Why do equally weighted portfolios beat value-weighted ones?

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Abstract

Equal-weighted (EW) portfolios have outperformed their value-weighted (VW) counterparts over multiple decades in various investment universes. This paper investigates the long-term evidence for the EW–VW return spread in a broad U.S. equity universe across multiple factor models. Unsurprisingly, EW investing comes with a highly significant positive size factor exposure. Given its acyclic rebalancing character, EW investing is also found to benefit from short-term reversal effects while suffering from negative momentum exposure. We also document a pronounced seasonality effect in EW investing that would see outsized returns in January. We revisit these findings in the more investible universe of S&P500 stocks and discuss how to best harvest the embedded factor premia in an efficient manner.

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The simple approach of equally weighting portfolio constituents is a popular choice of academics and investors to benchmark specific portfolio allocations. Indeed, equal-weighted (EW) strategies prove hard to beat out of sample even when using different optimized asset allocation strategies, see DeMiguel, Garlappi, and Uppal (2009). The success of the EW strategy has piqued many researchers' interest trying to rationalize and exploit the underlying drivers. Many different stock characteristics have been put to the fore, yet, there is no clear evidence which effects drive this outperformance. Given that many of the analyzed stock characteristics seem to only be relevant during specific periods and disappear over time, we take a systematic approach to understand the drivers behind the differences in performance between the value- and equal-weighted portfolios over six decades. Specifically, we analyze the difference of the market capitalization weighted portfolio (also referred to as value-weighted or VW portfolio) and its equally weighted counterpart to differentiate between persistent and transitory performance components. We thus analyse multiple setups ranging from single to multi-factor models utilizing well-known factors in the literature. To investigate the practicality of our findings, we not only focus on the broad CRSP universe but also the large cap S&P500 universe. Despite some sample-specific differences, we find the vast majority of systematic effects carry over.

Our work is related to recent research exploring the equal-weighting scheme and its performance, e.g., Pae and Sabbaghi (2015), Malladi and Fabozzi (2017), and Plyakha, Uppal, and Vilkov (2021), as well as size factor related literature like Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018) and Blitz and Hanauer (2020). Whilst previous research focuses on stock-specific characteristics to explain the different return profiles of the EW and VW portfolios, we take a closer look at the contribution of systematic factors to the EW–VW spread over time and across different factor models. Many of the previous papers pinpoint the different effects in terms of one or two components which prove consistent through the respective sample. The most obvious ones are the size tilt of the EW portfolio towards small caps as well as the rebalancing effects that derive from the necessity to maintain portfolio weights equal. We confirm that the size factor is the most significant driver of the performance of the difference between the EW and VW portfolio, yet, we also highlight the impact of other factors beyond size. Notably, factors such as momentum, profitability, short-term reversals, or low volatility also help to increase the explained variance within models during certain time periods.

We contribute to the literature in several ways. First, we analyze the impact of equal-weighting across some six decades for the broad CRSP equity universe, decomposing the long short EW–VW return spread into its systematic components. Second, we test a variety of factor models ranging from a single index model to well known multi-factor models such as the one proposed by Fama and French (2015) to further decompose the EW–VW spread. We confirm size as the prevailing factor component but also emphasize the relevance of other factors in order to explain the time-varying magnitude of the difference between the EW and VW portfolio. Third, we document the close relation of the EW–VW spread and the small minus big (SMB) size factor, resulting in an easy to implement alternative to small cap funds in order to harvest the size premium.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature about EW portfolios and describes the different factor model frameworks, capturing the single index model and multi-factor models. Section 3 documents the historical outperformance of the EW portfolio relative to its VW counterpart in the CRSP and S&P500 universes and associates it with multiple systematic components. Further analysis highlights the seasonality in the EW–VW spread. Section 4 investigates the possibility to participate in the size premium by investing in the EW–VW spread relative to purchasing small cap funds. Section 5 concludes.

SETTING THE THEORETICAL FOUNDATION

The virtue of equally weighting

Analyzing the performance of EW (or $1/N$) portfolios has garnered considerable interest from academics and practitioners alike. It is systematic and easy to implement because all N portfolio constituents are assigned the same weight, $w_i = \frac{1}{N}$ for $i = 1, ..., N$. It is though an active strategy since the portfolio requires rebalancing to maintain equal weights over time. At each rebalancing date, it sells winners and buys losers and it is thus considered a mean-reversion, contrarian strategy yielding concave payoffs equivalent to selling portfolio insurance (Perold and Sharpe, 1988). The deterministic weighting scheme does not require any expected return or variance input and also enables diversification. Therein, a naive investor is only reliant on the average correlation coefficient to determine acceptable risk-return trade-offs (De Wit, 1998). These features make the EW portfolio a strong contender compared to different allocation schemes as highlighted by DeMiguel, Garlappi, and Uppal (2009). In contrast, the VW portfolio is a passive buy and hold strategy which reflects market drifts. Historically, investing in EW portfolios was rewarded with a premium compared to investing in the VW portfolios.

Several researchers proposed explanations to rationalize the exceptional performance of EW portfolios relative to alternative allocation methods. Plyakha, Uppal, and Vilkov (2021) document a monotonic relation[1] between the EW–VW return spread and size, price, liquidity, and idiosyncratic volatility factors. Put differently, the higher the stocks' characteristics in the sampled portfolio, the larger the resulting EW–VW spread. They link the higher returns of the EW portfolios to systematically higher exposures to market, size and value factors; still, EW portfolios exhibit significantly positive four-factor alpha in the sense of Fama and French (1993) and Carhart (1997) models which they rationalize with the need for frequent rebalancing to maintain equal portfolio weights.

Naturally, EW investing can also be related to the rebalancing literature which suggests that there are benefits to the mere act of rebalancing, which has been labeled *diversification return* (Erb and Harvey, 2006), *volatility return* (Willenbrock, 2011) or *rebalancing premium* (Bouchey, Nemtchinov, Paulsen, and Stein, 2012). In this vein, a proportion of the difference between the EW and VW returns might just be related to the *rebalancing return* which is defined as the difference in growth rates of the rebalanced versus the buy-and-hold portfolio. Hallerbach (2014) analytically shows that the rebalancing return emerges as the difference between a volatility return and a dispersion discount. Since both components are strictly positive, it is not a given whether the rebalancing return is positive or negative. To investigate, one could split the return difference between the EW and VW portfolios into a rebalancing component return, as well as a component related to the difference in weighting. However,

[1] Based on the methodology of Patton and Timmermann (2010)

in order to split the rebalancing effects cleanly, one must have the same constituents over the full sample period, because any change of constituents involves rebalancing, which interferes with the buy and hold strategies. Against this backdrop, Maeso and Martellini (2020) analyze rebalancing returns for a constant sample of surviving S&P500 stocks and identify a sizable annual premium of the rebalanced strategy over its buy-and-hold counterpart. Malladi and Fabozzi (2017) develop a two-period, two-asset model in which the difference in weighting and the rebalancing effect are the two sources for outperformance. Their empirical results include randomized prices which also eliminate the urge for constituent change inferred rebalancing. Given the said caveat of using a constant sample of companies, we rather build our analysis on a more realistic setup that considers all investible companies at any point in time. Therefore, we cannot gauge potential rebalancing premia; yet, we are optimistic to rationalize the EW-VW spread in terms of different factor premia that will most likely play an important role in rationalizing rebalancing premia as well.

Another strand of the literature advocates market-related rationales to explain the differences between EW and VW portfolio performance: The *noisy market hypothesis*[2] expands the *efficient market hypothesis* by constructing a theory where securities are not always priced at their fair values but are over- or undervalued because of market inefficiencies. To deviate from market capitalization-weighted indexes, Arnott, Hsu, and Moore (2005) analyze several alternative fundamental measures besides firms' market capitalization. The resulting indexing schemes are referred to as *fundamental indexing* and the EW index can be considered to be an alternative in that regard. The initial claim of Arnott, Hsu, and Moore (2005) that VW portfolios are tilted towards over-valued stocks and under-represent value firms has been debated since, e.g. by Perold (2007) or Kaplan (2008). Despite the debate of its validity, the fundamental indexing framework implies that the difference in performance between the EW and VW portfolios is due to the mispricing of over-weighted firms in the VW portfolio. Hence, investing in an EW portfolio instead can be interpreted as investing in the passive VW portfolio plus an additional overlay similar to the SMB and HML factors by Fama and French (1993).

Factor models and EW investing

A single index model approach: We start exploring systematic effects of the EW–VW return differences by invoking the simplest factor model – the single index model (SIM) also known as the capital asset pricing model (CAPM).[3] Therein, the return of stock i is explained by its market beta, β_i (against the market return, r_M, with expected return, $\overline{r}_M$, and variance, σ_M^2), its alpha, α_i, and some zero-mean idiosyncratic risk ε_i. Empirically, this model aims for alphas to be statistically indistinguishable from zero to have high explanatory power from the systematic factor(s) of the model. The idiosyncratic risks are assumed to be stock-specific with an individual but independent magnitude σ_i^2 all equal to a common idiosyncratic variance, σ_I^2. In this case, the return, r_i, of stock i, its expectation and variance

[2] The term *noisy market hypothesis* was introduced by Siegel (2006).

[3] See Sharpe (1964), Lintner (1965), Mossin (1966) and Treynor (1961).

are given by

$$\begin{aligned} r_i &= (\alpha_i) + \beta_i r_M + \varepsilon_i, \\ E[r_i] &= \beta_i E[r_M] = \beta_i \overline{r}_M, \\ Var[r_i] &= \beta_i^2 \sigma_M^2 + \sigma_I^2. \end{aligned} \tag{1}$$

The returns r_i and r_M are in excess of the risk-free rate. Note that all parameters in the model are time-varying, but we omit time indices for readability.

We denote the value-based weights associated with the market capitalization of stock i as w_i^{mcap} such that we obtain the VW portfolio return, r_{VW}, which expected return $\overline{r}_{VW}$ matches that of the market:

$$r_{VW} = \sum_{i=1}^{N} w_i^{mcap} (\beta_i r_M + \varepsilon_i) = r_M \sum_{i=1}^{N} w_i^{mcap} \beta_i + \sum_{i=1}^{N} w_i^{mcap} \varepsilon_i. \tag{2}$$

From equation (2) we can infer that $\sum_{i=1}^{N} w_i^{mcap} \beta_i = 1$, which holds by definition.[4] As for the idiosyncratic risk, $\sum_{i=1}^{N} w_i^{mcap} \varepsilon_i$ goes to 0 for large N, assuming the stocks' idiosyncratic risks to be unbiased and independent of weights such that the weighted average error will be zero. The variance of this value weighted portfolio equals the variance of the market, i.e. $\sigma_{VW}^2 = \sigma_M^2$ as $\sigma_I^2/N \to 0$ for $N \to \infty$.

The EW portfolio has fixed weights $w_i = 1/N$ for all i. The return of the EW portfolio is labeled r_{EW}, and its expected return $\overline{r}_{EW}$ emerges as the sample average of beta times the expected market return $\overline{r}_M$.

$$\begin{aligned} r_{EW} &= \sum_{i=1}^{N} \tfrac{1}{N} (\beta_i r_M + \varepsilon_i) = r_M \tfrac{1}{N} \sum_{i=1}^{N} \beta_i + \tfrac{1}{N} \sum_{i=1}^{N} \varepsilon_i, \\ \overline{r}_{EW} &= E\left[r_M \tfrac{1}{N} \sum_{i=1}^{N} \beta_i\right] + E\left[\tfrac{1}{N} \sum_{i=1}^{N} \varepsilon_i\right] = \tfrac{1}{N} \sum_{i=1}^{N} \beta_i \overline{r}_M = \overline{\beta}\, \overline{r}_M, \end{aligned} \tag{3}$$

where $\overline{\beta} = \frac{1}{N}\Sigma_{i=1}^{N}\beta_i$ is the sample average of beta which may deviate from unity of the market itself $\overline{r}_M$. The variance of the EW portfolio is given by $\sigma_{EW}^2 = \overline{\beta}^2 \sigma_M^2$, that is, the EW portfolio is locally a $\overline{\beta}$ multiplier of the VW passive portfolio where $\overline{\beta}$ is scaling expected return and market volatility.

Using (2) and (3) we can express the difference in performance between EW and VW portfolios. Equation (4) thus suggests why and when the EW portfolio outperforms the VW one: The average constituent's beta, $\overline{\beta}$, intensifies the market return if $\overline{\beta} > 1$ and abates it if $\overline{\beta} < 1$. Hence, if $\overline{\beta} > 1$, the EW portfolio outperforms the VW one for positive r_M and vice versa, the relation is reversed for $\overline{\beta} < 1$.

$$r_{EW} - r_{VW} = \overline{\beta} r_M - r_M = \left(\overline{\beta} - 1\right) r_M. \tag{4}$$

By construction, the expected return correlation of EW and VW portfolios is 1. Empirically, the correlation of returns is less than one, given that the error term assumptions do not hold perfectly. Also, the drift in weights due to non-continuous rebalancing will break this relation occasionally.

[4] The single index model market return has a beta of 1 by definition. In our case, the market return is defined as the value weighted portfolio return.

Multi-factor models: The market factor in the single index model might not capture all systematic risk sources, so that further linear models such as Ross's (1976) arbitrage pricing theory (APT) have been developed. Under APT, the returns $\boldsymbol{r} \in \mathbb{R}^{N\times 1}$ of N risky assets follow a factor intensity structure given by:

$$\boldsymbol{r} = \boldsymbol{B} \cdot \boldsymbol{f} + \boldsymbol{\varepsilon}, \tag{5}$$

where $\boldsymbol{f} \in \mathbb{R}^{K\times 1}$ represents the returns of K factors with respective factor loadings $\boldsymbol{B} \in \mathbb{R}^{N\times K}$ and asset-specific idiosyncratic risks $\boldsymbol{\varepsilon} \in \mathbb{R}^{N\times 1}$, which have zero mean and are assumed to be uncorrelated across assets and factors. The expected asset returns can be expressed in terms of factor sensitivities, so that:

$$\mathbb{E}\left(\boldsymbol{r}\right) = \boldsymbol{r_f} + \boldsymbol{B} \cdot \boldsymbol{r_p}, \tag{6}$$

with $\boldsymbol{r_f} \in \mathbb{R}^{N\times 1}$ denoting the risk-free rate, and $\boldsymbol{r_p} \in \mathbb{R}^{K\times 1}$ denoting the risk premia associated with the corresponding systematic factors. Several factor models follow this paradigm, e.g., Fama and French (1993), Carhart (1997), Hou, Xue, and Zhang (2015), and Fama and French (2015). Our choice of factors is described in the next chapter.

ANALYZING THE EW-VW SPREAD

The historical outperformance of the EW portfolio

Empirical setup: To empirically investigate the equal-weighted portfolio, we construct the market-weighted portfolio as well as its equally weighted counterpart for a broad US equity universe as well as the S&P500 universe. Our full sample period is from July 1963 to December 2021, and we use monthly data from CRSP and Compustat covering stocks traded on the NYSE, AMEX, and NASDAQ with share codes 10 or 11. Exhibit 1 reveals the dominance of the EW portfolio over the long-term, depicting the performance of the two portfolios based on the full CRSP universe (EW) and the S&P500 (SPW) constituents only. In the CRSP universe, EW gives positive returns of 14.9% p.a. at a volatility of 20.6%; in the S&P500 universe we obtain 13.6% p.a. at 17.1% volatility. Both VW portfolios show similar annual returns (11.4%) at some 15% volatility over the same period. Note that the EW portfolios outperform their VW counterparts in 33 (37) out of the 59 years, an outperformance which comes at higher risks in terms of higher volatility and more severe drawdowns.

[Exhibit 1 about here.]

Exhibit 2 reveals the performance differences between the EW and VW for the CRSP (Panel A) and S&P500 samples (Panel B) across different time periods. These subperiods are the pre-publication (July 1963–December 1983) and post-publication (January 1984–December 1999) periods referring to the first size effect publications[5], the period before (January 2000–December 2009) the global financial crisis (GFC), as well as the time after it (January 2010–December 2021). The splits in these four subperiods resonate with the

[5]See Banz (1981) or Keim (1983).

strong and weak performance periods of the EW portfolio compared to its VW counterpart: Prior publication as well as prior to the GFC, the EW portfolios outperformed across both universes yielding annual excess returns of 7.5% and 10.1% (4.0% and 7.2% for the S&P500 universe) over the VW portfolios. Despite higher volatility and maximum drawdown (MDD) figures, the EW portfolios surpassed the VW ones on a risk-adjusted basis yielding Sharpe ratio (SR) differences of 0.08 and 0.13 (0.05 and 0.11 for S&P500). In contrast, EW portfolios did considerably worse during the other two subperiods. In the post-publication phase, the EW portfolios underperformed by -3.1% p.a. in the CRSP and -1.5% p.a. in the S&P500 sample, whereas they went fairly flat after the GFC, showing annual return differences of -0.1% and 0.0%. Yet, the EW portfolios come with higher risks during all periods resulting in risk-adjusted underperformances in the latter periods as well. These differences over time are most likely driven by the following phenomena: After the discovery of the size effect by Banz (1981) and Reinganum (1981), academics as well as practitioners started to account for this anomaly resulting in weaker performances of the EW portfolios thereafter, which are mechanically linked to small firms' performances. EW portfolios seem to recover well just after big market corrections like the dotcom burst in 2001 and the GFC in 2008. Underweighting large caps helped mitigating the extreme drawdowns but also participating in size effects during the recovery, ultimately boosting the spread in performance. In addition, EW portfolios lag in times of monotonic market trends and dominance of large caps, such as the FAANG[6] stocks rally during the 2010s.

[Exhibit 2 about here.]

Exhibit 2 also splits the returns of the VW and EW portfolios into the month of January versus the period from February through December (non-January), addressing the seasonality of the size effect as highlighted by, e.g., Keim (1983) and Roll (1983). We observe considerably higher annualized returns for the month of January compared to non-January months in both universes and across portfolios. This effect becomes even stronger for the EW portfolios resulting in 2.5–6 times higher returns over the non-January months. Finally, the last two columns of Panel A and B of Exhibit 2 report the average monthly return difference between the EW and VW portfolios for all subperiods as well as t-statistics for testing the hypothesis of returns being zero. Across both Panels we identify significant outperformances of the EW portfolios for the full sample period as well as the pre-publication and pre-GFC subperiods of 29 to 84 bps per month (with t-stats ranging from 2.42 to 3.35). This outperformance is more pronounced during the month of January with 401 bps (t-stat 6.57) for the CRSP sample and 103 bps (t-stat 3.40) for the S&P500 sample.

Thus, the effects of equal-weighting compared to value-weighting are significant for both universes despite considerable differences in universes: Whilst the S&P500 has 500 constituents by definition[7], the CRSP universe increases from 3,172 in the pre-publication phase[8]

[6]This acronym refers to the five best-performing U.S. technology firms: Facebook, Amazon, Apple, Netflix and Alphabet.

[7]Note that the exact number of available stocks in the CRSP database might slightly deviate from 500 due to information lags between CRSP's and Standard and Poor's listing dates. Additionally, the S&P500 includes several companies with two share classes increasing the total count, e.g. Alphabet's Class A (GOOGL) and Class C (GOOG) shares.

[8]The CRSP universe consists of 1,741 stocks at the start of the sample period in the early 1960s.

to about 6,000 in the post-publication period before shrinking back to 3,648 over the last decade. This development highlights the impact of extremely small companies, which is also reflected in the average market capitalization (Mcap) of the portfolio constituents. While the average Mcap in the whole universe increases from 0.3 to 6.4 billion USD, the average S&P500 firm is around 5 times bigger than the average firm in the CRSP universe peaking at a factor of more than 9 during the 1990s. These initial observations call for systematically analyzing factors driving the performance difference, which we investigate next.

A first glance using the single index model: To begin with, we estimate the SIM using the market factor MKT in excess of the risk-free rate as provided by Fama and French (1993). To account for the time-varying characteristic of individual stocks' beta as well as its short-term persistence we run regressions based on the different subperiods. Panel 3 of Exhibit 2 depicts the estimated model parameters α and β as well as their t-statistics and the overall R^2 for the six CRSP and S&P500 portfolios over the full sample period. These are the value-weighted one, its equal-weighted counterpart as well as the spread of EW–VW for each sample. The subsequent rows depict the parameter estimates for the EW–VW spreads in the highlighted subsamples.

The full sample CRSP VW portfolio shows the expected model parameters with α being statistically indistinguishable from 0 while β is equal to 1. As expected, the resulting R^2 is 100%. For the S&P500 universe we observe similar results; yet, the estimated R^2 of 98% for the VW portfolio indicates a slight variation from the market portfolio by missing out a considerable fraction of small caps. With β being significantly below 1 (t-stat -8.75; tested against hypothesis of H_0: $\beta = 1$) highlights the reduced market sensitivity. Conversely, the EW portfolios have significant betas of 1.15 (t-stat 5.77, H_0: $\beta = 1$) for the CRSP universe and 1.07 (t-stat 5.55, H_0: $\beta = 1$) for the S&P500 universe. The models' α increases to 0.20 (t-stat 1.67) and 0.14 (t-stat 2.56). At the same time, the unexplained variances increase compared to the VW portfolios resulting in R^2 of 0.73 and 0.92, respectively. Regressing the EW–VW spread on MKT for the CRSP and S&P500 universes gives significantly positive betas, however the SIM does only explain 5% and 9% of the respective return variations.

Analysing the EW–VW spread returns for different periods we report time-varying estimates. During the pre-publication and pre-GFC periods the spreads' alphas are significantly positive (t-stats ranging from 2.61 to 3.63) whilst the spreads' betas are significant with coefficients of 0.23 and 0.26 (t-stats 5.19 and 3.90) for the CRSP universe, and 0.15 and 0.13 (t-stats 6.13 and 3.71) for the S&P500 universe, respectively. These results indicate that the spread returns have benefited from the average (1/N) firm's beta $\overline{\beta}$ being greater than 1 as well as some further idiosyncratic effects. Yet, the SIM merely explains between 10% to 13% of return variation. During the post-publication and post-GFC periods however, alphas are negative and statistically insignificant whilst spreads' betas are closer to 0 (indicating that $\overline{\beta}$ is close to 1).

Given the above analysis, the SIM helps to explain the VW and EW portfolios' performances but fails to explain the differential performance. The latter effect is more pronounced for the CRSP universe where large caps are being extremely under-weighted with weights around 0.02% in each stock whereas the EW version in the S&P500 universe applies portfolio weights of 0.2%. Naturally, this outcome calls for additional systematic factors to help explain the EW-VW spread.

The EW–VW spread through a multi-factor lens

Factor set: To investigate the systematic drivers of the EW–VW spread, we focus on a set of common factors used among academics as well as practitioners. Specifically, we analyze the relevance of the size (SMB), value (HML), profitability (RMW), investment (CMA), momentum (WML), and short-term reversal (STR) factors provided by Kenneth R. French[9]. We also add the volatility (VOL) factor by Van Vliet and De Koning (2017)[10] to account for the low-risk anomaly. To test for robustness, we also use the quality-minus-junk (QMJ) factor of Asness, Frazzini, and Pedersen (2019)[11], as well as market equity (ME), investment (IA), return on equity (ROE), and expected growth (EG) from the q-factor database[12] as introduced by Hou, Xue, and Zhang (2015) and Hou, Mo, Xue, and Zhang (2021).

Our prior is that the EW–VW spread benefits from size as well as short-term reversal effects because of over-weighting small firms and a contrarian rebalancing style. In a similar vein, the spread should be negatively correlated to momentum, which thrives if winners continue to perform well, as well as volatility due to its increased risk. Based on the findings of Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018) and Blitz and Hanauer (2020) we expect the EW-VW spread to also be negatively correlated to the quality factor because of its close link to the size factor and no natural control for junk firms among the small stocks. Exhibit 3 depicts the correlation structure of the factors used in our analysis.

[Exhibit 3 about here.]

First, we note that the EW–VW spread in the CRSP universe is highly positively correlated with the S&P500 spread (0.63) indicating that similar effects drive the performance of both spread portfolios. Second, the size factor SMB is highly positive correlated with these spreads (0.87 and 0.63), highlighting their exposure to small firms. Size shows some negative correlation with the profitability factor RMW (-0.35) and it is highly positively correlated with the alternative size definition ME (0.97).

At the same time, the momentum factor WML is negatively correlated with the EW–VW spreads (-0.26 and -0.43), as is profitability (-0.40 and -0.12). In contrast, the short-term reversal factor is positively correlated with the spread, yielding correlation coefficients of 0.28 and 0.32 for the CRSP and S&P500 universes, respectively. The volatility factor shows negative correlations with the EW–VW spread of the CRSP sample (-0.37). The additional factors of the q-factor model show high correlations of 0.91 (IA vs. CMA) and 0.66 (ROE vs. RMW) with their Fama French counterparts as well as high correlations with QMJ (0.70 for ROE, 0.62 for EG). Most of the other factors seem to be fairly uncorrelated.

Such eyeballing of the underlying correlation structures confirms the size and short-term reversal tilt of the EW-VW spreads as well as negative momentum and quality exposures. Narrowing down the sample to the 500 largest stocks exacerbates the negative momentum

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html
[10] https://www.paradoxinvesting.com/data/
[11] https://www.aqr.com/Insights/Datasets
[12] http://global-q.org/index.html

exposure whilst attenuating the negative quality exposure due to higher concentration of blue chip firms amongst large caps.

Multi-factor regressions: In this section, we extend the single index model and investigate a variety of multi-factor models, seeking to further rationalize the EW–VW spread. Exhibit 4 depicts the corresponding regression coefficients as well as t-stats for various common factor models[13] for the full sample period from July 1963 to December 2021.

[Exhibit 4 about here.]

Based on our initial observations indicating a close link of size and the EW–VW spread as well as findings of Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018) and Blitz and Hanauer (2020), we include 1M-lagged market returns (MKT_{t-1}) in our models to account for non-synchronous trading of small stocks. Thus, we present the single index model results with additional lagged market returns in the first (seventh) column for our full period analysis of the two samples. Documenting significantly positive coefficients of 0.14 and 0.11 (t-stats 5.63 and 8.29) for the market factor indeed suggests the average stock's market beta $\overline{\beta}$ to be greater than one, i.e., $\overline{\beta}$ would be estimated as 1.14 (1.11) in the sample period. Highly significant positive loadings of the lagged market return in the CRSP universe (t-stat 8.30) and still significant ones for the S&P500 (t-stat 3.21) indicate illiquidity effects amongst the smaller stocks of the two samples. However, the adjusted R^2s are still small for both samples (13% and 10%) and leave a lot of unexplained variance in the EW–VW returns.

Second, we learn that regressing the EW–VW spread univariately on SMB gives an adjusted R^2 of 75% with a highly significant t-stat of 45.79, suggesting the spread to be mostly harvesting the size premium.[14]

Model (3) is based on Fama and French's (2015) five-factor model including value (HML), profitability (RMW) and investment (CMA) factors in addition to the market and size factors. The coefficient of HML is positive but not as powerful as the size factor (t-stat of 4.87), indicating that the spread might benefit from a value tilt. RMW has a negative coefficient on the EW–VW spread (t-stat -7.08) whilst CMA is just statistically significant at the 10% level (t-stat -1.83). Notably, the market factor becomes insignificant and negative in this model whilst the 1M-lagged market factor remains significant (t-stat 7.80). The adjusted R^2 of this five factor model is 79% and hence increases the explained variance by 4 percentage points relative to using the SMB as stand-alone factor.

Models (4) to (5) report alternative factor models: Instead of RMW and CMA they either include the quality-minus-junk (QMJ) factor by Asness, Frazzini, and Pedersen (2019) (in model (5)) or consider the q-factor model by Hou, Mo, Xue, and Zhang (2021) (model (4)). The EW–VW spread loads negative on the QMJ factor (t-stat -12.14) highlighting

[13] Note that we report factor exposures based on value-weighted factors. By and large, we confirm our findings when using equal-weighted factor versions. Specifically, EW factors are slightly more relevant explaining the EW–VW spread in the CRSP universe and explain slightly less variance in the S&P500 sample. These intuitive results underline the dominance of the largest stocks in a VW setup which become proportionally less significant in EW factor portfolios.

[14] In unreported univariate regressions we confirm the dominant role of SMB as most relevant single factor (adj. R^2 75%), followed by QMJ (34%) and RMW (16%) for the CRSP sample. The S&P500 sample is driven by SMB (40%), as well as QMJ and WML (both 19%).

the importance to control for junk amongst the smallest stocks in the EW portfolio. These results are in line with Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018), who analyze the impact of the size effect for different quality factors. Controlling for poor firm quality (or junk) in an EW portfolio is of similar relevance due to its natural exposure to small firms. The q-factor model shows similar loadings to the FF5 factor model, i.e., ME being highly significant (t-stat 34.15) and being complemented by ROE (t-stat -12.69) and EG (t-stat -2.52). Thus, all three models emphasize the impact of size, illiquidity and quality, but neither model seems to have superior power in explaining the variation of the EW–VW spread with R^2 ranging from 78% for the q-factor model to 81% for the model including QMJ.

Notably, extending the FF5-model with momentum (WML), short-term reversal (STR), and volatility (VOL) factors increases the adjusted R^2 to 85% with WML and VOL having significantly negative coefficients (t-stat -11.05 and -8.66, respectively). The spread loads positive on STR with a t-statistic of 6.48. At the same time, the CMA coefficient turns from negative to positive but is only marginally significant. The size factor SMB as well as the lagged market return (MKT_{t-1}) remain highly significant for all model specifications. These findings resonate with the contrarian rebalancing style of the EW–VW spread which benefits from a short-term reversal effect and momentum underperforming.

With the EW–VW spread return being largely driven by the size factor, it is presumable that other characteristics carry over. One well researched aspect of the size effect is its seasonality, that is, it has been found to be particularly pronounced in January (Keim (1983) and Roll (1983), amongst others). This phenomenon has been linked to investors' year-end tax-loss selling, rebalancing, and cash infusion at the beginning of the year, as well as window dressing by mutual fund managers at the year's end. Indeed, Exhibit 2 documents that the EW–VW spread outperformance exclusively accrues in January with a difference in monthly returns of 4.01% vs. -0.05% in non-January months for the CRSP universe. To further rationalize the EW–VW spread, model (7) includes a January dummy alongside MKT, MKT_{t-1}, SMB, HML, RMW, CMA, WML, STR, and VOL. This regression documents strong seasonality in the EW–VW spread return with an average January premium of 193 bps (t-stat 11.85) in the CRSP sample. The other factors remain significant with size still dominating (t-stat 46.34) followed by momentum (t-stat -11.36). The overall adjusted R^2 increases to 87% whilst the basis α of non-January returns is found insignificant (t-stat 0.16).

Having documented the systematic drivers of the EW–VW spread in the CRSP universe, we next examine whether these results carry over to a more investible universe and thus focus on the S&P500 index and its constituents. In fact, this selection focuses on the largest and most liquid stocks, with the average S&P500 stock being almost seven times bigger than the average stock in the CRSP universe (comp. Exhibit 2).

First, we focus on the factor model regressions of the S&P500 EW–VW spread in models (8) to (14) of Exhibit 4. Overall, we observe very similar factor sensitivities for the S&P500 sample compared to the CRSP evidence, yet there are some differences to highlight. On the one hand, the market factor sensitivity MKT for all used factor models is higher than in previous regressions and always statistically significant at the 1% level. At the same time, the lagged market factor becomes insignificant (except for the SIM in model (8)). This is due to the selection of the largest 500 stocks and, hence, a higher exposure to the value-weighted market portfolio and higher liquidity. Note that the relevance of the SMB factor decreases across all models, though it remains highly significant with t-stats ranging from 19.54 to 24.95. Conversely, the value factor HML increased in relevance and ranks third in terms of t-stats (ranging from 7.25 for model (14) to 15.68 in the model including QMJ as quality factor). While the single index model has only slightly lower explanatory power relative to the CRSP case, the average factor model lacks 15 to 35 percentage points in explaining the S&P500 EW–VW spread compared to the CRSP one. Since all S&P500 stocks are in the *big* bucket of the size factor SMB by construction, this factor cannot fully address the potential size effects inherent in the S&P500 universe.

Also, model (14) does not confirm a significant January premium for the S&P500 universe despite the higher return differences in January, comp. Exhibit 2. In fact, the January α is statistically and economically insignificant (t-stat 0.53). The full sample adjusted R^2 stands at 68%. The results are in line with the literature identifying a January premium in small and micro caps but do not confirm such premium for large caps in the S&P500 universe.

The EW–VW spread over time: To put the observed effects into perspective, we repeat regressions of models (7) and (14) in four subperiods: we specifically look at pre- and post-publication, as well as pre-GFC and post-GFC. Exhibit 5 depicts the sub-period regression results for the CRSP universe (Panel A) as well as the S&P500 universe (Panel B). In all subperiods of the CRSP sample, the January α is strictly positive with t-stats ranging from 4.03 (pre-GFC) to 7.95 (post-publication). The subperiod analysis also reveals the decreasing yet highly significant impact of the size factor on the EW–VW spread return over time: Whilst SMB was highly significant in the pre-publication phase (t-stat 44.96) and the model explained almost all variance (R^2 96%), its impact decreased to its low in the pre-GFC period (t-stat 13.57, R^2 84%). The impact of STR increased over time, from being completely insignificant in the pre-publication period (t-stat 0.56) to becoming a significant driver during the pre-GFC period (t-stat 4.71).

[Exhibit 5 about here.]

Having screened the spread returns in different subperiods helps to grasp the seasonality in the EW–VW characteristics with the January effect occurring predominantly in the CRSP universe. Also, the impact of the systematic factors varies over time with size and negative momentum being the only constant forces whilst the exposure to short-term reversal and profitability comes and goes during different time-periods.[15]

Impact of rebalancing frequency: An important aspect of the EW–VW spread is the need to rebalance frequently in order to keep the EW component equal-weighted. We next investigate the implications of different rebalancing frequencies in Exhibit 6, exploiting rebalancing frequencies ranging from one month (base case) to 60 months. Panel A shows

[15] In unreported results we also test EW–VW spread returns within quintile portfolios based on CRSP size breakpoints. They come with similar characteristics as the full sample spreads, albeit the smallest size quintile portfolio shows positive returns in all subperiods with a highly significant January alpha of 218 bps (t-stat 12.11). In terms of factor exposure, the only difference is the negative (albeit mostly insignificant) size exposure for all quintile portfolios but the largest one. This can be related to the missing large cap component of the long-short size factor amongst small and micro cap stocks, i.e. quintile 1-4.

performance characteristics for six differently rebalanced CRSP EW–VW spread portfolios for the full sample period. We observe the highest annualized return for the monthly rebalanced portfolio (3.48%). Interestingly, portfolios rebalanced at the next lower frequency (3M) seem to perform worst in terms of raw as well as risk-adjusted returns (2.15%) whilst performance tends to increase for lower rebalancing frequencies (e.g., 2.94% for 60M). Two-way annualized portfolio turnover decreases monotonically with decreasing rebalancing activities highlighting the impact of drifting weights towards the value-weighted portfolio.

[Exhibit 6 about here.]

Panel B depicts regression results of the six EW–VW spreads for the full sample period. First, we observe a monotonically declining yet always significant January effect for lower rebalancing frequencies with t-stats ranging from 11.85 (1M) to 2.16 (60M). These results are intuitive as the abnormal January returns are less likely captured if the portfolio is rebalanced at a lower frequency. Next, MKT and MKT_{t-1} indicate clear tendencies of the EW portfolio shifting towards the market portfolio: The negative MKT as well as MKT_{t-1} exposure of the spread lose significance with t-stats shrinking from -2.52 (1M) to -0.24 (60M) and 9.50 (1M) to 4.40 (60M), respectively. Thus, illiquidity and non-synchronous trading concerns become less of an issue given the decreased rebalancing activities.

Another interesting observation is the changing exposure of the EW–VW spread returns to the size factor. The exposure of the size factor decreases with lower rebalancing frequencies (from 0.78 to 0.73) whilst the individual significance of SMB is increased (t-stats ranging from 46.34 to 61.72). This effect can be attributed to the reduced differences of EW and VW portfolio returns due to drifting weights in the former for lower rebalancing frequencies. At the same time, the statistical fit of the value-weighted size factor SMB is increased the more the EW–VW spread tilts towards a value-weighted portfolio itself.

Moreover, reduced rebalancing frequencies lower and even invert the negative momentum exposure of the EW–VW spread: Whilst monthly rebalancing results in a contrarian strategy with exposure to WML of -0.13 (t-stat -11.36) and positive STR exposure, decreasing the rebalancing frequency to a trend following strategy peaking at a WML exposure of 0.05 (t-stat 6.15) for the 60M portfolio. Overall, the adjusted R^2 is slightly increased with declining rebalancing activities which is potentially linked to the alignment of the EW–VW spread returns with the value-weighted factor construction.

INVESTING IN THE SIZE FACTOR

Given the high correlations between size and the spread returns as well as size's dominant role in explaining the variation in spread one would expect the factor's performance to be close to that of the spread returns. In turn, an investor could directly participate in the size premium by simply investing in the EW–VW spread. Unlike SMB, which is difficult to implement, the latter can efficiently be implemented using VW and EW market ETFs which come at low costs compared to rebalancing of a long-short SMB factor portfolio.

In addition to SMB we thus construct another proxy for size effects within the S&P500 universe itself (labeld SMBSP). This proxy is designed in a similar vein to the original factor by Fama and French (1993) using mid-year median breakpoints to construct the long-short buckets. We compare this construct to alternative ways of harvesting the size premium as presented by the iShares Russell 2000 ETF (hereafter R2000 ETF), as well as the DFA US Small Cap and DFA US Micro Cap funds (hereafter referred to as small and micro cap funds) from July 2000 to December 2021. The latter two funds primarily invest in small (micro) cap companies whose market capitalizations are generally in the lowest 10% (5%) of total market capitalization. We choose these two funds because the investment process of DFA is heavily influenced by the works of Fama and French. To enable comparing these funds' ability to harvest the genuine size premium we subtract market returns (as given by the SPX return).

Panel A of Exhibit 7 depicts the correlation structure of the above return series. We are most interested in the ability of the different investment choices to capture the SMB premium. In this regard, the R2000ETF and DFA small cup fund show a very high correlation of 0.96, and the runner up is DFA's micro cap fund with a correlation of 0.94. Naturally, these three funds show high cross-correlation in excess of 0.9 as well. In line with earlier factor regressions, the SPW–SPX spread has a lower correlation to SMB but is still reasonable close (0.59).

Of course, we also wish to investigate alignment from a risk-return perspective, see Panel B. First we note that the SMB factor underperforms its S&P500 counterpart with 151 bps p.a. for the full period. This effect is even stronger in the Pre-GFC subperiod. The EW–VW spread has higher annual returns than its S&P500 counterpart (4.29% vs. 3.06%), yet coming with the caveat of higher volatility which results in smaller Sharpe ratios (0.40 vs. 0.56) over the full sample. This pattern holds in both subperiods with the exception of negative returns for the SPW–SPX spread in the Post-GFC subperiod. The two mutual fund spreads are fairly aligned with the R2000 ETF one in terms of risk and return (1.64% to 3.32% return p.a. at a volatility of 9.71% to 11.24%). We observe a slight increase in risk-adjusted return the smaller the invested firms becomes, especially during the recovery phase of the size effect.

[Exhibit 7 about here.]

However, the three fund spreads show weaker performance characteristics than SMB and the two EW–VW spreads. In fact, they carry more risk at lower returns resulting in smaller risk-adjusted ratios (Sharpe ratios around 0.17 to 0.30 vs 0.36 for SMB and 0.40 to 0.56 for the EW–VW spreads). This effect becomes even clearer when looking at the two subperiods: Whilst the size factors and the EW–VW spreads show strong performances during the Pre-GFC period with Sharpe ratios ranging from 0.75 (SMB) to 1.14 (SMBSP), all three fund spreads have Sharpe ratios between 0.52 (R2000 ETF) and 0.69 (Small cap). Moreover, size factors and spreads barely have positive returns and hence resulting Sharpe ratios close to zero during the Post-GFC period whereas the three funds report negative annual returns ranging from -0.55% to -1.37%.

Our performance observations combined with the given correlation structure suggest that the EW–VW spread is a good proxy for SMB. Moreover, the SPW–SPX spread is reasonably close to SMB given its similar performance characteristics during different subperiods as well as its correlation of 0.59. In fact, the EW–VW spread can be considered a cost-efficient alternative to harvest the size factor premium. A closer analysis of subperiods reveals that the characteristics of both EW–VW spreads are fairly close to SMB in terms of risk-adjusted returns whereas the overall correlation of SMB is closer to the Russell 2000 ETF and both DFA funds.

CONCLUSION

Historically, the equal-weighted portfolio has outperformed its value-weighted counterpart as well as a variety of other more intricate allocation approaches. In this paper, we identify the key drivers of the EW–VW spread through the lens of different factor models.

Focusing on the single index model, we first relate the performance patterns of the VW and EW portfolios to the time-varying market sensitivity β of the average portfolio constituent. However, whilst significant, the single index model cannot explain much of the variation of the EW–VW spread, giving single digit R^2 and thus calling for additional systematic factors in multi-factor regressions of the EW–VW spread.

By design, the EW portfolio is putting more weight into small cap companies which reflects in a massive size exposure relative to a VW portfolio. Also, regular rebalancing to equal weights sees the EW portfolio selling winners and buying losers which is reflected in negative momentum exposures and a positive loading to the Short Term Reversal factor. On average, the EW-VW spread is long higher volatility stocks and thus betting against the Low Volatility anomaly. The over-weighting of small firms also results in negative quality exposure and abnormal high January returns, resonating with the evidence for size-tilted portfolios.

Lastly, we investigate how an investor could participate in the size premium by directly investing in the EW–VW spread. The latter is reasonably close to SMB but comes at lower implementation costs than the long-short factor.

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REFERENCES

Arnott, Robert D., Jason Hsu, and Philip Moore (2005). "Fundamental indexation." *Financial Analysts Journal* 61 (2), 83–99.

Asness, Clifford S., Andrea Frazzini, Ronen Israel, Tobias J. Moskowitz, and Lasse H. Pedersen (2018). "Size matters, if you control your junk." *Journal of Financial Economics* 129 (3), 479–509.

Asness, Clifford S., Andrea Frazzini, and Lasse H. Pedersen (2019). "Quality minus junk." *Review of Accounting Studies* 24 (1), 34–112.

Banz, Rolf W. (1981). “The relationship between return and market value of common stocks.” *Journal of Financial Economics* 9 (1), 3–18.

Blitz, David and Matthias X. Hanauer (2020). “Settling the size matter.” *The Journal of Portfolio Management* 47 (2), 99–112.

Bouchey, Paul, Vassilii Nemtchinov, Alex Paulsen, and David M. Stein (2012). “Volatility harvesting: Why does diversifying and rebalancing create portfolio growth?.” *The Journal of Wealth Management* 15 (2), 26–35.

Carhart, Mark (1997). “On persistence in mutual fund performance.” *Journal of Finance* 52 (1), 57–82.

De Wit, Dirk P. M. (1998). “Naive diversification.” *Financial Analysts Journal* 54 (4), 95–100.

DeMiguel, Victor, Lorenzo Garlappi, and Raman Uppal (2009). “Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy?.” *The Review of Financial Studies* 22 (5), 1915–1953.

Erb, Claude B. and Campbell R. Harvey (2006). “The strategic and tactical value of commodity futures.” *Financial Analysts Journal* 62 (2), 69–97.

Fama, Eugene F. and Kenneth R. French (1993). “Common risk factors in the returns on stocks and bonds.” *Journal of Financial Economics* 33 (1), 3–56.

— (2015). “A five-factor asset pricing model.” *Journal of Financial Economics* 116 (1), 1–22.

Hallerbach, Winfried G. (2014). “Disentangling rebalancing return.” *Journal of Asset Management* 15 (5), 301–316.

Hou, Kewei, Haitao Mo, Chen Xue, and Lu Zhang (2021). “An augmented q-factor model with expected growth.” *Review of Finance* 25 (1), 1–41.

Hou, Kewei, Chen Xue, and Lu Zhang (2015). “Digesting anomalies: An investment approach.” *Review of Financial Studies* 28 (3), 650–705.

Kaplan, Paul D. (2008). “Why fundamental indexation might—or might not—work.” *Financial Analysts Journal* 64 (1), 32–39.

Keim, Donald B (1983). “Size-related anomalies and stock return seasonality: Further empirical evidence.” *Journal of Financial Economics* 12 (1), 13–32.

Lintner, John (1965). “Security prices, risk, and maximal gains from diversification.” *Journal of Finance* 20 (4), 587–615.

Maeso, Jean-Michel and Lionel Martellini (2020). “Measuring portfolio rebalancing benefits in equity markets.” *The Journal of Portfolio Management* 46 (4), 94–109.

Malladi, Rama and Frank J. Fabozzi (2017). “Equal-weighted strategy: Why it outperforms value-weighted strategies? Theory and evidence.” *Journal of Asset Management* 18 (3), 188–208.

Mossin, Jan (1966). “Equilibrium in a capital asset market.” *Econometrica* 34 (4), 768–783.

Pae, Yuntaek and Navid Sabbaghi (2015). “Equally weighted portfolios vs. value weighted portfolios: Reasons for differing betas.” *Journal of Financial Stability* 18, 203–207.

Patton, Andrew J. and Allan Timmermann (2010). “Monotonicity in asset returns: New tests with applications to the term structure, the CAPM, and portfolio sorts.” *Journal of Financial Economics* 98 (3), 605–625.

Perold, André F. (2007). “Fundamentally flawed indexing.” *Financial Analysts Journal* 63 (6), 31–37.

Perold, Andre F. and William F. Sharpe (1988). “Dynamic strategies for asset allocation.” *Financial Analysts Journal* 44 (1), 16–27.

Plyakha, Yuliya, Raman Uppal, and Grigory Vilkov (2021). “Equal or value weighting? Implications for asset-pricing tests.” *Financial Risk Management and Modeling*. Ed. by Constantin Zopounidis, Ramzi Benkraiem, and Iordanis Kalaitzoglou. Springer, 295–347.

Reinganum, Marc R. (1981). “Misspecification of capital asset pricing: Empirical anomalies based on earnings’ yields and market values.” *Journal of Financial Economics* 9 (1), 19–46.

Roll, Richard (1983). “Vas ist das?.” *The Journal of Portfolio Management* 9 (2), 18–28.

Ross, Stephen A. (1976). “The arbitrage theory of capital asset pricing.” *Journal of Economic Theory* 13 (3), 341–360.

Sharpe, William F. (1964). “Capital asset prices: A theory of market equilibrium under conditions of risk.” *Journal of Finance* 19 (3), 425–442.

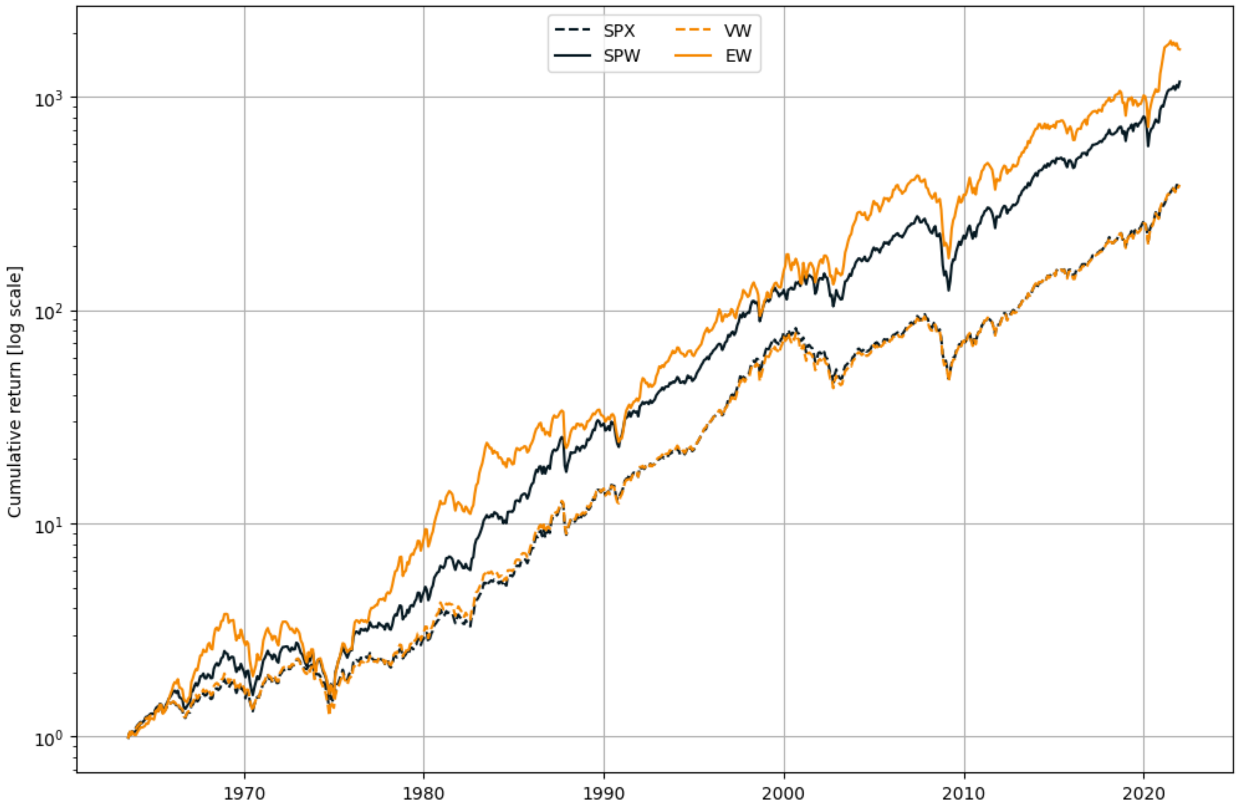
Siegel, Jeremy (2006). “The noisy market hypothesis.” *Wall Street Journal* 14, A14.

Treynor, Jack L. (1961). “Market value, time, and risk.” *Available at SSRN: https://ssrn.com/abstract=2600356.*

Van Vliet, Pim and Jan De Koning (2017). “High returns from low risk: A remarkable stock market paradox.” John Wiley & Sons.

Willenbrock, Scott (2011). “Diversification return, portfolio rebalancing, and the commodity return puzzle.” *Financial Analysts Journal* 67 (4), 42–49.

Exhibit 1: Cumulative Performance EW and VW Portfolios



This exhibit depicts the performance of value- and equal-weighted portfolios based on the S&P500 index (SPX, SPW), and all traded stocks on the NYSE, AMEX, and NASDAQ with share codes 10 and 11 (VW, EW). The sample period is July 31, 1963–December 31, 2021.

Exhibit 2: The Effect of Equal-weighting across Sample Periods and Universes

Sample	*Years*	*Ret p.a.*		*Std p.a.*		*SR*		*MDD*		*Mcap*	*Const*	*EW–VW*	
		VW	*EW*	*VW*	*EW*	*VW*	*EW*	*VW*	*EW*			*ret*	*t-stat*
Panel A: CRSP													
Full sample	1963–2021	11.4	14.9	15.3	20.6	0.13	0.15	-22.6	-28.2	2.1	4,349	0.29	2.42
January		17.3	65.4	17.5	26.0	0.21	0.68	-8.1	-9.5	2.0	4,372	4.01	6.57
Non-January		10.9	10.3	15.1	19.6	0.12	0.09	-22.6	-28.2	2.1	4,347	−0.05	−0.42
Pre-publication (Expansion)	1963–1983	9.8	17.3	15.3	21.6	0.06	0.14	-12.2	-18.8	0.3	3,172	0.63	3.01
Post-publication (Downfall)	1984–1999	17.1	14.0	15.1	17.7	0.22	0.14	-22.6	-28.2	0.8	6,003	−0.26	−1.25
Pre-GFC (Recovery)	2000–2009	1.0	11.1	16.5	24.1	−0.03	0.10	-17.1	-21.2	2.7	4,959	0.84	2.49
Post-GFC (Stagnation)	2010–2021	15.1	15.0	14.4	19.6	0.29	0.22	-13.2	-22.4	6.4	3,648	−0.01	−0.03
Panel B: S&P500													
Full sample	1963–2021	11.4	13.6	14.8	17.1	0.14	0.16	-21.6	-25.6	14.2	500	0.19	2.99
January		15.2	27.6	17.1	20.6	0.18	0.33	-8.3	-7.8	13.8	500	1.03	3.40
Non-January		11.0	12.4	14.6	16.8	0.13	0.14	-21.6	-25.6	14.3	500	0.11	1.80
Pre-publication (Expansion)	1963–1983	9.3	13.3	14.4	17.4	0.06	0.11	-11.8	-15.1	1.1	499	0.33	2.80
Post-publication (Downfall)	1984–1999	18.0	16.5	14.9	16.3	0.24	0.19	-21.6	-25.6	7.3	500	−0.12	−1.23
Pre-GFC (Recovery)	2000–2009	0.6	7.8	16.1	19.4	−0.04	0.07	-16.7	-20.8	21.5	500	0.60	3.35
Post-GFC (Stagnation)	2010–2021	15.2	15.2	13.8	15.8	0.31	0.27	-12.2	-18.8	39.8	503	−0.00	−0.01

Panel C: Single Index model results			CRSP					S&P500				
Sample	*Years*	*Portfolio*	α	t(α)	β	t(β)	R^2	α	t(α)	β	t(β)	R^2
Full sample	1963–2021	VW	0.00	−1.25	1.00	−5.28	1.00	0.02	0.87	0.95	−8.75	0.98
		EW	0.20	1.67	1.15	5.77	0.73	0.14	2.56	1.07	5.55	0.92
		EW–VW	0.20	1.68	0.15	5.85	0.05	0.12	2.00	0.11	8.44	0.09
Pre-publication (Expansion)	1963–1983	EW–VW	0.56	2.82	0.23	5.19	0.10	0.29	2.61	0.15	6.13	0.13
Post-publication (Downfall)	1984–1999	EW–VW	−0.24	−1.09	−0.03	−0.56	0.00	-0.19	−1.96	0.07	3.39	0.06
Pre-GFC (Recovery)	2000–2009	EW–VW	0.88	2.74	0.26	3.90	0.11	0.62	3.63	0.13	3.71	0.10
Post-GFC (Stagnation)	2010–2021	EW–VW	−0.27	−1.25	0.22	4.29	0.11	-0.14	−1.46	0.11	5.09	0.15

This exhibit reports key performance statistics of the VW and EW portfolios over time. Panel A and B focus on the CRSP and S&P500 sample, respectively. Return, volatility and 1-month maximal drawdown (MDD) are in percentage terms. Average market capitalization is in billion USD. The last two columns report the monthly average return difference between the EW and VW portfolios, as well as its t-statistic. Panel C reports Single Index Model results for both universes. α values are reported in percentage points per month. α t-stats are reported against the hypothesis of $\alpha = 0$. β t-stats are reported against the hypothesis of $\beta = 1$ for the two portfolios (EW, VW) and $\beta = 0$ for the EW–VW spread. The full sample period is July 31, 1963–December 31, 2021. All other sub-samples start in January and end in December of the reported years (except for the Pre-publication period, which starts end of July). January and Non-January (February–December) statistics are reported for the full sample period.

Exhibit 3: Correlation Matrix for Multi-Factor Universe

	EW-VW	SPW-SPX	MKT	MKT_{t-1}	SMB	HML	WML	STR	RMW	CMA	QMJ	VOL	ME	IA	ROE	EG
EW-VW	1.00															
SPW-SPX	0.63	1.00														
MKT	0.22	0.30	1.00													
MKT_{t-1}	0.30	0.13	0.06	1.00												
SMB	0.87	0.63	0.28	0.20	1.00											
HML	0.07	0.35	-0.21	0.02	-0.02	1.00										
WML	-0.26	-0.43	-0.16	-0.07	-0.06	-0.22	1.00									
STR	0.28	0.32	0.30	0.00	0.17	0.04	-0.31	1.00								
RMW	-0.40	-0.12	-0.19	-0.02	-0.35	0.09	0.09	-0.09	1.00							
CMA	-0.02	0.15	-0.38	-0.01	-0.09	0.67	-0.04	-0.11	-0.03	1.00						
QMJ	-0.58	-0.44	-0.51	-0.13	-0.49	-0.05	0.28	-0.28	0.70	0.07	1.00					
VOL	-0.37	0.06	0.01	-0.02	-0.33	0.42	-0.12	0.02	0.37	0.35	0.32	1.00				
ME	0.82	0.61	0.28	0.18	0.97	0.02	-0.05	0.19	-0.37	-0.04	-0.47	-0.29	1.00			
IA	-0.07	0.13	-0.36	-0.01	-0.14	0.65	0.00	-0.09	0.09	0.91	0.12	0.37	-0.11	1.00		
ROE	-0.54	-0.38	-0.22	-0.10	-0.40	-0.14	0.49	-0.21	0.66	-0.07	0.70	0.23	-0.33	0.03	1.00	
EG	-0.47	-0.38	-0.45	-0.13	-0.45	0.06	0.37	-0.32	0.39	0.24	0.62	0.19	-0.40	0.25	0.54	1.00

This exhibit depicts the correlation structure of the multi-factor universe, building on monthly data for the full sample period July 31, 1963–December 31, 2021, except for the q-factors (ME, IA, ROE, EG), which start on January 31, 1967. Colors range from dark red (correlation of -1) to dark blue (correlation of 1).

Exhibit 4: Factor Regressions of EW–VW Spread Returns

$$EW - VW_t = \alpha + \alpha_{Jan} + \beta_1 F_t^1 + ... + \beta_K F_t^K + \epsilon_t \quad for\ K\ factors$$

	CRSP							*S&P500*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
α	0.08	0.08	0.10	0.31	0.24	0.17	0.01	0.10	0.11	-0.03	0.08	0.02	0.04	0.03
	(0.75)	(1.38)	(1.64)	(4.46)	(4.21)	(3.32)	(0.16)	(1.63)	(2.23)	(-0.81)	(1.39)	(0.44)	(0.92)	(0.74)
α_{Jan}							1.93							0.07
							(11.85)							(0.53)
MKT	0.14		-0.03	-0.05	-0.09	-0.03	-0.03	0.11		0.09	0.07	0.08	0.06	0.06
	(5.63)		(-1.82)	(-3.37)	(-6.40)	(-2.36)	(-2.52)	(8.29)		(9.10)	(6.03)	(7.11)	(6.23)	(6.23)
MKT_{t-1}	0.21		0.10	0.10	0.09	0.10	0.09	0.04		-0.00	0.00	-0.00	-0.01	-0.01
	(8.30)		(7.80)	(7.88)	(7.41)	(8.94)	(9.50)	(3.21)		(-0.45)	(0.19)	(-0.27)	(-1.24)	(-1.25)
SMB		0.91	0.84		0.78	0.79	0.78		0.34	0.33		0.31	0.35	0.35
		(45.79)	(40.67)		(39.18)	(42.69)	(46.34)		(21.53)	(22.31)		(19.54)	(24.95)	(24.90)
HML			0.13		0.05	0.08	0.06			0.21		0.23	0.13	0.13
			(4.87)		(2.45)	(3.54)	(2.95)			(10.90)		(15.68)	(7.31)	(7.25)
WML						-0.14	-0.13						-0.12	-0.12
						(-11.05)	(-11.36)						(-12.72)	(-12.65)
RMW			-0.19			-0.09	-0.06			0.08			0.10	0.10
			(-7.08)			(-3.46)	(-2.76)			(4.16)			(5.05)	(5.07)
CMA			-0.07			0.06	0.05			0.05			0.08	0.08
			(-1.83)			(1.74)	(1.58)			(1.63)			(2.99)	(2.97)
STR						0.11	0.09						0.04	0.04
						(6.48)	(5.59)						(3.18)	(3.09)
QMJ					-0.36							-0.03		
					(-12.14)							(-1.09)		
VOL						-0.16	-0.13						0.03	0.03
						(-8.66)	(-7.94)						(1.98)	(2.02)
ME				0.74							0.28			
				(34.15)							(16.04)			
IA				0.01							0.24			
				(0.27)							(9.24)			
ROE				-0.35							-0.09			
				(-12.69)							(-3.91)			
EG				-0.10							-0.07			
				(-2.52)							(-2.28)			
Adj. R^2	0.13	0.75	0.79	0.78	0.81	0.85	0.87	0.10	0.40	0.58	0.48	0.57	0.68	0.68
Obs.	701	702	701	660	701	701	701	701	702	701	660	701	701	701

This exhibit presents the factor sensitivities of the EW–VW spread for the CRSP and S&P500 samples. Excess market return (MKT), its lagged version (MKT_{t-1}), size (SMB), value (HML), profitability (RMW), and investment (CMA) refer to the factors provided by Fama and French (2015). Momentum (WML) and short-term reversal (STR) refer to the factor returns as described on K. French's website. The volatility (VOL) factor is taken from Van Vliet and De Koning (2017) whilst the quality-minus-junk (QMJ) factor is from Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018). Market equity (ME), investment (IA), return on equity (ROE), and expected growth (EG) refer to the factors of Hou, Mo, Xue, and Zhang (2021). t-statistics are shown in parentheses. α values are reported for the months of January and non-January separately using dummy variables and are expressed in percentage points per month. The sample period is July 31, 1963–December 31, 2021 except for the q-factors, which start on January 31, 1967.

Exhibit 5: The EW–VW Spread in Different Sub-Periods

	$EW - VW_t = \alpha + \alpha_{Jan} + \beta_1 F_t^1 + ... + \beta_K F_t^K + \epsilon_t \quad for\ K\ factors$											
Period	α	α_{Jan}	MKT	MKT_{t-1}	SMB	HML	RMW	CMA	WML	STR	VOL	Adj.R^2
Panel A: CRSP												
Full sample	0.01	1.93	-0.03	0.09	0.78	0.06	-0.06	0.05	-0.13	0.09	-0.13	0.87
	(0.16)	(11.85)	(-2.52)	(9.50)	(46.34)	(2.95)	(-2.76)	(1.58)	(-11.36)	(5.59)	(-7.94)	
Pre-publication (Expansion)	0.03	1.42	-0.03	0.06	0.90	0.05	-0.08	0.01	-0.05	0.01	-0.08	0.96
	(0.51)	(7.68)	(-1.90)	(5.20)	(44.97)	(1.70)	(-1.97)	(0.25)	(-3.59)	(0.56)	(-3.31)	
Post-publication (Downfall)	-0.18	2.53	-0.07	0.09	0.86	0.08	-0.16	0.20	-0.04	0.07	-0.08	0.87
	(-1.86)	(7.95)	(-2.69)	(4.46)	(22.78)	(1.38)	(-2.55)	(2.98)	(-1.25)	(1.76)	(-1.93)	
Pre-GFC (Recovery)	0.34	2.14	-0.05	0.14	0.65	-0.02	-0.06	0.09	-0.20	0.15	-0.11	0.84
	(2.22)	(4.03)	(-1.09)	(4.74)	(13.57)	(-0.36)	(-0.99)	(1.12)	(-8.21)	(4.71)	(-3.41)	
Post-GFC (Stagnation)	-0.04	1.46	-0.00	0.05	0.73	0.07	-0.15	0.02	-0.08	0.05	-0.20	0.89
	(-0.43)	(5.11)	(-0.07)	(2.71)	(18.82)	(1.72)	(-2.97)	(0.29)	(-2.90)	(1.43)	(-5.31)	
Panel B: SP500												
Full sample	0.03	0.07	0.06	-0.01	0.35	0.13	0.10	0.08	-0.12	0.04	0.03	0.68
	(0.74)	(0.53)	(6.23)	(-1.25)	(24.90)	(7.25)	(5.07)	(2.97)	(-12.65)	(3.09)	(2.02)	
Pre-publication (Expansion)	0.03	-0.68	0.06	-0.01	0.44	0.15	-0.11	0.07	-0.08	0.11	-0.04	0.85
	(0.49)	(-3.44)	(4.11)	(-1.14)	(20.38)	(4.81)	(-2.63)	(1.71)	(-5.09)	(5.15)	(-1.45)	
Post-publication (Downfall)	0.00	-0.34	0.12	-0.03	0.32	0.13	0.08	0.09	-0.15	0.04	-0.02	0.63
	(0.04)	(-1.43)	(5.91)	(-2.39)	(11.30)	(3.07)	(1.65)	(1.73)	(-6.82)	(1.38)	(-0.56)	
Pre-GFC (Recovery)	0.16	0.14	0.09	0.01	0.27	0.10	0.15	0.18	-0.15	-0.00	0.04	0.69
	(1.37)	(0.36)	(2.86)	(0.40)	(7.53)	(2.25)	(3.21)	(2.85)	(-8.25)	(-0.02)	(1.46)	
Post-GFC (Stagnation)	-0.01	0.23	-0.01	-0.01	0.25	0.11	0.02	-0.02	-0.06	0.10	0.05	0.70
	(-0.16)	(1.08)	(-0.78)	(-0.44)	(8.64)	(3.78)	(0.42)	(-0.51)	(-3.11)	(4.06)	(1.65)	

This exhibit reports regression results for the EW–VW spread on the factors MKT, MKT_{t-1}, SMB, HML, RMW, CMA, STR, and VOL, where alphas are estimated for the months of January and non-January separately using dummy variables. Panel A shows results for the CRSP universe; Panel B for the S&P500 sample. Alphas are presented in percentage points per month. t-stats are in parenthesis. Results are reported over five sample periods: The full sample period (July 1963–December 2021) as well as pre-publication (July 1963–December 1983), post-publication (January 1984–December 1999), pre-GFC (January 2000–December 2009), and post-GFC (January 2010–December 2021) subperiods.

Exhibit 6: Alternative Rebalancing Periods

	Rebalancing frequencies					
	1M	3M	6M	12M	36M	60M
Panel A: Performance characteristics						
Ret	3.48	2.15	2.25	2.85	3.00	2.94
Std	11.00	10.44	10.14	9.96	9.69	9.01
Sharpe	0.32	0.21	0.22	0.29	0.31	0.33
MDD	-54.69	-63.61	-63.45	-57.86	-46.21	-39.49
Turnover	1.28	0.72	0.60	0.47	0.27	0.20
Panel B: Regression results						
α	0.01	-0.07	-0.07	-0.06	0.03	0.09
	(0.16)	(-1.56)	(-1.61)	(-1.26)	(0.80)	(2.49)
α_{Jan}	1.93	1.47	1.27	1.14	0.47	0.25
	(11.85)	(9.93)	(8.84)	(7.76)	(3.57)	(2.16)
MKT	-0.03	-0.03	-0.02	-0.01	-0.01	-0.00
	(-2.52)	(-2.67)	(-1.65)	(-0.87)	(-0.68)	(-0.24)
MKT_{T-1}	0.09	0.10	0.09	0.09	0.05	0.03
	(9.50)	(11.29)	(10.71)	(9.76)	(5.77)	(4.40)
SMB	0.78	0.78	0.78	0.78	0.76	0.73
	(46.34)	(50.79)	(52.65)	(51.39)	(56.68)	(61.72)
HML	0.06	0.08	0.09	0.12	0.02	0.00
	(2.95)	(3.96)	(4.76)	(5.90)	(0.95)	(0.08)
RMW	-0.06	-0.07	-0.04	-0.01	-0.15	-0.17
	(-2.76)	(-3.49)	(-1.99)	(-0.33)	(-8.28)	(-10.34)
CMA	0.05	0.06	0.08	0.09	0.10	0.01
	(1.58)	(2.15)	(2.90)	(2.97)	(3.83)	(0.35)
WML	-0.13	-0.10	-0.07	-0.03	0.06	0.05
	(-11.36)	(-9.55)	(-7.40)	(-2.64)	(7.14)	(6.15)
STR	0.09	0.02	-0.01	-0.01	0.01	-0.00
	(5.59)	(1.22)	(-0.57)	(-0.88)	(1.21)	(-0.05)
VOL	-0.13	-0.12	-0.11	-0.11	-0.10	-0.06
	(-7.94)	(-7.79)	(-7.79)	(-7.44)	(-7.88)	(-5.10)
Adj. R^2	0.87	0.88	0.88	0.87	0.89	0.91

This exhibit presents performance characteristics of the CRSP EW–VW spread portfolios with different rebalancing frequencies (Panel A) as well as regression estimates (Panel B) for the full sample. Return, volatility and 1-month maximal drawdown (MDD) are in percentage terms. Turnover refers to annualized two-way turnover. The EW–VW spread is regressed on the factors MKT, MKT_{t-1}, SMB, HML, RMW, CMA, WML, STR, and VOL, where alphas are estimated for the months of January and non-January separately using dummy variables. Alphas are presented in percentage points per month. t-stats are in parenthesis. The sample period is July 31, 1963–December 31, 2021

Exhibit 7: Performance Comparison of Size Related Portfolios

Panel A: Correlations

Full sample		EW –VW	SMB	SPW –SPX	SMBSP	R2000 ETF	Small cap	Micro cap
	EW–VW	1.00						
	SMB	0.79	1.00					
	SPW–SPX	0.58	0.59	1.00				
	SMBSP	0.47	0.62	0.90	1.00			
	R2000 ETF	0.73	0.96	0.63	0.64	1.00		
	Small cap	0.76	0.96	0.68	0.69	0.95	1.00	
	Micro cap	0.79	0.94	0.57	0.57	0.91	0.96	1.00

Panel B: Performance overview

Sample	*Portfolio*	*Ret p.a.*	*Std p.a.*	*Sharpe*	*MaxDD*	*Calmar*	*Sortino*	*CVaR*
Full sample	EW–VW	4.29	10.70	0.40	−33.58	0.13	0.84	−4.77
	SMB	3.45	9.49	0.36	−28.59	0.12	0.66	−4.93
	SPW–SPX	3.06	5.48	0.56	−18.34	0.17	0.90	−3.09
	SMBSP	4.96	7.53	0.66	−23.16	0.21	1.13	−4.15
	R2000 ETF	1.64	9.71	0.17	−31.89	0.05	0.29	−5.26
	Small cap	2.96	10.00	0.30	−38.07	0.08	0.51	−5.34
	Micro cap	3.32	11.24	0.30	−41.30	0.08	0.54	−5.82
Pre-GFC	EW–VW	9.77	12.15	0.80	−26.20	0.37	2.04	−4.48
	SMB	7.58	10.05	0.75	−15.54	0.49	1.44	−4.88
	SPW–SPX	6.91	6.66	1.04	−12.75	0.54	1.77	−3.53
	SMBSP	10.29	9.04	1.14	−13.46	0.76	2.20	−4.33
	R2000 ETF	5.41	10.32	0.52	−13.83	0.39	0.94	−5.18
	Small cap	7.57	10.95	0.69	−17.55	0.43	1.25	−5.46
	Micro cap	8.16	12.34	0.66	−22.71	0.36	1.30	−5.88
Post-GFC	EW–VW	−0.08	9.25	−0.01	−33.58	−0.00	−0.02	−4.85
	SMB	0.16	8.94	0.02	−28.59	0.01	0.03	−4.85
	SPW–SPX	−0.01	4.13	−0.00	−18.34	−0.00	−0.00	−2.56
	SMBSP	0.70	5.81	0.12	−23.16	0.03	0.17	−3.67
	R2000 ETF	−1.37	9.14	−0.15	−31.89	−0.04	−0.24	−5.16
	Small cap	−0.72	9.06	−0.08	−38.07	−0.02	−0.13	−5.02
	Micro cap	−0.55	10.18	−0.05	−41.30	−0.01	−0.09	−5.60

This exhibit shows portfolio correlations (Panel A) and performance characteristics (Panel B) of EW–VW spread and size factor returns for the full CRSP universe (SMB) and the SP500 index (SMBSP), respectively, as well as the three size related portfolios iShares Russell 2000 ETF (R2000 ETF), DFA US Small Cap Portfolio (Small cap) and DFA US Micro Cap Portfolio all minus the SPX return. Return, volatility, maximal drawdown (MaxDD) and expected shortfall (CVaR) are in percentage terms. Results are reported over three sample periods: The full sample period (July 2000–December 2021) and pre-GFC (July 2000–December 2009), and post-GFC (January 2010–December 2021) subperiods.