	8.4	10.5	–30.3	–23.8
VSMV	174.8	172.3	10.2	9.9	14.8	16.2	13.7	12.4	–19.2	–22.2
Avg	**173.8**	**181.9**	**9.0**	**9.7**	**18.7**	**16.8**	**10.2**	**11.5**	**–27.8**	**–23.2**
Avg-O	**182.5**	**172.4**	**10.5**	**9.4**	**16.2**	**16.8**	**12.9**	**11.4**	**–22.0**	**–23.3**
Avg-U	**170.1**	**185.9**	**8.3**	**9.8**	**19.2**	**16.9**	**9.5**	**11.5**	**–29.5**	**–23.1**

NOTES: This exhibit shows the ticker, terminal value (TV) on March 2023 of $100 invested at the end of each fund's inception month, annualized return (AR), annualized standard deviation (SD), annualized risk-adjusted performance (RAP), and maximum drawdown (MD) for all multifactor funds and their respective target factors portfolios (TFP). The last three rows show averages across all funds (Avg), as well as averages across all the funds that outperformed (Avg-O) and underperformed (Avg-U) their respective TFPs with respect to each evaluation variable considered. All figures in % except for TV (in dollars).

of RAP did so, on average, by 1.5% (= 12.9%–11.4%); the 24 that underperformed did so, on average, by 2% (= 11.5%–9.5%). Once again, then, many more multifactor funds underperformed than outperformed, and the margin of underperformance was larger than that of outperformance.

Finally, multifactor funds did not excel in protecting investors from severe downturns. The last two columns of the exhibit show that, on average, their maximum drawdown was 4.6% (= 27.8%–23.2%) larger than that of their respective TFPs. Only 7 funds mitigated the downside more than TFPs, and they did so, on average, by 1.3% (= 22.0%–23.3%); the 23 funds that fell more than TFPs did so, on average, by 6.4% (= 29.5%–23.1%). As was the case with all the other evaluation variables, few multifactor funds outperformed and they did so by a smaller margin than the many more than underperformed.

In short, this evidence shows that if investors had decided which factors they wanted to be exposed to, multifactor funds would have underperformed a simple homemade strategy of combining those factors by equally weighing single-factor funds in a portfolio. For each of the five evaluation variables considered here (TV, AR, SD, RAP, and MD), the average multifactor fund underperformed the average TFP. In addition, and again for each of the five variables considered, the number of underperforming multifactor funds far outnumbered the number of outperforming funds, and the margin of underperformance was larger than that of outperformance.

Multifactor Funds vs. All Factors Portfolios

Exhibit 2 reports the results of the evaluation of multifactor funds relative to the second homemade factor diversification strategy considered here; that is, relative

EXHIBIT 2

Multifactor Funds vs. All Factors Portfolios

	TV		AR		SD		RAP		MD	
Ticker	**Fund**	**AFP**	**Fund**	**AFP**	**Fund**	**AFP**	**Fund**	**AFP**	**Fund**	**AFP**
AUSF	140.0	135.8	7.6	6.9	19.9	18.6	9.5	9.1	–31.6	–22.4
DEUS	196.1	204.3	9.6	10.2	16.8	15.6	10.7	11.9	–27.3	–22.4
DYNF	143.0	139.6	9.4	8.7	18.9	18.5	11.5	11.0	–25.9	–22.4
FCTR	142.9	140.8	7.9	7.6	21.8	18.5	9.1	9.8	–26.7	–22.4
FLQL	182.3	171.5	10.7	9.5	16.2	16.8	13.0	11.5	–21.1	–22.4
FLQM	183.6	171.5	10.8	9.5	18.3	16.8	12.0	11.5	–25.1	–22.4
FLQS	145.5	171.5	6.5	9.5	19.4	16.8	7.6	11.5	–31.7	–22.4
FSMD	137.9	141.0	8.2	8.8	21.3	18.3	9.5	11.0	–29.3	–22.4
GSLC	232.7	220.5	11.9	11.1	15.7	15.6	13.6	12.9	–24.5	–22.4
GSSC	147.6	167.7	7.0	9.4	19.8	17.0	8.0	11.4	–26.5	–22.4
JHMM	210.3	220.5	10.4	11.1	18.2	15.6	10.8	12.9	–27.5	–22.4
JHSC	129.8	151.0	5.0	8.0	22.0	17.6	6.3	10.1	–32.0	–22.4
JPME	189.7	198.9	9.8	10.6	17.6	15.8	10.6	12.3	–29.1	–22.4
JPSE	169.2	186.6	8.7	10.3	21.1	16.3	8.8	12.2	–33.6	–22.4
JPUS	216.3	220.5	10.8	11.1	16.1	15.6	12.3	12.9	–26.0	–22.4
LRGF	192.9	209.8	8.7	9.8	15.9	15.4	10.1	11.6	–22.9	–22.4
MFUS	165.3	159.7	9.6	8.9	17.2	17.4	11.7	10.9	–23.9	–22.4
OMFL	196.6	151.0	13.5	8.0	19.2	17.6	14.6	10.1	–22.1	–22.4
OMFS	143.5	151.0	7.0	8.0	23.3	17.6	7.7	10.1	–33.3	–22.4
OUSM	160.1	182.4	7.8	10.1	18.7	16.4	8.7	12.0	–28.7	–22.4
PSC	174.7	189.7	9.0	10.4	22.4	16.2	8.6	12.1	–38.4	–22.4
QLC	205.7	220.5	10.1	11.1	16.5	15.6	11.3	12.9	–23.3	–22.4
QUS	224.2	209.8	10.7	9.8	15.0	15.4	12.8	11.6	–21.7	–22.4
ROSC	173.4	208.5	7.1	9.6	18.3	15.3	7.7	11.3	–34.0	–22.4
ROUS	185.1	207.2	7.9	9.4	15.6	15.2	9.4	11.1	–22.1	–22.4
SMLF	193.0	209.8	8.7	9.8	19.3	15.4	8.8	11.6	–31.9	–22.4
SQLV	151.9	164.8	7.7	9.2	24.8	17.1	7.7	11.2	–40.5	–22.4
USMF	164.6	167.7	9.1	9.4	16.7	17.0	11.2	11.4	–22.9	–22.4
VFMF	141.8	149.1	7.1	8.2	20.5	17.8	8.4	10.2	–30.3	–22.4
VSMV	174.8	167.7	10.2	9.4	14.8	17.0	13.7	11.4	–19.2	–22.4
Avg	**173.8**	**179.7**	**9.0**	**9.5**	**18.7**	**16.6**	**10.2**	**11.4**	**–27.8**	**–22.4**
Avg-O	**178.5**	**166.8**	**10.2**	**9.0**	**16.0**	**16.7**	**12.5**	**11.1**	**–21.3**	**–22.4**
Avg-U	**171.5**	**186.1**	**8.3**	**9.7**	**19.3**	**16.6**	**9.2**	**11.5**	**–29.1**	**–22.4**

NOTES: This exhibit shows the ticker, terminal value (TV) on Mar/2023 of $100 invested at the end of each fund's inception month, annualized return (AR), annualized standard deviation (SD), annualized risk-adjusted performance (RAP), and maximum drawdown (MD) for all multifactor funds and their respective all factors portfolios (AFP). The last three rows show averages across all funds (Avg), as well as averages across all the funds that outperformed (Avg-O) and underperformed (Avg-U) their respective AFPs with respect to each evaluation variable considered. All figures in % except for TV (in dollars).

to equally weighted portfolios of single-factor funds that combine the five factors most widely used by asset management companies (size, style, quality, volatility, and momentum). These homemade strategies are referred to here as All Factors Portfolios (AFP).

The second and third columns of the exhibit show that, on average, multifactor funds underperformed their respective AFPs by 3.4% (= $179.7/173.8–1). Of the 30 multifactor funds considered, only 10 outperformed AFPs and they did so, on average, by 7% (= $178.5/166.8–1); the 20 funds that underperformed did so, on average, by 8.6% (= $186.1/171.5–1). Furthermore, the fourth and fifth columns show that, on average, multifactor funds underperformed their respective AFPs by 0.5% (= 9.5%–9.0%) a year. The 10 multifactor funds that outperformed did so, on average, by 1.2% (= 10.2%–9.0%); the 20 funds that underperformed did so, on average, by 1.4% (= 9.7%–8.3%).

The sixth and seventh columns show that the average multifactor fund was 2.1% (= 18.7%–16.6%) more volatile than the average AFP. The 5 multifactor funds that outperformed (that is, they were *less* volatile than) their respective AFPs did so, on average, by 0.7% (= 16.7%–16.0%); the 25 funds that underperformed did so, on average, by 2.6% (= 19.3%–16.6%).

The eighth and ninth columns show that the average multifactor fund underperformed the average AFP by 1.2% (= 11.4%–10.2%) a year in terms of risk-adjusted performance. The 9 multifactor funds that outperformed their respective AFPs did so, on average, by 1.4% (= 12.5%–11.1%); the 21 funds that underperformed did so, on average, by 2.3% (= 11.5%–9.2%).

Finally, the last two columns of the exhibit show that the average multifactor fund provided less protection during severe downturns than the average AFP, falling 5.4% (= 27.8%–22.4%) more. The 5 multifactor funds that outperformed mitigated the downside, on average, by 1.1% (= 22.4%–21.3%) more than their respective AFPs; the 25 that underperformed mitigated the downside, on average, by 6.7% (= 29.1%–22.4%) less than their respective AFPs.

In short, this evidence shows that if individuals had invested in multifactor funds, rather than simply building an equally-weighted portfolio of five single-factor funds, one for each of the five most popular factors, they would have clearly underperformed the homemade strategy. In fact, in terms of all the evaluation variables considered here, investors would have underperformed not just on average but in the case of most funds and with the margin of underperformance being larger than that of outperformance.

Further Discussion

The evidence in the previous two sections clearly shows that multifactor funds underperformed two very simple homemade factor diversification strategies, both within easy reach of individual investors. Regardless of whether the evaluation is performed with respect to TFPs or AFPs, investors in multifactor funds pocketed lower returns, suffered higher volatility, obtained lower risk-adjusted returns, and were less protected during severe downturns. What went wrong with the seemingly good idea of multifactor funds then?

A usual suspect is costs. As already mentioned, the average multifactor fund in the sample has an expense ratio of 29 basis points; the average expense ratio of the five single-factor funds used in the homemade strategies, on the other hand, is just 11 basis points. The difference of 18 basis points, however, is lower than the difference of 70 (50) basis points between the average annualized

EXHIBIT 3

Averages

	TV	AR	SD	RAP	MD
Multifactor Funds	173.8	9.0	18.7	10.2	–27.8
TFP	181.9	9.7	16.8	11.5	–23.2
AFP	179.7	9.5	16.6	11.4	–22.4
IVV	199.9	11.5	17.2	13.1	–23.9

NOTES: This exhibit shows averages for the terminal value (TV), annualized return (AR), annualized standard deviation (SD), annualized risk-adjusted performance (RAP), and maximum drawdown (MD) for all multifactor funds, target factors portfolios (TFP), all factors portfolios (AFP), and the market (IVV). All figures in % except for TV (in dollars).

return of multifactor funds and TFPs (AFPs). Therefore, expense ratios alone cannot fully explain the underperformance in terms of returns.[10]

The two homemade strategies considered here involve annual rebalancing to equal weights, and the cost of such rebalancing is not included in the figures reported for TFPs and AFPs. However, annually rebalancing a portfolio of five funds or less is unlikely to cost the 32 (= 50–18) basis points unaccounted for by the difference in expense ratios, let alone 52 (= 70–18) basis points. Furthermore, differences in expense ratios and rebalancing costs would not be able to explain the underperformance of multifactor funds in terms of all the five evaluation variables considered here.

In terms of individual performance, relative to TFPs only 2 of the 30 multifactor funds in the sample (FLQL and VSMV) outperformed in terms of all five of the evaluation variables considered here; relative to AFPs, only 3 (FLQL, QUS, and VSMV) did so. Two of these funds (FLQL and QUS) have relatively low expense ratios (15 basis points) but the third (VSMV) is relatively expensive (35 basis points).

Exhibit 3 collects the averages already reported in Exhibits 1 and 2 (in the "Avg" rows) and adds, for perspective, the same metrics for the market, represented by the IVV ETF. Interestingly, in terms of compounding power, easily/cheaply available broad diversification outperformed multifactor funds (by 2.5%), TFPs (by 1.8%), and AFPs (by 2.0%) in terms of annualized return. In terms of risk, broad diversification proved to be less volatile than multifactor funds (by 1.5%), and slightly more volatile than TFPs (by 0.4%) and AFPs (by 0.6%).

Combining return and risk in the risk-adjusted performance metric shows that broad diversification outperformed multifactor funds (by 2.9% a year), TFPs (by 1.6%), and AFPs (by 1.7%). Finally, in terms of downside protection, broad diversification outperformed multifactor funds (mitigating the downside by 3.9% more), and slightly underperformed TFPs (by 0.7%) and AFPs (by 1.5%).

All these results reinforce those reported by Estrada (2023) and suggest that being very broadly diversified at a very low cost (buying the haystack, as John Bogle would say) is a perfectly reasonable strategy for investors. They also suggest that, should some investors decide to diversify across factors instead, they are quite likely to be better off by combining single-factor funds than by investing in multifactor funds.

CONCLUSIONS

Academics and practitioners currently seem to generally agree on the fact that stock returns are largely driven by factors. Combining exposure to several factors in a single fund, then, seems to follow rather directly. The implementation of this seemingly good idea by asset management companies, however, has been mostly disappointing.

The evidence reported and discussed in this article shows that multifactor funds have, by and large, underperformed two very simple homemade factor diversification strategies, both within easy reach of all investors. Both strategies equally weigh

[10] To be sure, the difference of 18 basis points between the average expense ratio of multifactor funds and single-factor funds is that as of March, 2023. It is possible that this difference has been wider (or narrower) over the sample period.

single-factor funds, in one case by matching the factor exposure offered by multifactor funds, and in the other by simply combining the five most popular factors.

Multifactor funds largely underperformed both homemade factor diversification strategies in terms of return, risk, risk-adjusted return, and downside protection; and they did so not just on average. For each and every evaluation variable considered here, more multifactor funds underperformed than outperformed, and the former did so by a larger margin than did the latter. The relatively high cost of multifactor funds may explain part of (but not all of) the story.

All in all, the results here suggest that those investors that choose to diversify their portfolios across factors should largely stay away from multifactor funds; rather, they should diversify their portfolios themselves by combining single-factor funds. Alternatively, they could just take advantage of the wide availability and very low cost of broad market index funds and ETFs; after all, rather than looking for needles in the haystack, it may just be simpler and better to buy the haystack.

APPENDIX

EXHIBIT A1
Sample Characteristics

Ticker	Fund	NA	ER	Inception	*T*	*N*
Multifactor Funds						
AUSF	Global X Adaptive U.S. Factor ETF	164.8	0.27	8/24/2018	55	173
DEUS	Xtrackers Russell U.S. Multifactor ETF	142.5	0.17	11/23/2015	88	819
DYNF	BlackRock U.S. Equity Factor Rotation ETF	30.0	0.30	3/19/2019	48	83
FCTR	First Trust Lunt U.S. Factor Rotation ETF	228.0	0.65	7/25/2018	56	154
FLQL	Franklin LibertyQ U.S. Equity ETF	877.0	0.15	4/26/2017	71	213
FLQM	Franklin LibertyQ U.S. Mid Cap Equity ETF	166.7	0.30	4/26/2017	71	203
FLQS	Franklin LibertyQ U.S. Small Cap Equity ETF	17.0	0.35	4/26/2017	71	480
FSMD	Fidelity Small-Mid Multifactor ETF	103.2	0.29	2/26/2019	49	597
GSLC	Goldman Sachs ActiveBeta U.S. Large Cap Equity ETF	10,820.5	0.09	9/17/2015	90	445
GSSC	Goldman Sachs ActiveBeta U.S. Small Cap Equity ETF	436.1	0.20	6/28/2017	69	1229
JHMM	John Hancock Multifactor Mid Cap ETF	2,916.1	0.41	9/28/2015	90	656
JHSC	John Hancock Multifactor Small Cap ETF	341.4	0.42	11/8/2017	64	384
JPME	JPMorgan Diversified Return U.S. Mid Cap Equity ETF	321.5	0.24	5/11/2016	82	364
JPSE	JPMorgan Diversified Return U.S. Small Cap Equity ETF	352.8	0.29	11/15/2016	76	578
JPUS	JPMorgan Diversified Return U.S. Equity ETF	497.4	0.18	9/29/2015	90	353
LRGF	iShares MSCI USA Multifactor ETF	1,241.3	0.08	4/28/2015	95	310
MFUS	RAFI Dynamic Multi-Factor U.S. Equity ETF	123.4	0.29	8/31/2017	66	890
OMFL	Invesco Russell 1000 Dynamic Multifactor ETF	2,791.0	0.29	11/8/2017	64	307
OMFS	Invesco Russell 2000 Dynamic Multifactor ETF	272.9	0.39	11/8/2017	64	708
OUSM	O'Shares U.S. Small Cap Quality Dividend ETF	208.5	0.48	12/30/2016	75	116
PSC	Principal U.S. Small-Cap Multi-Factor ETF	192.7	0.38	9/21/2016	78	501
QLC	FlexShares US Quality Large Cap Index Fund	129.5	0.25	9/23/2015	90	180
QUS	SPDR MSCI USA StrategicFactors ETF	955.4	0.15	4/15/2015	95	625
ROSC	Hartford Multifactor Small Cap ETF	34.1	0.34	3/23/2015	96	333
ROUS	Hartford Multifactor U.S. Equity ETF	451.8	0.19	2/25/2015	97	347
SMLF	iShares MSCI USA Small-Cap Multifactor ETF	979.0	0.15	4/28/2015	95	874
SQLV	Legg Mason Small-Cap Quality Value ETF	24.8	0.61	7/12/2017	68	248
USMF	WisdomTree U.S. Multifactor Fund	262.6	0.28	6/29/2017	69	200
VFMF	Vanguard U.S. Multifactor ETF	175.0	0.18	2/13/2018	61	574
VSMV	VictoryShares US Multi-Factor Minimum Volatility ETF	122.0	0.35	6/22/2017	69	67

(continued)

EXHIBIT A1 *(continued)*

Sample Characteristics

Ticker	Fund	NA	ER	Inception	*T*	*N*
Single-Factor Funds						
IJR	iShares Core S&P Small-Cap ETF	66,800.9	0.06	5/22/2000	97	677
IUSV	iShares Core S&P U.S. Value ETF	13,284.0	0.04	7/24/2000	97	705
MTUM	iShares MSCI USA Momentum Factor ETF	9,884.0	0.15	4/16/2013	97	125
QUAL	iShares MSCI USA Quality Factor ETF	26,657.0	0.15	7/16/2013	97	124
USMV	iShares MSCI USA Min Vol Factor ETF	28,645.0	0.15	10/18/2011	97	164
Market-Wide Benchmark						
IVV	iShares Core S&P 500 ETF	305,449.9	0.03	5/15/2000	97	503

NOTE: This exhibit shows the funds in the sample, their ticker, net assets (NA, in millions), and expense ratio (ER, in %) on March 31, 2023, inception date, number of monthly returns in the sample (*T*), and number of stocks in each fund (*N*).

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