

# INTRODUCING MSCI FaCS

A New Factor Classification Standard for Equity Portfolios

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**January 2018**

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## EXECUTIVE SUMMARY

Factors are important systematic sources of risk and return in equity portfolios. They have been documented extensively in academic research and are used widely in active portfolio management. Recently, factor indexes have also been developed to provide a transparent and efficient method to seek exposure to factors. Given the pervasive use of factors in the active investment process and the growing popularity of factor investing through indexed strategies, a standard approach is needed for defining factors and evaluating the factor characteristics of portfolios.

We introduce MSCI FaCS, a classification standard and framework for analyzing and reporting style factors in equity portfolios. The standard is based on the factor structure in the latest global Barra equity factor risk model, the Barra Global Total Market Equity Model for Long-Term Investors (GEMLT, Morozov, 2016). The standard organizes the 16 style factors of GEMLT into eight factor groups – Value, Size, Momentum, Volatility, Quality, Yield, Growth and Liquidity.

MSCI FaCS creates a common language and definitions around style factors, for use by asset owners, managers, advisors, consultants and investors. Managers can use the framework to analyze and report factor characteristics, while investors and consultants can use the data to compare funds and monitor exposures over time using common definitions.

In a sample of over 3,000 actively managed U.S. and global mutual funds, we found most reflected the style exposures implied by their names, but we also found a number of funds with exposures that deviated from what one might have expected. Such data can help potential and current investors understand whether a fund's exposures are aligned with its investment objectives.

## INTRODUCTION

Factors are important systematic sources of risk and return in equity portfolios. While equities are our focus here, factors are not unique to the equity asset class. Indeed, factors can and are used in other asset classes such as fixed income, real estate and currencies. Factors are used in models to both explain and forecast risk and return of portfolios. There are three main categories of factors and factor models used by investors today: fundamental, statistical and macroeconomic.<sup>1</sup> Our focus is on fundamental factors, which can include categorical factors such as country or industry membership, as well as continuous, real-valued style factors such as earnings yield or company market cap.

Barra GEMLT, on which MSCI FaCS is based, is the fourth generation Barra global equity factor risk model. The model is built from a long and distinguished pedigree of factor model research, from the pioneering work of Rosenberg and McKibben (1973) who were among the first to describe the importance of fundamental factors in explaining stock returns. Their research led to the creation of the first multi-factor Barra risk model, a U.S. model, in 1975. The first global Barra model was released in 1989. Barra GEMLT incorporates numerous enhancements in methodology, data, factors, timeliness and other areas built up from the prior generations of Barra models.

Our research (Rosenberg, 2017) as well as that of others (for example, see Ang, 2009) has continued to show that factors have been significant contributors to active returns (the return above or below the benchmark) in active equity portfolios. Specifically, we found that industry, country, currency and style factors (such as value, size or momentum) accounted for approximately 55% of the active return of a sample of 882 actively managed global mutual funds over the September 2003 – December 2016 period. Within the factor contribution, style factors made up the largest fraction of about 35%. Country and industry factors contributed about 25% each, while currency factors contributed 15%.

Understanding the return drivers of active portfolios can help asset owners in allocating capital among managers and in integrating factor and active mandates. We have investigated this challenge using a risk-budgeting framework (Rao, 2017). In short, we found that a hypothetical asset owner would have been able to implement a sizeable return-seeking, or risk-reducing, factor allocation without defunding its current managers; the optimal allocation to each depended on the relationship between the factor and active allocations, and also the desired distribution of active risk.

The first systematic model of stock returns involving factors was the Capital Asset Pricing Model (Sharpe, 1964), which contains a single factor – beta, defined by a security's exposure

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<sup>1</sup> For a complete review of the various factors and factor models, see Zangari (2003).

to the market. The model, known as CAPM, became a foundation of modern financial theory; it was simple, intuitive and elegant. However, its power in explaining observable security returns and market behavior is limited. Subsequently, numerous other factors and factor models have been proposed, such as the Fama-French 3-factor model (Fama and French, 1992, 1993), which added two more factors – company market cap (size) and book-to-market ratio (value) – to the CAPM factor. New factors have been proposed and explored; for example, momentum (Carhart, 1997), quality (Sloan, 1996; Novy-Marx, 2013), volatility (Ang et al., 2006), dividend yield (Litzenberger and Ramaswamy, 1979) and liquidity (Amihud, 2002). In fact, Harvey (2016) counted at least 313 papers on factors and their relation to the cross section of security returns. Many are related to one another, or related to a common theme, such as serial correlation, valuation, mean reversion or company operating performance.

To make sense of this ever-growing factor “zoo,” we propose creating a framework for the classification of style factors. We leverage the power and structure of the Barra GEMLT to arrive at our framework. The style factors in GEMLT are comprised of 41 individual metrics, or “descriptors,” combined into 16 factors, which we then combine into eight factor groups in MSCI FaCS.

In the following sections, we describe the structure of MSCI FaCS, present an analysis of hypothetical active equity portfolios using the standard and show examples of how MSCI FaCS can be used for fund reporting, monitoring, and comparisons.

## CONSTRUCTION OF MSCI FaCS

In constructing MSCI FaCS, we sought to combine factors of a common theme together. The classification standard structure is displayed in Exhibit 1. In assigning the weights, we used the same methodology as when assigning weights to the descriptors of a factor – a combination of factor statistics and our intuition of the factor group. The factor statistics we explored included factor returns, volatilities, information ratios (IRs), t-statistics and  $R^2$  from cross-sectional regressions. In this paper, we present the structure of MSCI FaCS and explain how we create the classification standard by combining factors into factor groups. Definitions of the factor statistics and details on how we construct individual factors, together with interpretation of security and portfolio-level factor exposures can be found in the Appendix.

**Exhibit 1: Structure of MSCI FaCS**

 VALUE	 SIZE	 MOMENTUM	 QUALITY	 YIELD	 VOLATILITY	 GROWTH	 LIQUIDITY
Book-to-Price (30%) Earnings Yield (60%) LT Reversal (10%)	Mid Cap (10%) Size (90%)	Momentum (100%)	Leverage (12.5%) Investment Quality (25%) Earnings Variability (12.5%) Earnings Quality (25%) Profitability (25%)	Dividend Yield (100%)	Beta (60%) Residual Volatility (40%)	Growth (100%)	Liquidity (100%)

*The 16 style factors of Barra GEMLT are combined into eight factor groups.*

When assigning weights to factors in each factor group, we put more emphasis on factor returns and information ratios (IRs) for Systematic Equity Strategy<sup>2</sup> (SES) factor groups (quality and value), and more emphasis on factor volatilities, t-stats and cross-validated (CV) R<sup>2</sup> gain for the non-SES factor groups (i.e., the size and volatility factor groups). Within the quality group, for example, our multi-variate cross-sectional regression statistics, provided in Exhibit 2, also show that the three SES quality factors of earnings quality, investment quality and profitability generated significantly higher factor returns and IRs than the non-SES quality factors of leverage and earnings variability. Variants of the SES quality factors have also been extensively discussed in the academic literature — see Sloan (1996) for the earnings quality factor, and Fama and French (2015) and Novy-Marx (2013) for the profitability and investment quality factors — as providing explanatory power in the cross section of stock returns and generating risk premia over long horizons.

Exhibit 2 shows that the non-SES factors generated t-stats, factor volatilities and CV R<sup>2</sup> gains comparable to those of the SES quality factors. These results demonstrate that the non-SES quality factors added explanatory power to the cross section of security returns even though their annualized factor returns were not as large as those of the SES quality factors.

<sup>2</sup> See Bayraktar (2013) for a detailed description of SES factors.

Therefore, we assigned a 25% weight to each of the three SES quality factors and a -12.5% weight to each of the other two quality factors.<sup>3</sup>

**Exhibit 2: Factor Statistics from Multi-variate Cross-sectional Regressions in GEMLT**

Factor Group	Factor	Mean  t-stats	Annual Return (%)	Annual Volatility (%)	IR	CV R <sup>2</sup> Gain (bp)	Weight in FaCS group
Value	Earnings Yield	2.17	3.64	1.74	2.09	3.21	<b>60%</b>
	Book-to-Price	2.03	2.18	1.59	1.38	2.38	<b>30%</b>
	LT Reversal	1.96	1.42	1.36	1.05	1.69	<b>10%</b>
Size	Size	4.32	-0.05	2.26	-0.02	19.92	<b>90%</b>
	Mid Cap	2.21	0.04	1.48	0.03	3.44	<b>-10%</b>
Quality	Leverage	1.70	-0.18	1.01	-0.18	1.11	<b>-12.5%</b>
	Earnings Var	1.71	-0.37	1.13	-0.32	0.99	<b>-12.5%</b>
	Profitability	1.67	1.17	1.12	1.05	0.49	<b>25%</b>
	Earnings Qual	1.47	1.41	0.81	1.73	0.03	<b>25%</b>
	Investment Qual	1.48	1.16	0.82	1.42	0.12	<b>25%</b>
Volatility	Beta	6.99	0.20	5.93	0.03	44.18	<b>60%</b>
	Residual Vol	3.94	-2.28	3.05	-0.75	13.18	<b>40%</b>
Momentum	Momentum	4.74	4.38	3.54	1.24	22.69	<b>100%</b>
Yield	Div Yield	1.85	0.91	1.26	0.72	1.81	<b>100%</b>
Growth	Growth	1.72	0.89	1.12	0.80	0.78	<b>100%</b>
Liquidity	Liquidity	3.18	-1.13	2.15	-0.53	8.33	<b>100%</b>

Sample period is 1995 to 2016.

For the factor groups composed of more than one factor – value, size, volatility and quality – we re-standardize the factor combination using the same standardization methodology as for the individual factors (see the Appendix for details on the factor construction methodology, including standardization). Each factor group is standardized to have a market-cap-weighted mean of zero and unit equal-weighted global standard deviation. The volatility group is standardized using a global mean while the size, value and quality groups are standardized using a country-specific mean and a global standard deviation.

As an example of the MSCI FaCS calculation, we evaluate Microsoft Corp.’s exposure to the quality factor group. On Sept. 29, 2017, Microsoft’s factor exposures for profitability,

<sup>3</sup> Leverage and earnings variability received negative weight because *low* leverage and *low* earnings variability are associated with *high* quality companies.

investment quality, earnings quality, earnings variability and leverage were 0.169, -0.055, 0.403, -0.442 and 0.289, respectively. Combining these factor exposures with the quality weights listed in Exhibit 2 gives us the raw, pre-standardized quality group combination:

$$0.25 \times 0.169 + 0.25 \times (-0.055) + 0.25 \times 0.403 - 0.125 \times (-0.442) - 0.125 \times 0.289 = 0.148$$

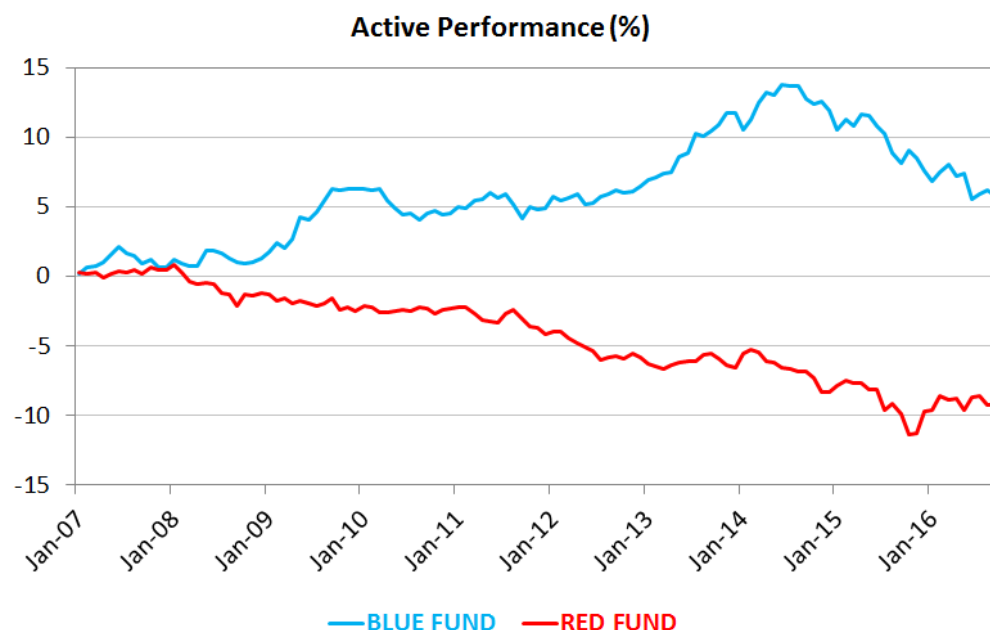
For all U.S. companies in the MSCI ACWI Investable Market Index (IMI), the raw, pre-standardized quality group combination had a market-cap weighted mean of 0.000 and a global equal-weighted standard deviation of 0.513 on this date. Thus, our final MSCI FaCS quality group exposure for Microsoft on this date was 0.288, calculated via

$$(0.148 - 0.000) / 0.513$$

As a simple illustration of the importance of style factors in explaining active returns of portfolios, we used the Barra Open Optimizer to construct and back test two sample portfolios created on the large- and mid-cap MSCI World Index universe. The two portfolios were designed to have nearly identical sector and country weights, but significantly different factor exposures. Relative to the MSCI World Index, we specified the optimizer to maximize the exposure to the value factor group for the “Blue Fund” and to the volatility group for the “Red Fund,” while keeping all other style factor exposures near zero and minimizing tracking error to the benchmark. We also constrained the active weights to industries and countries to be near zero in both portfolios. We display the active returns of these portfolios – “Red Fund” and “Blue Fund” – in Exhibit 3.



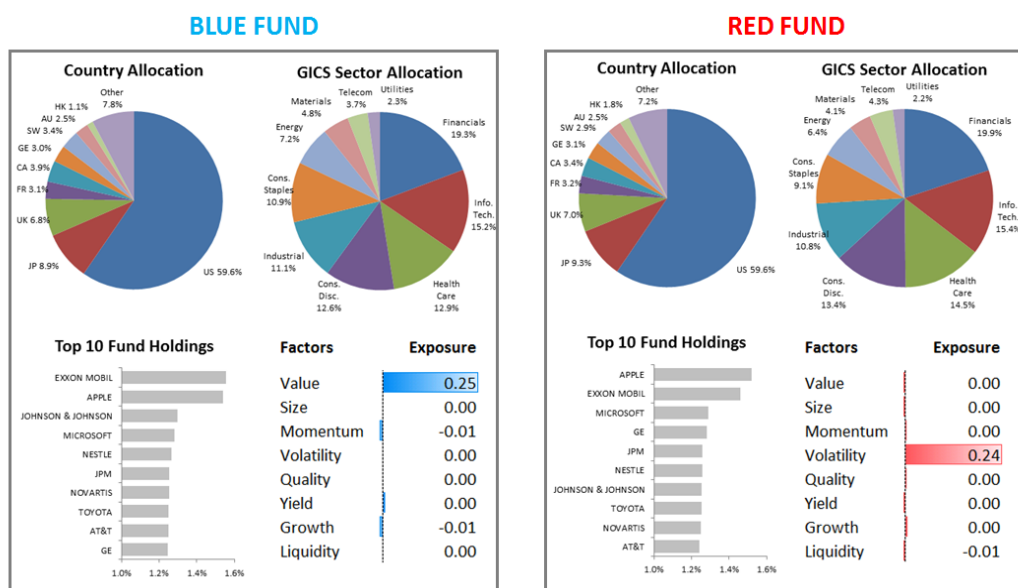
**Exhibit 3: Active Returns of Two Simulated Portfolios**



Over the roughly 10-year period, the two funds diverged in active return by approximately 15 percentage points. In Exhibit 4, we display the sector and country weights, the top 10 holdings and the average MSCI FaCS factor group exposures of the two funds. While the top 10 holdings of the two funds were identical, their weights differed. The sector and country weights were essentially identical. As expected, the major difference between the funds, and the driver of the active return difference, was their style factor exposures: The Blue Fund had a significant positive exposure<sup>4</sup> to the value group, while the Red Fund had a significant positive exposure to the volatility group. By design, the exposures to all other MSCI FaCS factor groups were near zero.

<sup>4</sup> Factor exposures are in standardized z-score units – the number of standard deviations away from the mean. Details on how we construct a factor and standardized exposures are provided in the Appendix.

Exhibit 4: Average Composition of Two Simulated Portfolios



While this example was only a simulation, it demonstrates the potential importance of factors in contributing to the performance of equity portfolios. We examine the exposures of actual mutual fund portfolios in the following section.

## EXPOSURES OF ACTIVE PORTFOLIOS

As part of our research process in constructing MSCI FaCS, we also examined the style factor exposures of active portfolios. In all the following analyses, for consistency we calculated exposures relative to the MSCI ACWI IMI universe, which is the native universe for the factor exposure calculations in GEMLT and MSCI FaCS.

We grouped a sample of 3,071 diversified actively managed U.S. and global equity mutual funds over the 14-year period ended November 2017, we grouped them into categories based on key words found in the fund name. We used the key words “Value,” “Large,” “Mid,” “Small,” “Momentum,” “Volatility,” “Quality,” “Income,” “Yield” and “Growth” to group funds into categories. The “Income” category contains funds with “Yield,” “Income” or “Dividend” in their name. Note that some funds can be assigned to more than one bucket. For example, a fund with “Large-Cap Growth” in its name would be assigned to the “Large” and “Growth” groups. We also applied some filters, such as excluding funds with both

“Growth” and “Value” in their name from the Value and Growth categories to make our groupings more accurately reflect the true strategies of the funds.<sup>5</sup>

Of the 19 funds with “Volatility” in their name, 13 were “Low Volatility” funds that sought to consistently achieve lower volatility than their benchmark, and the other six were “Managed Volatility” funds, some of which may have intentionally varied their exposure to beta and volatility based on the manager’s views and/or market conditions. Thus, we expect the majority of funds in the Volatility category to have negative exposure to the factors in the volatility group.

In Exhibit 5, we show the average exposure of each GEMLT factor within each of these categories of funds, as of November 2017. We see that the exposures of actual active funds were consistent with the groupings of factors in MSCI FaCS. Most fund categories had significant exposures to the factors in their named category. We also see that funds often had significant exposures to factors outside of their named category.

**Exhibit 5: Average Factor Exposures of Active Mutual Funds**

Factors	Fund Classification Based on Key Words								
	Value	Large	Mid	Small	Momentum	Volatility	Quality	Income	Growth
Earnings Yield	0.15	0.07	-0.07	-0.18	-0.09	0.12	0.05	0.18	-0.28
Book to Price	0.31	-0.02	0.03	0.12	-0.05	-0.06	-0.27	0.05	-0.29
LT Reversal	0.05	-0.13	-0.09	-0.10	-0.26	-0.14	-0.05	-0.03	-0.22
Size	-0.65	0.18	-0.97	-2.00	-0.79	-0.10	0.19	0.15	-0.39
Midcap	0.06	-0.03	0.69	0.07	0.05	0.17	-0.13	-0.07	0.10
Momentum	-0.19	0.04	-0.06	-0.05	0.38	0.02	-0.05	-0.12	0.19
Beta	0.22	-0.04	0.22	0.48	0.48	-0.61	-0.43	-0.17	0.17
Residual Volatility	-0.28	-0.14	-0.46	-0.23	-0.05	-0.36	-0.22	-0.21	-0.07
Profitability	-0.29	0.08	-0.05	-0.06	0.02	0.17	0.44	-0.09	0.33
Earnings Quality	0.01	-0.03	-0.01	0.03	-0.10	-0.03	-0.15	-0.02	0.00
Investment Quality	0.07	0.05	-0.21	-0.38	-0.13	0.25	0.21	0.21	-0.36
Earnings Variability	0.08	-0.03	0.11	0.32	0.20	-0.27	-0.38	-0.18	0.14
Leverage	-0.02	-0.04	-0.01	-0.21	-0.22	0.01	0.00	0.09	-0.15
Dividend Yield	-0.03	-0.10	-0.39	-0.50	-0.37	0.22	0.10	0.48	-0.53
Growth	-0.19	0.07	0.04	0.08	0.18	-0.24	-0.18	-0.24	0.37
Liquidity	0.14	0.03	0.46	0.38	0.33	-0.03	-0.17	-0.11	0.27
Number of funds	485	187	177	367	10	19	15	183	497

Average factor exposures are equal-weighted, grouped by key words found in the fund names. Data are based on the most recent holdings reported as of Nov. 30, 2017. Target factors are boxed.

<sup>5</sup> Additional filters we applied: exclude funds with “Growth” in the name from the Income category, funds with “Value,” “Income,” “Dividend” or “Yield” in the name from the Growth category, funds with “Mid” in the name from the Large and Small categories and funds with “Small” or “Large” in the name from the Mid category.

We also performed the same analysis for the MSCI FaCS factor groups and show the results in Exhibit 6. Again, we found the exposures of active mutual funds to be consistent with the MSCI FaCS factor groups. In general, for each fund category we see that the largest exposures tended to be those of the associated named factor group.

**Exhibit 6: Average MSCI FaCS Factor Group Exposures of Active Mutual Funds**

Factor Group	Fund Classification Based on Key Words								
	Value	Large	Mid	Small	Momentum	Volatility	Quality	Income	Growth
<b>Value</b>	0.26	0.04	-0.04	-0.09	-0.12	0.06	-0.08	0.17	-0.36
<b>Size</b>	-0.69	0.18	-1.10	-2.10	-0.83	-0.12	0.35	0.17	-0.42
<b>Momentum</b>	-0.19	0.04	-0.06	-0.05	0.38	0.02	0.19	-0.12	0.19
<b>Volatility</b>	0.03	-0.11	-0.07	0.27	0.37	-0.70	-0.46	-0.26	0.10
<b>Quality</b>	-0.11	0.07	-0.15	-0.23	-0.10	0.25	0.40	0.07	-0.01
<b>Yield</b>	-0.03	-0.10	-0.39	-0.50	-0.37	0.22	0.05	0.48	-0.53
<b>Growth</b>	-0.19	0.07	0.04	0.08	0.18	-0.24	-0.10	-0.24	0.37
<b>Liquidity</b>	0.14	0.03	0.46	0.38	0.33	-0.03	-0.20	-0.11	0.27
<b>Number of funds</b>	<b>485</b>	<b>187</b>	<b>177</b>	<b>367</b>	<b>10</b>	<b>19</b>	<b>15</b>	<b>183</b>	<b>497</b>

Average MSCI FaCS factor group exposures are equal-weighted, grouped by key words found in the fund names. Data are based on the most recent holdings reported as of Nov. 30, 2017. Target factors groups are boxed.

This analysis indicates that MSCI FaCS is generally consistent with the strategies of active mutual funds, and can provide investors with greater transparency on the strategies of active funds. Such data can help inform potential and current investors in such funds.

## APPLICATIONS

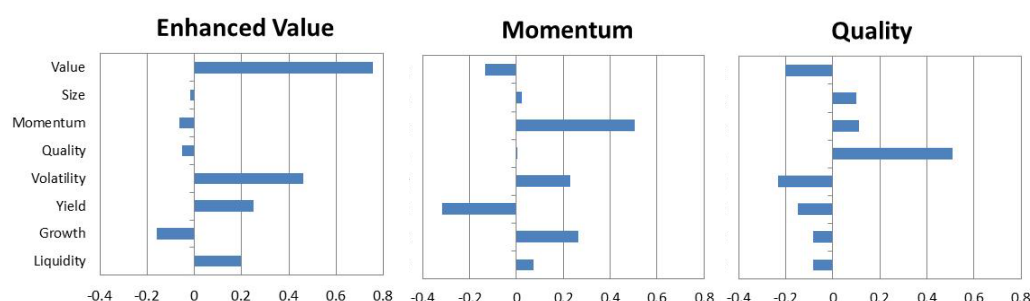
We envision many ways in which MSCI FaCS can be useful to investment professionals. We will explore three of them here: fund reporting, comparing funds and assessing style drift. Unless specified otherwise, we calculate and display factor exposures relative to the MSCI ACWI IMI.

### FUND REPORTING

Currently, product managers at asset management firms lack a consistent way in which to communicate their exposure to factors, especially to retail investors. While current factor models such as GEMLT provide valuable insight into how factor exposures affect performance, such models may be too detailed for many investors. MSCI FaCS aims to provide a common language for reporting on factor exposures, to institutional and retail investors alike, providing an easy and efficient way to communicate factor tilts. Exhibit 7 illustrates how factor exposures can be graphically displayed, using a sample of MSCI World

Factor indexes. We show the exposures to the MSCI FaCS factor groups for the MSCI World Enhanced Value, Momentum and Quality indexes relative to the MSCI World benchmark.<sup>6</sup>

### Exhibit 7: MSCI FaCS Factor Group Exposures of Three MSCI World Factor Indexes



Exposures as of Nov. 30, 2017

### COMPARING FUNDS

In our sample of over 3,000 actively managed equity mutual funds, we examined the distribution of exposures to the target factor group in each fund group to gauge how much exposures varied. For example, an investor seeking exposure to value could use MSCI FaCS to see if funds under consideration had the desired exposure to the factor. We also counted how many funds had an exposure to their named factor group that was *opposite in sign* to what we would expect based on the fund name. We show these results in Exhibit 8.

<sup>6</sup> The exposures relative to MSCI World Index vs. MSCI ACWI IMI are nearly identical, with the exception of the Size group exposure, as MSCI World is a large and mid-cap index while ACWI IMI includes small caps.

### Exhibit 8: Distribution of MSCI FaCS Factor Group Exposures in Mutual Fund Categories

Percentile	Distribution of Exposure to Named Factor Group								
	Value	Large	Mid	Small	Momentum	Volatility	Quality	Income	Growth
<b>0 (min)</b>	-0.53	-1.62	-2.00	-3.02	0.15	-1.12	-0.03	-0.42	-0.32
<b>1</b>	-0.29	-0.61	-1.75	-2.76	0.16	-1.11	0.00	-0.15	-0.20
<b>5</b>	-0.09	-0.22	-1.62	-2.59	0.18	-1.06	0.16	0.09	-0.09
<b>10</b>	0.01	-0.12	-1.52	-2.38	0.21	-1.05	0.22	0.13	0.03
<b>25</b>	0.15	0.05	-1.21	-2.29	0.27	-0.94	0.29	0.33	0.20
<b>50 (median)</b>	0.26	0.24	-1.03	-2.11	0.36	-0.84	0.38	0.49	0.38
<b>75</b>	0.40	0.37	-0.94	-1.93	0.53	-0.47	0.50	0.68	0.52
<b>90</b>	0.51	0.45	-0.85	-1.75	0.59	-0.33	0.55	0.80	0.68
<b>95</b>	0.61	0.49	-0.80	-1.62	0.61	-0.25	0.57	0.91	0.76
<b>99</b>	0.73	0.61	-0.66	-1.44	0.62	0.12	0.60	1.12	1.16
<b>100 (max)</b>	0.92	0.99	-0.30	-1.05	0.63	0.21	0.61	1.19	1.40
<b>Number of funds</b>	485	187	177	367	10	19	15	183	497
<b>Number inconsistent</b>	40	36	0	0	0	1	1	6	36
<b>% inconsistent</b>	8.2%	19.3%	0.0%	0.0%	0.0%	5.3%	6.7%	3.3%	7.2%

*Distribution of MSCI FaCS factor group exposures for the target factor group of categories of active mutual funds classified by keywords. The “Number inconsistent” represents the number of funds with an exposure to their named factor group that is opposite in sign to what we would expect based on the fund name. Data are as of Nov. 30, 2017.*

For example, we see that within the value category of funds, the lowest exposure to the value group was -0.53; out of 485 funds, 40 (8.2%) had a negative exposure to the value group. Looking more closely at the fund with the most negative exposure to value (data not shown), we find that this fund had exposures of -0.65 to earnings yield and -0.14 to book-to-price, +0.34 to LT reversal and +0.10 to growth. Investors seeking exposure to value may wish to be aware of these characteristics, and MSCI FaCS can provide that additional transparency. The Large category is the one with the largest fraction of funds (19.3%) that had an exposure opposite in sign to what we would have expected based on fund names.

There are other examples where the fund exposure was opposite in sign from what one might expect based on the fund name. Investors may wish to be aware of these biases:

- **Volatility group:** The one fund with positive exposure to the volatility group turned out to be a “managed volatility” fund that dynamically adjusted its beta exposure to changing risk environments, instead of maintaining a consistent negative exposure to the volatility factor. Given that late 2017 (when these data were extracted) was clearly a low risk, low volatility environment, it is not surprising that the fund was tilted away from a traditional low volatility stance.
- **Quality group:** The one fund that had a negative (-0.03) exposure to the quality group was a “quality dividend” fund. Looking more closely at its exposures, we find it had a very high (+0.93) exposure to the yield group. Thus, at the time of this

snapshot, it appears that the fund emphasized the high dividend yield component more than the quality component of its strategy.

- **Growth group:** Of 498 growth funds, 36 (7.2%) had negative exposures to growth. Looking more closely at these funds (data not shown), we found that on average they had near zero exposure to value, momentum and yield but a significant positive exposure (0.21) to quality. That positive exposure to quality was also fairly pervasive – 30 of the 36 had a positive exposure to quality and most of the remaining six had only small negative exposures.

Overall, we generally found that only a small percentage of funds had exposures that appeared inconsistent (opposite in sign) with their fund name. With a little digging, and with the help of the MSCI FaCS exposure data, it is often possible to uncover the likely drivers of these inconsistencies.

We also found significant variation in exposure within a fund category. An investor seeking exposure to a particular factor could use MSCI FaCS to quickly and easily compare funds and identify those with factor profiles nearest to the investor's target.

MSCI FaCS data can also be used to compare a particular fund's exposures to its peer group. To illustrate this point, we compare the exposures of sample funds fully replicating the MSCI World Enhanced Value, Momentum, Quality, Equal Weighted, Minimum Volatility and High Dividend Yield indexes to the eight MSCI FaCS factor groups relative to the MSCI World Index in Exhibit 9. In general, the largest exposure for each sample fund was to its target factor group. In the last row of Exhibit 9, we also show where each sample fund's target MSCI FaCS group exposure fell in the distribution of exposures among the corresponding category of our sample of active mutual funds. For example, the sample fund replicating the MSCI Enhanced Value Index had an exposure to the MSCI FaCS value group of 0.75, putting it at the 99.6<sup>th</sup> percentile of value exposures among our sample of 485 value funds. As a check, we can see in Exhibit 8 that the 99<sup>th</sup> percentile of value exposure among value funds was 0.73 and that the maximum exposure was 0.92. Thus, the fund's exposure would have been between the 99<sup>th</sup> and 100<sup>th</sup> percentile of value exposures. Similar analyses for funds replicating the other MSCI factor indexes are shown in the bottom row of Exhibit 9 below.

We also show the exposures of sample funds replicating two MSCI indexes that target multiple factors. The Diversified Multiple-Factor (DMF) Index is a best-in-class, optimization-based index that aims to maximize the exposure to value, momentum, quality and low size in a multi-factor alpha score while maintaining a total risk profile similar to that of the underlying parent index. The Factor Mix Index represents an equal-weighted combination of the six individual factor indexes. As of Nov. 30, 2017, the DMF Index sample fund had significant exposures to all its target factor groups, but these exposures were generally smaller than for the individual factor index sample funds. The factor exposures for the

Factor Mix Index sample fund were generally smaller than the DMF sample fund exposures, largely due to dilution effects. For example, the MSCI World Enhanced Value Index sample fund tended to have a negative exposure to momentum, while the MSCI World Momentum Index sample fund tended to have a negative exposure to value, which serves to lower the exposures of both. Also, the dilution of combining six indexes together naturally resulted in lower exposures. Yet both the DMF and Factor Mix index sample funds outperformed their benchmarks on an absolute and risk-adjusted basis over long horizons.<sup>7</sup>

### Exhibit 9: MSCI FaCS Factor Group Exposures of MSCI World Factor Index Sample Funds

Factor Group	MSCI World Factor Indexes						Diversified	
	Enhanced Value	Equal Weighted	Momentum	Quality	Min Volatility	High Dividend Yield	Multiple-Factor (DMF)	Factor Mix
Value	0.75	-0.02	-0.13	-0.20	-0.19	0.16	0.22	0.06
Size	-0.02	-0.76	0.02	0.10	-0.27	0.20	-0.77	-0.12
Momentum	-0.06	-0.11	0.51	0.11	0.06	-0.11	0.21	0.03
Quality	-0.05	-0.04	0.00	0.51	0.19	0.18	0.18	0.13
Volatility	0.46	0.04	0.23	-0.23	-0.82	-0.36	-0.06	-0.14
Yield	0.25	-0.13	-0.32	-0.15	0.10	0.61	-0.12	0.06
Growth	-0.16	-0.07	0.26	-0.09	-0.24	-0.32	-0.12	-0.10
Liquidity	0.20	0.24	0.07	-0.08	-0.16	-0.13	0.20	0.01
Percentile rank in fund category to target FaCS family	99.6%	100.0%	73.9%	94.3%	54.4%	72.1%	N/A	N/A

Data as of Nov. 30, 2017. Data represents active exposures relative to the MSCI World Index. Target factors groups are boxed. The “percentile rank in fund category to target MSCI FaCS group” indicates where a sample fund fully replicating an index’s exposure to its target MSCI FaCS factor group falls within the distribution of funds in the corresponding category.

### ASSESSING STYLE DRIFT

MSCI FaCS data can be used to gauge style drift and gain an understanding of the variability in factor exposures over time. As shown in Exhibit 9, sample funds based on MSCI Factor Indexes generally had their largest exposure to their target MSCI FaCS factor group. However, these exposures can and do vary over time. To get an idea of the level of variation in exposure to their target factor groups, we plotted this for each sample fund in Exhibit 10. Each underlying factor index was rebalanced semi-annually (with the exception of the Equal Weighted Index, which was rebalanced quarterly) in May and November of each year. We generally see steps in the sample fund target factor exposures at rebalance dates, followed by slow drift as we move farther away from rebalancings.

<sup>7</sup> Further details on the DMF and Factor Mix Indexes can be found in their respective MSCI Index methodology documents.



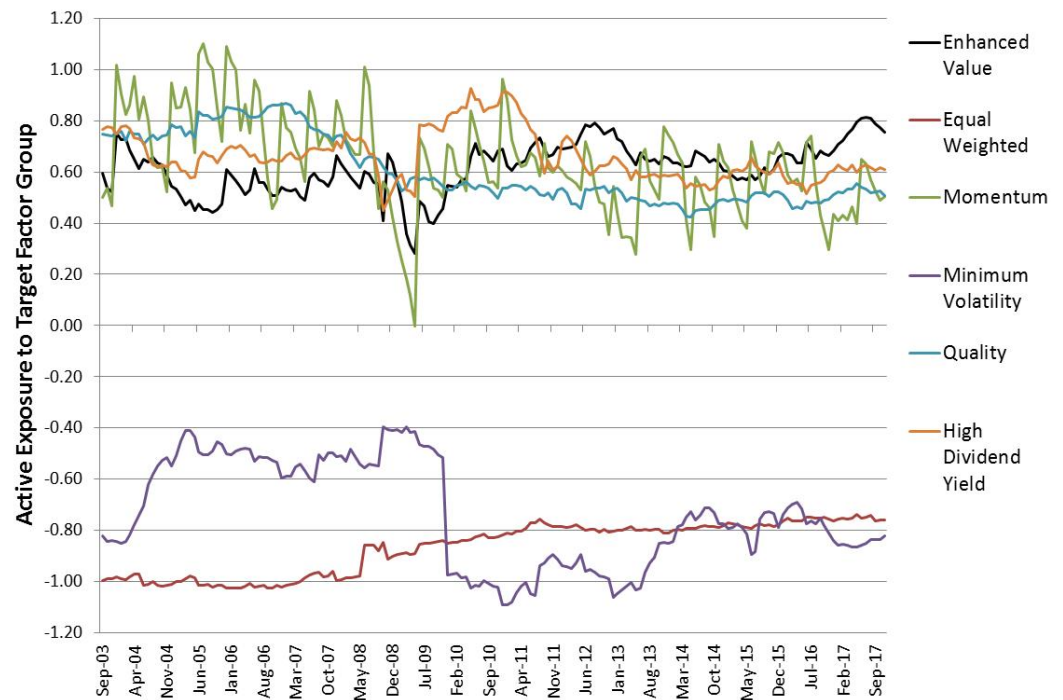
The MSCI World Momentum Index showed the largest step changes in exposure at rebalance dates and the fastest drift in exposure between rebalances, as the momentum factor had the highest turnover of all the factors represented by the factor indexes. At severe market turning points, such as between the November 2008 and May 2009 rebalance dates, there were large drifts in the momentum exposure due to rapid changes in the market environment and momentum exposures of individual securities. Nevertheless, we found that the sample funds based on the MSCI World Momentum Index and other factor indexes generally maintained significant exposures to their target factors.

In addition, the large change in the volatility exposure of the Minimum Volatility Index at the November 2009 rebalance date stemmed from switching to the second-generation Barra Global Equity Model from the first generation Barra Global Equity Model at that time. The first generation model used only one descriptor in the volatility factor, while the second generation model added three additional descriptors measuring historical beta, realized volatility and cumulative range, the same descriptors used in the volatility group in GEMLT.<sup>8</sup>

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<sup>8</sup> Barra GEMLT, on which MSCI FaCS is based, is the fourth generation Barra Global Equity Model and it incorporates the same descriptors as the second generation Barra model in the volatility factor group.

**Exhibit 10: Exposures of MSCI World Factor Indexes to Target MSCI FaCS Factor Group**

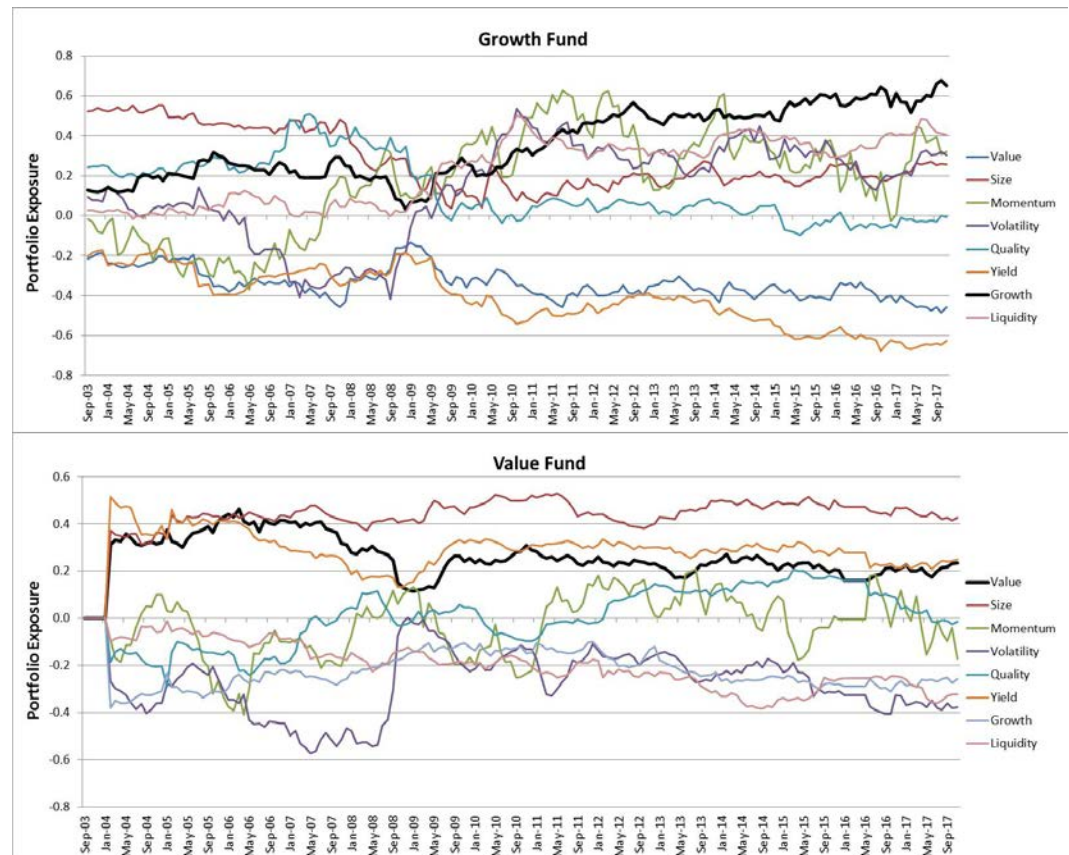


Sample period is September 2003 – November 2017.

In another example of style drift, we analyzed two large actively managed mutual funds, one from the growth category and one from the value category, tracing their MSCI FaCS factor group exposures over time (Exhibit 11). Using our framework, we see that the growth fund experienced a significant change in some factor exposures around 2009 when the manager of the fund changed. Since 2009, the exposures have been fairly stable, with significant positive exposure to growth and volatility, and generally positive exposure to momentum. The fund has also had significant negative exposure to value and yield.

In comparison, the value fund had positive exposure to value and yield but negative exposure to growth during this period. It also had variable, but mostly small, exposures to momentum and quality.

**Exhibit 11: MSCI FaCS Factor Group Exposures of a Large Active Growth and Value Fund**



MSCI FaCS exposures of a large actively managed growth mutual fund (top panel) and a large value fund (bottom panel) over the September 2003 - November 2017 period.

In short, portfolio exposures varied over time for numerous reasons, such as changing security exposures, rebalancing frequency, portfolio manager and/or investment strategy changes, macroeconomic shifts or stock-specific news. MSCI FaCS can help investors become aware of and understand the drivers behind the variation and changes in factor exposures.

## LIMITATIONS OF MSCI FaCS

We believe MSCI FaCS will be a valuable tool for reporting, analyzing, comparing and monitoring the factor characteristics of funds and portfolios. However, this framework is not a substitute for full risk and return attribution and analysis, which requires additional sophisticated tools and data, such as those available via the more comprehensive Barra GEMLT factor model. MSCI FaCS will provide information on portfolio exposures to style

factors, but it cannot assess how much of a portfolio's risk or return could be attributed to each style factor, industry or other factors. MSCI offers a full suite of products and models to provide such additional insights.

## THE FUTURE OF MSCI FaCS

MSCI FaCS is based on an extensive, yet parsimonious, set of factors that explain global long-term risk and risk premia. We recognize that other factors do exist, such as those that are more regional or narrow in focus and/or short-term in nature.

Indeed, a number of other factors and categories of factors exist in regional, country, and short-term trading versions of Barra models. For example, trading versions of some Barra models contain high-turnover sentiment factors constructed from analyst revisions, news, short interest and/or options data. Further, the latest European Barra model includes an ESG factor, as today we find it to be an important contributor to explaining risk and return in Europe. While it is not currently included in GEMLT or MSCI FaCS, these models are regularly updated.

We expect that much like GICS<sup>®</sup>,<sup>9</sup> MSCI FaCS will evolve slowly over time. Factors or factor groups may be added, modified or removed. We will conduct annual reviews of the standard to ensure it accurately reflects a robust set of factors and factor groups that explain global long-term equity risk and return at a given point in time.

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<sup>9</sup> GICS is the global industry classification standard jointly developed by MSCI and Standard & Poor's.

## CONCLUSION

It is well established that factors have historically been important sources of risk and return in equity portfolios. Among different categories of fundamental factors, such as industry, country, currency and style, our research indicates that style factors accounted for the largest share of active return in active portfolios during the time period of our study. Standards already exist for factors based on industries and countries, but no standard had yet existed for style factors.

We have constructed MSCI FaCS with an aim to fill this gap. The classification standard is based on the factor structure of the latest global Barra equity factor risk model, the Barra Global Total Market Equity Model for Long-Term Investors, and groups the 16 factors of GEMLT into eight factor groups. The factor groups have been extensively discussed in the literature and most have been shown to generate risk premia over long horizons.

We believe MSCI FaCS will facilitate transparency and understanding in the reporting and analysis of style factor exposures in equity portfolios. MSCI FaCS creates a common language and definitions around factors that may be used by asset owners, managers, advisors, consultants and investors. Managers can use the framework to analyze and report factor characteristics, while investors and consultants can use its data to compare funds using common definitions.

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## APPENDIX

### CONSTRUCTION OF A FACTOR

All style factors in the Barra GEMLT and other Barra fundamental equity factor models are constructed in five primary steps:

1. Calculate descriptor values. Raw values of each descriptor going into the factor are calculated.
2. Drop extreme outliers and winsorize<sup>10</sup> the remaining values to be within three standard deviations from the mean.
3. Standardize the raw descriptor values so that each descriptor has a market-cap-weighted mean of zero and unit standard deviation.
4. Linearly combine descriptors. The standardized scores of the descriptors are linearly combined, with weights that are determined by a combination of intuition and statistical metrics from the factor model.
5. Re-standardize the descriptor combination (the factor) to have a market -cap-weighted mean of zero and unit standard deviation.

We first calculate the raw descriptor values. This process can be as simple as taking the ratio of two numbers or can be considerably more complicated, such as conducting a regression or other processing of a multi-year time series of a security. The next step is to remove extreme outliers and winsorize the remaining values. This involves calculating a robust mean and standard deviation of the raw descriptor distribution, which are determined iteratively. We use the robust mean and standard deviation to winsorize the descriptor values to be within three standard deviations of the mean. Outlier removal and winsorization aim to prevent extreme values from having an undue influence on the final standardized descriptor values.

After removing outliers and winsorizing, we standardize the descriptor values to have a market-cap-weighted mean of zero and an equal-weighted standard deviation of one. This completes the standardization process. The Barra GEMLT model estimation universe, which is based on the MSCI ACWI IMI universe, is used to determine the parameters in the winsorization and standardization processes, but they are applied to the entire coverage universe.

We use the market-cap-weighted mean to standardize descriptor values, so that a well-diversified cap-weighted global index, such as MSCI ACWI IMI, has approximately zero

<sup>10</sup> Winsorization limits [extreme values](#) in the data to reduce the effect of [outliers](#).



exposure to all style factors. For the standard deviation, however, we use equal weighting to prevent large-cap constituents from having an undue influence on the overall scale of the exposures.

In GEMLT, descriptors and factors based on price, such as momentum, beta and residual volatility, are standardized on the global universe. Descriptors based on fundamental data, such as book-to-price, profitability and earnings yield, are standardized with a country-specific mean but a global standard deviation. We find that using country-specific standard deviations can result in undesirable and unintended instability in the descriptor values, particularly for countries with small numbers of stocks. We standardize fundamental descriptors with a country-specific mean because values of some fundamental descriptors tend to be systematically low or high in some countries. In the end, each descriptor is standardized to a common scale, which makes combining descriptors into a factor straightforward.

In creating each factor, we seek to incorporate and combine similar descriptors. We examined the academic and practitioner literature, and conducted our own research to identify descriptors that complement each other and that thoroughly capture a theme. For example, the profitability factor in the quality group contains four descriptors, each of which captures slightly different elements of profitability – asset turnover, gross margin, gross profit relative to assets and return on assets. Although each of these descriptors has significant explanatory power on its own, naively including them as separate factors in a factor model may lead to serious multi-collinearity problems. Combining these descriptors into a single style factor overcomes this difficulty, creates a factor that is more comprehensive and powerful, and also leads to a more parsimonious factor structure.

To calculate a factor, we linearly combine the appropriate standardized descriptors using a weighting scheme that is Bayesian in nature and determined by a combination of intuition and statistics. Our starting point is always equal weighting. However, we will modify the weights accordingly if we identify strong reasons why we should deviate from equal weighting. Such adjustments could stem from examining factor volatilities, t-stats, information ratios (IRs), marginal added explanatory power, our intuition behind the “essence” of a particular style factor and investors’ expectations or other measures. When deviating from equal weighting, we are conservative, and keep the weights to round numbers. We used the same process for setting the weights in the MSCI FaCS factor groups.

The final step is to re-standardize the descriptor combination to have a market-cap-weighted mean of zero and unit standard deviation. This re-standardized descriptor combination is then the factor.

## SECURITY AND PORTFOLIO LEVEL FACTOR EXPOSURES

Given that each factor is standardized, the concept of factor exposure for a security is straightforward. A security's exposure represents how far away from the market-cap-weighted average a given security is, and the units are in number of standard deviations. Values above zero indicate the security has a value higher than the market-cap-weighted average on the given factor, and exposures below zero indicate the security scores below that average on the given factor. For example, an exposure of +2 indicates that the security is two standard deviations higher than the average for the particular factor.

Calculating the exposure (to a descriptor, factor or factor group) of a portfolio is also straightforward. The exposure of a portfolio is simply the weighted average exposure of all the holdings in the portfolio, where the weights are identical to the portfolio weights.

When considering the magnitude of the exposure and identifying what would constitute a "large" or "significant" exposure for a portfolio, and to identify when exposures are likely to be intentional and not likely to occur simply from a random selection of securities, one can use the statistics of combinations of identically distributed independent random variables. Expressing these concepts mathematically, the portfolio exposure of n stocks is defined as:

$$\text{Portfolio exposure} = \sum_{i=1}^n w_i X_i$$

where the  $w_i$  are the individual stock weights and the  $X_i$  are the individual stock exposures.

Assuming stock exposures are independent and have identical distributions, if we take the variance of the above equation we get:

$$\text{Var}(\text{Portfolio exposure}) = \sum_{i=1}^n w_i^2 \text{Var}(X_i) = \sum_{i=1}^n w_i^2$$

since  $\text{Var}(X_i) = 1$

For an equal-weighted portfolio of n stocks (each stock has weight =  $1/n$ ), the variance of the portfolio exposure is simply

$$\sum_{i=1}^n \left(\frac{1}{n}\right)^2 = n \left(\frac{1}{n}\right)^2 = \frac{1}{n}$$

The standard deviation of an equal-weighted portfolio of n stocks is then  $\frac{1}{\sqrt{n}}$

We can also generalize this result to a portfolio with arbitrary security weights using a measure of the effective number (EN) of securities in the portfolio based on the Herfindahl-Hirschman Index (HHI). The effective number of stocks is a measure of portfolio concentration and ranges between 1 (for a single stock) and the number of stocks in the portfolio (for an equal-weighted portfolio), and is given by the inverse of the sum of squares of the weights of the portfolio

$$EN = 1 / \sum_{i=1}^n w_i^2$$

Thus, the variance of a portfolio exposure is simply  $1/EN$ . For a typical portfolio with  $EN \sim 100$ , this implies a portfolio standard deviation of exposure of 0.1. For such a portfolio, a two sigma exposure would be about 0.2, and therefore we adopt the threshold of 0.2 as constituting a “significant” portfolio exposure for a typical portfolio. In a well-diversified portfolio, exposures outside of  $[-0.2, 0.2]$  are unlikely to have been produced by a random selection of securities but can readily be generated, and are most likely to have been generated, by intentional positioning and tilts. We saw in Exhibits 8 and 9 that portfolios targeting a specific factor often had exposures to that factor considerably larger than 0.2.

## DEFINITIONS OF FACTOR STATISTICS

**Annual Factor Return.** Component of security returns attributed to a factor as determined by a multi-variate, cross-sectional regression, accounting for the market factor, other style factors, industries and countries, expressed on an annualized basis. It can be interpreted as the return to a factor given a unit exposure to the factor and zero exposure to all other factors.

**Annual Factor Volatility.** Standard deviation of factor return, expressed on an annualized basis. A high factor volatility indicates that at times stocks make large moves due to the factor, indicating that the factor is an important contributor to explaining the cross section of security returns.

**Factor Information Ratio (IR).** Annualized factor return divided by annualized factor volatility.

**Mean |t-stat|.** Average of the absolute value of the t-statistic of the regression coefficient to a factor in the multi-variate cross-sectional regressions.

**CV  $R^2$  Gain.** Gain in  $R^2$  in multi-variate, cross-sectional regressions due to adding the factor, when all other factors are present in the regression, as determined through hold-one-out cross validation (CV).

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