Foundations of Factor Investing

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Executive Summary

Factor investing has become a widely discussed part of today's investment canon. In this paper, we discuss the rationale for factor investing and how indexes can be constructed to reflect factor returns in cost-effective and transparent ways.

A factor can be thought of as any characteristic relating a group of securities that is important in explaining their return and risk. A large body of academic research highlights that long term equity portfolio performance can be explained by factors. This research has been prevalent for over 40 years; Barra (now an MSCI company) for instance has undertaken the research of factors since the 1970s.

Certain factors have historically earned a long-term risk premium and represent exposure to systematic sources of risk. Factor investing is the investment process that aims to harvest these risk premia through exposure to factors. We currently identify six equity risk premia factors: **Value, Low Size, Low Volatility, High Yield, Quality and Momentum.** They are grounded in academic research and have solid explanations as to why they historically have provided a premium.

MSCI has created a family of factor indexes that are designed to reflect the performance of those six equity risk premia factors. In turn, indexation has provided a powerful way for investors to access factors in cost-effective and transparent ways. Factor allocations can be implemented passively using factor indexes, which may bring potential cost savings to institutional investors. Furthermore, factor indexes bring transparency to factor allocations, which helps alleviate the well-known problem of manager style drift and has positive implications for risk management.

We note that factor indexes should not be viewed as replacements for market cap indexes. Market capitalization weighted indexes represent both the opportunity set of investors as well as their aggregate holdings. Market cap weighted indexes are also the only reference for a truly passive, macro consistent, buy and hold investment strategy. They aim to capture the long term equity risk premium with structurally low turnover, very high trading liquidity and extremely large investment capacity. In contrast, factor indexes rebalance away from a neutral market cap starting point. As such, they represent the result of an active view or decision. Investors must form their own belief about what explains the historical premium and whether it is likely to persist.

Factor returns have also been highly cyclical. These systematic factors have been sensitive to macro-economic and market forces and have underperformed the overall market for long periods of time. However, they have not all reacted to the same drivers and, hence, any one of them can have low correlations relative to other factors. Diversification across factors has historically reduced the length of these periods of underperformance. Thus, the MSCI Factor Indexes provide building blocks that allow investors to assemble multi-factor allocations based on their preferences for performance and risk, their investment beliefs on individual factors, and their investability constraints.

Introduction

Factor investing has become a widely discussed part of today's investment canon. This paper is the first in a three-paper series focusing on factor investing. In this paper we lay out the rationale for factor investing and how indexation can capture factors in cost-effective and transparent ways.[1] Specifically, institutional and individual investors around the world have asked many of the same questions:

- ***What are factors? Why have they provided better risk-adjusted return historically and how likely is that to persist in the future?***

- ***How does one capture factors via allocations to investable indexes?***

- ***How should investors think of factor indexes relative to market cap weighted indexes and active management?***

This paper focuses on the above questions. In Section I, we highlight that factors should be grounded in the academic literature and should be important in explaining portfolio returns in standard performance risk and attribution models. We also distinguish between generic factors and factors that reflect risk premia. The latter are factors that earn a persistent risk-adjusted premium over time and reflect exposure to sources of systematic risk.

In Section II, we discuss the proposed drivers of factors' excess returns. Understanding the potential drivers of factor returns is critical to forming a belief about their likelihood to persist in the future. Different theories have been advanced to explain why factors have historically earned a premium. One view is that factor returns are compensation for bearing systematic risk. A second view is that factor returns arise from systematic errors; either investors exhibit behavioral biases or investors are subject to different constraints (e.g., time horizons, ability to use leverage, etc.).

In Section III, we address the question of how factors should be viewed relative to market capitalization weighted portfolios. The latter represent both the opportunity set of investors as well as their aggregate holdings. The market cap weighted benchmark is the only reference for a truly passive, macro consistent, buy and hold investment strategy which aims to capture the long term equity risk premium with extremely low turnover, very high trading liquidity and infinite investment capacity. Factor portfolios on the other hand rebalance away from a neutral market cap starting point. As such, they represent an active view.

In Section IV, we note the significant cyclicality of factor returns. There is importantly no free lunch attached to factor investing. All factors have experienced periods of underperformance and some factors have been highly cyclical. Their cyclicality may in fact be one of the reasons they have not been arbitraged away.

In Section V, we introduce the concept of capturing factors through indexation. Until recently, capitalizing on systematic factors could only reasonably be done by active managers. Factor indexes allow institutional investors to create passive factor allocations in the transparent and cost efficient framework of indexation. Finally in Section IV, we illustrate the use of indexation through the MSCI Factor Indexes.

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[1] The next paper in this series covers various aspects of implementation including use cases we have seen.

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I.   What Are Factors?

Factors Have Their Roots in the Academic Literature

The question of what drives stock returns has been a staple of modern finance. The oldest and most well-known model of stock returns is the Capital Asset Pricing Model (CAPM), which became a foundation of modern financial theory in the 1960s (Lintner, 1965; Mossin, 1966; Sharpe, 1964 and Treynor, 1961). In the CAPM, securities have only two main drivers: systematic risk and idiosyncratic risk. Systematic risk in the CAPM is the risk that arises from exposure to the market and is captured by beta, the sensitivity of a security's return to the market. Since systematic risk cannot be diversified away, investors are compensated with returns for bearing this risk. In other words, the expected return to any stock could be viewed as a function of its beta to the market.[2]

Later, Ross (1976) proposed a different theory of what drives stock returns. "Arbitrage pricing theory" (APT) holds that the expected return of a financial asset can be modeled as a function of various macroeconomic factors or theoretical market indexes[3]. We can credit Ross with popularizing the original term "factors," as the models he popularized were called "multi-factor models."   Importantly, APT, unlike the CAPM, did not explicitly state what these factors should be. Instead, the number and nature of these factors were likely to change over time and vary across markets. Thus the challenge of building factor models became, and continues to be, essentially empirical in nature.

In general, a factor can be thought of as any characteristic relating a group of securities that is important in explaining their returns and risk.   As noted in the early CAPM-related literature, the market can be viewed as the first and most important equity factor. Beyond the market factor, researchers generally look for factors that are persistent over time and have strong explanatory power over a broad range of stocks.[4]   Since, unlike stock returns, factors cannot be directly observed, there of course remains a vigorous debate about how to define and estimate them.[5] There are three main categories of factors today: macroeconomic, statistical, and fundamental.[6] Macroeconomic factors include measures such as surprises in inflation, surprises in GNP, surprises in the yield curve, and other measures of the macro economy (see Chen, Ross, and Roll (1986) for one of the first most well-known models).   Statistical factor models identify factors using statistical techniques such as principal components analysis (PCA) where the factors are not pre-specified in advance.[7]

Arguably the mostly widely used factors today are fundamental factors. Fundamental factors capture stock characteristics such as industry membership, country membership, valuation ratios, and technical indicators, to name a few. The most popular factors today – Value, Growth, Size, Momentum – have

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[2] The expected return to a stock would just be its beta times the assumed market return. Investors would need no compensation for the idiosyncratic return which would diversify across many stocks.

[3] The model-derived rate of return would then be used to price the stock correctly. The stock price should equal the expected end of period price discounted at the rate implied by the model, and if the price diverged, arbitrage would bring it back into line.

[4] Miller (2006) discusses three key statistical criteria for factors: persistence over time, "large enough" variability in returns relative to individual stock volatility, and application to a "broad enough" subset of stocks within the defined universe.

[5] Factor returns can be constructed by building factor portfolios that "mimic" the target factor (as in the Fama-French approach). Factor returns can alternatively be estimated through cross-sectional regression (as in the Barra approach). As far as estimation techniques go, there is a nearly infinite range of techniques that have been applied to factor estimation – principal components analysis, panel regressions, Bayesian models, latent factor models, to name a few.

[6] Connor (1995) gives a comprehensive overview of these three types of factor models.

[7] The question of which type of model is the best continues to be hotly debated. Typically, the appropriateness of a model comes down to the use case. And of course, within each type of model, there continue to be many debates over the best way to construct a model and specify factors.

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been studied for decades as part of the academic asset pricing literature and the practitioner risk factor modeling research. Rosenberg and Marathe (1976) were among the first to describe the importance of these stock traits in explaining stock returns,[8] leading to the creation of the multi-factor Barra risk models. Later, one of the best known efforts in this space came from Eugene Fama and Kenneth French in the early 1990s. Fama and French (1992, 1993) put forward a model explaining US equity market returns with three factors: the "market" (based on the traditional CAPM model), the size factor (large vs. small capitalization stocks) and the value factor (low vs. high book to market). The "Fama-French" model, which today includes Carhart's (1997) momentum factor, has become a canon within the finance literature. In the past few decades, researchers have studied a host of other stock traits, from income statement and balance sheet measures like earnings revisions and accruals to technical indicators like volatility and relative strength (momentum). The latest research has even looked at non-traditional factors like the number of "Google" hits a stock receives or the number of times it is mentioned in mainstream media.

Exhibit 1 summarizes six of the most widely studied factors. More recently, Low Volatility, Yield, and Quality factors have become increasingly well-accepted in the academic literature (see Appendix A).

Exhibit 1: Well-Known Systematic Factors from the Academic Research

Systematic Factors	What It is	Commonly Captured by
Value	➢ Captures excess returns to stocks that have low prices relative to their fundamental value	➢ Book to price, earnings to price, book value, sales, earnings, cash earnings, net profit, dividends, cash flow
Low Size (Small Cap)	➢ Captures excess returns of smaller firms (by market capitalization) relative to their larger counterparts	➢ Market capitalization (full or free float)
Momentum	➢ Reflects excess returns to stocks with stronger past performance	➢ Relative returns (3-mth, 6-mth, 12-mth, sometimes with last 1 mth excluded), historical alpha
Low Volatility	➢ Captures excess returns to stocks with lower than average volatility, beta, and/or idiosyncratic risk	➢ Standard deviation (1-yr, 2-yrs, 3-yrs), Downside standard deviation, standard deviation of idiosyncratic returns, Beta
Dividend Yield	➢ Captures excess returns to stocks that have higher-than-average dividend yields	➢ Dividend yield
Quality	➢ Captures excess returns to stocks that are characterized by low debt, stable earnings growth, and other "quality" metrics	➢ ROE, earnings stability, dividend growth stability, strength of balance sheet, financial leverage, accounting policies, strength of management, accruals, cash flows

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[8] In fact, they argued that the impact of macroeconomic events on individual securities was better captured through these stock characteristics.

Empirical studies show that these factors have exhibited excess returns above the market.[9] For instance, the seminal Fama and French (1992) study found that the average small cap portfolio (averaged across all sorted book-to-market portfolios) earned monthly returns of 1.47% in contrast to the average large cap portfolio's returns of 0.90% from July 1962 to December 1990. Similarly, the average high book-to-market portfolio (across all sorted size portfolios) earned 1.63% monthly returns compared to 0.64% for the average low book-to-market portfolios. Fama-French's cumulative factor returns through August 2013 are shown in Exhibit 2 (sourced from Kenneth French's website).[10] The factors are long-short portfolios that do not include the market portfolio; the positive cumulative returns reflect returns excess of the market.

Exhibit 2: Well-Known Systematic Factors from the Academic Research (Cumulative Returns)
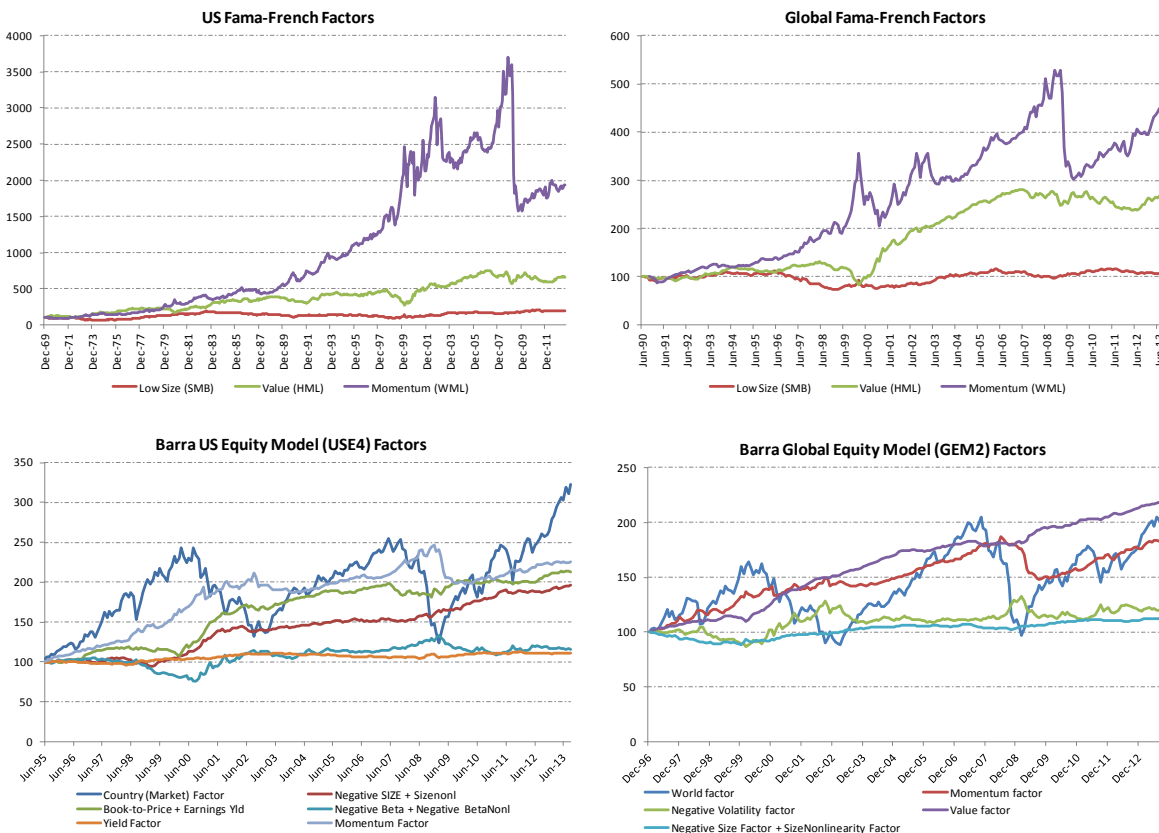
Also shown are factor returns from the Barra US and Global Equity Risk Models (USE4 and GEM2).[11] These factor portfolios and their accompanying returns are estimated in a different way from Fama-French, but they are all long-short portfolios without features or constraints that would make them investable in practice (e.g. limits on position sizes).[12] Decades of research by Barra has also found empirical evidence of several important factors beyond the Fama-French factors. (Note that within the

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[9] Note that the Barra Volatility factors reflect <u>high</u> volatility stocks relative to <u>low</u> volatility stocks. The premium to low volatility stocks can be assessed by taking the negative of the Volatility factors' returns.

[10] Note that Fama-French US factor returns are available beginning in July 1926. The chart begins in December 1969 for visual clarity.

[11] In some cases, factor returns have been combined or the sign has been reversed so the magnitudes of the premia are visually comparable.

[12] For factor researchers, the difference between the Fama-French and Barra approaches is not trivial. Fama-French factors are found through a process of sorting and bucketing stocks to build factor-mimicking portfolios while Barra factors are found through cross-sectional multivariate regression. Menchero (2010) provides a good discussion of the differences in factor estimation methodologies.

language employed by multi-factor models like Barra, we refer here to style and strategy factors and not industry and country factors.) The charts confirm the historical premiums observed to value, momentum, smaller cap, higher yield, and lower volatility stocks.

Risk Premia: Factors Which Earn Persistent Premium Over Long Periods

We must stress here that the term "factor" is often used throughout the industry liberally and may refer to one of thousands of different stock characteristics. The term "factor" is often applied to any stock characteristic that can be shown to be important, either in explaining risk or returns (typically relative to the market but not always). In the Barra Risk Models, for instance, there are factors that are significant in explaining returns but which do **not** earn a premium over reasonably long horizons. For instance, as shown in Exhibit 3, factors such as Growth and Liquidity, which capture high growth stocks and highly liquid stocks, have not outperformed the market over long periods. These types of factors are not considered good candidates for long-term factor investing.

Exhibit 3: Differentiating Between Factors Reflecting Risk Premia and Other Factors (Cumulative Returns to Barra Global Equity Model (GEM2) Factors)
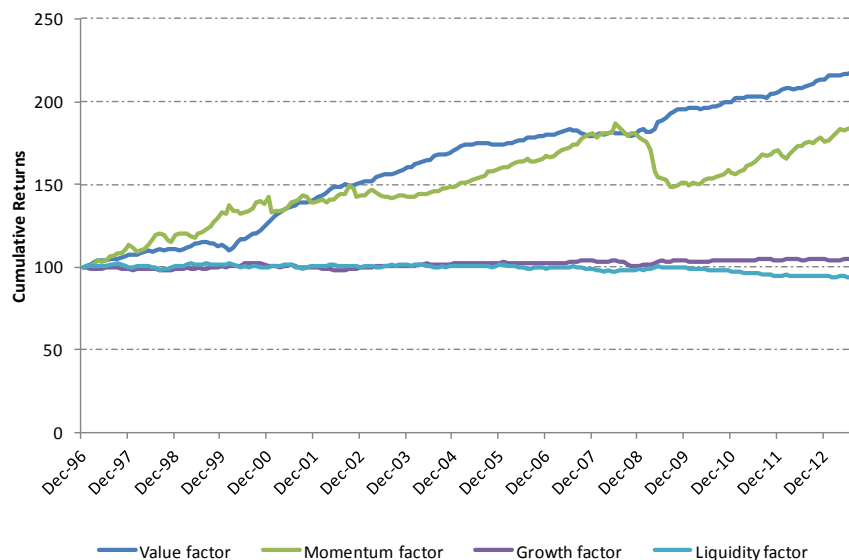
Note: Factors that can earn a premium over long periods include Value and Momentum while other factors do not, such as Growth and Liquidity.

Thus we distinguish between generic factors and "risk premia factors," which have earned a persistent significant premium over long periods and reflect exposure to sources of systematic risk. All of the Fama-French factors count as risk premia factors since the aim of those original studies was to isolate asset pricing drivers. However, not all of the Barra Risk Model factors are candidate factors since the purpose of those models focuses on forecasting risk and explaining fund performance.

In another vein, there are well-known alpha signals such as earnings revisions or earnings momentum, which have been used over the years by active managers to generate excess returns. These stock characteristics are typically called "alpha signals" because they do not explain risk well (i.e., they are not volatile) but do earn persistent premia over time. In our nomenclature, alpha signals could potentially

be candidates for risk premia factors though they must, going back to the previous section, have strong theoretical foundations that support their existence.

Factors Are Important in Explaining Manager Returns

In addition to historically exhibiting excess returns above the market, an equally important rationale for factor investing is the wealth of evidence that they can account for a significant portion of mutual fund returns and institutional active fund returns. Empirical studies confirm that it is difficult for active managers to earn alpha. Studies by Malkiel (1995), Gruber (1996), Wermers (2000, 2003), and Jones and Wermers (2011) found that the median active manager generally does not outperform the cap weighted benchmark net of fees and even the small subset of those who do outperform are only able to maintain that outperformance for short periods.

Studies have also found that active managers often tilt their portfolios towards well-known factors such as Value and Size and that these tilts account for a substantial portion of managers' returns over market capitalization weighted benchmarks. For instance, Fama and French (2010) found that mutual funds in aggregate (CRSP database) experienced net returns that underperformed the Fama-French factor benchmarks by about the costs in expense ratios from 1984 to 2006. Ang, Goetzmann and Schaefer (2009) applied a similar analysis to the Norwegian Government Pension Fund's active returns and found that although added value from active management was still net positive, much of the behavior of the Fund's small active return could be explained in terms of systematic factors. Recently, Mok, Bender, and Hammond (2013) showed that traditional Fama-French factors accounted for roughly 50% of average alpha using US institutional fund returns.[13]

In fact, two of the systematic factors, Value and Size, form the basis of what has become a fund categorization standard -- "style box investing." Style box investing, sometimes referred to as style investing, was first popularized by Morningstar in 1992[14] and is a framework in which institutions allocate to managers within style segments (large/mid/small and value/growth). In fact, style investing was originally based on the research of Sharpe (1988, 1992) who identified the importance of these factors in driving fund returns.[15]

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[13] Manager returns were sourced from eVestment from March 2002 to March 2012.

[14] http://news.morningstar.com/pdfs/FactSheet_StyleBox_Final.pdf

[15] Arguably Sharpe's and other similar empirical studies became the foundation for the "Morningstar Style Box" in 1992.

II. How Likely is it that Excess Returns to Risk Premia Factors will Persist in the Future?

A question that comes up repeatedly from institutional investors is "how likely are the factors' excess returns to persist in the future?" There is a vigorous debate about this question across academics and practitioners alike, but the short answer is, it depends on what forces have driven a factor historically and whether those forces will continue to persist.

What Drives Factor Returns: Systematic Risk vs. Systematic Errors

In general, there are two main camps in the debate over what drives factor returns—one based on the view that markets are efficient and that factors reflect "systematic" sources of risk, and one based on the view that investors either exhibit behavioral biases or are subject to different constraints (e.g., time horizons, ability to use leverage, etc.).

In the first camp, the term "systematic" refers to the fact that risks to these stock traits cannot be diversified away (in the true spirit of Ross' (1976) APT Model). This argument is consistent with "efficient markets theory" which assumes markets are efficient and investors are rational. Here, factors earn excess returns because there is "systematic risk" attached to them. For example, some have argued that the small cap premium is return earned for exposure to companies that are less liquid (Liu, 2006), less transparent (Zhang, 2006), and more likely to be distressed (Chan and Chen, 1991; Dichev, 1998). Others have argued that factors like Value, Size, and Momentum are linked to important macroeconomic factors such as growth and inflation and because of their sensitivity to shocks in the economy, must bear a return premium (Winkelmann et al., 2013).

In the second camp, factors are thought to earn excess returns because of investors' "systematic errors." One subgroup of this camp, rooted in the "behavioral finance" literature, suggests that investors exhibit behavioral biases due to cognitive or emotional weaknesses. Examples include chasing winners, over-reacting, overconfidence, preferring "familiar" investments such as securities of the companies they work for or the country they live in ("home bias"), and myopic loss aversion. If enough investors exhibit these biases, as long as it is prohibitively costly for rational investors to arbitrage these biases away, it can lead to the factor anomalies we observe.

Within this second camp, another subgroup has tied factor performance to investor constraints and frictions/flows that arise from regulatory and industry practice. In these studies, anomalies can arise from investors behaving rationally but subject to constraints. For instance, consider different investor time horizons. Studies have shown that stocks with low liquidity earn a premium over long horizons (10 years plus) since most investors have shorter horizons (3- and 5-year horizons) and prefer stocks that are liquid over the shorter horizons. Investors with longer horizons earn a premium for bearing this horizon risk. Other examples have applied constraint-based arguments for Low Volatility and Momentum. For instance, Baker et al. (2011) cite the use of institutional benchmarks, and the subsequent preference for relative returns, as one reason why the low volatility premium exists. Dasgupta, Prat and Verardo (2011) argue that reputation concerns cause managers to herd, and this generates momentum under certain circumstances.[16]

In fact, many of the well-known factors have multiple theories supporting them. Exhibit 5 summarizes main theories proposed for factor anomalies.

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[16] Specifically that the market makers trading with the managers are either monopolistic or myopic.

Exhibit 5: Theories Behind the Excess Returns to Systematic Factors

Systematic Factors	Systematic Risk-based Theories[17]	Systematic Errors-based Theories[18]
Value	➢ Higher systematic (business cycle) risk	➢ Errors-in-expectations ➢ Loss aversion ➢ Investment-flows-based theory
Low Size (Small Cap)	➢ Higher systematic (business cycle) risk ➢ Proxy for other types of systematic risk	➢ Errors-in-expectations
Momentum	➢ Higher systematic (business cycle) risk ➢ Higher systematic tail risk	➢ Underreaction and overreaction ➢ Investment-flows-based theory
Low Volatility	➢ N/A	➢ Lottery effect ➢ Overconfidence effect ➢ Leverage aversion
Dividend Yield	➢ Higher systematic (business cycle) risk	➢ Errors-in-expectations
Quality	➢ N/A	➢ Errors-in-expectations[19]

For example, let's consider the theories behind the Value factor. Value investing has been widely discussed since Graham and Dodd first wrote about it 1934 ("*Security Analysis*"). The Value factor captures the positive link between stocks that have low prices relative to their fundamental value and returns in excess of the capitalization weighted benchmark. There are several explanations for the existence of this effect. In the efficient markets view, the value premium is compensation for higher real or perceived risk. Cochrane (1991, 1996) and Zhang (2005) suggest that contrary to their leaner more flexible, growth counterparts, value firms have less flexibility to adapt to unfavorable economic environments. Chen and Zhang (1998) later found that value stocks are riskier due to their high financial leverage and large uncertainty in future earnings. Recently, Winkelmann et al. (2013) show value and small cap portfolios are more immediately sensitive to economic (real GDP) shocks than growth and large cap portfolios. The premium to value can consequently be viewed as compensation for macro risk.

From a behavioral perspective, the premium may exist as a result of loss aversion and mental accounting biases. According to Barberis and Huang (2001), investors become less concerned about future losses on stocks with recent good performance because any losses will be cushioned by prior gains ("loss aversion" bias). This bias induces investors to perceive the stock to be less risky than before and discounts its future cash flows at a lower rate. Conversely, if a stock performs poorly in the recent

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[17] These include all efficient markets-based theories which assume investors are fully rational.

[18] These include behavioral theories that assume investors are not fully rational as well as constraint-based theories that assume investors are rational but operate under constraints.

[19] Investors may mistakenly value stocks based on reported earnings if reported earnings are not reflective of a company's true fundamentals.

past, investors will raise its discount rate. This results in a value premium in the cross-section of stocks since a stock with a high price-dividend ratio (a growth stock)[20] is often one that has done well in the past, accumulating prior gains for the investor who then views it as less risky and requires a lower average return. A stock with a low price-dividend ratio (a value stock) has often had dismal prior performance; an investor may now view it as riskier, and require a higher future return. Lakonishok, Shleifer and Vishny (1994) proposed other behavioral biases that may help explain the Value premium such as investors extrapolating past growth into the future, chasing high-flying glamour stocks, or simply overreacting to news.

More recently, using an institutional framework/constraint-based argument, Vayanos and Woolley (2011) propose that value and momentum effects arise because negative shocks to assets' fundamental values trigger outflows from funds holding those assets. Outflows cause asset sales, which amplify the shocks' negative effects. If the outflows are gradual because of investor inertia or institutional constraints, then the amplification is also gradual and momentum effects arise. Moreover, because flows push prices away from fundamental value, value effects also arise. Both effects arise despite investors and fund managers being rational.

The examples discussed above represent just a small part of the wealth of research on the value premium.   Additional references and discussions of other factors can be found in Appendix A.

Assessing the Likelihood of Future Performance

For institutional investors evaluating factor allocations, arguably the most critical part of the process for adopting the approach is forming a **_view or belief_** about what drives the factor(s) in question. In practice, this first step often focuses on assessing the academic literature and the theories behind what drives excess returns to factors.

For institutional investors who subscribe to the "systematic risk" perspective, a factor can potentially persist indefinitely if it is actually compensation for bearing undiversifiable risk. For those who subscribe to the "behavioral bias" perspective, a factor can potentially persist as long as there are strong reasons why investors will continue to exhibit the behavioral biases in question and their actions are too costly to be arbitraged away by rational investors (or those who recognize these biases as such).[21] Lastly, for those who subscribe to the "constraint-based" view, a factor can potentially persist only as long as those constraints remain in place.

Regardless of their drivers, Melas, Briand, and Urwin (2011) point out that as factor strategies become increasingly popular, institutional investors may over time begin to experience relatively lower factor returns. The reason is that, unlike market capitalization weighted portfolios, factor portfolios lack macro consistency. An index or a portfolio is macro consistent if it can be held by all institutional investors without disturbing market prices. If all institutional investors tried to hold the same factor portfolio, the factor would experience diminishing active returns relative to the market. The interplay of investor flows and factor premia is complex particularly when viewed over time. While the idea that increasing popularity could diminish future returns is widely appreciated, investors should keep in mind that increased capital flows going into a popular strategy will produce a tailwind to the strategy's performance over the medium term, prior to any possible future reversal.

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[20] Note that Barberis and Huang (2001) define value/growth using price-to-dividend ratio but the argument would apply to other definitions such as price-to-book value and price-to-earnings.

[21] Some have argued that the return to factors observed in the data is roughly equal to the cost of arbitrage; see Shleifer and Vishny (1997). In practice, institutional investors may have different costs of arbitrage; thus their ability to exploit certain return anomalies may vary as well. Institutions with low costs of arbitrage may be able to exploit mispricings which average investors may not. These points should likely be factored into an evaluation of factor investing by large institutions.

III. Factor Investing versus Market Cap Investing

Some researchers have argued that market cap weighting is inherently flawed and have advocated replacing market cap allocations with factor allocations; see for example, Arnott, Hsu, and Moore (2005). Our position is quite the opposite. First, a market capitalization weighted index reflects the available opportunity set of equity investments as well as the aggregate holdings of all investors. If an investor wants to understand how equities have performed, the best gauge is a market cap weighted benchmark.[22] Second, market cap investing, the strategy that replicates a market cap index, is unique in being macro-consistent, meaning it is the only portfolio that all investors can hold.

Factor indexes do not reflect the full equity opportunity set and they are not macro consistent. Instead, they represent strategic tilts away from market capitalization weighted benchmarks. Exhibit 6 shows one way to view factor indexes relative to the market capitalization weighted index using the MSCI World Index as an example. Some factors (and factor combinations) have higher returns and higher volatility while others have higher returns and lower volatility. They represent active decisions away from the market capitalization weighted index. One intuitive way to view them is in the rubric of traditional active funds (e.g., defensive, balanced, and dynamic strategies).

Exhibit 6: Factors Represent Strategic Bets Away from the Market Capitalization Weighted Index (Return and Risk, June 1988 to June 2013)
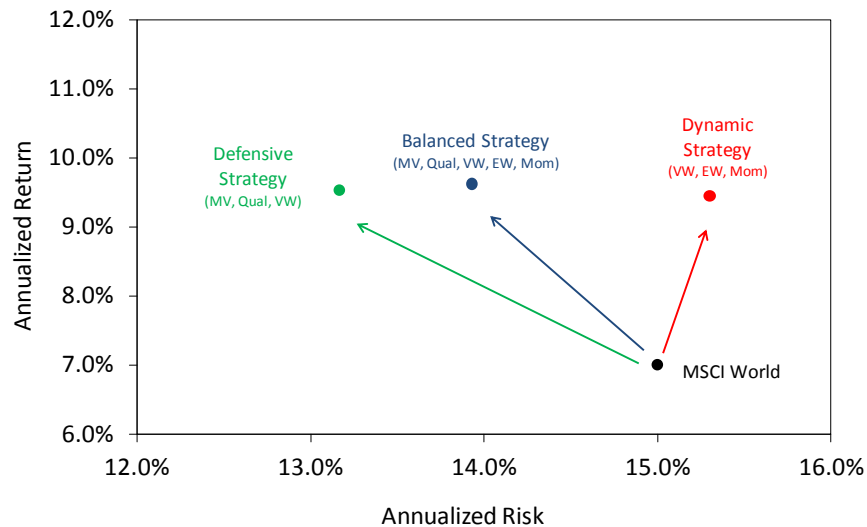
Note: The strategies in Exhibit 6 are equally weighted combinations of the MSCI Factor Indexes shown in parentheses. VW = MSCI World Value Weighted Index, EW = MSCI World Equal Weighted Index, Qual = MSCI World Quality Index, Mom = MSCI World Momentum Index, MV = MSCI World Minimum Volatility Index. All are MSCI Factor Indexes based on the MSCI World Index.

In sum, a market capitalization weighted index is the only appropriate candidate for a truly passive, macro consistent, buy and hold investment strategy that aims to capture the long term equity risk premium with structurally low turnover, very high trading liquidity and extremely large investment capacity. In contrast, investing in factors represents active views away from the market portfolio and investors must form their own belief about what explains the premium and whether it is likely to persist. Thus, like traditional active strategies, factor index strategies should be assessed in the long run against a market capitalization weighted benchmark.

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[22] Moreover, market capitalization weighted can be viewed as the equilibrium portfolio if investors are rational.

IV. Is Factor Investing A Free Lunch? The Importance of Factor Cyclicality

A key element of factor investing is factor cyclicality. While factor indexes have exhibited excess risk-adjusted returns over long time periods, over short horizons factors exhibit significant cyclicality, including periods of underperformance. Exhibit 7 shows that each of the factor indexes has experienced at a minimum a consecutive two-to-three year period of underperformance. Some factors historically have undergone even longer periods; the Small Cap or Low Size factor (captured by the MSCI World Equal Weighted Index in the exhibit) went through a six-year period of underperformance in the 1990s.

Exhibit 7: All Systematic Factors are Cyclical (Cumulative Relative Returns, June 1988 to June 2013)
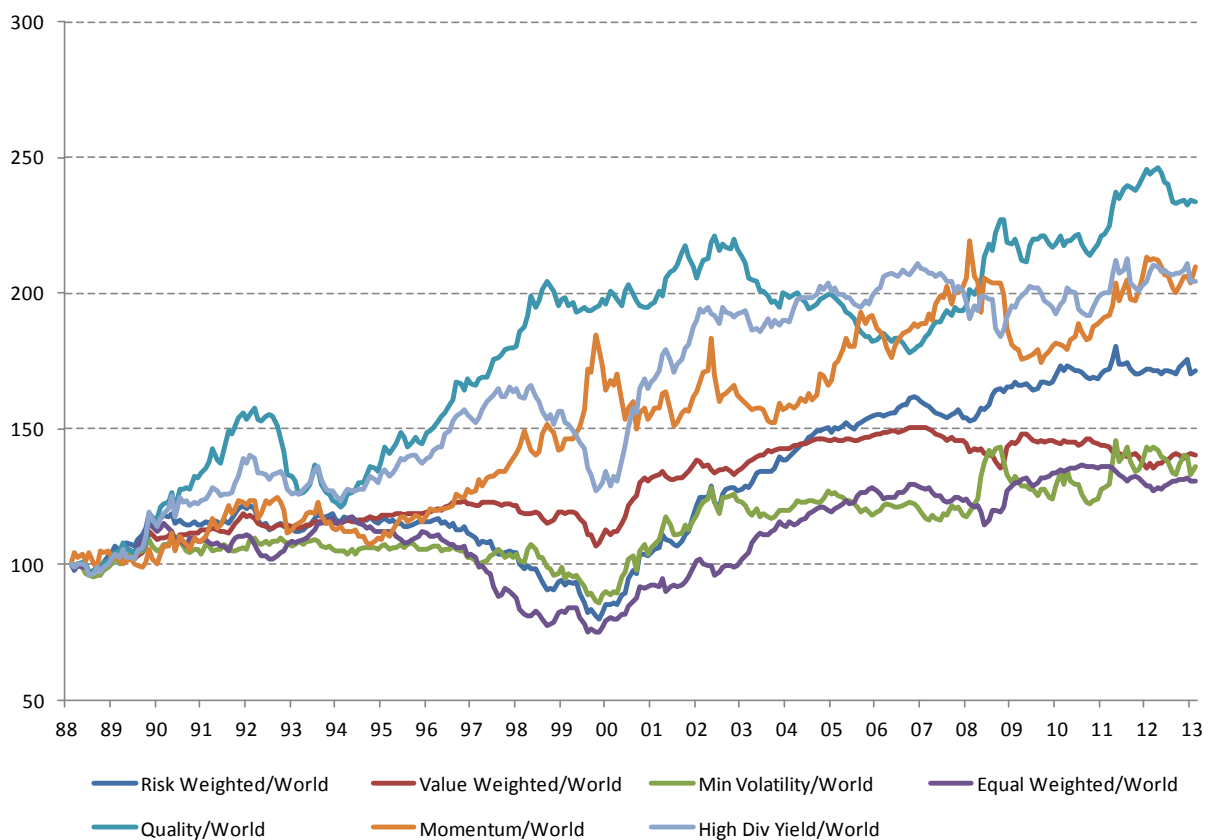
Thus, there is no free lunch attached to factor investing. Given strong anecdotal evidence that the majority of investors have relatively shorter horizons, their cyclicality may in fact be one of the reasons they have not been arbitraged away. Investors with shorter horizons would not be able to benefit from the full cycle required for factor investing. Some may argue the premia exist to reward long-horizon investors for bearing that risk.

A key part of the decision process for institutional investors implementing factor allocations is what to do about the cyclicality. Possible approaches include the following:

- Setting an appropriately long time horizon

- Establishing an explicit timing mechanism for the initial investment; and

- Adopting a multiple factor approach and employing factors that diversify each other

The first is difficult in practice because the horizon required would typically be far longer than most institution's strategic reviews.   Only institutional investors with extremely long time horizons (15 years and up for most of the factors shown in Exhibit 7) would be arguably insensitive to the timing of entry. The second option is challenging since factors, like markets, have been documented to be extremely hard to time. Most institutions would rather avoid timing decisions given their inherent difficulty.

The third is the most straightforward option. While all factors have been historically cyclical, their periods of underperformance have not coincided. For instance, during the period between 2001 and 2007, the MSCI World Momentum, MSCI World Value Weighted, MSCI World Risk Weighted, and MSCI World Equal Weighted Indexes all outperformed the MSCI World Index, but the MSCI World Quality Index underperformed. From 2007-on, in contrast, the MSCI World Quality Index outperformed while the MSCI World Momentum and MSCI World Value Weighted Indexes did not fare as well.   Combining Quality with Momentum and Value Weighted factor indexes for instance can yield a "smoother ride" and diversify across multi-year cycles. Or said another way, employing multiple factors is one way to address their cyclicality. In the second paper of the series "Deploying Multi-Factor Index Allocations in Institutional Portfolios", we discuss in more detail the allocation of equity portfolios across multiple factors.

V. Capturing Factors Through Allocations to Investable Indexes

The original studies on factors were intended to identify which stock characteristics explained returns. These studies were not concerned with whether those factors were actually investable. Specifically, the factor portfolios constructed by the academics in these studies were not designed for actual implementation. For instance, the Fama-French portfolios include all listed equities (in the US, listed on NYSE and AMEX) including many small illiquid names, are pure long/short portfolios with no accommodation to the size of short positions, and are rebalanced monthly leading to turnover that is considerably higher than institutional benchmarks. In other words, because these factor studies did not assume investors were necessarily investing in these factors, the factors they described did not, nor were they meant to, take into account features key to implementation: transaction costs, liquidity, investability, and capacity.

Until recently, the ability to capitalize on factors could only reasonably be done by active managers. Value investing and small cap investing have been staples of active management for decades. But over the last decade, index providers recognized that factors could be captured in transparent rules-based ways. Investors realized that factor strategies could outperform the market similar to their theoretical factor counterparts while having strong liquidity and investability characteristics.[23] Today, these indexes go by a number of names -- alternative beta, smart, beta, fundamental indexing, etc.

What has this ability to capture factors through indexation meant for institutional investors? Factor indexes could, in fact, revolutionize the investment industry by providing a new way of investing beyond traditional market capitalization weighted portfolio and active portfolios.   Factor indexes could provide:

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[23] Melas, Briand, and Urwin (2011) first discussed ways to capture factors through transparent rules-based long-only investable portfolios.

- *More relevant benchmarks:* Assigning an active manager a more relevant benchmark means investors can more accurately gauge what active managers are adding

- *Potentially more cost-effective implementation choices:* Funds that passively track these indexes can now potentially deliver returns previously only available through active management at potentially lower fees

- *Transparent implementation choices:* Funds that passively track these indexes can now be used in lieu of more opaque active options with positive implications for risk management

The benefits to institutional investors of factor indexes could be significant. As illustrated in Exhibit 8, factor allocations can be implemented in simple and low cost ways like traditional passive market cap weighted allocations. We note here that factors do ***not*** replace active management (at least fully) because many value-added activities such as stock selection cannot be replicated by factor indexes.

Exhibit 8: Passive Factor Allocations Combine Attractive Elements of Both Traditional Passive and Active Mandates
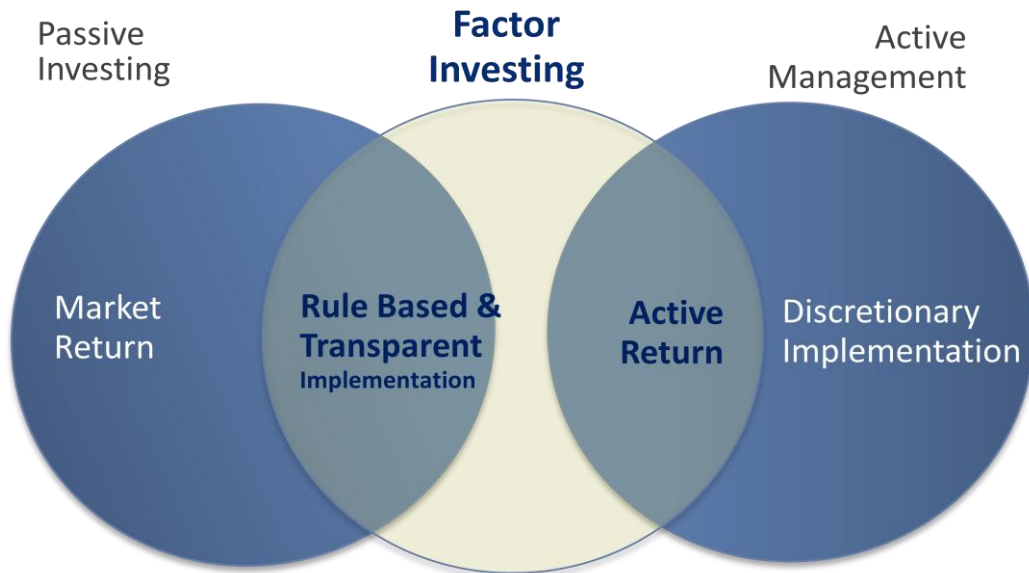
Beyond cost implications, factor indexes offer a fully transparent way to passively invest in factors. Transparency alleviates the well-known problem of manager style drift and also has positive implications for risk management. Institutions have full "look-through" of how exposed their portfolios are to the factors.

The advent of factor indexes also heralds a change in traditional investing paradigms. As shown in Exhibit 9, index-based factor allocations could imply a significant shift in the way institutional investors view the asset allocation and active management process. Instead of focusing on diversifying across active managers in multiple alpha mandates, institutions would focus first on diversification across multiple index mandates. Risk control would then focus principally on managing exposure to these factors while active management would be defined more narrowly as sources of return that exclude factors.

Exhibit 9: Potential Redefinition of the Way Institutions Invest

	Current Framework	**Possible New Framework**
Strategy	➢ Diversification across managers in multiple alpha mandates ➢ Asset owner manages strategy through asset allocation and manager selection	➢ Diversification across strategies in multiple factor index mandates ➢ Asset owner manages strategy through factor allocation
Roles and Tools	➢ Alpha is defined broadly: bottom-up skill, top-down sources and timing ➢ Risk control is principally through asset allocation and manager diversification	➢ Alpha is defined more narrowly excluding factors ➢ Risk control focuses on managing exposure to risk factors
Economics	➢ Active mandates dominate the portfolio's costs ➢ Large line-up of external managers with small internal asset owner staff	➢ Active mandates co-exist with factor mandates producing lower costs ➢ Larger internal staff managing more assets with fewer external managers

VI. An Illustration with MSCI Factor Indexes

MSCI's family of factor indexes, comprising the six key factors—Value, Low Size, Low Volatility, High Yield, Quality and Momentum —are shown in Exhibit 10. These indexes are constructed for flagship global indexes like the MSCI ACWI, MSCI World, MSCI Emerging Markets, and MSCI EAFE Indexes, as well as many individual country indexes.

Exhibit 10: MSCI Family of Factor Indexes

Systematic Factors	MSCI Indexes
Value	➢ **MSCI Value Weighted Indexes:** Capture Value factor by weighting according to four fundamental variables (Sales, Earnings, Cash Flow, Book Value)
Low Size (Small Cap)	➢ **MSCI Equal Weighted Indexes:** Capture low size effect by equally weighting all stocks in a given parent index
Momentum	➢ **MSCI Momentum Indexes:** Reflect the performance of high momentum stocks by weighting based on 6- and 12-month momentum scaled by volatility
Low Volatility	➢ **MSCI Minimum Volatility Indexes:** Reflect empirical portfolio with lowest forecast volatility using minimum variance optimization ➢ **MSCI Risk Weighted Indexes:** Capture low volatility stocks by weighting based on the inverse of historical variance
Dividend Yield	➢ **MSCI High Dividend Yield Indexes:** Select high dividend stocks with screens for quality and potential yield traps
Quality	➢ **MSCI Quality Indexes:** Capture high quality stocks by weighting based on debt-to-equity, return-on-equity, and earnings variability

Just as "there is more than one way to skin a cat," there is indeed more than one way to capture systematic factors through indexes. Index methodology comprises several aspects: the choice of stock universe, weighting scheme, and rebalancing frequency. All three have important implications for the traits investors care about in the resulting index--investability and liquidity, factor exposure, returns, risk, and tracking error. For instance, the index could contain all the names in the starting universe and merely reweight the names. Alternatively, the index could contain a narrow subset of names.[24] The former would have lower tracking error, higher investability, but lower exposure to the pure factor and potentially lower returns.

More generally, there is a tradeoff between the exposure to the factor (and potential returns) and the investability of a factor index. One can generally only achieve purer factor exposure by sacrificing investability and being willing to take on greater amounts of active risk. Detailed discussion about

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[24] MSCI Factor Indexes span both types. MSCI Factor Indexes that contain a broad universe of names (denoted by having the term "Weighted" in the index name) usually contain all the names in a broad "parent index" such as the MSCI ACWI Index and reweight the stocks (differently from market capitalization weighted) based on the desired factor characteristic.   These broad indexes are characterized by very low tracking error and high degrees of investability.

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different index choices is discussed later in the second paper of this series "Deploying Multi-Factor Index Allocations in Institutional Portfolios".

Exhibit 11 shows key characteristics including the performance of some of the MSCI World Factor Indexes for the period June 1988 to June 2013.

Exhibit 11: MSCI World Factor Indexes (Main Characteristics, June 1988 to June 2013)

Index	Factor Exposures*	Total Return	Total Risk	Active Return	Active Risk	Annual Turnover	Pairwise Correl- ation
MSCI World	--	7.1	15.4	0.0	0.0	3.9	NA
MSCI World Equal Weighted	Size	8.3	16.3	1.2	5.2	31.8	0.22
MSCI World Minimum Volatility	Volatility	8.5	11.6	1.4	6.7	20.0	0.30
MSCI World Value Weighted	Value	8.6	15.6	1.5	3.6	20.3	0.30
MSCI World Risk Weighted	Size, Volatility	9.5	13.7	2.4	5.3	27.2	0.46
MSCI World Quality	Growth, Leverage	10.9	14.0	3.8	5.9	27.6	0.13
MSCI World Momentum	Momentum	10.4	15.9	3.3	8.5	127.5	0.03
MSCI World HDY	--	10.3	14.6	3.2	6.5	22.0	0.41

* In the column "Factor Exposures" we show the Barra Global Equity Model (GEM2) factors which are statistically significant on average (>+/- 0.20), with the expected sign, since December 1997. Note that there is no "Yield factor" in the GEM2 Model. Instead, Yield is a component (with a weight of 10%) in the GEM2 Value factor. Turnover reported is the average annual one-way turnover based on history from June 1988-June 2013.

Higher capacity indexes include the MSCI Value Weighted Index. As illustrated in Exhibit 17 using MSCI World variants, it exhibits the lowest tracking error among the available indexes since it holds all the constituents of the parent index. The other indexes (the MSCI Momentum Indexes, MSCI Quality Indexes, and MSCI Minimum Volatility Indexes) are more concentrated indexes, holding only a subset of the names in the parent index. These indexes exhibit higher tracking errors and lower levels of investability. (The MSCI Minimum Volatility Indexes are turnover-constrained to 20% but other measures of investability are more similar to the MSCI Momentum and Quality Indexes.) The MSCI Momentum and MSCI Quality Indexes historically exhibited the strongest historical returns while the MSCI Minimum Volatility Indexes exhibited sizable risk reduction.

All the MSCI World Factor Indexes shown in Exhibit 11 outperform the MSCI World Index over the period shown, June 1988 to June 2013. Moreover, they all have turnover levels that are well within

reason. For instance, assuming 50 bps in one-way trading costs, the cost of trading for the indexes would range between 20.3 basis points annually for the MSCI World Value Weighted Index to 127.5 bps annually for the MSCI World Momentum Index. Both estimates are more than offset by their historical return premiums over this period – 150 bps and 330 bps respectively.

Conclusion

Factor investing is based on the existence of factors that have earned a premium over long periods, reflect exposure to systematic risk, and are grounded in the academic literature. Early financial theory established that for stocks, exposure to the market was a significant driver of returns (e.g., the CAPM). Later, researchers like Barr Rosenberg, Eugene Fama and Kenneth French extended the CAPM to include certain systematic factors that also were important in explaining returns. Tilts towards these factors such as Value, Low Size, and Momentum historically produced excess long-term returns and there were strong theoretical foundations behind these factors.

Until now, passive investing has focused on capturing market beta through market capitalization weighted indexes. The only way institutional investors could get access to factors was through active management. Indexation is opening a new way for factor investing today by allowing investors to access factors through passive vehicles that replicate factor indexes. MSCI Factor Indexes provide access to six solidly grounded factors—Value, Low Size, Low Volatility, High Yield, Quality and Momentum. These indexes have historically earned excess returns over market capitalization weighted indexes and experienced higher Sharpe Ratios.

This paper is the first in a three-paper series focusing on factor investing. In the next paper of this series, "Deploying Multi-Factor Index Allocations in Institutional Portfolios", we address the topic of allocating across factors and what role they play in the institutional portfolio.

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Appendix

Appendix A: Additional Information about the Academic Literature

There is a vast literature on systematic factors. Subgenres which fall under the umbrella of systematic factors include asset pricing anomalies, stock market anomalies, multi-factor models, risk factor models, alpha signals, etc. To start, it is useful to begin with several good general references on these issues:

- "Dissecting Anomalies" by Eugene Fama and Ken French (2008)
- "Explaining Stock Returns: A Literature Review" by James L. Davis (2001)
- "Market Efficiency, Long-Term Returns, and Behavioral Finance" by Eugene Fama (1997)
- "The Efficient Market Hypothesis and It's Critics" by Burton Malkiel (2003)
- "The New Palgrave Dictionary of Economics" (2008) by Steven Durlauf and Lawrence Blume, 2nd ed.
- "Anomalies and Market Efficiency" by G. William Schwert[25] (Ch. 15 in *Handbook of the Economics of Finance*, by Constantinides, Harris, and Stulz, 2003)
- "Investor Psychology and Asset Pricing," by David Hirshleifer (2001)[26]

While the construction of factor models occupies a somewhat segregated landscape from the market anomalies literature, this research provides guidance on how alpha signals and risk factors are identified and estimated by quantitative managers. Some good starting references include:

- *The Barra Equity Risk Model Handbook*
- *Active Portfolio Management: A Quantitative Approach for Producing Superior Returns and Controlling Risk* by Richard Grinold and Ronald Kahn
- *Modern Investment Management: An Equilibrium Approach* by Bob Litterman
- *Quantitative Equity Portfolio Management: Modern Techniques and Applications* by Edward Qian, Ronald Hua, and Eric Sorensen

Additional references are provided below for the main systematic factors discussed in this paper: Value, Low Size, Momentum, Low Volatility, Quality, and Yield.

Value

The Value factor captures the positive link between stocks that have low prices relative to their fundamental value and returns in excess of the capitalization-weighted benchmark. A value strategy consists of buying stocks that have low prices normalized by some indicator of company fundamentals (such as book value, sales, earnings, or dividends, etc.) and selling stocks that have high prices (also normalized). Value investing has been widely discussed since Graham and Dodd first wrote about it 1934 ("*Security Analysis*"). It was later formalized by Basu (1977), who was the first to test the notion that value-related variables might explain violations of the CAPM. He found a significant positive relation between E/P ratios and average returns for US stocks that could not be explained by the CAPM. Later studies documented a significant positive relation between Book-to-Price ratios and average returns as well; see Rosenberg, Reid and Lanstein (1985) and DeBondt and Thaler (1987) for example. Other measures of value have also been found to have positive excess returns including value ratios that use cash flow. The Value effect in its many forms has been reproduced by numerous researchers for many different sample periods and for most major securities markets around the world (see Hawawini and

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[25] http://schwert.ssb.rochester.edu/hbfech15.pdf

[26] "Investor Psychology and Asset Pricing," David Hirshleifer, Journal of Finance, 56(4), August, (2001):1533-1597.

Keim (2000)). We note that critics of the value premium have argued that empirical evidence is based on data mining and point out the sample-dependency of empirical studies; see for instance Black (1993).

A discussion of theories behind the Value premium appears in Section II.

Low Size

The Size factor captures the excess returns of smaller firms (by market capitalization) relative to their larger counterparts even after adjusting for betas and other factors like Value. This result was first discovered by Banz (1981), and triggered a vast literature on the topic. Banz (1981) showed smaller companies listed on the NYSE on average delivered higher risk-adjusted returns than larger companies using data from 1936-1975. This "size effect" was later generalized by the Fama-French Three Factor Model in the early 1990's.

The small cap premium has been found to exist even after influences are controlled for: market beta, the value effect, the momentum effect, liquidity effects, leverage, and so forth. Moreover, the phenomenon has been identified across the world in both developed and emerging markets; see Rizova (2006) for a synopsis of work applying the Fama-French framework to individual countries such as Australia, Canada, France, Germany, and the UK.

There are several theories explaining this phenomenon, and the debate continues today. In the efficient market view, Fama and French (1992, 1993) originally hypothesized that small caps have higher systematic risk which earns them a higher return premium. Subsequent researchers suggested that size may proxy for other unobservable and underlying risk factors associated with smaller firms such as liquidity (Amihud, 2002), information uncertainty (Zhang, 2006), financial distress (Chan and Chen, 1991) and default risk (Vassalou and Xing, 2004). Chan, Chen and Hsieh (1985) in particular argue the most powerful factor in explaining the size effect is the spread between low and high quality corporate bonds, which is essentially an indication of the macro environment and default risk.

From the behavioral perspective, similar behavioral arguments for the value premium are also made for the size effect, i.e. incorrectly extrapolating past into the future, chasing high-flying glamour stocks, or overreacting to news; see (Lakonishok, Shleifer, and Vishny, 1994). The explanations of the size effect remain highly debated.

Skeptics of the size premium point to the survivorship bias in the relevant research, which typically does not include busted companies. This seems a legitimate claim given small companies often have sustainability issues. Others argue the size premium is difficult – if not impossible – to capture in the real world given the low trading volume of small cap stocks.

Momentum

The Momentum factor reflects future excess returns to stocks with stronger past performance. In other words, stock prices tend to exhibit trend over certain horizons; winners continue to win and losers continue to lose. Jegadeesh and Titman (1993) led one of the first seminal studies on momentum in the US stock market, which shows buying past winners and selling past losers produced significant "abnormal" returns in 1965-1989. In a study of mutual fund performance, Carhart (1997) expanded the Fama-French Three Factor Model to a Four-Factor Model to include momentum as an additional explanatory variable. Rowenhorst (1998) found an internationally diversified portfolio of past winners outperformed a portfolio of past losers by about 1% per month, using a sample of 2,000 European stocks from 1978 to 1995. Fama and French (2012) found strong momentum returns in North America, Europe, and Asia Pacific but not Japan in the sample period of 1989-2011. They also confirmed the robustness of the Four Factor Model, i.e. momentum is a persistent factor not captured by either value or size. Empirically the Four Factor Model seems to work best with global stocks excluding micro caps.

Asness (1995, 1997) not only confirmed earlier findings on the momentum effect at the country level, but also showed that winners and losers tend to revert over the long-term, i.e. winners underperforming and losers outperforming in 3-5 years out. In fact, empirical research suggests the momentum effect is most prominent in the following 3-12 months, after which it will likely disappear. This implies the momentum strategy requires relatively high turnover in order to work. Geczy and Samonv (2013) conducted a 212-year backtest of the momentum strategy in the US market, which shows the momentum effect is statistically significant and not a product of data-mining.

The theory underlying this premium is still matter of extensive discussion. Unlike value and size, there is no satisfactory efficient markets-based theory to explain the momentum factor. The most widely cited theories are all behavioral. Investors either over-react (Barberis, Sheleifer and Vishny 1998, and Daniel, Hirshleifer and Subrahmanyam 1998) or under-react to news (Hong, Lim and Stein 2000), both of which may lead to the momentum effect under varying assumptions. Without diving deep into behavioral finance, these "irrational" reactions are driven by overconfidence, self-attribution, conservatism bias, aversion to realize losses, representative heuristic (tendency to identify an uncertain event by the degree to which it's similar to the parent population), or simply lack of analyst coverage. Or as another example, Dasgupta, Prat and Verardo (2011) argue that reputation concerns cause managers to herd, and this generates momentum under certain assumptions.[27] More recently, Vayanos and Woolley (2011) propose a framework based on the dynamics of institutional investing rather than individual biases. In their framework, momentum and value effects jointly arise because of flows between investment funds. Negative shocks to assets' fundamental values trigger outflows from funds holding those assets while outflows cause asset sales, which amplify the shocks' negative effects. If the outflows are gradual because of institutional constraints or inertia, then momentum effects arise. Moreover, because flows push prices away from fundamental value, value effects also arise.

Common criticisms of the momentum strategy include data mining, high turnover, crowded trading, and the risk of a sudden reversal – which is difficult to predict and manage. History shows the probability of a short-term reversal is positively correlated with volatility, and forecasting volatility is anything but easy. In addition, like other factor strategies, momentum could go through an extended period of negative performance. This suggests it's perhaps better to combine momentum with other factor strategies than using it alone. Asness, Moskowitz and Pedersen (2010) supported this argument with a study on the interaction between value and momentum. They found potential diversification benefits

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[27] Specifically that the market makers trading with the managers are either monopolistic or myopic.

from combining the two strategies as value and momentum can be negatively correlated within and across asset classes.

Low Volatility

The Low Volatility factor captures excess returns to stocks with lower than average volatility, beta, and/or idiosyncratic risk. The empirical evidence for this factor is a puzzle since it is clearly at odds with one of the most basic principles in finance, that higher volatility is associated with higher returns (Blitz and Vliet, 2007). While the CAPM model asserts that riskier assets should earn higher returns, research around the Low Volatility factor shows that the opposite is true--less risky stocks outperform the market.

Haugen and Baker's (1991) critique of capitalization-weighted benchmarks was the first to document the effect. They showed that for the 1972 to 1989 period, low volatility stocks in the US performed better than the capitalization-weighted alternative. Later, Chan, Karceski and Lakonishok (1999), Schwartz (2000), Jagannathan and Ma (2003) and Clarke, de Silva and Thorley (2006) confirmed these results for the US market using a range of volatility measures. Geiger and Plagge (2007), Nielsen and Subramanian (2008) and Poullaouec (2008) all find qualitatively similar results for global markets. Ang et al (2006, 2009) found that the low volatility effect persists both in the US and globally, based on extensive periods of time (for US stocks, 1963 to 2003, and for international stocks, 1980 to 2003).

Metrics used for identifying low volatility stocks range along a broad spectrum, with realized volatility on one end and forecast volatility and correlations on the other. Some operationalize low volatility as low beta. The metrics for identifying low volatility stocks also vary, with realized (historical) volatility on one end, and forecasted (implied) volatility and correlations on the other end. However, the research findings appear robust despite such differences.

The low volatility anomaly clearly contradicts the EMT and assumptions of the CAPM. The explanations here are mostly behavioral. The most common explanation is the "lottery effect", i.e. people tend to take bets with a small expected loss but a large expected win, even though the probability of a loss is much higher than the win, and the weighted average of the outcome may be negative. This is similar to buying a lottery whereby the customer pays a small sum for potentially winning a large amount of money albeit at a very low probability. Some argue that buying a low price, volatile stock is similar to buying a lottery with similar risk-return payoffs, and thus it can be an attractive bet for investors. Therefore investors often overpay for high volatility stocks and underpay for low volatility stocks due to the "irrational" preference for volatile stocks.

Other behavioral explanations include:

- Representativeness – The success of a few, well publicized high volatility stocks make all volatile stocks seem good investments, and the speculative nature of such stocks is often ignored by investors.
- Overconfidence – Investors are overconfident in their ability to forecast the future, and the extent of their differences in opinions are higher for stocks with more uncertain outcomes (high volatility stocks). In the real world, it is easier and more practical to express a positive view (buy) than a negative view (short sell). This means the pessimists cannot effectively express their view of a volatile stock, leaving only the optimists to keep driving up its price. The result is overpricing and lower returns for high volatility stocks.
- Agency issue – There appears to be a natural tendency to avoid low volatility stocks in asset management because there is often less attention and support (in the form of research and trading) for low volatility stocks.

■ Asymmetric behaviors in bull vs. bear markets – Investors behave differently in bull markets vs. bear markets. When the market is going down, there is often a huge dispersion of beta between low volatility and high volatility portfolios (i.e. the low volatility portfolio will have much lower beta). Therefore, the low volatility portfolio experiences much less drawdown than the high volatility portfolio. When the market is going up, this dispersion is not so great, and thus the low volatility portfolio underperforms only slightly. Net, the low volatility portfolio still does better over the long term (Sefton et al., 2011)[28]

Finally, Baker, Bradley, and Wurgler (2011) propose a theory that is not based on behavioral bias but instead based on the use of equity benchmarks. Low volatility stocks often have lower betas, and overweighting them leads to higher tracking errors for institutional investors. Such tracking errors need to be justified by sufficient excess returns (alpha). In other words, institutional investors cannot buy low volatility stocks indiscriminately. To a certain extent, the benchmark issue prohibits institutional investors from fully exploiting the low volatility anomaly.

Critics of the volatility factor argue that buying a basket of low volatility stocks may lead to unintended bets on valuation and sectors, because such stocks tend be expensive and concentrated in just a few sectors (such as financials). There is also a philosophical argument that low volatility investing is successful at reducing risk but lacks an investment thesis on returns. Therefore technically speaking it is a risk management as opposed to an investment tool.

Quality

The Quality factor aims to capture the excess return of "high quality" companies vs. the market. This has been a widely adopted concept in fundamental analysis (stock selection) but a relatively new phenomenon in quantitative investments. The main challenge is how to define the "quality" factor consistently and objectively using quantitative indicators.   The quality of companies is a highly subjective matter. Though there is no standard definition, it is commonly associated with a company's competitiveness, efficiency, transparency, growth, financial and operating leverage, profit sustainability, and return-on-equity (ROE).

Sloan (1996) was one of the first to validate the excess returns to high earnings quality stocks, where accruals proxy for earnings quality. (Low accruals reflect higher earnings quality). Besides accruals, other measures of earnings quality include, earnings persistence, smoothness, and loss avoidance, and they are reviewed by Dechow, Ge, and Schrand (2010)[29]. These other measures have been related to stock returns by Perotti and Wagenhofer (2011), although the general finding is that accruals have been the strongest quality-based predictor of stock returns. In recent years, Bender and Nielsen (2013) and Kozlov and Petajisto (2013) have reconfirmed the accruals effect for the 2000s. Also, Asness, Frazzini, and Pedersen (2013) recently show that quality as measured by profitability, stable growth, and high payout ratio, has significantly higher risk-adjusted returns.

More recently, some have argued that the original Dodd & Graham and Buffett investing styles include an important quality component.   "[T]he secret to Buffett's success is his preference for cheap, safe, high-quality stocks combined with his consistent use of leverage to magnify returns while surviving the inevitable large absolute and relative drawdowns this entails" according to Frazzini, Kabiller and

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[28] This "minimal drawdown" advantage can be easily demonstrated as follows: A high volatility portfolio may go down 50% in value in a bear market, and will need to go up 100% (double) in order to recover to its original value. However, a low volatility portfolio may go down only 30% in value, and need to go up only 43% to recover to its pre-crisis level. This puts the low volatility portfolio well ahead of the high volatility portfolio during the initial stage of a recovery.

[29] Chen, Novy-Marx and Zhang (2011) made an ambitious attempt to include ROE in an alternative three-factor model for explaining the cross-sectional stock returns.

Pedersen (2012). In other words, the original "value"-based style of investing pioneered by Dodd & Graham is really one that favors stocks that appear to be safe and have high quality, but are priced as bargains. Frazzini, Kabiller and Pedersen (2012) show that Berkshire Hathaway's alpha becomes insignificant when controlling for "Betting-Against-Beta" and quality factors.

There is very little literature on why the Quality factor works. It's also difficult to provide a unified theory since the definition of quality varies. According to the Fama-French model, all systematic risks are ultimately economic risks. In light of this argument, it is not difficult to see the connection between stock returns and quality measures such as financial leverage and earnings growth. Campbell, Polk and Vuolteenaho (2010) offered a form of this "fundamental" explanation, arguing the primary source of systematic risks of both growth and value stocks is the cash flow fundamentals as opposed to market sentiments. From a corporate finance angle, it is easy to see how firm quality impacts stock prices. For example, a well-run company often manages its capital carefully and reduces the risk of over-leveraging or over-capitalization. The steady growth in earnings will further reduce its need for capital market financing, which will support its stock price. This will trigger a positive feedback loop making the company more competitive in the eyes of its customers and investors.

Critics of the Quality factor argue it is highly subjective and contains behavior biases. Active managers are often strong proponents of the Quality factor but argue it can only be captured through fundamental analysis and stock picking.

Yield

The Yield factor aims to capture the outperformance of high dividend yield stocks. Dividend yield is commonly used as a valuation tool and closely related to price-to-book and price-to-earnings ratios. Therefore, assuming the payout ratio is uniformly distributed. The compounding of dividend reinvestments also contributes to the excess return of high dividend yield stocks. In addition, changes in the dividend tax regulations may also account for the dividend factor.

Blume (1980) found a positive relationship between the risk-adjusted returns and the expected dividend yield of dividend-paying stocks. Litzenberger and Ramaswamy (1979) later confirmed there is a positive but non-linear relationship between stock returns and expected dividend yields, assuming investors have no knowledge of the future ex-dividend month. Fama and French (1988) found the dividend yield has more explanatory power for longer term returns over 2-4 years. Tweedy, Browne Company LLC (2007) offered a summary of the empirical evidence of the dividend factor in both US and UK markets for over 40 years. Various attempts have been made to integrate the dividend yield into a model to forecast stock returns using creative statistical techniques (Hodrick, 1992). Dividend yield has also been shown to have cross-sectional return predictability. Although similar in construction to the value ratios, the explanatory power of dividend yields is most often attributed to the differential taxation of capital gains and ordinary income as described in the after-tax asset pricing models developed by Brennan (1970) and Litzenberger and Ramaswamy (1979).

The Yield factor can be controversial. Black and Scholes (1974) concluded there is no significant relationship between dividend yield and stock returns after adjusting for risks. Ang and Bekaert (2007) found the excess return predictability by the dividend yield is not statistically significant or robust, which is contrary to Fama and French's findings above. The difference is mainly due to the statistical techniques used by the two research groups. Ang and Bekaert (2007) further noted the dividend is an unreliable indicator since it is "smoothed and manipulated" by the company.

Appendix B: References for Appendix A

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[1] As of March 31, 2013, as reported on July 31, 2013 by eVestment, Lipper and Bloomberg

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