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INVESTING WITH STYLE

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Investors are bombarded by a variety of investment strategies from a growing and increasingly complex financial industry, each claiming to improve returns and reduce risk. Amid the clamor, academic research has sifted through the vast landscape and found four intuitive investment strategies that, when applied effectively, have delivered positive long-term returns with low correlation to each other and traditional markets. The four "styles"—value, momentum, carry, and defensive—have uniquely held up across a multitude of asset classes, markets, and time periods using very liquid securities and form the core foundation for explaining the cross-section of returns in most asset classes. We discuss the intuition and evidence for these four pervasive styles and detail how to implement a strategy that can access these style premia to improve the risk and returns of traditional portfolios.

1 Introduction

Most existing portfolios, even seemingly diversified ones, are dominated by equity risk. For example, a 60%/40% stock/bond portfolio is 0.99 correlated to a 100% stock portfolio. This concentrated bet proved especially painful during the 2008 global financial crisis. In addition, most investors are currently concerned that traditional sources of returns, such as stocks and bonds, may not do as well as they have in the past for a variety of reasons, ranging from past good luck and today's lower equity and bond market yields to increased financial market competition and global economic uncertainty. Consequently, investors have turned their attention to alternative sources of return, specifically those attempting to be uncorrelated with traditional assets.

One way to achieve uncorrelated returns is to seek pure "alpha." In theory, alpha is the extra return achieved beyond any known risks or common systematic strategies. It is therefore often

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taken as a measure of unique managerial skill. Unfortunately, alpha is at best elusive and, more often than not, illusive. First, the definition of alpha is often confusing and frequently misused. Academics and practitioners struggle to define true alpha and debate its very existence. Second, even if we can agree on a definition, alpha is often cloaked inside a broader portfolio that contains simple market exposures (i.e., betas). Because a single fee is charged for the portfolio, investors willing to pay high fees for true alpha end up paying exorbitant fees for traditional market beta.[1] But, even if alpha is identifiable and attainable, it is sometimes packaged in illiquid vehicles, making it difficult to scale up to large dollar amounts, and often with little transparency and very high fees. For example, hedge fund investors have often paid too much and accepted unfriendly terms for strategies that may contain some alpha but are clearly mixed in with a lot of market beta.[2]

While the definition and pursuit of alpha is elusive and the generation of alpha is opaque, expensive, and not easily scalable, there are other ways to seek returns that can significantly improve traditional investor portfolios and that most investors are underutilizing. Putting semantics aside, all an investor should care about is receiving positive average returns that are uncorrelated with what she currently owns. In this paper, we focus on a proven set of strategies that can produce such returns, which we call "styles." Style investing delivers long-term positive returns with little correlation to traditional asset classes. And, it achieves this aim in an intuitive and cost-effective manner using liquid securities that allow for significant scalability. In essence, investing can be made much simpler and more effective by focusing on the core foundations of returns—building blocks we call styles. Practically speaking, if an investor is not already exposed to these style premia, it is alpha to them. But, it is identifiable alpha, not concealed amongst traditional betas, and not claiming to be the elusive magic of literal alpha, and importantly offered (we hope and expect) at significantly better terms.

What is a style? We define a style as a disciplined and systematic method of investing that produces unique long-term positive average returns across markets and asset classes, with low to zero correlation with major long-only asset classes, backed by significant scientific evidence, both in- and out-of-sample, and with strong economic intuition underlying it. For years, academics and practitioners have been studying markets, trying to identify persistent, systematic sources of return. Many attempts to discover additional return premia have turned out to lack robustness, possibly the result of data mining (for some extreme examples, there is research claiming to find stock return predictability from sun spots, seasonal affective disorder, and moon phases—no kidding!). However, sifting through the research and data has resulted in the identification of a set of classic long–short styles backed by sound economic reasoning that deliver consistent long-term performance across many unrelated asset classes and different markets, and in out-of-sample tests. They are value, momentum, carry, and defensive.

We will emphasize the "pure" use of style premia through long–short strategies, but the same styles can also be usefully applied as tilts to cap-weighted, long-only portfolios that will still have significant market exposure. These types of style portfolios are often referred to as "smart beta" portfolios.

Style investing has been most widely studied in equity markets, with a classic example being the influential work of Eugene Fama and Kenneth French (1992, 1993), who describe the cross-section of U.S. stock returns through two main styles—value and size—in addition to the equity-risk premium. Subsequent research into stocks added two additional styles, namely momentum,[3] first documented by Jegadeesh and Titman (1993) and Asness (1994) and low-beta or low-risk, first suggested by Black (1972) and recently documented by Frazzini and Pedersen (2013). Research on value, momentum, and low-beta has been extended to international stocks as well as to other asset classes that include bonds, currencies, commodities, other derivatives, and real estate, with similarly strong results.[4]

Finally, the carry style was first applied in currencies and bonds (and later extended to commodities where it passed another out-of-sample test) as a powerful investment tool and more recently has been studied in equity indices, individual stocks, credit, and options.[5]

Our paper focuses on four styles—value, momentum, carry, and defensive. There are two additional styles that readers may be familiar with that are not considered in our paper, namely size and illiquidity. The size style has not proven as robust as the four styles we focus on (for one thing its realized premium is significantly smaller than the others) and has had varied success in out-of-sample tests.[6] More importantly, size cannot be easily applied across other asset classes such as currencies or commodities and entails betting to a large degree on less liquid securities, which is a feature we aim to avoid in constructing a very liquid and scalable strategy.

In addition to size, there are other sources of returns that can be achieved through illiquidity, providing insurance, and arbitrage-type trades, but these are separate topics and strategies not considered here since we wish to focus only on liquid and scalable strategies. Together, these other sources might be considered a fifth style called "liquidity," though there may be significant heterogeneity in this category. These sources of returns have been extensively studied in the literature, most notably by Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Amihud (2002), Sadka (2003) and Ibbotson *et al.* (2013).[7]

Identifying robust return sources is the first ingredient of successful style premia investing, and finding consistent evidence in many markets and asset classes achieves this aim. The second key ingredient is diversifying across as many styles and asset classes as possible, especially since the styles have low correlation (sometimes even negative correlation) to each other. Finally, and most importantly, proper long–short implementation of these styles provides for hedged returns that have low correlations with traditional equity (and other passive long) risk premia. Historically, investors may have been exposed to individual styles through portfolios that simply add a single style tilt onto predominantly long equity-market exposure.[8] This is certainly a step in the direction we argue for, but we believe it is only a small step as it usually does not tilt towards many styles and certainly does not do so across many asset classes. In addition, the typical active risk taken in such portfolios is small compared to the risk coming from passive market exposure. Worse, such tilts are often disguised and priced as alpha. Breaking from this common approach, our paper provides support for direct style exposure that is separate from traditional sources of risk and applied to all four styles simultaneously, not one at a time, as there are significant synergies between the styles (diversification, hedging, and trading cost minimization to name a few).

A skeptic might say "there must be a catch." There is, of course, but it is one that can (and must) be managed. In order to achieve proper risk balance and attain the high average returns and low correlation properties investors seek, style investing requires the "three dirty words in finance"—leverage, short-selling, and derivatives. This is a consequence of three desires: market neutrality (or removing traditional betas which obviously entails shorting); risk (not dollar) diversification (which entails taking bigger dollar bets, using explicit leverage in some asset classes, and using derivatives in other asset classes); and economically significant expected returns. Leverage, shorting, and derivatives are necessary to achieve these important objectives efficiently. Hence, putting together a portfolio of style premia requires careful portfolio design, proper portfolio construction, effective implementation and cost control, as well as sound risk management.

The rest of this paper is organized as follows. Section 2 describes style premia in greater detail and the wealth of scientific theory and evidence behind them. Section 3 describes our data and portfolios. Section 4 provides empirical support for style investing. Section 5 addresses the benefits of adding style premia to a traditional portfolio and analyzes hedge fund returns through the style premia lens. Section 6 concludes.

2 What are style premia?

We focus on four classic styles: value, momentum, carry, and defensive. We first discuss the basis for each of these styles, including the underlying economic intuition behind them. Then, we present empirical evidence showing their long-term returns, risks, and correlations.

Value investing is probably the best-known style, especially in stocks. The idea of buying undervalued assets and selling overvalued ones dates back to at least Benjamin Graham. For almost 30 years, value investing in stocks has been studied extensively in academia, most prominently by Fama and French.[9] The implementation of the value style can be straightforward. Take a set of stocks and sort them by some measure of fundamental value to price. Go long or overweight the stocks that have high fundamental value to price ("cheap" stocks) and short or underweight the ones that have low fundamental value to price ("expensive" stocks). By being explicitly long and short, the resulting portfolio has very little correlation with the overall equity market, and when applied across many stocks, can capture the aggregate return to value investing while diversifying away idiosyncratic security risk. The traditional choice of value measure in stocks is the ratio of the book value of a company relative to its market price (B/P), but other measures can be used and applied simultaneously to form a view of a stock's value. For example, investors can look at a variety of fundamentals beyond book value, including earnings, cash flows, and sales, relative to price. It is our view that more measures provide for more robust portfolios.[10]

Value can be applied beyond the original context of stock selection to equity indices and other asset classes. In equity indices, an aggregate measure of B/P for the entire market can be used to implement value investing. Extending the value concept to bonds, currencies, and commodities requires using fundamental measures not derived from accounting statements, but that still retain the notion of fundamentals to price. For bonds, a measure of real bond yields is used. In the case of currencies and commodities, measures of purchasing power parity, or real exchange rates, and five-year reversal in price, respectively, represent value.[11] In all cases, a systematic process that first sorts assets by these measures, going long the cheap (relative to fundamentals) assets and short the expensive ones, is applied.

Academics still debate why the value premium exists. For example, there are explanations rooted in investor behavioral biases, such as excessive extrapolation of growth trends and delayed overreaction to information (e.g., Lakonishok *et al.*, 1994; Barberis *et al.*, 1998; Daniel *et al.*, 1998), as well as risk-based explanations like value assets having greater default risk (Fama and French, 1993, 1996; Campbell *et al.*, 2008), dynamic betas (Lettau and Ludvigson, 2001; Campbell and Vuolteenaho, 2004; Campbell *et al.*, 2010), or higher long-run consumption risks (Parker and Julliard, 2005; Hansen *et al.*, 2008; Malloy *et al.*, 2009). Both sets of theories are grounded in economic intuition with ample theoretical foundation, and we do not adhere to one or another in this paper. The solid economic motivation and empirical evidence make a strong case for value investing as a persistent source of excess returns.

Momentum investing is an almost equally well-known style, supported by evidence that is as robust and pervasive as the evidence behind value investing. Momentum is the tendency of securities, in every market and asset class, to exhibit persistence in their relative performance for some period of time. After being documented in academia in the early 1990s among U.S. equities (Jegadeesh and Titman, 1993; Asness, 1994), momentum has been studied extensively in a variety of contexts. The typical approach is to look at the past 12 months of returns for a universe of assets, going long the ones that have outperformed their peers and short the underperformers. By being long and short, the resulting portfolio has little correlation to passive exposure to traditional markets, and when applied across many assets, captures the aggregate return to momentum while diversifying away idiosyncratic security risk.

Similar to value investing, momentum investing does not need to be confined to a single measure, in this case own-price momentum. It has been shown that measures of fundamental momentum, such as earnings momentum, changes in profit margins, and changes in analysts' forecasts for stocks, are also useful in forming profitable portfolios (and correlated to, while not being the same as, simple price momentum). For both price and fundamentally based momentum strategies, the evidence of strong risk-adjusted returns is pervasive across time and markets. In this paper, we only use own-price momentum measures to illustrate the concept but real-life implementations need not accept such a boundary.

Similar to the debate about why value investing works, there is active academic discussion about why momentum is related to average returns. This discourse again centers on two possible sets of explanations: risk-based and behavioral theories. Risk-based stories posit that high-momentum stocks are riskier and therefore command a higher discount rate. An example is high-momentum stocks containing more growth options in earnings that make them more sensitive to aggregate shocks (e.g., Gomes *et al.*, 2003; Zhang, 2005; Li *et al.*, 2009; Belo, 2010; Li and Zhang, 2010; Liu and Zhang, 2008; Berk *et al.*, 1999; Johnson, 2002; Sagi and Seasholes, 2007; Liu *et al.*, 2009) or liquidity risks (Pastor and Stambaugh, 2003; Sadka, 2006; Asness *et al.*, 2013). In addition, strong correlations among momentum stocks suggest the presence of a common source of risk (Asness *et al.*, 2013). Behavioral theories, on the other hand, argue that underreaction in the short-term to new information due to anchoring or inattention, and/or overreaction to price moves in the medium-term due to feedback trading (becoming more confident in one's positions and beliefs when they are supported) and investor herding may be prominent sources of momentum (see Barberis *et al.*, 1998; Daniel *et al.*, 1998; Hong and Stein, 1999; for models of this type). In addition, the disposition effect, which is the tendency for investors to sell winners too soon and hold on to losers too long, may be a significant contributor to momentum (Grinblatt and Han, 2005; Frazzini, 2006).

Carry is a well-known style particularly among macroeconomists and practitioners in currency markets. At its core, carry is based on investing (lending) in higher yielding markets or assets and financing the position by shorting (borrowing) in lower yielding markets or assets. A simplified description of carry is the return an investor would receive (net of financing) if market conditions (e.g., prices) remain the same. A classic application is often found in currency markets, where sorting countries by their short term (say, three-month) lending rate, and going long the currencies of countries with the highest rates and short the currencies of countries with the lowest rates has been a profitable strategy over several decades. Likewise, carry strategies in fixed income, based on the shape of the yield curve, and commodity futures, where backwardation or contango in the futures maturity curve is exploited across various commodities, have also been profitable over time. As discussed further in Section 3, a measure of carry for stocks is the expected dividend yield, which is also a natural valuation measure and highly correlated with the equity value indicator, B/P, we use in this paper.

One economic motivation behind carry is the process of balancing out supply and demand for capital across markets. High interest rates can signal an excess demand for capital not met by local savings; low interest rates suggest an excess supply of capital. Traditional economic theory would argue, in the case of currencies, for example, that the rate differentials would be offset by currency appreciation or depreciation, such that the return an investor would experience would be the same across currency markets. The evidence is that a currency carry strategy not only can collect the yield differential, but also has often captured some capital gains from currency appreciation as well (so the traditional theory, called uncovered interest rate parity, is not simply wrong but empirically backward). This is perhaps caused by the presence of non-profit-seeking market participants, such as central banks, who may introduce inefficiencies into currency markets and interest rates, due to other more political motives, or may represent compensation for exposure to macroeconomic, crash, and liquidity risks (Brunnermeier *et al.*, 2008; Bacchetta and van Wincoop, 2010; Lustig and Verdelhan, 2007; Farhi and Gabaix, 2008; Lustig *et al.*, 2010; Burnside *et al.*, 2011).

The carry strategy is certainly not without risk, as there can be sharp periodic unwinds when capital flees for low-yielding "safe havens." The long-run reward could therefore be compensation for investing in a strategy with negative skewness and larger left tails, specifically in bad economic environments (though it is important to note that despite including these periods the strategy has still delivered strong positive performance historically). However, and importantly, those risks tend to be asset-class specific and are largely diversified away in a portfolio where carry is applied across many asset classes simultaneously.[12] Hence, strong positive carry returns can be captured while greatly mitigating (though not entirely avoiding) much of the occasional carry crashes that occur in a particular asset class like currencies, for example. Koijen *et al.* (2013) show that carry strategies in other asset classes are not subject to crashes the way currency carry strategies are. The concept of carry, applied more broadly across other asset classes besides currency trades, where it is most well-known, is a clear example of how style investing, when applied universally, can generate more attractive risk and return opportunities.

Defensive, or low beta/low risk, is a strategy with a long pedigree that has experienced a resurgence in recent years. The initial motivation for defensive strategies dates back to Fischer Black, who in 1972 saw that the security market line in U.S. equities (the line linking market beta to average returns) was too flat relative to what theory (specifically, the Capital Asset Pricing Model, or

CAPM) would predict. In other words, high-risk assets did not offer high-enough returns relative to low-risk assets. Subsequent research by Frazzini and Pedersen (2011, 2014) has shown that this phenomenon applies to many different markets and asset classes beyond stocks. In the case of stocks, sorting equities by forecasted betas and going long the stocks with the lowest betas and short the ones with the highest betas yields positive risk-adjusted returns. By de-levering the higher-beta stocks to equalize the short portfolio's beta with the long portfolio's beta, a portfolio retains its market neutrality, while capturing the fact that the lower-beta stocks offer a better risk-adjusted return than the higher-beta stocks. Diversifying across many assets captures the defensive return premium while diversifying away idiosyncratic security risk. Extending the low-risk vs. high-risk concept more broadly, we can go beyond statistical measures like beta to include more fundamental measures of risk—or conversely "quality"—by seeking high profitability, low leverage, and stable earnings among stocks,[13] or by favoring short-duration assets in fixed income. However, in this paper we simply use beta to define low risk or high quality/safe assets. Like momentum, where we do not study fundamental measures in this paper for simplicity and clarity, in practical applications there is room to improve upon the defensive measures we do study by including fundamental measures of defensiveness or quality. More measures results in a more robust and stable strategy, but we err on the side of simplicity in this paper.

There are a number of competing theories for why lower-risk assets may offer higher risk-adjusted returns.[14] We believe the most compelling reason resides in the fact that leverage needs to be applied to lower-risk assets to raise the overall risk and return expectations. Since many investors are leverage-averse or leverage-constrained, they typically choose to hold the higher-risk assets, thereby lowering the prospective returns for those assets.[15] As a result, an investor who is willing to take the other side of these trades and hold the levered, lower-risk asset may be additionally compensated in the long run. Frazzini *et al.* (2012) show that Warren Buffett is one extraordinarily successful example of such an investor.

It is important to note that our criterion for selecting these four styles was stringent and no other anomaly in the literature passed. There had to be out-of-sample evidence through time and testing in other asset classes. There had to be a solid economic story (or stories) steeped in the risk and behavioral literature. No style could be spanned by the other styles. They each had to be liquid and capable of being implemented in large capacity. We believe that these four styles pass these tests, while other documented anomalies, such as size, do not pass all of these criteria, and others, such as accounting accruals and net issuances, are spanned by the four styles we do examine and are not applicable outside of equities.

3 Data and portfolio construction

To provide empirical evidence of style premia, we create composites of the four styles and a combination of all four styles by applying long–short strategies across seven different asset classes (or contexts): individual stocks globally, industries, country equity indices, government bond indices, interest rate futures, currencies, and commodities. In all cases, we choose asset universes that emphasize liquidity and capacity. We analyze strategies in stocks and industries separately because of a wealth of evidence showing distinct predictability among industries separate from individual stocks (Asness *et al.*, 2000; Moskowitz and Grinblatt, 1999). Next, we detail our data and measures to define the styles, our portfolio construction methodology, and our weighting scheme to create the style composite portfolio.

3.1 Data

Global individual stocks: We examine style portfolios of individual stocks globally across four equity markets: the U.S., the U.K., continental Europe (excluding the U.K.), and Japan. For each market, we start with a base universe that consists of all common equity in XpressFeed and relevant stock indices. We exclude ADR's, REITS, financials, closed-end funds, foreign shares, stocks with share prices less than $1 at the beginning of each month, and names with fewer than 12 months of past return history or missing book values from at least six months prior. We limit the remaining universe of stocks in each market to a very liquid set of securities that could be traded for reasonably low cost at reasonable trading volume size. Specifically, we rank stocks, in descending order, on a past four-month average measure of market capitalization and liquidity, defined as the past 90-day median dollar volume traded in the stock. We include in our universe the number of stocks that account cumulatively for 90% of the total market capitalization of the entire stock market. On average this translates into about 1,100 stocks in the U.S., 150 in the U.K., 600 in continental Europe, and 400 in Japan. This universe corresponds to an extremely liquid and tradeable set of securities that effectively excludes small-cap stocks in each market. Gross returns to the style strategies we examine are typically larger among small caps, but net of trading cost returns may not be. We use both local currency returns, for constructing momentum signals, and U.S. dollar (USD) returns for portfolios, obtained from XpressFeed.

Global industries: We use the same universe of individual stocks to form industry portfolios within each of the four regions using industry designations from BARRA. There are approximately 55 industries for the U.S., 16 for the U.K., and 22 each for continental Europe and Japan. Stocks are aggregated within industries using market capitalization weights.

Global equity indices: The universe of country equity index futures from developed and emerging equity markets are Australia, Brazil, Canada, China, European Union, Hong Kong, India, Japan, Russia, South Africa, South Korea, Sweden, Switzerland, Taiwan, the U.K., and the U.S. Returns and price data come from Bloomberg, and book values are obtained from MSCI. The returns on the country equity index futures do not include any returns on collateral from transacting in futures contracts, hence these are comparable to returns in excess of the local risk-free rate and are effectively currency hedged.

Currencies: We obtain spot and forward exchange rate data from WMCO, MSCI, and various brokers (as necessary to have a complete set of data) covering the following developed and emerging currencies: Australia, Brazil, Canada, Germany (spliced with the Euro), Japan, Korea, Mexico, New Zealand, Norway, Russia, Singapore, Sweden, Switzerland, Turkey, the U.K., and the U.S. We compute returns from currency forward contracts or, prior to the availability of forward contract data, we approximate returns using spot exchange rates and three-month Libor rates. Our currency returns are all dollar denominated and implicitly include the local interest rate differential. For computing real exchange rates, we obtain ratios of price levels from the Penn World Tables and the OECD (similar to Rogoff, 1996).

Global government bond futures: Bond futures returns come from Bloomberg and Morgan Markets and are effectively currency hedged. Short rates and 10-year government bond yields come from Bloomberg, and inflation forecasts are obtained from Consensus Economics, who compile estimates from many sources, including investment banks, universities, and large corporations. We obtain government bond data for the six countries with the most liquid bond futures: Australia, Canada, Germany, Japan, the U.K., and the U.S.

Global interest rate futures: Global interest rate futures returns come from Bloomberg and are effectively currency hedged returns. We obtain interest rate returns for the following markets: Australia, Canada, European Union, the U.K., and the U.S.

Commodity futures: We cover the eight most liquid commodity futures. Data on Copper is from the London Metal Exchange (LME). Brent Crude is from the Intercontinental Exchange (ICE). Corn and Soybeans are from the Chicago Board of Trade (CBOT). WTI Crude and Natural Gas are from the New York Mercantile Exchange (NYMEX). Gold and Silver are from the New York Commodities Exchange (COMEX). Returns for commodity futures are calculated as follows. Each day we compute the daily excess return of the most liquid futures contract, which is typically the nearest- or next nearest-to-delivery contract, and then compound the daily returns to an excess return index from which we compute returns at a monthly horizon. Bessembinder (1992), de Roon *et al.* (2000), Moskowitz *et al.* (2012), and Koijen *et al.* (2013) compute futures returns similarly. All returns are denominated in U.S. dollars and do not include the return on collateral associated with the futures contract.

Published indices: For comparison with our results, we use a number of published indices. As a proxy for a traditional, global stock and bond portfolio, we use the MSCI World Index, with dividends (net of withholding tax) reinvested in USD and not hedged for local currency moves, and the Barclays Global Aggregate bond index in USD, hedged for local currency moves. We combine the two indices by allocating 60% of the weight to equities and 40% to bonds. For hedge fund indices, we use the Hedge Fund Research broad hedge fund index, in USD, and the subcomponent hedge fund indices, in USD. The subcomponent hedge fund types are convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income relative value, global macro, long–short equity, and managed futures.[16] For commodities we use the GSCI commodities index.

Risk models: We form volatility and correlation estimates for the assets we study, as well as betas, using the following risk models. For stocks (and industries), we use BARRA risk models for the corresponding region of each stock.[17] For all other assets classes, our volatility, correlation, and beta estimates are based on three-year rolling estimates using weekly returns. While more sophisticated risk estimates are available, for simplicity and to allay concerns of overfitting we simply use the three-year trailing returns to measure risk.

All series are monthly and end in June 2013. For stocks and industries, developed market equity indices, and developed market currencies, all series start in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging market equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. We use the MSCI World Index, Barclays Global Aggregate bond index and the GSCI commodities Index starting in January 1990. For hedge fund indices, we use the Hedge Fund Research broad hedge fund index which starts in January 1990. All futures and long–short strategy returns are excess returns in the sense that they exclude cash income.

3.2 Style measures

To measure value, momentum, carry, and defensive styles, we use the simplest and, to the extent a standard exists, most standard indicators. Our goal is to maintain a simple and fairly uniform approach that is consistent across asset classes and minimizes concerns of possible data snooping. More sophisticated measures can significantly improve performance of these styles, but must be balanced against the pernicious effects of data mining. For our purposes here, we choose to err on the simpler, more conservative side. Not only does this mitigate the effects of data mining, but it also provides clarity and makes communication easier.

Value: For individual stocks, the commonly used value signal of the ratio of the book value of equity to market value of equity, or book-to-market ratio, BE/ME (see Fama and French, 1992, 1993; Lakonishok *et al.*, 1994) is used. Book values are lagged six months to ensure data availability to investors at the time, and the most recent market values are used to compute the ratios as in Asness and Frazzini (2013). We treat individual stocks within industries as one asset class/category and industry selection as another distinct asset class. Industry value measures are formed by aggregating from the stock level by weighting each stock's book-to-market ratio by the latest market capitalization of the stock. We exclude financials from both the stock level and industry level computations following Fama and French (1993). For equity indices, we use the previous month's BE/ME ratio for the MSCI index of each country, including financials. Again, a more robust and somewhat improved measure of value could be formed by averaging across multiple fundamental-to-price measures, but the core results of this paper are unchanged by different value measures and we err on the side of simplicity.

For other asset classes, we similarly try to use simple and consistent measures of value. For currencies, our value measure is the real exchange rate defined as the rate at which goods and services in one country can be transferred for those in another. It is computed by dividing the nominal exchange rate by the ratio of price levels, similar to Rogoff (1996). For bonds, we use the 10-year government yield minus the consensus inflation forecast as described above (i.e., real long rates). For interest rate futures, we use the forward rate minus the consensus inflation forecast (i.e., real short rates). For commodities, in the absence of a consistent fundamental-to-price measure (such as book-to-price), we rely on long-run mean reversion. Specifically, we compare the spot price five years ago with the most recent spot price, essentially capturing the negative of the spot return over the last five years. These definitions of value follow those used in Asness *et al.* (2013) to measure value across asset classes and are highly correlated to fundamental measures of value in other asset classes. For instance, Asness *et al.* (2013) find that equity portfolios formed from sorting stocks globally by their negative past five-year returns are 0.86 correlated with portfolios formed from sorting stocks by their BE/ME ratios.

Momentum: For momentum, we use the common measure of the past 12-month cumulative raw return for individual stocks (see Jegadeesh and Titman, 1993; Asness, 1994; Fama and French, 1996; Grinblatt and Moskowitz, 2004), skipping the most recent month's return. We skip the most recent month, which is standard in the momentum literature since Asness (1994), to avoid the one-month reversal in stock returns, which may be related to liquidity or microstructure issues (Jegadeesh, 1990; Lo and MacKinlay, 1990; Boudoukh *et al.*, 1994; Asness, 1994; Grinblatt and Moskowitz, 2004). For all other asset classes, we define momentum as the return over the past

12 months without skipping the last month, since the microstructure issues are less relevant outside of individual stocks.

Carry: We do not define carry for stocks, industries, or equity indices since a natural measure of carry for equities is the dividend yield, which is very highly correlated to our value measure for equities, BE/ME.[18] For bonds, we define carry as the 10-year government yield minus the three-month Treasury bill rate (slope of the yield curve). For interest rate futures, we define carry as the three-month roll-down return (slope of the very short end of the yield curve). Intuitively, this assumes that the term structure of interest rates stays constant such that the carry is the bond yield plus the "rolling down" of the futures contract along the term structure of interest rates, which captures the price increase due to the fact that the bond follows the (assumed constant) yield curve. Since yields are just inverted prices, this is consistent with our definition of the carry return, which is the return achieved if prices do not change. For currencies, we use the three-month onshore cash rate or local interest rate. Finally, for commodities, we use the slope of the futures curve (favoring markets with the most backwardated curves and disliking the least backwardated markets or those with the largest contango). These definitions of carry follow closely those of Koijen *et al.* (2013).

Defensive: We do not define defensive strategies for interest rate futures, currencies, and commodities because it is difficult to apply the low-beta or quality concepts in these markets.[19] For individual stocks, we use the stock's equity market beta, measured using the risk models described previously. We also aggregate betas to an industry beta measure by weighting each stock's equity market beta by the stock's market capitalization. For equity indices, we use a country's beta to a market capitalization-weighted world index of equities. For bonds, we use a bond's beta to a GDP-weighted country index of bonds. These betas are also estimated from the risk models previously discussed.

3.3 Portfolio construction

Once a measure is defined for each style, we follow a set of transformations that is consistent across asset classes and styles to convert the raw measures into portfolios. Specifically, we first rank the universe of securities by the raw measure of a given style. We then standardize the ranks by subtracting the mean rank from each rank and dividing each rank by the standard deviation of ranks (i.e., we create z-scores) to convert them into a set of standardized weights. This step creates a set of positive weights and a set of negative weights that add up to zero, which will form the basis of our long–short portfolios. We then volatility-adjust each of the long and short sides such that the volatility of the long (positive weight) portfolio is equal to the volatility of the short (negative weight) portfolio, using the volatility measures defined from the various risk models described above. Finally, we scale the resulting long and short positions such that the resulting long–short portfolio is at 10% annual forecasted (*ex ante*) volatility, using the volatility measures defined from the various risk models. The idea here is to scale the long and short sides of each style portfolio to the same (*ex ante*) volatility and then scale each style portfolio to the same volatility for ease of comparison across styles and for ease of combining multiple styles into a single portfolio.

Once we have a constant-volatility style portfolio for each applicable style in each asset class, we combine the style portfolios into a composite for each asset class, based on equally risk weighting the styles that are present in each asset class. We then rescale the resulting combined long–short portfolio, using the same risk models, to a constant 10% annual volatility as before for ease of comparison.

In combining the various individual stocks and industry portfolios we weight each market by its relative liquidity and breadth as follows: U.S., 50%; Japan, 16.7%; Europe ex-U.K., 16.7%; and U.K., 16.7%, scaling the resulting portfolio to 10% annual volatility using the *ex post* sample measures of volatility.[20] Equity country allocation and currency allocation are separately conducted in developed markets (2/3 weight) and emerging markets (1/3 weight), motivated by their relative liquidity. We then combine all of the asset classes into one composite portfolio by assigning a 30% risk weight to individual stocks, 10% to industries, 15% to equity indices, 10% to government bonds, 5% to interest rate futures, 15% to currencies, and 15% to commodities, scaling the resulting portfolio to 10% annual volatility.[21] Overall, 55% of total risk is equity-related[22] (stocks, industries, and country equity indices) and 45% of risk is in other asset classes (fixed income, currencies, and commodities). To be clear, these are allocations of the risk budget to long–short style portfolios, not asset class allocations. As a result of these allocations, the portfolio does not have any passive asset class exposure. These allocations are based on trying to balance building as diversified a portfolio as possible while trading off considerations for liquidity and breadth of assets. Small perturbations in these weights have little effect on our results. Again, our goal is to build as diversified a portfolio as possible both at the style and asset group level. All portfolios are rebalanced monthly.

Table 1 summarizes the indicators we use to represent style premia for each style in each asset class. Specifically, for each of the four styles in each of the asset classes we study, the table lists the various measures we use to construct long–short style portfolios for each style within each asset class, including referencing the original studies that proposed the relevant measures we use.

4 Empirical evidence

4.1 Individual styles

Table 2 presents the historical performance results of the diversified style premia portfolios over the sample period.[23] The positive risk-adjusted returns to each style are highlighted, where value, momentum, carry, and defensive deliver a positive 2.9%, 8.3%, 8.7%, and 5.8% average annual excess return, respectively. Sharpe ratios range from 0.29 (value) to 0.87 (carry).[24] In addition to the positive returns, the ability to diversify away from equity-directional risk is also evident, as realized historical correlations to global equities are 0.00, –0.03, 0.20, and –0.31 for value, momentum, carry, and defensive, respectively. Likewise, the correlations to a 60%/40% stock-bond allocation are also quite low, ranging from –0.29 to +0.22. Maximum drawdown, equity tail return, which is the return to the strategy during the most extreme negative 10% equity return months, and higher moment statistics are also reported.

One interesting thing to note is that the skewness of the momentum style is near zero (in fact, slightly positive at 0.05), despite the evidence in Daniel and Moskowitz (2013) showing momentum to be a negatively skewed strategy. Daniel and Moskowitz (2013) study separate momentum strategies in various asset classes which each possess negative skewness, but when they combine momentum strategies across asset classes, the negative skewness, while still present, is mitigated. Our results are more striking which may be due to differences in methodology or time periods studied.

Table 1 Summary of style measures.

	Value	Momentum	Carry	Defensive
Stock selection	BE/ME following Fama and French (1992, 1993), Recent ME are used following Asness and Frazzini (2013)	Twelve-month cumulative raw return following Jegadeesh and Titman (1993), Skip most recent month following Asness (1994)		Beta to equity market, following Frazzini and Pedersen (2011)
Industry selection	BE/ME following Fama and French (1992, 1993), Recent ME are used following Asness and Frazzini (2013)	Twelve-month cumulative raw return following Jegadeesh and Titman (1993)		Beta to equity market, following Frazzini and Pedersen (2011)
Equity country selection	BE/ME following Fama and French (1992, 1993), Recent ME are used following Asness and Frazzini (2013)	Twelve-month cumulative raw return following Jegadeesh and Titman (1993)		Beta to equity market, following Frazzini and Pedersen (2011)
Bonds country selection	Real yield, defined as 10-year government yield minus consensus inflation forecast	Twelve-month cumulative raw return following Asness *et al.* (2013)	10-year yield minus three-month treasury bill yield following Koijen *et al.* (2012), except use three-month treasury bill rather than 2-year bond	Beta to GDP-weighted index, following Frazzini and Pedersen (2011)
Interest rate futures	Real yield, defined as forward rate minus consensus inflation forecast	Twelve-month cumulative raw return	Three-month rolldown return	
Currencies	Real exchange rate, defined as the rate at which goods and services in one country can be transferred for those in another, computed by dividing the nominal exchange rate by the ratio of price levels, similar to Rogoff (1996)	Twelve-month cumulative raw return following Asness *et al.* (2013)	Three-month onshore cash rate following Koijen *et al.* (2012)	
Commodities	Five-year reversal following Asness *et al.* (2013)	Twelve-month cumulative raw return following Asness *et al.* (2013)	Slope of the futures curve following Koijen *et al.* (2012)	

The table summarizes our measures for each style. For each of the applicable styles in each of the seven asset classes we study, the table lists the various measures we use to construct long–short style portfolios, including referencing the original studies that proposed the relevant measures used.

Table 2 Style premia simulations, 1990–2013.

	Value	Momentum	Carry	Defensive
Annual excess return	2.9%	8.3%	8.7%	5.8%
Volatility	10.0%	10.0%	10.0%	10.0%
Sharpe ratio	0.29	0.83	0.87	0.58
Correlation to equities	0.00	−0.03	0.20	−0.31
Correlation to 60% equities/40% bonds	−0.01	−0.02	0.22	−0.29
Maximum drawdown	−42.1%	−29.6%	−25.7%	−37.8%
Equity tail return	4.2%	4.5%	−6.4%	20.7%
Skew	−0.26	0.05	−0.99	−0.34
Kurtosis	0.86	0.58	4.82	0.85
Autocorrelation	0.26	0.16	0.07	0.04

For each of the four style composites, we report the annualized return in excess of the risk-free rate ("Annual excess return"), the annualized volatility of monthly excess returns ("Volatility"), the Sharpe ratio (annualized return in excess of the risk-free rate divided by the annualized volatility of monthly excess returns), the monthly correlation to equities (MSCI World Index), the monthly correlation to a portfolio that is 60% equities (MSCI World Index) and 40% bonds (Barclays Global Aggregate Bond Index), the maximum drawdown (defined as the maximum peak-to-trough cumulative decline), the equity tail return (defined as the style's annualized average performance in the worst 10% of months for global, MSCI World, equities), the skewness, kurtosis, and autocorrelation of monthly returns. All composites are defined as in Section 3 and represent long–short portfolios across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. The MSCI World Index and the Barclays Global Aggregate bond index start in January 1990. All returns used in this analysis are in excess of the risk-free rate.

Table 3 presents the Sharpe ratios of the styles broken out by asset class (in Table 2 they were aggregated into composite styles across all the asset classes). The Sharpe ratios typically range from 0.2 to 0.8, with only a few (bonds and interest rate futures) being slightly negative, but essentially zero. Each of these styles was first discovered prior to our starting point in 1990, hence the average positive performance of these styles out of sample mitigates data mining concerns (had they been the result of data mining one would expect zero average returns across the styles out of sample, and as many big negatives as big positives). As the table shows, there is pervasive and robust evidence across many asset classes of the efficacy of these four styles. In addition, a combination of styles, which we examine later, provides even more impressive and stable returns due to the benefits of diversification. For example, the negative correlation between value and momentum generates stronger and more stable performance from a combination of both than from either by themselves (see Asness *et al.*, 2013; Asness and Frazzini, 2013, particularly their examples in Japanese equities).

The existence of these style premia across vastly different contexts also suggests that applying style strategies in many asset classes simultaneously will yield substantial diversification benefits. Comparing the results in Table 3 with those in Table 2, large benefits of diversification are directly observable. For all four styles—value, momentum, carry, and defensive—the Sharpe ratios of the style strategies diversified across asset classes (Table 2) are much higher than the

Table 3 Style premia Sharpe ratios by asset class, 1990–2013.

	Value	Momentum	Carry	Defensive
Stock selection	0.26	0.82		0.61
Industry selection	0.03	0.72		0.24
Equity country selection	0.00	0.28		0.39
Bonds country selection	0.04	–0.02	0.78	–0.11
Interest rate futures	0.22	0.19	–0.01	
Currencies	0.28	0.20	0.55	
Commodities	0.11	0.56	0.51	

For each of the four style composites, we show the Sharpe ratio (annualized return in excess of the risk-free rate divided by the annualized volatility of monthly excess returns), broken out by the seven asset-class contexts, as applicable. All composites are defined as in Section 3 and represent long–short portfolios across the seven asset-class contexts, as applicable, with equal weighting to each available style within an asset class. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies and interest rate futures, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. All returns used in this analysis are in excess of the risk-free rate.

average of the individual Sharpe ratios of the same style strategies applied in each context separately (Table 3), and often higher than the maximum Sharpe ratio attainable for any single asset class. For example, the maximum Sharpe ratio for carry strategies in any single asset class is 0.78 for bonds, but the diversified carry strategy across all asset classes yields a 0.87 Sharpe ratio.

The top panel of Table 4 reports results from regressions of each of the four style composites on equities (MSCI World Index) and bonds (Barclays Global Aggregate bond index). Each of the styles exhibits positive alphas with respect to the various passive indices, and all but value are highly statistically significant, with value having only a marginally statistically significant alpha (t-statistics of 1.67). Furthermore, the beta coefficients on the passive indices are typically small, implying that the styles are not highly exposed to traditional long-only equity or fixed income risk. Value and momentum exhibit no significant exposure to long-only equity or fixed income markets, and while the carry strategy exhibits statistically significant coefficients, the betas are small (0.12 and 0.45 on equities and fixed income, respectively). The defensive style has a significant negative loading on equity markets, but again the economic magnitude of this effect is small (beta of -0.21). Overall, none of the styles exhibit substantially meaningful equity or bond exposure and hence have the potential to offer substantial diversification benefits to traditional investment portfolios. We will directly explore the diversification benefits of these style premia with respect to traditional long-only portfolios in the next section.

The bottom panel of Table 4 also reports regression results for each style that add the other three styles as regressors in addition to the long-only equity and fixed income benchmarks. As the table shows, there are significant alphas to each style that are not subsumed by the other styles—a criterion we aimed for in defining the styles. Moreover, the betas of each style with respect to the other styles are typically zero or strongly negative, suggesting that there are

Table 4 Regression of style portfolios on long-only benchmarks and other styles, 1990–2013.

	Value	Momentum	Carry	Defensive
Alpha (annualized)	3.55%	7.56%	7.17%	5.51%
	(1.67)	(3.56)	(3.46)	(2.73)
Equities market	0.01	−0.03	0.12	−0.21
	(0.17)	(−0.66)	(3.16)	(−5.59)
Bonds market	−0.27	0.30	0.45	0.35
	(−1.37)	(1.54)	(2.35)	(1.87)
Alpha (annualized)	9.68%	9.91%	8.44%	6.27%
	(5.74)	(5.73)	(3.92)	(2.82)
Equities market	0.00	−0.02	0.11	−0.20
	(0.12)	(−0.76)	(2.91)	(−5.30)
Bonds market	0.01	0.14	0.39	0.36
	(0.08)	(0.88)	(2.10)	(1.89)
Value		−0.64	−0.28	−0.07
		(−13.14)	(−3.88)	(−0.94)
Momentum	−0.60		0.00	−0.02
	(−13.14)		(−0.02)	(−0.28)
Carry	−0.18	0.00		−0.05
	(−3.88)	(−0.02)		(−0.80)
Defensive	−0.04	−0.01	−0.05	
	(−0.94)	(−0.28)	(−0.80)	

For each of the four style composites, we regress its monthly excess of risk-free rate returns on the excess of risk-free rate returns of equities (MSCI World Index) and bonds (Barclays Global Aggregate bond index), as well as on these two long-only benchmarks plus the other three styles as regressors. All style portfolios are defined as in Section 3 and represent long–short portfolios across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. The MSCI World Index and the Barclays Global Aggregate bond index start in January 1990. All returns used in this analysis are in excess of the risk-free rate. t-statistics are shown in parentheses.

tremendous diversification benefits from combining all four styles into one portfolio. In particular, the annualized alpha for value, which was only a modestly positive 3.55% (t-statistics = 1.67) with respect to the long-only equity and bond benchmarks, becomes a significantly positive 9.68% (t-statistics = 5.74) when the other styles are added as regressors. This increase is mainly driven by value's strong negative correlation with momentum (and to a lesser extent carry) that makes value an extremely attractive style in the presence of these other factors. This is consistent with other applications of value and momentum (see Asness, 1997; Asness *et al.*, 2013; Asness and

Frazzini, 2013) that argues for examining these styles jointly with each other rather than individually in isolation. We argue that all four styles, not just value and momentum, should be viewed in combination. From the regressions in Table 4, it is apparent that all four styles each offer unique risk premia not spanned by the other styles and hence can offer substantial diversification benefits that we now explore further.

Building on the results in Table 4, Table 5 further highlights the potential diversification benefits of combining the four styles into one portfolio by presenting the correlations of the various style premia. When applied in long–short strategies, the styles provide substantial diversification for each other. The correlation between value and momentum is –0.64, indicating the two styles are powerful diversifiers of each other while still both having long-term positive risk-adjusted returns. Value is also negatively correlated with the carry premium (–0.29 correlation). The other correlations are very close to zero, with the most positive correlation between momentum and carry of only 0.18.

The correlations reported in Table 5 are for style returns applied across asset classes. However, while not presented here, the low correlations among styles are also evident within an asset class. In the extreme example of value and momentum, where their composites are –0.64 correlated, we obtain consistently large negative correlations between these styles when looking within each asset class separately. Similarly, the other pairs have near-zero correlations inside most other asset classes, too.

Table 5 also includes correlations with the overall composite that combines all style premia using the weights described in the previous section. The composite has a correlation of 0.12, 0.45, 0.32, and 0.56 with value, momentum, carry, and defensive, respectively. Table 5 also reports

Table 5 Style premia correlations to major markets, 1990–2013.

	Value	Momentum	Carry	Defensive	Composite	60/40	Equities	Bonds	Commodities
Value	1.00								
Momentum	–0.64	1.00							
Carry	–0.29	0.18	1.00						
Defensive	–0.05	0.03	–0.08	1.00					
Composite	0.12	0.45	0.32	0.56	1.00				
60% equities/ 40% bonds	–0.01	–0.02	0.22	–0.29	–0.10	1.00			
Equities	0.00	–0.03	0.20	–0.31	–0.12	0.99	1.00		
Bonds	–0.08	0.09	0.16	0.07	0.12	0.24	0.11	1.00	
Commodities	–0.12	0.17	0.19	–0.01	0.13	0.22	0.24	–0.08	1.00

For each of the four styles and the overall composite, we show the correlations of excess returns to other styles as well as major market indices. All composites are defined as in Section 3 and represent long–short portfolios across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. The MSCI World Index, Barclays Global Aggregate bond index, and the GSCI Commodities index start in January 1990. All returns used in this analysis are in excess of the risk-free rate.

correlations of each style and the overall style composite with the major market indices that include global equities, bonds, a 60/40 combination of equities and bonds, and commodities. To be clear, the first five rows pertain to the style portfolios that represent long–short returns, whereas the final rows represent passive long-only indices. Since many institutional portfolios hold 60% in equities and 40% in bonds, it is appealing that the correlation between the style premia composite and the global 60/40 stocks and bonds portfolio is –0.10 on average.[25] Similarly, the correlation of the overall composite portfolio with the other major market indices is low, being –0.12 to equities, +0.12 to bonds, and +0.13 to commodities. Hence, style premia provide extremely low correlations to traditional portfolios, making them a very attractive diversifier to most existing portfolios, an issue we investigate further in the next section.

Figure 1 plots the cumulative returns of each style composite, diversified across all asset classes, over time. The figure plots returns from 1990 to 2013, but evidence on the efficacy of these styles in many markets goes back much further.[26] The plot also highlights that while each style generates long-run positive returns, they each can experience significant drawdowns. However, those losses tend to show up at different times, suggesting that a combination of styles, integrated into one portfolio, will be a powerful diversifier that can produce a much more stable long-run stream of positive returns. Close examination also indicates some intuitive periods, such as value losing and momentum winning in the late 1990s,

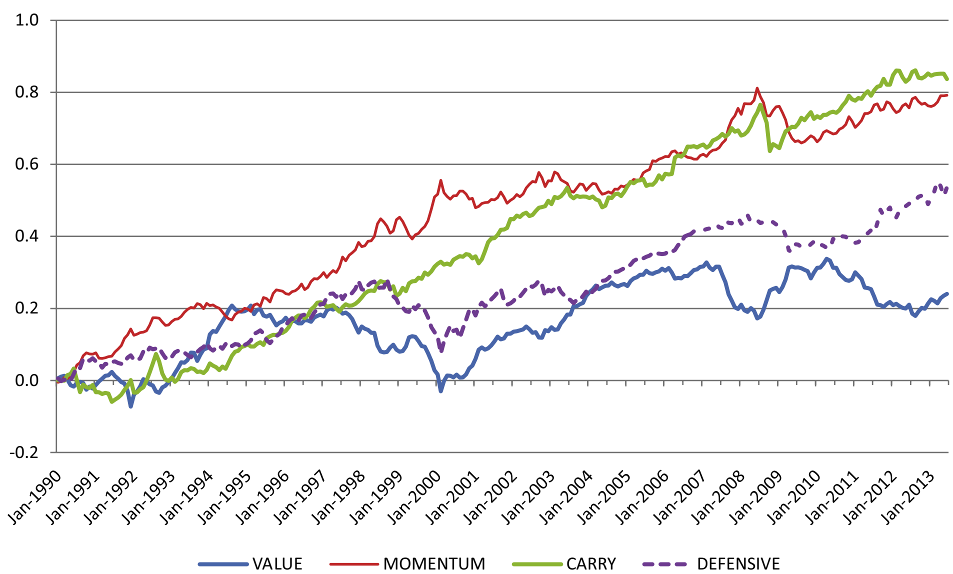

Figure 1 Style premia growth of $1 in log terms, 1990–2013.

For each of the four style composites, we plot the cumulative gains in excess of the risk-free rate of each style composite over time in logarithmic terms. All composites are defined as in Section 3 and represent long–short portfolios across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. All returns used in this analysis are in excess of the risk-free rate.

followed by a sharp reversal over the next few years with value gaining (and a smaller reversal for momentum). Other periods defy common intuition, but often because common intuition is wrong, like carry doing well up until the end of the painful 2007–2008 financial crisis. While currency carry strategies suffered during this time, our carry strategy is comprised of more than just currency carry, and other carry strategies (e.g., commodities) did not suffer over this time period, such that our diversified carry strategy was relatively immune to this episode.

4.2 Multi-style portfolio

The previous results highlight that there appear to be large diversification benefits from applying styles across all markets and asset classes, and thus, it is logical to combine multiple styles into one portfolio to reap the large positive returns and offsetting risk benefits of uncorrelated, or negatively correlated, return premia. A diversified portfolio that combines all four styles across all asset classes should deliver the best risk-reward tradeoff. Although the notion of style premia is straightforward, there are a number of factors to consider to properly implement a style premia portfolio that combines multiple styles across vastly different assets, in order to efficiently harvest returns and manage risk.

Diversification is one of the key elements in style premia portfolio design. While each of the styles employed is strong by itself, they also naturally diversify each other (as shown in Table 5) to provide even stronger performance. Furthermore, a robust portfolio of all style-asset pairs should lead to more consistent returns over time. While some style-asset pairs appear stronger than others over our sample period, the long-term efficacy of each pair is sufficiently similar to and statistically indistinguishable from others. Hence, we build a balanced diversified portfolio and do not attempt to over- or under-weight certain styles or style pairs. Again, we take a conservative approach here and do not attempt to strategically or dynamically weight the styles or asset classes to avoid the risk of overfitting as well as to maintain simplicity.

To illustrate the potential benefits of diversification, we simulate a composite portfolio as described previously that uses the weights described in the previous section and is roughly equally weighted (in risk terms) across the four styles.[27] Table 6 presents summary statistics for the composite portfolio, which yields an astounding 1.74 annualized Sharpe ratio, with returns that are –0.12 correlated with traditional equity returns and –0.10 correlated with the 60%/40% stock-bond allocation. Combining all four style premia into one portfolio effectively doubles the maximum Sharpe ratio obtainable from any single-style strategy.

In addition, the diversified style portfolio also significantly reduces rare or “tail” risks associated with each individual style. Figure 2 analyzes the risk-reward relationship of different style premia to equity markets using a concept of “tail return,” defined as the style’s annualized average performance in the worst 10% of months for global equities. This risk measure captures an investment’s correlation with extremely bad times for equity markets, when investors may care most about performance. This analysis is useful for not only understanding how these style premia perform when traditional equity exposure is punished, but according to financial theory may also help identify what drives these risk premia, since investors may require additional compensation if these styles are particularly exposed to these bad times. Figure 2, which sorts style-asset pairs by the average performance in the worst 10% of months for global equities, shows that the bond defensive and currency carry premia are particularly risky in terms of performance during equity tails. (These currency carry results will surprise few readers, but we have little intuition on why

Table 6 Style premia composite simulations, 1990–2013.

	Composite
Annual excess return	17.4%
Volatility	10.0%
Sharpe ratio	1.74
Correlation to equities	−0.12
Correlation to 60% equities/40% bonds	−0.10
Maximum drawdown	−15.0%
Equity tail return	17.3%
Skew	−0.23
Kurtosis	0.23
Autocorrelation	0.08

For the overall composite style portfolio, we report the annualized return in excess of the risk-free rate ("Annual excess return"), the annualized volatility of monthly excess returns ("Volatility"), the Sharpe ratio (annualized return in excess of the risk-free rate divided by the annualized volatility of monthly excess returns), the monthly correlation to equities (MSCI World Index), the monthly correlation to a portfolio that is 60% equities (MSCI World Index) and 40% bonds (Barclays Global Aggregate bond index), the maximum drawdown (defined as the maximum peak to trough cumulative decline), the equity tail return (defined as the style's annualized average performance in the worst 10% of months for global, MSCI World, equities), the skewness, kurtosis, and autocorrelation of monthly returns. The style premia composite is defined as in Section 3 and represents a long–short portfolio across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. The MSCI World Index and the Barclays Global Aggregate bond index start in January 1990. All returns used in this analysis are in excess of the risk-free rate.

low beta bond markets get hurt, beta adjusted, relative to high beta bond markets in equity tail events.) On the other hand, other styles do very well during these times, including defensive in stock selection and value in equity indices and fixed income. The tail returns of the other styles and asset classes oscillate around zero, suggesting that a broad composite of style premia diversify away most of the "tail returns" of each style in each asset class and provide for long-term equity market neutrality. This is consistent with the plots from Figure 1 that showed that individual style drawdowns do not occur at the same time and consistent with the low correlations from Table 5.

Table 6 also shows the maximum drawdown, skewness, and kurtosis of the diversified style portfolio. Compared to the same statistics for each individual style, which are reported in Table 2, the diversified style portfolio has a significantly smaller maximum drawdown of only –15% (Table 6) compared to –42%, –30%, –26%, and –38%, respectively, for value, momentum, carry, and defensive by themselves. The skewness and kurtosis measures for the diversified portfolio are closer to zero than those for each of the individual styles as well. Hence, the diversification benefits of combining styles also helps ameliorate tail events and risks, leading to an extremely large return-to-risk ratio.

Of course, a Sharpe ratio of more than 1.7 is unlikely to be achievable in practice, since, as is common in academic papers, this Sharpe ratio is based on simple, simulated gross returns of long–short portfolios without subtracting trading costs or fees and without any discounting for the possibility of overfitting or "the world has changed" arguments.[28] However, given our use of only large, liquid securities in our strategies' construction, and given our use of simple not-overly-data-mined measures for each style, it is less likely that out-of-sample degradation will have an overwhelming impact on the performance of our style composite. Moreover, Frazzini *et al.* (2013) present evidence on real-world trading costs of stock selection strategies, including value and momentum, two of the styles considered in this paper. In their paper they show that trading

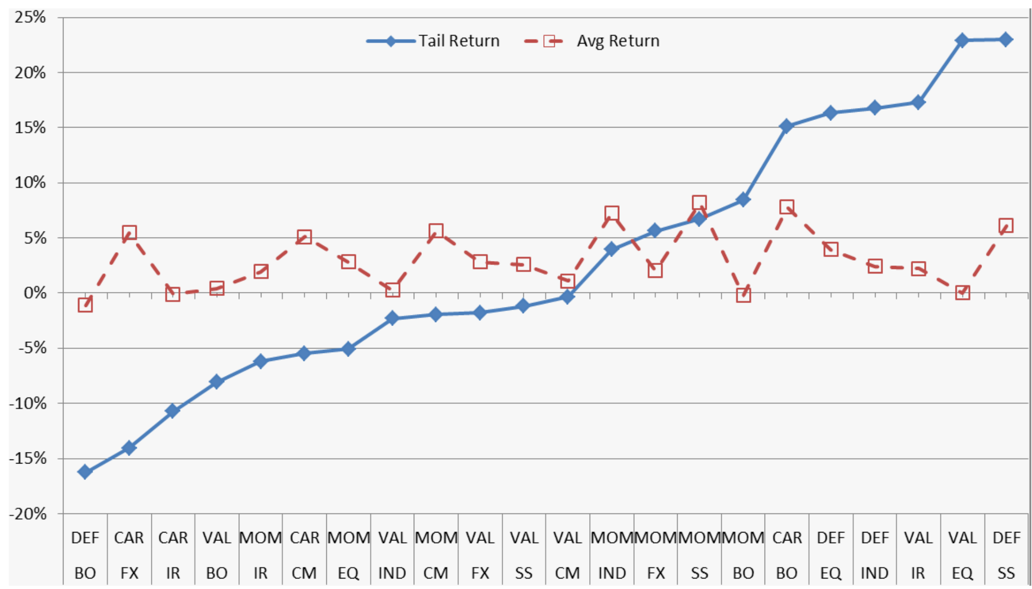

Figure 2 "Tail return" of style premia by asset class, 1990–2013.

For each style in each asset class, as applicable, we plot the average annualized, monthly return of the style portfolio for the full period and the style's equity tail return (defined as the style's annualized average performance in the worst 10% of months for global, MSCI World, equities). All style portfolios are defined as in Section 3 and represent long–short portfolios in each asset class context. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. The MSCI World Index starts in January 1990. All returns used in this analysis are in excess of the risk-free rate.

costs are, of course, a drag on performance, but that the strategies survive these trading costs at quite large fund sizes, especially for netted, multi-style portfolios, such as the ones we contemplate in this paper.

To assess the potential impact of trading and implementation costs, Figures 3 and 4 plot the time-series of leverage for longs and shorts separately, defined as the gross amount of notional exposure per dollar invested on the long and short sides, and turnover per gross amount of notional exposure, defined as the sum of all buys (buy long and buy to cover) and sells (sell long and sell short) per dollar of gross notional, for the style composite portfolio. As shown in Figure 3, leverage is required to achieve a reasonable risk and return target for the composite, given the diversifying nature of the underlying styles and low risk-per-dollar nature of some of them. This trade-off is ubiquitous. The better hedged your strategy is, the more leverage is generally needed to make it matter. Specifically, leverage is applied to lower volatility assets, while higher volatility assets like commodities do not require the same amount of leverage. While implementation costs are investor-specific, the levels of leverage and trading required to replicate the style composite portfolio are not implausibly large at reasonable dollar amounts. Moreover, simple adjustments to building a similar portfolio that can greatly mitigate these costs are easily achievable. For instance, in results not provided in this paper, we also simulate a realistic portfolio that starts with the composite portfolio presented above, overlays some simple real-world value-added portfolio design and implementation considerations (such as patient trading and constraints on percentage

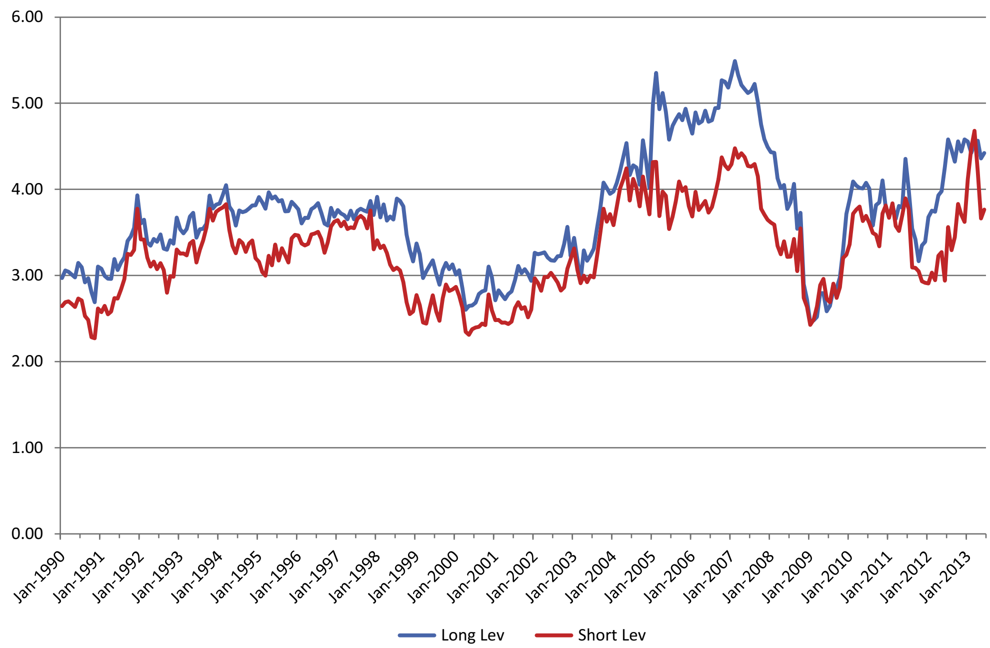

Figure 3 Embedded long and short leverage of style composite strategy, 1990–2013.

For the overall style composite, we plot the time-series of embedded leverage separately for the long and short sides of the style composite portfolio, defined as the gross amount of notional exposure per dollar invested on the long and short sides, respectively. The style composite is defined as in Section 3 and represents a long–short portfolio formed across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997.

of total dollar volume allowed to trade), and then applies conservative, estimated transactions costs and a level of discounting (as high as 50%) to adjust for any upward biases that might be present in the simulated results. This resulting portfolio still provides strong risk-adjusted returns with little correlation to traditional assets.

5 Style premia as a portfolio diversifier (alone and versus hedge funds)

The broad style portfolio itself is highly diversified, but it is more important to many investors that it serves as an effective diversifier for their own portfolios. We examine the correlation of our style premia composite to traditional portfolios as well as to alternatives such as hedge funds.

5.1 Time-varying correlations

Figure 5 plots the time-series of correlations between the style premia composite portfolio and the global 60/40 stock/bond strategy as well as a hedge fund index (the HFRI total return index). Correlations are estimated using rolling 36-month windows. There is significant time variation in the correlations through time. The green line in the graph shows that the correlation of the style premia portfolio with the traditional global 60/40 stock/bond portfolio ranges from –0.6 to +0.6, and averages zero over the full sample period. Even at the most extreme positive correlation, which is +0.6 over the sample period, there are still significant diversification benefits from investing in style premia, and over time

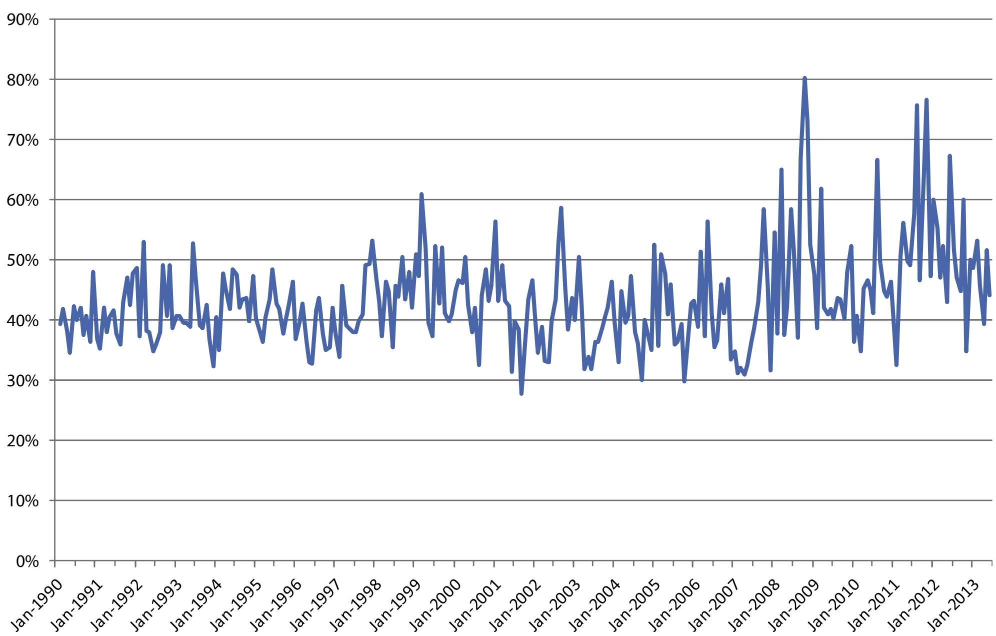

Figure 4 Turnover of style composite strategy, 1990–2013.

For the overall style composite, we plot the time-series of two-sided turnover defined as the sum of all buys (buy long and buy to cover) and sells (sell long and sell short) per dollar of gross amount of notional exposure. The style composite is defined as in Section 3 and represents a long–short portfolio formed across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. (Note, the initial investment from cash trade is excluded from the graph.)

these benefits appear to have gotten larger as longer-term correlations are near zero.

The same time-series pattern holds for the correlation between style premia and the hedge fund index, indicated by the red line (in fact, it looks almost the same for reasons that will soon become clear). The correlations range from –0.6 to +0.6, implying that diversification benefits exist even at the most extreme times, and tremendous hedging benefits are present most of the time. Finally, the blue line on the graph plots the correlation between the traditional global 60/40 portfolio and a hedge fund index. Here, the correlations are much higher, averaging +0.6 over time and ranging from +0.2 to +0.9, with a steady increase in correlations over time.[29] Not only do hedge funds average a significantly positive long-term correlation, unlike the style composite, but even when the style composite is at its most correlated, it is still below the concurrent hedge fund correlation. Thus, the diversification benefits of combining a traditional portfolio with hedge fund alternatives are much smaller than they are from using style premia, and have become even smaller over time. Conversely, no such drift has occurred in the correlation of style premia with long-only markets, where, in fact, the correlations are negative over the most recent three years. The disturbing upward trend in correlations between the traditional 60/40 strategy and hedge funds, which was always high but has crept up over time, currently hovering around 0.9, should raise

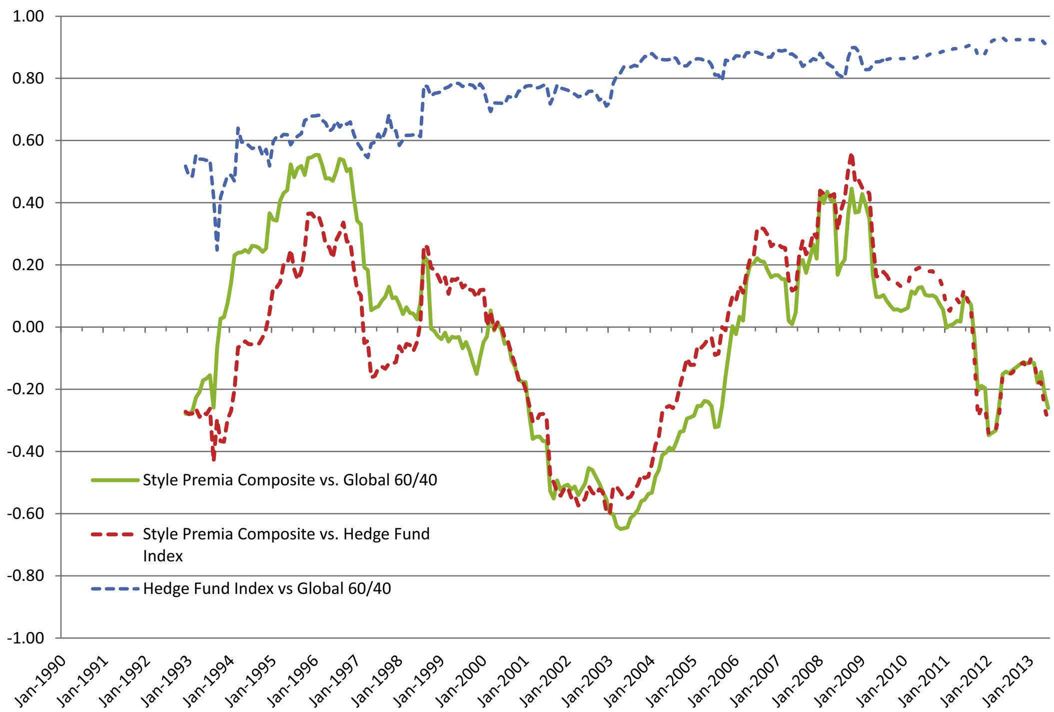

Figure 5 Rolling 36-month correlation of style premia composite to global 60/40 portfolio and hedge fund index, 1990–2013.

For the overall style composite style, we plot the time-series of correlations between the style composite, the global 60/40 portfolio that is 60% equities (MSCI World Index) and 40% bonds (Barclays Global Aggregate bond index), and a hedge fund index. Correlations are estimated using rolling 36-month windows. The style composite is defined as in Section 3 and represents a long–short portfolio formed across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. The MSCI World Index, Barclays Global Aggregate bond index, and the GSCI Commodities index start in January 1990. For the hedge fund index, we use the Hedge Fund Research broad hedge fund index, in USD, starting in January 1990. All returns used in this analysis are in excess of the risk-free rate.

some concern for investors seeking alternative sources of returns from a diversified portfolio of hedge funds. The style premia portfolio, on the other hand, does not exhibit these trends and offers much lower correlation and much greater diversification benefits.

5.2 *Asset allocation*

To illustrate and quantify the potential benefits of style investing as a diversifier for traditional portfolios, Table 7 shows the impact of allocating pro-rata away from the 60/40 stock/bond portfolio into the style composite at three levels of investment: 10%, 20%, and 30% devoted to the style premia composite portfolio. As the table shows, the Sharpe ratio of the resulting combinations improves steadily, and by a wide margin, going from the base case 0.31 to 0.52 with a 10% style allocation, increasing to 0.76 with a 20% allocation and to 1.04 with a 30% allocation to styles. Even adding fairly modest

Table 7 Impact of adding the style premia composite to global 60/40, 1990–2013.

	60/40	+10% Styles	+20% Styles	+30% Styles
Annual excess return	3.0%	4.4%	5.8%	7.3%
Volatility	9.5%	8.5%	7.7%	7.0%
Sharpe ratio	0.31	0.52	0.76	1.04
Correlation to equities	0.99	0.98	0.95	0.89
Equity tail return	−61.6%	−53.7%	−45.8%	−37.9%

For the global 60/40 portfolio that is 60% equities (MSCI World Index) and 40% bonds (Barclays Global Aggregate bond index), a portfolio that is 90% global 60/40 and 10% style premia composite, a portfolio that is 80% global 60/40 and 20% style premia composite and a portfolio that is 70% global 60/40 and 30% style premia composite, we report the annualized return in excess of the risk-free rate ("Annual excess return"), the annualized volatility of monthly excess returns ("Volatility"), the Sharpe ratio (annualized return in excess of the risk-free rate divided by the annualized volatility of monthly excess returns) and the monthly correlation to equities (MSCI World Index). The style premia composite is defined as in Section 3 and represent a long–short portfolio across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. The MSCI World Index, Barclays Global Aggregate bond index, and the GSCI Commodities index start in January 1990. All returns used in this analysis are in excess of the risk-free rate.

allocations to a broad style composite can significantly improve performance and reduce risk exposure substantially. Of course, none of these portfolios incorporate trading costs, and the simulated results are from a period since 1990 which was benign for both asset class premia and style premia. Hence, the level of Sharpe ratios may be too optimistic. However, it is reasonable to believe that the relative improvement from adding styles at various allocations is likely more stable and reliable. The last row of Table 7 presents the tail performance of the various asset allocation combinations as well. Here, the diversification benefits of adding style premia are also evident, even over a fairly volatile sample period.

5.3 Hedge funds and style premia

Flipping the analysis around, we can also examine how much of hedge fund returns are tied to the style premia we showcase. Specifically, we ask how much of hedge fund returns can be explained by simple long-only market and long–short style exposure and if this has changed over time.

We regress the monthly hedge fund index return series from HFRI on a global market portfolio (MSCI World), a lag on this market (following Asness *et al.*, 2001), and each of our four style portfolios: value, momentum, carry, and defensive. We focus on slope coefficients, not the intercepts, because we make no effort to adjust the hedge fund index returns for survivorship, backfill, or other biases that may upwardly bias the average returns and the intercepts.[30] Also, to be fair we have noted that our style returns may be upward biased in the past which would, if hedge funds load positively on them, reduce the intercepts. All of this makes interpreting the intercepts difficult. As the first column of Table 8 shows, over the full 1990–2013 sample period the average hedge fund has very large long-only equity market exposure, and loads significantly positively on momentum, significantly negatively on

Table 8 Regression of hedge fund indices, 1990–2013.

	HF index	Convertible arbitrage	Dedicated short	Emerging markets	Market neutral	Event driven	FI relative value	Global macro	Long–short equity	Managed futures
Alpha (annualized)	5.02%	1.49%	−7.01%	−1.05%	1.38%	5.27%	4.05%	5.17%	6.97%	6.29%
	(5.23)	(1.06)	(−2.49)	(−0.45)	(2.22)	(5.20)	(5.12)	(3.33)	(5.35)	(4.30)
Market	0.30	0.22	−0.69	0.58	0.06	0.27	0.14	0.16	0.39	0.19
	(17.73)	(8.64)	(−13.71)	(13.81)	(5.48)	(15.12)	(9.80)	(5.89)	(16.78)	(7.22)
Market (lagged)	0.07	0.12	−0.04	0.12	0.01	0.10	0.07	0.01	0.06	−0.01
	(4.39)	(5.07)	(−0.76)	(3.02)	(0.95)	(6.09)	(5.62)	(0.47)	(2.88)	(−0.33)
Value	0.05	−0.04	0.26	0.21	0.04	0.12	0.08	0.11	0.01	−0.03
	(1.65)	(−0.74)	(2.68)	(2.41)	(1.96)	(3.50)	(3.09)	(1.99)	(0.15)	(−0.52)
Momentum	0.15	−0.04	0.02	0.22	0.16	0.09	0.06	0.27	0.20	0.19
	(4.75)	(−0.77)	(0.19)	(2.80)	(7.66)	(2.68)	(2.11)	(5.22)	(4.56)	(3.93)
Carry	0.01	0.19	0.17	0.23	−0.02	0.06	0.08	0.00	−0.03	−0.10
	(0.52)	(4.73)	(2.16)	(3.36)	(−1.28)	(2.16)	(3.49)	(0.07)	(−0.73)	(−2.45)
Defensive	−0.13	0.00	0.66	−0.10	0.00	−0.07	0.00	−0.08	−0.20	−0.16
	(−5.15)	(−0.05)	(8.75)	(−1.68)	(0.21)	(−2.43)	(−0.21)	(−1.87)	(−5.72)	(−4.14)
R^2	0.65	0.39	0.58	0.53	0.27	0.59	0.42	0.23	0.63	0.30

This table shows the results of a full-period, in-sample regression of hedge fund indices, reporting the alpha (annualized), the beta coefficients, the *t*-statistics of the beta coefficients, and the *R*-squared. The left-hand side of the regression is the hedge fund index monthly excess of the risk-free rate returns. The explanatory variables are the contemporaneous market, lagged market, value, momentum, carry and defensive composite excess of the risk-free rate returns. All composites are defined as in Section 3 and represent long–short portfolios across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. The MSCI World Index starts in January 1990. For hedge fund indices, we use the Hedge Fund Research broad hedge fund index, in USD, and the subcomponent hedge fund indices, in USD, starting in January 1990. All returns used in this analysis are in excess of the risk-free rate.

defensive (meaning hedge funds prefer high-risk stocks), and slightly positively but insignificantly on value and carry.

The remaining columns of Table 8 present results for similar regressions using the subcomponents of the hedge fund index, obtained from HFRI and covering the same period. The subcomponent hedge fund types are convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income relative value, global macro, long–short equity, and managed futures. Table 8 indicates that exposure to value is significantly positive for dedicated short bias (since they are short the market, this implies that they are short the parts of the market that appear most expensive on our value measures), emerging markets,

Panel A: Rolling 36-month *t*-statistics of the beta coefficients

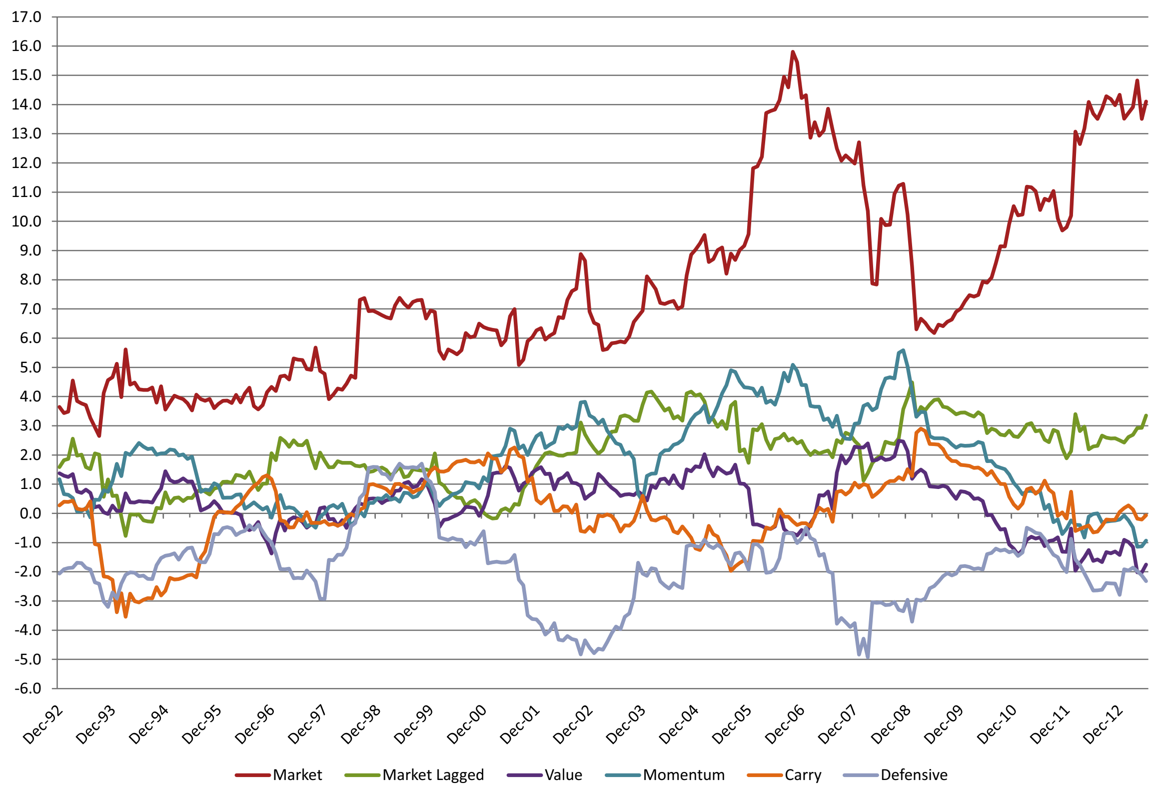

Figure 6 Rolling 36-month regression alpha (annualized) and beta *t*-statistics of hedge fund index, 1990–2013.

This figure plots the *t*-statistics of the beta coefficients (Panel A) and annualized alpha (Panel B) from a rolling 36-month regression of the hedge fund index. The left-hand side of the regression is the hedge fund index monthly excess of the risk-free rate returns. The explanatory variables are the contemporaneous market, lagged market, value, momentum, carry, and defensive composite excess of the risk-free rate returns. All composites are defined as in Section 3 and represent long–short portfolios across the seven asset-class contexts, as applicable, according to the following weighting: 30% weight to individual stocks, 10% weight to industries, 15% weight to equity indices, 10% weight to government bonds, 5% weight to interest rate futures, 15% weight to currencies, and 15% weight to commodities. All series are monthly, scaled to 10% annual volatility and end in June 2013. For stocks (and industries), developed market equity indices, and developed market currencies, the series starts in January 1990. For commodities, the series starts in February 1990. For government bonds, the series starts in January 1991. For interest rate futures, the series starts in April 1990. For emerging equity indices the series starts in January 1996, and for emerging currencies the series starts in April 1997. The MSCI World Index starts in January 1990. For the hedge fund index, we use the Hedge Fund Research broad hedge fund index, in USD, starting in January 1990. All returns used in this analysis are in excess of the risk-free rate.

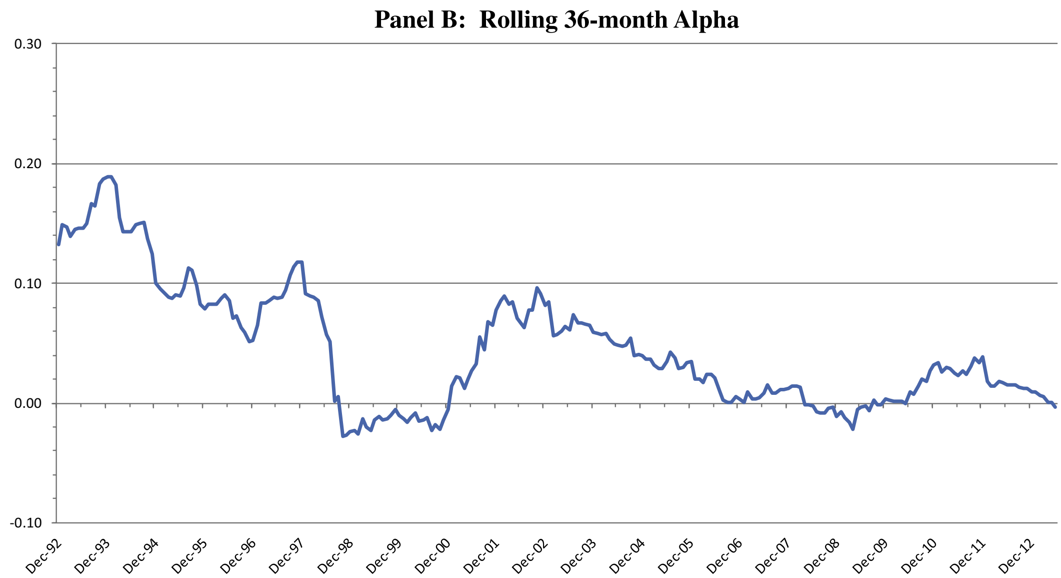

Figure 6 (*Continued*)

equity market neutral (though only marginally significant), fixed income relative value, and event-driven hedge funds and is zero for the other hedge fund types: convertible arbitrage, long–short equity, and managed futures. Thus, some hedge fund strategies have significant value exposure, while others have no value exposure, but no fund type has significant negative value exposure.

Momentum exposure is large and significantly positive for all hedge fund types, except for convertible arbitrage and dedicated short bias, where there is zero momentum exposure. Like value, no hedge fund type has significant negative exposure to momentum. All exposures are either positive or zero. Interestingly, casual empiricism says that long–short equity managers talk a lot about value but empirically seem far more related to momentum investing. For managed futures, momentum is the only positive exposure found, which is consistent with the results in Moskowitz *et al.* (2012), who show that simple time-series momentum strategies, which are related to the cross-sectional momentum styles we use here, can capture a great deal of the performance of managed futures hedge funds.

Carry exposure is almost the opposite of momentum. For carry, there is significant positive exposure for the fixed income strategies—convertible arbitrage and relative value—and significant positive exposure for dedicated short bias, too. Likewise, the managed futures strategy, which has a strong positive loading on momentum, is the only strategy that exhibits a significant negative loading on carry. All other hedge fund types have exposure to carry that is indistinguishable from zero (with emerging markets and event driven being marginally positive). The lack of apparent carry exposure for global macro hedge funds seems surprising, given that currency carry is often a stated part of their strategy. However, we also ran regressions using only the currency carry returns as a regressor and still found no significant effect.

Finally, defensive exposure is typically negative or zero for all hedge fund types, except for dedicated short bias, where it is significantly positive, meaning they are shorting risky stocks.

These results make intuitive sense in that most hedge funds are long momentum and value and short defensive (i.e., long high beta securities), with variation across hedge fund types in exposure to carry. Fixed income-type strategies are more exposed to carry and more equity-related strategies are more exposed to momentum and value. Overall, however, hedge funds either exhibit positive or zero loading on value, momentum, and carry, where all are return enhancing according to our findings. No fund type exhibits significant negative loadings on these profitable styles.

Market and style premia also explain a large portion of the variation in hedge fund returns, as indicated by the high R-squares from the regressions. The regressors are able to explain 65% of the total hedge fund index returns and 23–63% of the subcomponent returns. While most of the explanatory power is coming from general market exposure, the styles themselves add significant additional explanatory power for hedge fund returns across all types of hedge fund categories. An F-test on the joint significance of the styles is easily rejected for each hedge fund subcomponent, implying that the style returns add significant explanatory power for each type of hedge fund strategy above and beyond general equity market exposure. Finally, the regressions in Table 8 only use the composite style portfolios diversified across asset classes (e.g., using value, momentum, carry, and defensive for the whole composite across all asset classes, rather than asset-class-specific style portfolios), which may limit the explanatory power of the styles. Using asset-class-specific style portfolios as explanatory variables can capture even more of the variation in hedge fund returns but are beyond the scope of this paper.

Table 8 reports the average exposures of hedge funds over time. However, the exposures of hedge funds have changed through time. Panel A of Figure 6 plots the rolling 36-month t-statistics of the beta coefficients (to both traditional markets and styles) through time. As the figure indicates, hedge funds have increased their exposure to passive equities significantly through time, while at best retaining their mild exposures to style premia. While there is some movement in style exposures over time, the largest being for the defensive style (albeit negative), most of the changes in exposure are small and within random variation. The only significant time-series trend we detect is a rise in equity market exposure. This rise in equity exposure also coincides with a significant reduction in estimated hedge fund alpha over time, as illustrated in Panel B of Figure 6, where the average, annualized rolling 36-month alpha has degraded to essentially zero in recent years.

These results suggest that hedge funds are not on average giving much exposure to the proven investment styles we highlight. At the same time, hedge funds on average have had more difficulty in producing and maintaining alpha against the market or these styles. Hence, simple style investing can provide a positive source of returns that appears largely distinct from what hedge funds are currently doing (and still mostly distinct from what they have done historically). Combining these results with those shown earlier, style premia appear to offer an alternative source of returns quite different from traditional equity markets and hedge funds, and therefore can offer an attractive alternative investment with tremendous diversification benefits for most investors' portfolios.

6 Conclusion

Although the equity premium has historically been thought to be the most reliable source of long-run returns, many investors today question that assumption going forward and feel that they are over-exposed to it. Excessive dependence on any single source of risk is inefficient diversification, even (or perhaps especially) if everyone does it. In a world with multiple risk factors, there are better and more efficient ways to construct portfolios. The most reliable way to sustained investment success involves cost-effectively harvesting multiple return sources that have low correlation with each other. In this paper, we focus on the return and diversification benefits of market-neutral style premia and show how to construct an efficient, diversified style strategy in a transparent and cost-effective way to enhance any investment portfolio. We apply a strict set of criteria—in- and out-of-sample evidence, economic theory and intuition, liquidity, and low correlation—to choose these styles and find four such styles that fit these criteria: value, momentum, carry, and defensive.

Given the evidence on the efficacy of these styles, why have not more investors embraced simple style premia? One answer might be lack of knowledge. Although the evidence in favor of these styles has existed in the literature for some time, it is somewhat scattered and not previously linked together. Among other things, this paper shows that value, momentum, carry, and defensive are styles that on average work "everywhere" across a variety of markets and asset classes. In addition, investors often view each style premium separately, where their diversification benefits are less appreciated, and often chase returns across styles as their performance varies, investing in only a single style at a time and switching from one style to another. Switching among individual styles (and doing it poorly) can lead to dissatisfaction with the whole notion of style premia and fails to elucidate the significant diversification benefits that exist from combining all styles simultaneously.[31]

A second possible answer is the continual pursuit of alpha. Too many investors think that they can identify alpha and find alpha producers. The reality is that the pursuit of alpha is very difficult, and even if identified, is expensive. Moreover, this pursuit has led to an overinvestment in high-fee hedge funds whose largest exposure is traditional equity risk and whose exposure to equity risk has been increasing through time.

A third possible answer is the prevalent aversion to leverage, shorting, and/or derivatives. An efficient style premia strategy uses these tools. Indeed, one of the main style premia—defensive—may itself be the result of taking advantage of other investors' leverage aversion. For the investor who can take a little LSD (leverage, shorting, and derivatives, that is!), or accept their delegated use, there is the potential for large rewards in terms of better and more stable returns. While many will claim it through long-only assets, volatile assets, idiosyncratic assets, and especially illiquid assets (which look diversifying but often are not), there is simply no way to be truly uncorrelated across a broad set of strategies without shorting, no way to balance different strategies in different asset classes and attain diversification without leveraging some and deleveraging others, no way to effectively implement many macro type strategies without derivatives like futures, and no way to target a significant return goal without applying some leverage. Not everyone has the ability to manage these risky tools, but we believe that they can be managed successfully and effectively to produce large and needed diversification benefits to most investors today.[32]

Finally, there is also the risk of deviating from the herd, sometimes called "maverick risk" or "peer risk". In almost every endeavor, it is famously dangerous to lose unconventionally—far more dangerous, in fact, than losing conventionally. On the other hand, being a maverick has its rewards, too, and is the impetus for changing convention. Style investing provides a vehicle and an opportunity to break from the pack.

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Appendix

This appendix contains results for some of our key tables using monthly data and a simple rolling

Table 2A Style premia simulations, 1990–2013.

	Value	Momentum	Carry	Defensive
Annual excess return	2.3%	10.1%	9.3%	7.2%
Volatility	10.6%	10.7%	10.4%	11.3%
Sharpe ratio	0.21	0.94	0.90	0.64
Correlation to equities	0.01	0.00	0.18	−0.25
Correlation to 60% equities/40% bonds	0.00	0.01	0.19	−0.24
Maximum drawdown	−46.4%	−26.4%	−24.4%	−36.4%
Equity tail return	3.3%	4.2%	−6.5%	17.5%
Skew	−0.53	0.45	−0.57	−0.17
Kurtosis	1.05	1.01	3.59	1.01
Autocorrelation	0.26	0.15	0.06	0.02

Table 3A Style premia Sharpe ratios by asset class, 1990–2013.

	Value	Momentum	Carry	Defensive
Stock selection	0.16	0.92		0.65
Industry selection	0.05	0.81		0.29
Equity country selection	0.00	0.33		0.42
Bonds country selection	–0.08	0.02	0.90	–0.17
Interest rate futures	0.35	0.19	–0.10	
Currencies	0.31	0.21	0.57	
Commodities	0.15	0.51	0.67	

Table 5A Style premia correlations to major markets, 1990–2013.

	Value	Momentum	Carry	Defensive	Composite	60/40	Equities	Bonds	Commodities
Value	1.00								
Momentum	–0.65	1.00							
Carry	–0.29	0.19	1.00						
Defensive	–0.08	0.06	–0.07	1.00					
Composite	0.07	0.45	0.31	0.53	1.00				
60% equities/ 40% bonds	0.00	0.01	0.19	–0.24	–0.08	1.00			
Equities	0.01	0.00	0.18	–0.25	–0.09	0.99	1.00		
Bonds	–0.06	0.09	0.13	0.06	0.09	0.24	0.11	1.00	
Commodities	–0.12	0.18	0.19	–0.02	0.13	0.22	0.24	–0.08	1.00

Table 6A Style premia composite simulations, 1990–2013.

	Composite
Annual excess return	17.4%
Volatility	10.3%
Sharpe ratio	1.69
Correlation to equities	−0.09
Correlation to 60% equities/40% bonds	−0.08
Maximum drawdown	−18.5%
Equity tail return	15.1%
Skew	−0.35
Kurtosis	0.69
Autocorrelation	0.03

Table 7A Impact of adding the style premia composite to global 60/40, 1990–2013.

	60/40	+10% Styles	+20% Styles	+30% Styles
Annual excess return	3.0%	4.4%	5.9%	7.3%
Volatility	9.5%	8.5%	7.7%	7.1%
Sharpe ratio	0.31	0.52	0.76	1.03
Correlation to equities	0.99	0.98	0.95	0.89
Equity tail return	−61.6%	−54.0%	−46.3%	−38.6%

36-month estimate of volatilities and correlations as the risk model instead of the risk models described in Section 3. See the corresponding table headers for a definition of the data presented in each table in the appendix.

Notes

1 Asness *et al.* (2001) and Asness (2004).

2 Berger *et al.* (2012), Fung and Hsieh (2004), and Ibbotson *et al.* (2010).

3 Note that in this paper we will only study cross-sectional momentum strategies that are designed to be market-neutral. Market-directional, time-series momentum strategies (trend following) are not studied, as again our focus is on market-neutral implementations of styles, despite the fact that such strategies have historically offered attractive return and diversification characteristics (see Moskowitz *et al.*, 2012).

4 Asness *et al.* (2013), Asness *et al.* (1997), Frazzini and Pedersen (2011, 2013), and Dimson *et al.* (2008, 2013).

5 Koijen *et al.* (2013).

6 Berk (1995), Knez and Ready (1997), and Israel and Moskowitz (2013) question the robustness of the size effect. Asness *et al.* (2013) show that when controlling a company's quality, the performance of small versus large stocks is far more robust and perhaps further study will resurrect this potential style.

7 Ilmanen (2011) provides an overview of many expected return sources, including the styles we focus on.

8 Increasingly the term "smart beta" is used for such a long-only tilted portfolio; see Blitz (2013) and Economist (2013).

9 Fama and French (1992, 1993, 1998, 2006, 2008, 2012).

10 See Israel and Moskowitz (2013) for evidence that more measures of value and growth lead to more stable portfolios and more reliable predictability in returns.

11 DeBondt and Thaler (1985, 1987), Fama and French (1996), and Asness *et al.* (2013).

12 Koijen *et al.* (2013) and Ilmanen (2011, Chapters 13 and 22).

13 Novy-Marx (2013), Asness *et al.* (2013). There is currently overlap in what academics and practitioners call "defensive" (the term we use throughout this paper) and "quality".

14 Blitz *et al.* (2013) provide an overview of possible explanations for the low-risk style including leverage constraints, regulatory constraints, constraints on short-selling, relative utility, agents maximizing option value, crash aversion, and preference for skewness (lottery-like characteristics), as in Ilmanen (2012).

15 Frazzini and Pedersen (2013) and Asness *et al.* (2012) show that the same idea applies to asset classes, where bonds are the low beta and equities the high beta asset classes.

16 We specifically map the subcomponent hedge fund types as follows: broad hedge fund index: HFRI Fund Weighted Composite Index; convertible arbitrage: HFRI RV Fixed Income-Convertible Arbitrage Index; dedicated short bias: HFRI EH Short Bias Index; emerging markets: HFRI Emerging Markets (Total) Index; equity market neutral: HFRI EH Equity Market Neutral Index; event driven: HFRI Event-Driven (Total) Index; fixed income relative value: HFRI Relative Value (Total) Index; global macro: HFRI Macro (Total) Index; long–short equity: HFRI Equity Hedge (Total) Index; and managed futures: HFRI Macro Systematic Diversified Index.

17 We use various BARRA risk models depending on the availability and robustness through time. Specifically, we use the short-term risk models (S) for the U.S. and the U.K. for the entire sample. In continental Europe, we use the GEMM risk model up until February 1997, the EUE2 model from then on and up until December 2009, the EUE2L model from then on and up until April 2012 and the EUE3L model for the remainder. In Japan, we use the JPE3S model up until October 1997 and the JPE3 model for the remainder. It is possible that BARRA's model adjustments over time cause some look-ahead bias in the risk measures.

18 We emphasize that equity carry strategies are excluded solely due to the overlap and the high correlation with equity value, and, as a result, we did not want to double-count this theme. They are not excluded based on empirical evidence. In fact, we could just as easily not consider value but include carry, using dividend yield as our measure. In this sense, equities still provide out-of-sample support for the carry style. Future research may provide less overlapping or otherwise more suitable strategies that can define these styles in these asset classes.

19 Defensive macro strategies were excluded because they were hard to define or resulted in static positions through most of the samples (such as long gold and short natural gas in commodities). Again, they are not excluded based on empirical evidence. Future research may provide suitable strategies that can define these styles in these asset classes.

[20] The full-sample risk model (*ex-post* data) is only used when we combine a portfolio of style strategies and target its volatility when there is no corresponding risk model as defined in Section 3. The results are similar when using a rolling 36-month *ex ante* estimate of volatilities and correlations as detailed in the Appendix.

[21] Again, as in the prior footnote, the results are similar when using a rolling 36-month *ex ante* estimate of volatilities and correlations as detailed in the Appendix.

[22] Equity-related risk does not mean long equity market exposure. In this case 55% of the risk is in long–short styles that use some form of equities, from individual stocks, industries, or equity index futures, but the exposure is equity-neutral (non-directional) in the sense that equity risk is taken equally on the long and short sides.

[23] Note, in this table and throughout this paper, we will use Sharpe ratios to evaluate and compare the risk-adjusted returns of these styles. Since the style portfolios we examine in this paper are long–short portfolios and are designed to be market-neutral, we feel this is the most relevant measure to evaluate the efficacy of each strategy. One could also compare the returns of each strategy with a benchmark portfolio (either stocks, or a 60/40 combination of stocks and bonds) and report the Information ratio (average difference in the monthly returns between the style portfolio and the benchmark portfolio, divided by the standard deviation of those differences). We feel that this is a much less informative comparison, as the benchmark portfolio is not a market-neutral portfolio, and thus, the differences between the style portfolios and the benchmark portfolio will be dominated by the differences in market-neutrality and the returns of the market.

[24] While value has the lowest stand-alone Sharpe ratio, this is partially a consequence of using up-to-date price in forming our value measures, which means our value measures are very short, or negatively correlated with, momentum, unlike some measures of value which lag price. Given this negative correlation, value is still extremely valuable as a style, when combined with other styles such as momentum, and as Asness and Frazzini (2013) show, even more valuable when constructed this way. In addition, we use the standard single measure, BE/ME, which does not work as well as a combination of related fundamental-to-price measures (e.g., a combination of book equity, earnings, cashflows, and sales), especially over this sample period (see Israel and Moskowitz, 2013). Hence, our results may be understated, though we stick with the single valuation measure to ameliorate data mining concerns and for simplicity.

[25] We present style premia as long–short strategy returns. More constrained investors may apply style tilts to their long-only portfolios and get a meaningful portion of the return improvements but limited diversification benefits. Ilmanen and Kizer (2012) show that style diversification is more effective than asset class diversification mainly when short-selling is allowed. Long-only style-tilted portfolios have higher correlations with each other, with equity markets, and with other traditional portfolios. Still, if a long–short, diversified implementation is not possible due to constraints, while not as strong as our results here, a long-only portfolio with style tilts can still offer a significant improvement over traditional portfolios.

[26] For example, there is evidence going back to 1926–1927 in U.S. stocks for all four styles, 1970 in commodities and currencies, and 1980 for bonds. There is even evidence from Chabot *et al.* (2008) of momentum effects going back to the Victorian age and from Geczy and Samonov (2013) of momentum from 1801–2012 in what the authors call, with some justifiable pride, "the world's longest backtest".

[27] It is not perfectly equal risk-weighted as we do not have each style represented for each asset class. Also, we do not overweight the value/momentum combination due to its negative correlation, which is something that does not affect the aggregate result much, but could be a reasonable thing to do.

[28] Even if every researcher individually is meticulously careful about not overfitting, or data mining, as we believe we have been here at each step, the general field of study may still contain overfitted results due to the literature and practice focusing on those studies that yielded significant results and discarding or ignoring those that did not, where it is likely that some of those results could have been generated by chance (e.g., Lo and MacKinlay, 1990). Again, we do not see a big problem here, particularly as most of our period is out of sample from the style's original discovery. But, while less dangerous, choosing styles that have held up out of sample is still a form of data mining, just a more stringent one! Apart from overfitting concerns, it may be argued that when factors become well known, or the costs of accessing them fall, their prospective returns decline, so assuming future results will not equal the past is prudent.

[29] Monthly correlations likely understate hedge fund correlation with long-only markets due to illiquidity in hedge fund returns (Asness *et al.*, 2001). Hence, the correlations over longer horizons are even higher.

[30] In unreported results using the Credit Suisse hedge fund index from 1994 onwards, we obtain qualitatively similar results, yet observe lower alphas, consistent with the notion that the survivorship and backfill bias of the HFRI index may have been greatest in the early period, specifically 1990–1993.

[31] We have not studied it here, and are a bit cynical that it can be done while minimizing data mining concerns, but a more rational approach to "timing" these styles (e.g., not just return chasing, which may figure in through momentum, but valuation of the strategy itself and use of other timing measures) may be worth exploring. Still, the power of diversifying across these styles is so strong that timing the individual styles can be dangerous, if not detrimental.

[32] Use of liquid assets, high cash levels, timely and precise risk estimation, drawdown control, and exposure estimation and management are just some of the techniques that can help successfully manage the use of leverage, shorting, and derivatives.

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