

What's in Your Benchmark?

A Factor Analysis of Major Market Indexes

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Abstract

We examine the factor exposures of several popular market capitalization indexes and how they vary over time. We find that most market capitalization weight indexes are effectively exposed to only two or three factors, with value and momentum being increasingly dominant. We find that the proportion of the index movements explained by factors has materially increased in recent years, which is consistent with a more top-down, macro-driven environment or the increasing importance of economy-wide risks for financial markets.

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1. Introduction

A large asset pricing literature following Ross (1976) has shown that there are only a few drivers of stock returns, or factors. All stocks are exposed to these systematic factors—only to greater or lesser degrees—and thus different portfolios have different factor exposures. One type of portfolio of particular interest is the class of market capitalization indexes (which often serve as a proxy for the “market”). In this paper, we ask: What are the factor loadings of market cap index portfolios and how have these changed over time?

Market cap benchmarks play an extremely important role in investments. In practice, although benchmarks themselves are not investible, there are low cost funds that seek to track these benchmarks, and these benchmarks are used as a yardstick for many active funds. These funds (both ETFs and index mutual funds) serve as core holdings for many individuals’ portfolios. In theory, benchmarks are held by a representative agent in economic models following Lucas (1978) and, with no entry or exit of firms, are self-rebalancing. On the other hand, in a multi-factor framework market cap portfolios have been shown to be inefficient—so there are well-known investing styles which have consistently outperformed the market in historical data.¹

Further, the composition of the market changes over time: Sector weights change, different types of firms outperform in different economic regimes, and new firms with similar technologies often list or default around the same time. Similarly, valuation ratios of the aggregate market change over time, as does the cross-section of firm valuation ratios. This is also true of trends in past returns in the aggregate market and across firms. Thus, it is not surprising that market capitalization indexes—which are a particular type of portfolio with a weighting scheme dependent on firm size within a given universe—exhibit dynamic factor exposures.

¹ The single-factor capital asset pricing model (CAPM) assumes representative investors who holds the same efficient tangency portfolio, which implies the total market portfolio will—by definition—be cap weighted. Without the CAPM’s restrictive assumptions and if there are factors beyond the market that carry a risk premium, the market portfolio will no longer be mean-variance efficient (see Huberman and Kandel (1987), Haugen and Baker (1991), Grinold (1992), and many others). Clarke, de Silva, and Thorley (2016) provide a framework to compare the mean-variance efficiency of a portfolio of individual securities and an optimal portfolio with four factors: low beta, small size, value, and momentum.

To estimate the factor exposures of major market indexes, we must make two important choices, although our methodology can be used in more general cases. First, we follow Fama and French (1993), Carhart (1997), and others to use style factors as the systematic factors: value, size, quality, momentum, and minimum volatility. A large number of academic studies show that these style factors have delivered excess returns compared to market-weighted benchmarks.² Fama and French (1993) themselves develop mimicking portfolios for value and size style factors. The style factors correspond to intuitive investment strategies which have long been practiced by active managers. Economically, the style factor premiums arise due to a risk premium beyond what can be obtained in the cap weight market portfolio, structural impediments, or investors' behavioral biases.

After deciding which factors should be used, the second decision is in what form we represent these factors. We deliberately choose a long-only, investable representation for the factors. This is a different assumption to most of the literature, which uses long-short mimicking portfolios for the style factors. Most of these portfolios, however, are not directly tradeable as they do not consider transaction costs, especially the real costs of shorting and the possibility of the recall of stock loans, if shorting can actually be accomplished. Further, the stocks held in most theoretical long/short portfolios in the finance literature also tend to range down to the micro-cap spectrum, where there are liquidity issues in the long positions, large borrow costs, and it is often difficult to locate stocks to borrow for short positions. Instead, we perform the analysis using transparent, third-party indexes for the style factors which are tradeable via Exchange Traded Funds (ETFs). We adjust the index returns for expense ratios. This long-only, investible representation makes our factor replication results more implementable, especially by smaller investors.

² See Ang (2014) for a literature summary of these style factors and their economic rationales. There are at least two other approaches but both have drawbacks compared to using style factors: (1) macro factors, following Chen, Roll and Ross (1986), but these are so-far not directly tradeable by individual investors; and (2) statistical factors, estimated with latent factors following Connor and Korajczyk (1993) and Jones (2001), but these lack intuitive, economic interpretations.

We estimate the factor loadings of common indexes using holdings data following Ang, Madhavan, and Sobczyk (2017). The usual approach to estimating factor loadings is to use time-series regressions, which assume the regression coefficients are constant over the period of the regression. These approaches can only react to time-varying exposures with a lag. In contrast, Ang, Madhavan, and Sobczyk (2017) estimate dynamic factor loadings using *cross-sectional* risk characteristics and show, at any point in time, how to estimate the factor loadings of a fund by optimally matching the risk characteristics of a given portfolio to the risk characteristics of a set of factor indexes, third-party style indexes. The resulting factor mimicking portfolio is: (a) transparent, (b) investible, (c) long-only, and (d) tradable via ETFs or other low-cost instruments.

Given a set of time-varying factor loadings for any given index, we construct two metrics to measure the concentration of factor exposures and measure how much variability of a market index can be explained by factors. For the former, we define factor breadth as the inverse of the Herfindahl-Hirschman Index (HHI), which has a long history of use in the economics literature, especially in measuring industry concentration and the distribution of individual attributes, like income inequality. The lower the factor breadth, the fewer the factors the cap weight index is exposed to, and the less effective is the diversification.

We measure the amount of variability explained by factors as the standard deviation (tracking error) of the major market index vs. the dynamic factor mimicking portfolio. The lower the tracking error, the higher the proportion of its movements due to factors. We also compare and contrast common indexes in the same region. The distribution of factor exposures across common benchmarks may exhibit greater similarity than might be suggested by their constituents. For example, the Russell 1000 and S&P 500 indexes differ by at least 500 constituents, but we find that their factor profiles have been similar. We find the Russell 3000 has an effective breadth of 4.2 factors vs. 2.1 factors for the Russell 1000 Growth Index.

The rest of this paper is organized as follows. In Section 2, we describe the methodology including how we estimate the factor exposures of the market cap indexes,

and detail the construction of the factor concentration statistic and our measure of factor explanatory power. Section 3 describes our data sources and Section 4 contains our empirical results. Finally, Section 5 concludes and we discuss the implications of our findings for investment practitioners.

2. Methodology

2.1 Factor Replication of Major Market Indexes

Distinct indexes are likely to differ in their representation of sectors, industries and regions. For example, US large cap indexes tend to have a higher exposure to technology while European indexes may give greater weight to banking. The differences between indexes extends beyond sectors: different regions tend to have more companies in different stages of their life cycles, different regulatory frameworks, and access to different production technologies. We would expect such differences to lead to different factor exposures. In this section, we discuss our approach to representing an index in factor space.

To build intuition, suppose value and momentum are the only risk factors. We measure each stock's exposure to value based on stock characteristics like forward earnings/price or book/price. We measure momentum using various characteristics of past returns. We create stock-specific factor loadings across the relevant index universe so every stock has a value score and a momentum score. Thus, since any given portfolio or index consists of individual stocks, each portfolio also has a value score and a momentum score, which can be computed by weighting the value and momentum scores of each constituent stock.

Suppose there is a particular index portfolio with scores of 0.4 and 0.25 to value and momentum, respectively. We assume there are two investible long-only factor portfolios, A and B. These could be ETFs or other vehicles, but the point is that they are accessible to investors. To be concrete, suppose portfolio A is a value fund and is assumed to have an average factor loading of 0.8 to value and -0.2 to momentum, while fund B has a loading of 0.0 to value and 0.7 to momentum. Then, we can exactly reproduce the

factor exposure of the index with an equally weighted factor portfolio of investible funds A and B:

	Value Score	Momentum Score
Portfolio A	0.8	-0.2
Portfolio B	0.0	0.7
$\frac{1}{2} A + \frac{1}{2} B$	0.4	0.25

Put another way, a portfolio equally weighted between funds A and B has value and momentum scores of 0.4 and 0.25, respectively, which matches the index. Since the portfolio of ($\frac{1}{2} A$ and $\frac{1}{2} B$) has the same factor scores as the index, we say that the portfolio ($\frac{1}{2} A$ and $\frac{1}{2} B$) reproduces the factor exposure of the index. In the language of Chen, Roll and Ross (1986), we have found a factor-mimicking portfolio for the index, which is the equally weighted portfolio of funds A and B.

In our analysis, we will use well-known benchmarks like the S&P 500 and the MSCI World as the major market indexes. We will use factor indexes capturing value, momentum, and other factors as the funds A and B. The factor indexes are tracked by investible ETFs, so the exposures are available via actual tradeable portfolios.

In reality, there are many more risk factors than just value and momentum. There may also exist several long-only investible portfolios that give the same factor exposures and we require a way to select from multiple mimicking factor portfolios. We use the benchmark index's current style exposures at a given time—based on a bottoms up constituent analysis—and find the combination of factors that provides the best fit in terms of characteristics that is closest to the fund's characteristics. That is, we find the best match of the mimicking factor portfolios to match the benchmark index by matching the stock-by-stock style scores. The resulting portfolio weights of the factor portfolios is the style exposure of the index.³

³ We are careful to use only information measurable at a given time in the calculation. The procedure to define "best" requires an optimization, which is described by Ang, Madhavan, and Sobczyk (2017) and is summarized in the appendix. In our context, this is a mean-square error minimization subject to the constraints that the portfolio is long-only and fully invested.

We may not always be able to create a fully invested portfolio that tracks the index perfectly. To see why, consider another index whose exposure to value were, say, -0.1 (i.e., a growth tilt, versus 0.4 in the last example), and zero to momentum. Then, we are not able to replicate the factor exposures of the index exactly with just long only combinations of funds A and B. In this case, the closest match (albeit imperfect) is a portfolio of 100% fund B. Accordingly, we now introduce the notion of tracking error in matching factor exposures.

2.2 Factor Goodness-of-Fit

Because of the long-only and potentially other constraints, the style scores of the major market benchmark index may not *exactly* match the factor exposures of a given collection of factor funds in the mimicking factor portfolio.⁴ We now introduce two metrics to track this fit. The factor mimicking portfolio has return, R_t^F , given by:

$$R_t^F = \sum_{j=1}^J w_{j,t}^{ETF} R_{j,t}^{ETF}. \quad (1)$$

In equation (1), there are $j=1 \dots J$ factor indexes in the mimicking factor portfolio where the j th factor has weight $w_{j,t}^{ETF}$ and returns $R_{j,t}^{ETF}$. We define the tracking difference (TD) to be the difference in returns between the factor portfolio and the index benchmark return, R_t^B :

$$TD_t = R_t^F - R_t^B \quad (2)$$

The tracking difference is a signed measure, and to the extent the mimicking portfolio captures the factor characteristics of the underlying index, this difference should be, on average, zero over shorter periods of time. Over longer period, if the mimicking factors are rewarded (in the sense they provide a risk premium over the benchmark), we would expect TD to be positive.

By contrast, the tracking error (TE) captures the absolute differences in return between the index and the mimicking portfolio, and is thus a measure of the goodness of

⁴ Clearly, if we were to relax the long-only constraint, we would always be able to find a unique set of mimicking portfolios as long as the matrix of portfolio factor loadings has full rank; that is, if there are J risk factors and J investible portfolios, we solve J linear equations in J unknowns (weights) to exactly match the factor exposures of any given index with a long/short combination of investible funds.

fit of the optimization exercise to create a long only representation. Here, factor tracking error is defined as the standard deviation of the tracking difference over a recent past period, which we take to be 30 days.

$$TE_t = \sigma(R_t^F - R_t^B) \quad (3)$$

The lower the tracking error, the higher the proportion of the variation of the index movements due to factors. The higher the tracking error, the more important are idiosyncratic, or non-factor components, in driving the returns of the market index.

2.3 Breadth of Factor Exposures

We can quantify the extent to which factor exposures are concentrated at any point in time t by the factor breadth of an index, denoted by B_t . We define factor breadth as the inverse of the Herfindahl-Hirschman Index (HHI), which is the sum of squares of the dynamic weights $w_{j,t}^{ETF}$ in the J investible factor portfolios:

$$B_t = 1 / \sum_{j=1}^J (w_{j,t}^{ETF})^2 \quad (4)$$

The HHI is widely used in economics to measure industry concentration and the distribution of individual attributes, like income inequality, and its inverse reflects breadth. For example, suppose the Herfindahl-Hirschman index for market share in a given industry with, say, 100 firms is 0.25. One way to interpret the Herfindahl-Hirschman index of 0.25 is that it corresponds to that of an industry with just $1/0.25 = 4$ equally-sized firms (because $4 \times 0.25^2 = 0.25$), an indication of relatively high concentration. If HHI = 0.05, the industry breadth is 20 (equally-sized) firms.

In our context, breadth captures the effective number of factors in an index. The lower the factor breadth, the fewer the factors the cap weight index is exposed to and the lower the diversification benefits of investing in that index. A related measure is relative breadth, which define as the ratio of breadth at a point in time to the breadth if all investible factors were equally represented, i.e., by B_t/J . Relative breadth is important because it offers a way to compare diversification across indexes using a single score between zero and one: zero representing no factors in the portfolio and one representing

all factors are present in the index. For example, if there were five factors and the HHI were 0.25, relative breadth would be 0.8. In words, most (80%) of the factors in our set are observed in this particular index.

2.4 Diversification Across Indexes

Finally, we are interested in comparing different benchmarks within the same region in terms of their diversity of factor exposures. The distribution of factor exposures across common benchmarks may exhibit greater similarity than might be suggested by their constituents. For example, the Russell 1000 and S&P 500 indexes differ by—at least—500 stocks, but their factor profiles may be relatively similar.

To capture the factor similarity of indexes A and B in the same region or globally, we compute the Active Factor Share (AFS) which is defined as the average difference between the J investible *factor* shares at any point in time:

$$AFS_t = (1/J) \sum |w_{j,t}^A - w_{j,t}^B|, \quad (1)$$

where the weights $w_{j,t}^M$ are the factor loadings for factor j in the factor mimicking benchmark for index M (here M is either A or B). Like the factor breadth measure, the AFS ranges between 0 and 1.

Smaller Active Factor Share numbers imply there are greater similarities in the factor space between two indexes, with zero denoting the factor representation is completely identical. At the opposite extreme, if index A loads only on, say, momentum and Index B loads only on, say, value, the Active Factor Share is equal to one. Thus, larger Active Factor Share numbers can be interpreted as indicating greater dissimilarity in terms of the factor representation between two indexes. The time dimension lets us see how diversification has varied across common benchmarks in the same region.

3. Data

We estimate the long-only factor representation of popular, major equity market indexes. In this section, we describe the factor portfolios, which we represent by widely used factor indexes. There are liquid, tradeable fund vehicles, especially ETFs, on all of the index benchmarks we study.

3.1 Factor Scores

In reality, of course, practitioners use models with multiple risk characteristics. For example, the MSCI Barra United States Equity Risk Model includes characteristics for Momentum, Volatility, Size, Size Non-linearity (a proxy for midcap), Value, Trading Activity, Growth, Earnings Yield and Variability, Leverage, Currency Sensitivity, and Dividend Yield, as well as 52 individual industry exposures. We use these factor scores to match those of the five factor portfolios defined below.

3.2 Factor Portfolios

Ross (1976) provides the original theoretical formulation of a linear multi-factor model of expected returns based on the absence of arbitrage. His theory, however, makes no determination as to the number of such factors which is ultimately an empirical question. Ang (2014) provides a summary of the empirical research on factors across regions and over time. A constant theme is that there are relatively few rewarded factors. For example, although many regard “growth”, which is the opposite of low prices relative to fundamental value, as a driver of returns, it is not in fact a *rewarded* factor based on prior empirical research (see, for example, Fama and French, 1993). The literature shows that there are a relatively small set of rewarded factors.

The individual factors we focus upon are size, value, momentum, (minimum or low) volatility, and quality. All five of these factors have been shown to be the source of return premiums, either because of a risk premium, structural market impediments, behavioral reasons, or a combination of all three. For example, smaller sized firms may

offer a liquidity premium, and value stocks may be undervalued relative to growth stocks, perhaps because they are less flexible in redeploying fixed capital or because of investors' biases. Similarly, momentum may arise because of delays in incorporating information or trend-chasing. Investors appear to over-pay or are over-optimistic on higher beta, higher volatility stocks, which may underlie the minimum volatility premium. Irrespective of the economic rationale for the risk premium, these factors have been shown (see, e.g., Ang, 2014) to be rewarded over the long-run across regions and time.

For the long-only investible factors, we select the MSCI single and diversified multiple factor (DMF) indexes, which offer a variety of targeted factor exposures and can be traded by an investor at low cost through US-domiciled ETFs. Index constituents were sourced on quarterly basis. We define the factor portfolios in terms of their risk characteristic scores. We estimate the factor exposures because we match on these scores. We map the U.S. indexes using the characteristic scores of the BARRA United States Equity Risk model risk to the following five long-only MSCI factor indexes:

- Value: MSCI USA Enhanced Value Index
- Momentum: MSCI USA Momentum Index
- Size: MSCI USA Risk Weighted Index
- Low Volatility: MSCI USA Minimum Volatility Index
- Quality: MSCI USA Sector Neutral Quality Index

For international indexes, we take characteristics from the BARRA GEM2 Global Equity Risk model, and use the following long-only MSCI factor indexes, which are also tracked by ETFs:

- Value: MSCI World Enhanced Value Index
- Momentum: MSCI World Momentum Index
- Size: MSCI World Mid-Cap Equal Weighted Index
- Low Volatility: MSCI World Minimum Volatility Index
- Quality: MSCI World Sector Neutral Quality Index.

We turn now to the results of our analysis.

4. Empirical Results

We estimate the amount of global indexed equity assets to be \$11.9 trillion (versus \$17.3 trillion that is actively managed) out of a total world market capitalization of \$67.9 trillion.⁵ In this context, index funds include ETFs, institutional indexing and index funds. Indexing is thus a relatively small fraction (17.5%) of total global equity. Nevertheless, the total size of indexed assets indicates the importance of investors understanding the factor exposures in their benchmarks. We first estimate factor loadings of the most popular US stock indexes, including the S&P 500 index and the Russell 1000 Index in Section 4.1. We investigate international MSCI indexes in Section 4.2, and compare and contrast these benchmarks to popular US indexes.

4.1 Major US Equity Indexes

The S&P 500

The S&P 500 is an important index benchmark for large-cap US equities. The index includes 500 large companies, selected by a committee, which represent about 80% of the total U.S. stock market. As of June 30 2017, the S&P 500 total market capitalization is about \$21 trillion; approximately \$7.8 trillion was benchmarked to the index, with index assets comprising approximately \$2.2 trillion.⁶

In Exhibit 1, we plot the factor decomposition of the S&P 500 over time at the quarterly frequency from the first quarter of 2002 to the first quarter of 2017. We map the S&P 500 index to our five investible long-only factors: value, quality, size, momentum, and minimum volatility following the procedure outlined in the appendix. As of March 31, 2017, the mimicking factor portfolio for the S&P 500 was 46.6% quality, 27.2% value, and 26.2% momentum. However, the factor exposures of the S&P 500 have not been constant. The minimum factor decomposition to quality, for example, occurs at December

⁵ Primary sources: S&P Dow Jones Indexes based on survey data. World Federation of Exchange Database (WFED), SIFMA, ECB, BIS, HFR, Cerulli, Simfund (data as of Dec 2016), iShares GBI (data as of Dec 2016), and McKinsey data.

⁶ Source: S&P Dow Jones Indexes, as of June 30, 2017. The amount indexed to the S&P 500 is an estimate (based on survey methods by the index provider).

2008 where quality represented 28.0% of the index. The maximum exposure of the S&P 500 to quality of 58.1% occurred in September 2009. Momentum had minimum and maximum exposures of 0.0% and 36.8% at June 2005 and December 2012, respectively.

What explains these changes in the factor composition of the index? In the period post the 2008 financial crisis, the U.S. large cap segment has experienced strong returns, driven by many companies in the technology sector and a recovery in financial and energy stocks which had low valuations during the financial crisis. It is not surprising that over the past five years, we observe lower weight on minimum volatility and quality factors, with increasing weight in momentum and value factors. Recent speculation about reduced taxes and deregulation have only strengthened these trends.

It is interesting that there is no minimum volatility present in the S&P 500 in the most recent period, March 2017. This is *not* by construction—the optimization process chooses the factor mimicking portfolio that best represents the present, stock-by-stock, style exposures of the index. The absence of minimum volatility as of March 2017 thus implies that the other factors dominate at present.

We find that the proportion of the S&P 500 index movements explained by factors has materially increased in recent years. Exhibit 2 shows the tracking error and the tracking difference of the investible factor portfolio for the S&P 500 Index. Recall that at each point in time, we compute the tracking error using the past 30 days. Exhibit 2 smooths these monthly tracking error numbers with a five-year moving average to identify more long-term trends. In recent periods, both the tracking error and the tracking difference have decreased from their longer term averages. (This phenomenon is consistent across the global benchmarks we analyze, as discussed below.) This implies that factors are increasingly able to represent the movements of major benchmarks. Note that the tracking difference has been generally positive, which is consistent that rewarded factors are providing a long-term risk premium over and above market returns.

Even though the factor composition of the S&P 500 has changed dynamically, the factor breadth of the S&P 500 index has remained relatively constant. Over 2002 to 2016 there are, on average, effectively a breadth of 2.9 factors. Recall that the *relative* factor

breadth is the ratio of breadth at a point in time to the breadth if all investible factors were equally represented.⁷ In quarter ended March 31, 2017, the factor breadth was 2.78 and the relative factor breadth was 55.6%. In practical terms, this means that the effective number of factor bets has been small, and there was much less diversification than might be suggested by a 500 stock portfolio. For example, the share of minimum volatility at March 2017 is zero, which suggests that a passive investor who blends a minimum volatility portfolio with the S&P 500 index can increase diversification by improving the diversity of factor exposures. The lesson here is that passive investors are accidental factor investors and need to be aware of their benchmark factor exposures from a diversification and return viewpoint.

Russell Indexes

Exhibit 3 graphs the factor representation of the Russell 3000, Russell 1000 and Russell 1000 Growth Indexes over time. The most striking difference is between Russell 1000 Growth (the category with the most active mutual fund assets), which is essentially a low breadth bet on momentum and quality. Interestingly, other U.S. indexes show very different factor patterns compared to the S&P 500. The Russell 3000, one of the broadest benchmarks for US equity markets, has a much larger factor breadth, on average 4.2 factors. Indexes with more narrow ranges, like the Russell 1000 Growth, show even lower factor breadth, at 2.1 factors, on average, as shown in Exhibit 4. Thus, even though there are around 2000 stocks that are different between the Russell 3000 and the Russell 1000, the addition of 2000 smaller cap names to the Russell 1000 index does not significantly expand factor diversification.

4.2 International Indexes

We turn now to an analysis of major indexes outside the U.S.

Exhibit 5 plots the realized five-year and 15-year (full sample) factor tracking error across nine key global benchmarks ending in March 2017. In all cases, the most recent

⁷ Note that if all 5 factors were equally represented (20% weight each), the breadth would be 5.

smoothed five-year tracking error estimate is lower compared to the full-sample estimate over the last 15 years. For example, the tracking error for MSCI World Index in the last five years, which is 1.04%, was only 59% of the full sample 15-year estimate, which is 1.76%. This reduction in factor tracking error could be explained by the growing importance of a macro-driven environment or the increased significance of economy-wide risk on financial markets post the financial crisis.

We also observe that the tracking error for the Emerging Markets (EM) index is much higher than other indexes. This reflects the fact that there are more idiosyncratic drivers of returns for the EM index. For example, many emerging markets (e.g., Russia, Mexico) are subject to commodity price shocks that are not well tracked by the equity factor mimicking portfolios. Further, the EM index constituents are relatively diverse in size, geography, regulatory jurisdiction and there is large heterogeneity in other considerations such as state ownership relative to U.S. indexes like the S&P 500.

Exhibit 6 lists the factor mimicking portfolios for major global, market-cap weighted benchmarks as of March 2017. The broadest market capitalization benchmarks experience the largest declines in factor tracking error: MSCI World (59%), MSCI EAFE (54%), Russell 3000 (70%), and MSCI EMU (72%). Again, this is consistent with the idea that factors—not idiosyncratic return elements—are becoming increasingly important. There is considerable diversity of factor breadth across the global indexes. Interestingly, European indexes have exhibited strong exposure to quality and value, echoing other authors that posit a link between culture in different countries and factor exposure (see Chui, Titman, and Wei, 2010). We also find that growth indexes have shown large exposure to momentum: the Russell 1000 Growth for example had a momentum share of 50% as of March 2017.

We compute the Active Factor Share (AFS) at March 2017 of the major indexes relative to the factor composition of the MSCI All Country World Index (ACWI). Interestingly, the S&P 500, with large global constituents had an AFS of just 4.1%. This is similar to the 6.5% active factor share for the MSCI EAFE index. By contrast, more specialized regional or style indexes had much higher Active Factor Shares. For example,

the Russell 1000 Value and Growth Indexes have AFS measures of 19.8% and 17.0%, respectively.

The pattern of cross country variation shown in Exhibit 7 is also of interest, with a clear increase in tracking error as we get to smaller countries. This is seen directly in Exhibit 7, which orders the countries by factor tracking error. Our analysis shows that European market cap benchmarks have had much more pronounced value exposure. In contrast, in the U.S., we observe a higher proportion of momentum and quality, which themselves are indicative of growth characteristics. Put another way, Europe indexes have been mostly value, whereas U.S. indexes have been mostly growth.

5. Conclusion

Market capitalization portfolios are special. They have important theoretical roles in economic models in representing exposure of a representative agent, as a proxy for an average investor, and because of the wide-spread availability of low-cost index funds and ETFs, market cap indexes are now standard building blocks for investor portfolios. The market cap portfolio, however, is just one type of portfolio. All stocks are exposed to a few factors—broad and persistently rewarded drivers of return—and, therefore, market cap indexes are also exposed to these systematic factors.

We show what factors are in major market indexes, and describe how the factor exposures vary over time. Our methodology constructs a factor mimicking portfolio of any market index using cross-sectional risk attributes, rather than traditional time-series approaches. Consistent with the predominately long-only mandates in asset management, we conduct our factor analysis using long-only factor portfolios. We find that most cap weighted indexes are effectively exposed to only two or three factors, with value and momentum being increasingly prevalent. The major U.S. equity indexes often contains little, and often no, exposure to minimum volatility. These results imply that there can be significant diversification benefits to including these omitted factors to investors' portfolios.

We find that the proportion of the index movements explained by factors has materially increased in recent years, which is consistent with a more top-down, macro-driven environment or the increasing importance of economy-wide risks for financial markets. This makes factor analysis and allocation—a deliberate and thoughtful top-down approach to understanding the factors present in portfolios—increasingly important for investors seeking maximum performance, reduced risk, or superior diversification. Another important reason that investors should know what factors are in their index is we show that the type and distribution of factor exposures across common benchmarks may exhibit greater similarity than might be suggested by their constituents.

Our methodology can be extended in several ways. Although we used a long-only lens in our analysis, our approach can be extended to long-short factors. There are many other types of exposures that are available in an index format besides market capitalization weights. Analyzing the factor exposures of Environmental, Social and Governance (ESG) indexes, for example, is an interesting area for further research.

Appendix

The objective is to translate an index's cross-sectional risk characteristics (exposures) into investible factor index exposures. At the start of period t , for a given index, define a *factor portfolio* comprising weights $w_{j,t-1}^{ETF}$ in an investible index factor $j=1...J$ where the number of investible funds (e.g., ETFs) does not exceed the number of possible risk factors. We require the weights in the index portfolio to satisfy $0 \leq w_{j,t-1}^{ETF} \leq 1$ and $\sum_{j=1}^M w_{j,t-1}^{ETF} = 1$, i.e., the portfolio is long-only and fully invested. Denote by $\hat{\beta}_{j,k,t}^{ETF}$ the exposure of investible fund j to risk factor k in period t . Note that $\hat{\beta}_{j,k,t}^{ETF}$ is taken as the weighted average exposure to factor k over the individual stocks held by the investible fund j , where (in keeping with our goal of capturing total returns) we use each stock's total (not active) weight at the start of period t . It follows that the expected return of the *index factor portfolio* with weights $w_{j,t-1}^{ETF}$ (where $j=1...M$) in t is $E[R_t^{ETF}]$ where:

$$E[R_t^{ETF}] = \sum_{j=1}^M w_{j,t-1}^{ETF} \left(\sum_{k=1}^K E(\hat{\beta}_{j,k,t}^{ETF}) E(F_{k,t}) \right) \quad (A.1)$$

Note that as index factor funds are constructed as passive vehicles, the timing and alpha components in the decomposition are zero by construction, so that the expected return contribution from a position in investible fund j to risk factor k is $E(\hat{\beta}_{j,k,t}^{ETF}) E(F_{k,t})$.

The difference between the fund's expected total return attributable to static exposures to the K risk factors (from equations (1) and (5)) and the expected return of the index factor portfolio (from equation (A.1)) is denoted by $\hat{\eta}_t$ where:

$$\hat{\eta}_t = \sum_{k=1}^K E(\hat{\beta}_{k,t}) E(F_{k,t}) - \sum_{j=1}^M w_{j,t-1}^{ETF} \left(\sum_{k=1}^K E(\hat{\beta}_{j,k,t}^{ETF}) E(F_{k,t}) \right) \quad (A.2)$$

The ordinary least-squares estimate for the index factor portfolio at time t is the set of M weights $w_{j,t-1}^{ETF}$ that minimizes the squared residual in equation (A.2) subject to the following constraints:

$$\begin{aligned} & \sum_{j=1}^M w_{j,t-1}^{ETF} = 1, \\ & \text{and } 0 \leq w_{j,t-1}^{ETF} \leq 1, \text{ for each } j=1...M. \end{aligned} \quad (A.3)$$

To estimate the unknown index factor portfolio weights w_{t-1}^{ETF} (for the start of time t), we first estimate expected factor exposures for the mutual fund using data available at time $t-1$. Since factor exposures are likely to evolve slowly from quarter to quarter, we model the mutual fund's exposures to factor k as in time t as:

$$E(\hat{\beta}_{k,t}) = \hat{\beta}_{k,t-1} \quad (A.4)$$

Note that equation (A.4) can be interpreted as follows: the optimization results in a cross-sectional regression that uses only current information at time $t-1$ to set the weights for the coming quarter and translates risk characteristics into investible factor index exposures (factor portfolio weights). Moreover, this procedure also works for any set of factors.

To map the risk model factors to commonly understood style factors, we project the fund's risk exposures using the BARRA USE3 model (all style characteristics and sectors) to the corresponding matrix of MSCI single factor index exposures (see below) for size, value, momentum, minimum volatility, and quality.

We adjust risk management factor exposures to report aggregated style factor decompositions. One drawback of using risk management factors is that they may not line up with our prior intuition from Fama and French (1993) and others who construct investment strategies using particular characteristics to capture the effects of various investment styles. The empirical implementation of equations (A.1)-(A.4) is as follows: The Smart Beta investible factor proxies are: Size (MSCI USA Risk Weighted Index), Value (MSCI USA Enhanced Value Index), Momentum (MSCI USA Momentum Index), Minimum Volatility (MSCI USA Minimum Volatility Index), and Quality (MSCI USA Sector Neutral Quality Index), and the MSCI USA Diversified Large/Mid Cap Multiple factor index, and MSCI Diversified Small Cap Multiple factor index. For the index in question, each quarter, we estimate index factor weights using risk characteristic exposures at $t-1$, so there is no look-ahead bias.

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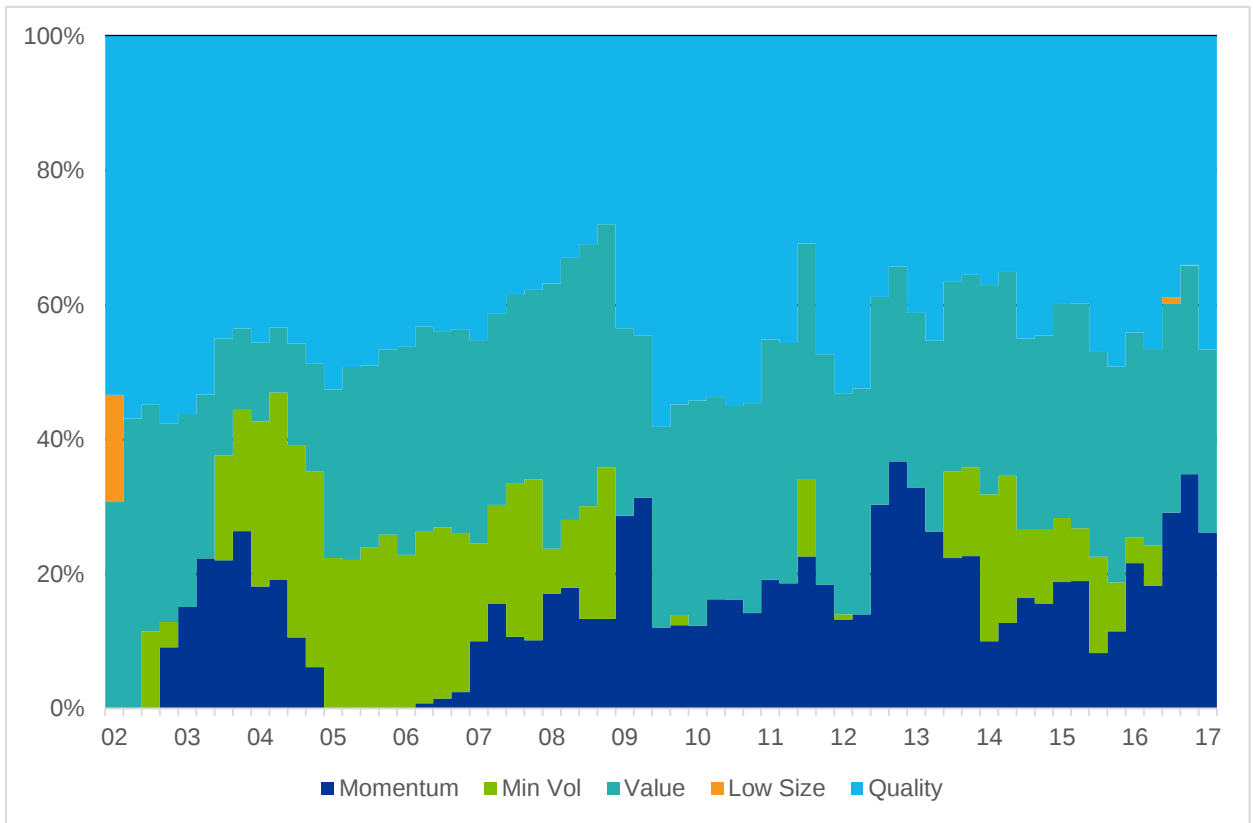
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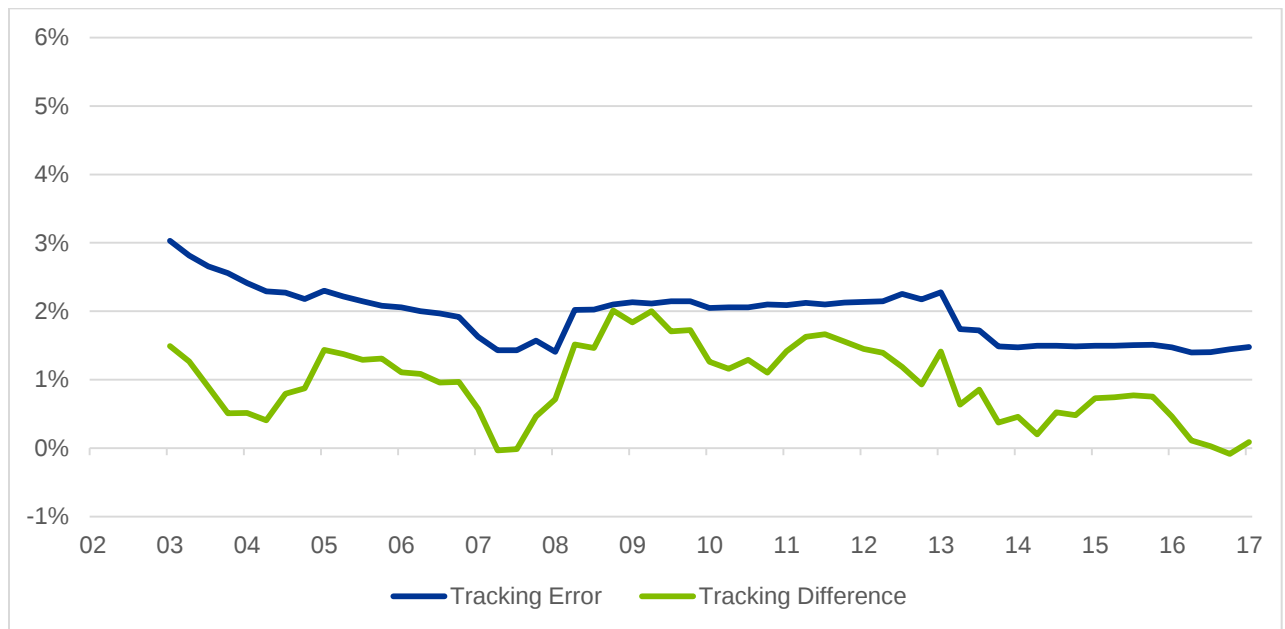
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Exhibit 1
Investible Factor Decomposition of S&P 500 Index



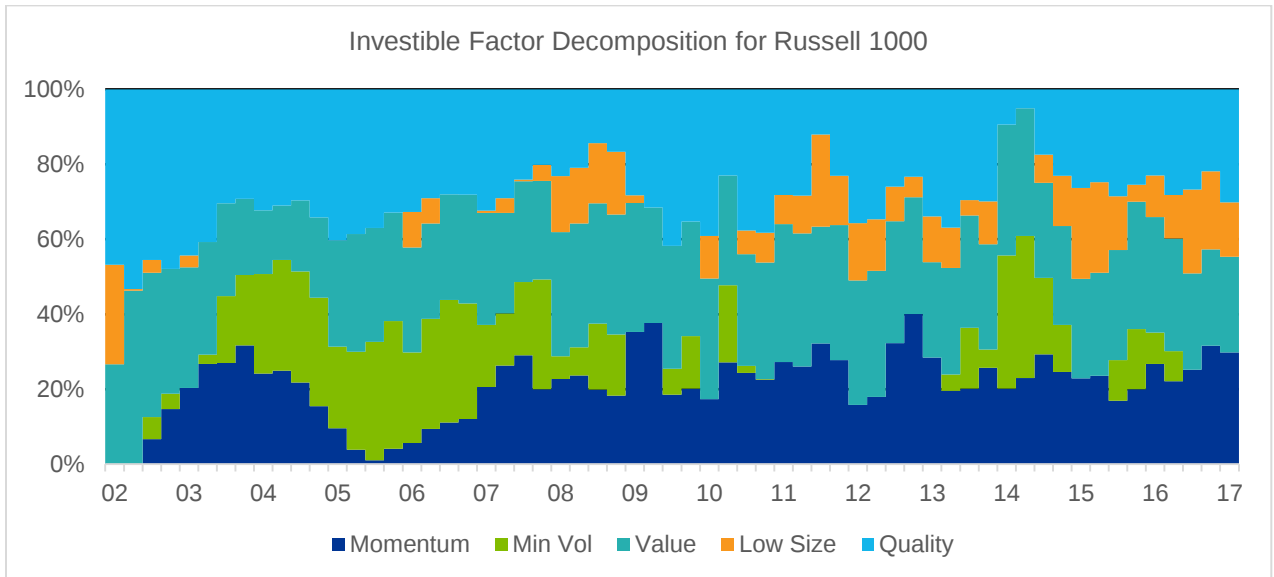
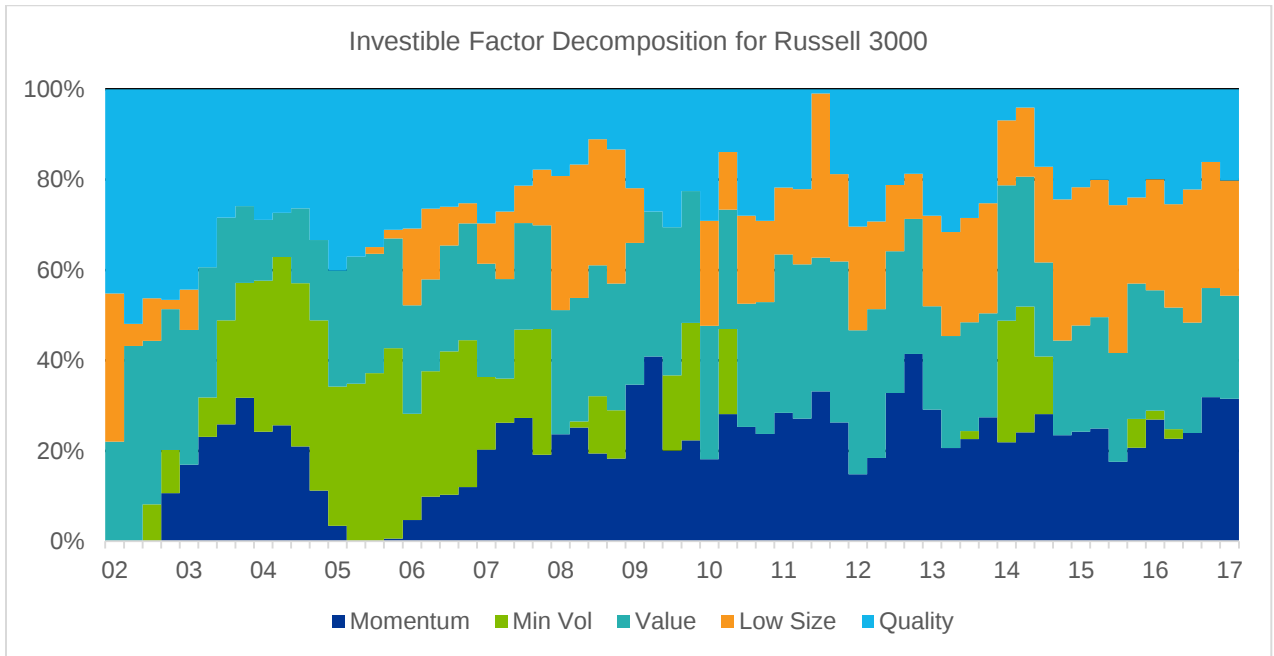
Source: Based on data from Morningstar, MSCI, and Russell for 3/31/2002 - 3/31/2017

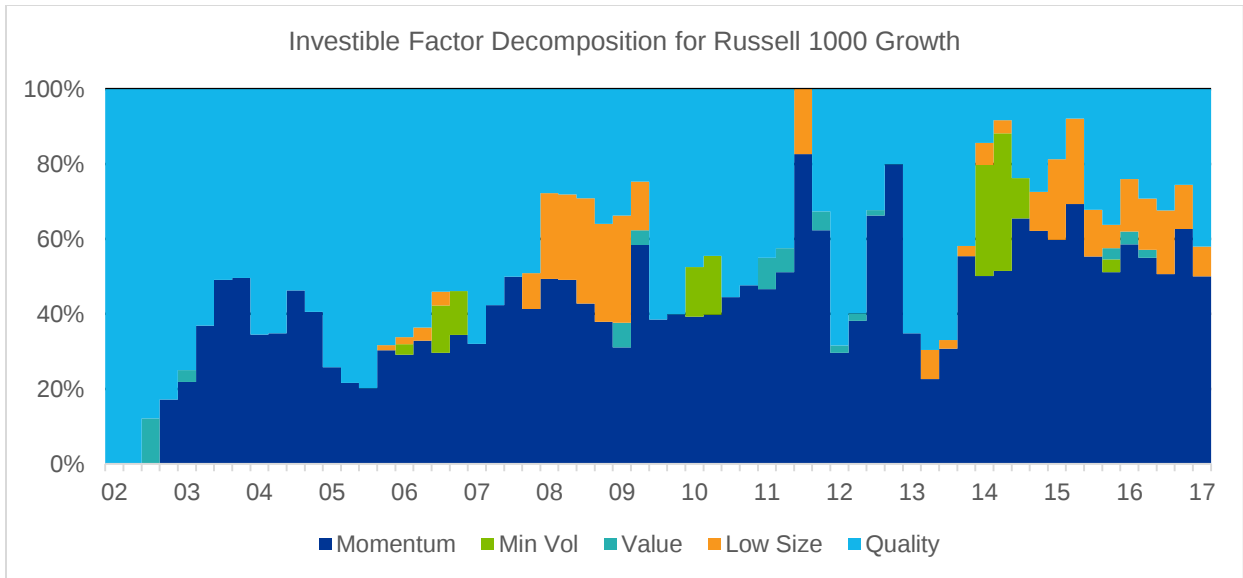
Exhibit 2
Tracking Error and Tracking Difference (Rolling 5-year estimate) for S&P 500 Index



Source: Based on data from Morningstar, MSCI, and Russell from 3/31/2002 - 3/31/2017

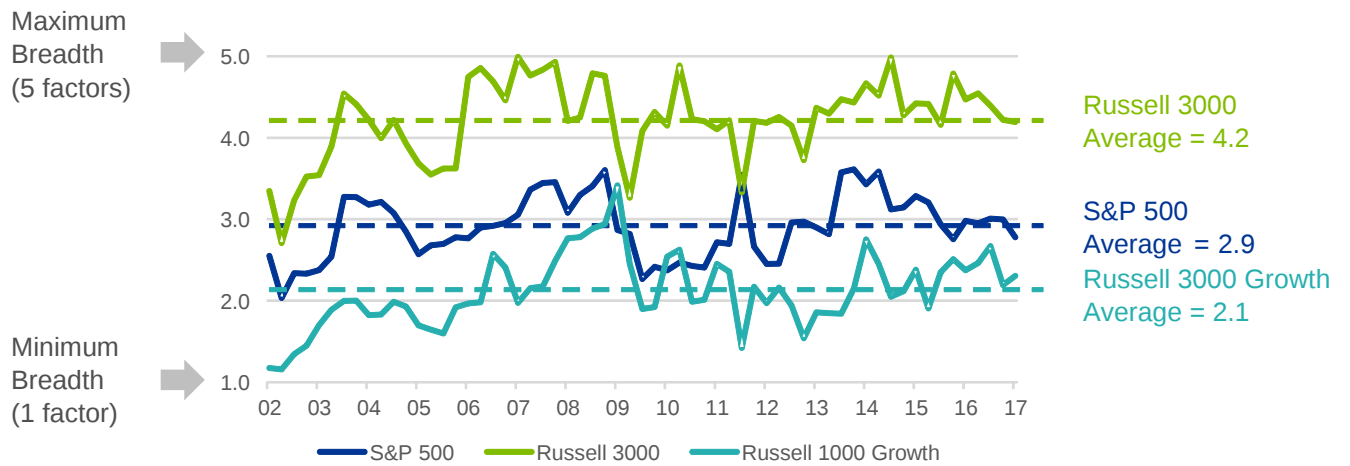
Exhibit 3
Investible Factor Decomposition for Russell 3000, Russell 1000, and Russell 1000
Growth Indexes





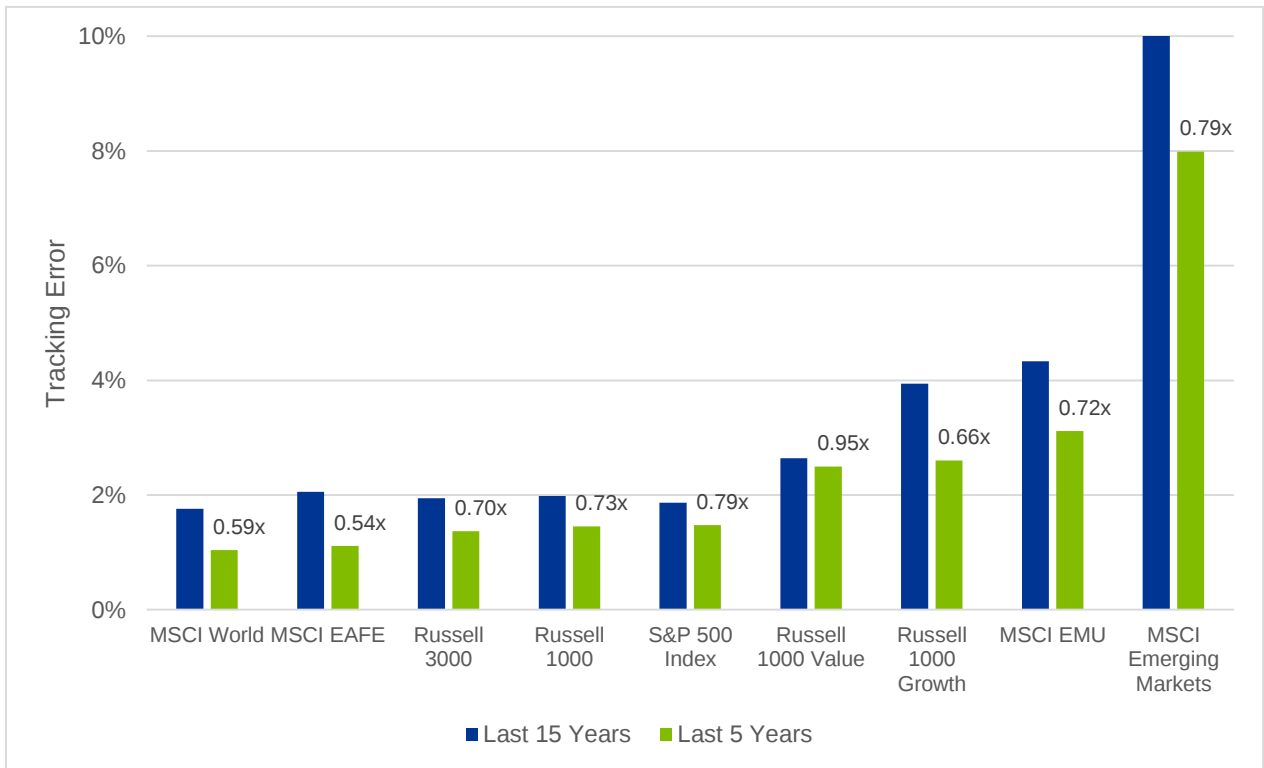
Source: Based on data from Morningstar, MSCI, and Russell for 3/31/2002 - 3/31/2017

Exhibit 4 **Factor Breadth of the S&P 500, Russell 3000, and Russell 1000 Growth Indexes**



Source: Based on data from Morningstar and S&P Dow Jones, 3/31/2002 - 3/31/2017

Exhibit 5 Comparison of Tracking Error Estimates for Global Benchmarks



Source: Based on data from Morningstar, MSCI, and Russell for 3/31/2002 - 3/31/2017

Exhibit 6
Factor Mimicking Portfolios for Major Market-Cap Weighted Benchmarks as of
3/31/2017

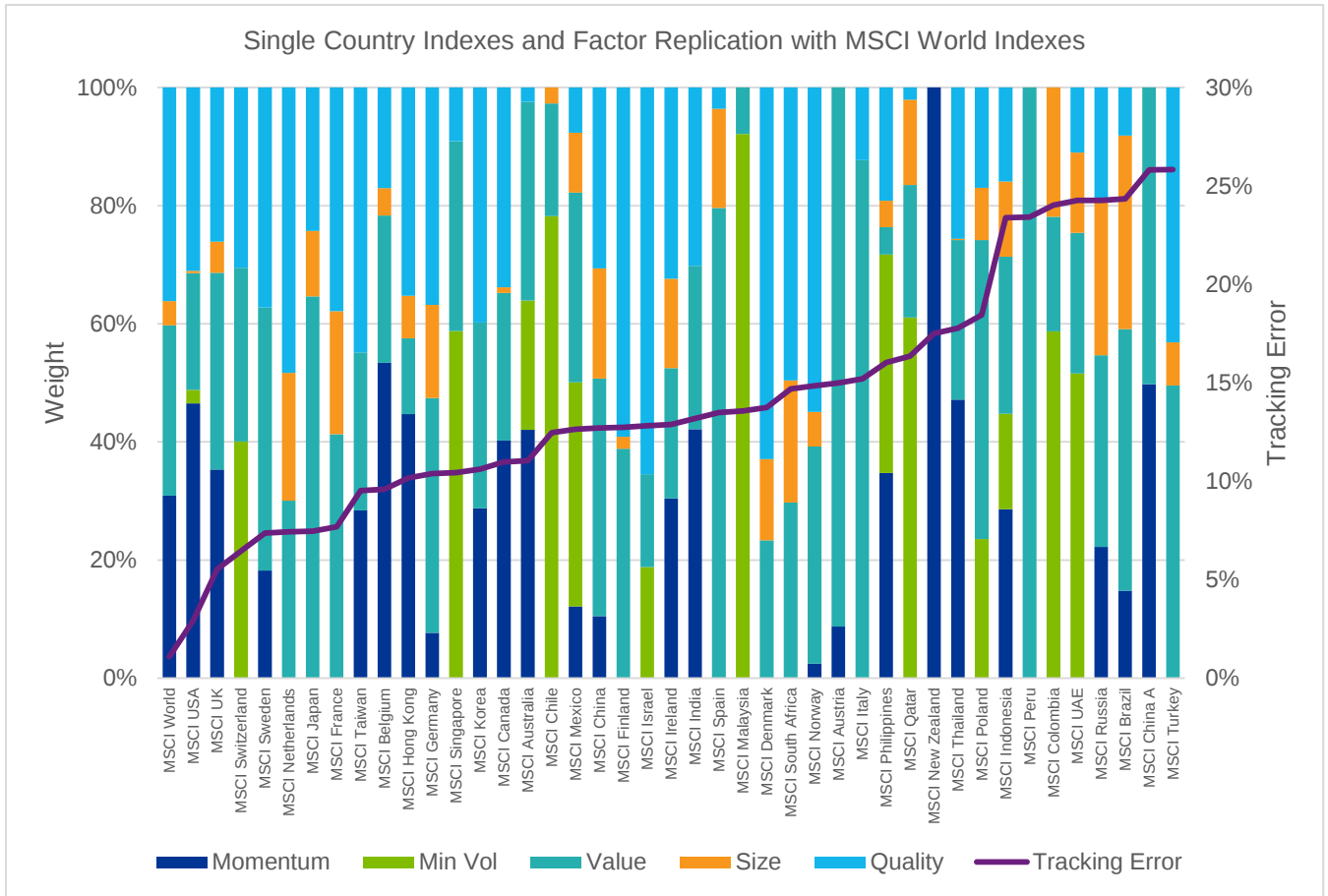
Index Name	Market Cap (\$T)	Current Factor Breadth	Tracking Error (5Y)	Tracking Error (15Y)	Current Factor Mimicking Portfolio				
					Momentum	Min Vol	Value	Low Size	Quality
MSCI World	36.6	3.56	1.04%	1.76%	26.4%	10.3%	32.3%	0.0%	31.0%
MSCI ACWI	41.2	3.48	1.74%	2.20%	27.0%	8.3%	32.8%	0.3%	31.6%
MSCI ACWI and FM	51.1	3.49	1.75%	2.19%	27.0%	8.5%	32.8%	0.3%	31.5%
MSCI EAFE	17.7	3.32	1.11%	2.05%	18.4%	9.6%	41.5%	1.3%	29.2%
MSCI EMU	5.6	2.74	3.12%	4.33%	14.4%	2.8%	47.3%	0.9%	34.6%
MSCI Emerging Markets	4.5	3.67	7.99%	10.10%	26.3%	13.8%	34.8%	0.0%	25.1%

Index Name	Market Cap (\$T)	Current Factor Breadth	Tracking Error (5Y)	Tracking Error (15Y)	Current Factor Mimicking Portfolio				
					Momentum	Min Vol	Value	Low Size	Quality
Russell 3000	26.3	4.19	1.37%	1.95%	31.5%	0.0%	22.8%	25.5%	20.2%
Russell 1000	24.1	3.76	1.45%	1.98%	29.8%	0.0%	25.5%	14.4%	30.2%
S&P 500	20.5	2.78	1.48%	1.87%	26.2%	0.0%	27.2%	0.0%	46.6%
Russell 1000 Value	15.5	2.07	2.50%	2.64%	5.8%	33.6%	60.6%	0.0%	0.0%
Russell 1000 Growth	16.1	2.31	2.60%	3.94%	50.0%	0.0%	0.0%	7.9%	42.1%

Source: Based on data from Morningstar, MSCI, and Russell as of 3/31/2017

Exhibit 7

Factor Mimicking Portfolios for Single Country Indexes



Source: Based on data from Morningstar, MSCI, and Russell as of 3/31/2017

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