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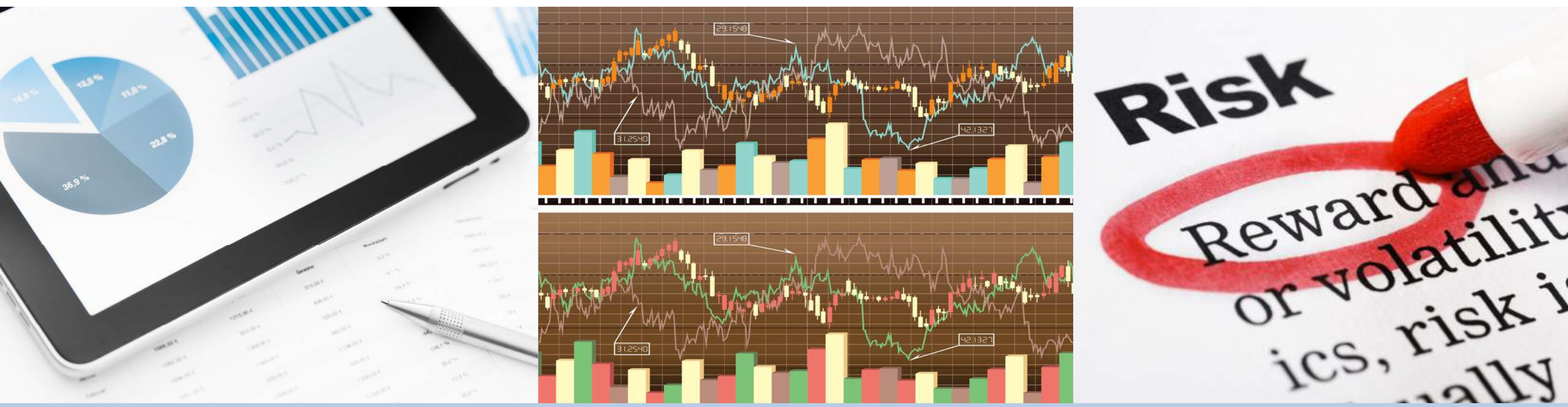

Equity Risk Premia Strategies

Risk Factor Approach to Portfolio Management

Quantitative and Derivatives Strategy

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See page 135 for analyst certification and important disclosures, including non-US analyst disclosures.

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Dear Investor,

In recent years we have witnessed increased interest in a Risk Factor approach to investing and portfolio management across asset classes. In our guide to Systematic Strategies Across Assets Classes, we developed a framework to classify Risk Factors, tested Factor regimes, and analyzed risk methodologies for building an optimal Factor portfolio.

The concept of Risk Factors has been at the center of **Quantitative Equity Investing** for many years. Equity Risk Factor exposures are expected to deliver positive long-term returns (also called Equity Risk Premia), and the correlation between Equity Risk Factors is expected to be low across market cycles. While one can define Equity Risk Factors with mathematical tools such as principal/independent component analysis, we adopted a more intuitive approach. We define Equity Risk Factors as thematic long-short portfolios with stable correlation properties and sound economic rationale. These quantitatively designed portfolios give exposure to investment theses such as long-term outperformance of stocks with Small Capitalization, Low Price-to-Earnings ratio, High Momentum or Low Volatility.[1]

Individual Equity Risk Factors that have similar correlation, performance, and regime properties can be categorized into Risk Factor Styles (or families). Factor Styles include Value, Momentum, Quality, Growth, and Volatility. Factors and Styles can have performance cycles, often influenced by market regimes such as economic growth, inflation and market liquidity. Some factors can lose effectiveness over time (e.g. become crowded) and their performance can deteriorate.

In the aftermath of the 2008-9 financial crisis, a number of stock fundamental and macro managers started exploring Equity factors as a tool to build more robust portfolios. The goal of using a Factor approach is two-fold: to shield a portfolio from market volatility through lower correlations, and to 'harvest' the premia that can be delivered by Equity Risk Factors.

In this report we introduce a framework for Equity Risk Factor investing based on **Momentum, Value, Quality, Growth and Volatility** styles. In the first chapter of the report, we design and analyze several prototype factors for each Style and geographic region (US, Europe, Asia ex-Japan, Japan). The second chapter is dedicated to studying the correlation properties of factors within and across styles and regions. Finally, we analyze portfolios of Factors and various Multi-Factor Models in the third chapter.

Our analysis and tests were performed on 20 years of historical data for a dozen prototype Equity Risk Factors in each of the regions. These prototype factors can be used as a set of investable benchmarks to build factor portfolios, hedge a portfolio factor bias, or simply monitor performance across styles and regions.

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[1] We have published extensively on Equity Risk Factors in the past. For instance, our Factor Reference Handbooks provide a comprehensive overview of commonly used equity factors in Europe, the Americas and Asia.

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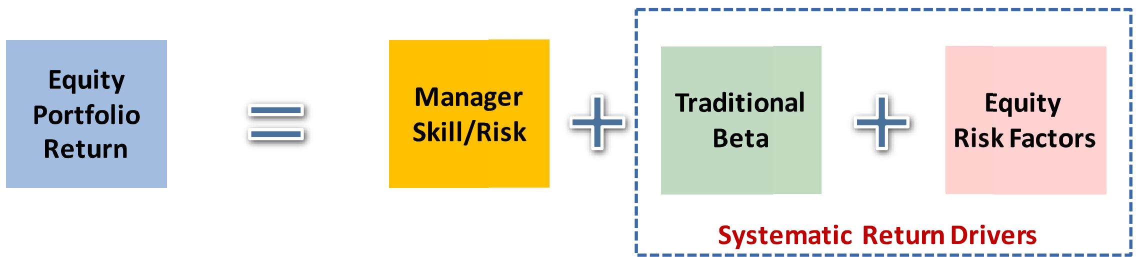
Equity Risk Factors

Factor Classification

Returns of an Equity Portfolio can be attributed to **Broad Market and Sector Exposures (Traditional Beta),** exposure to various **Equity Risk Factors (Alternative Beta)** and **Manager-Specific Risk (Idiosyncratic Risk, Alpha)** (see Figure 1). **Traditional Beta** can be attributed to the portfolio's exposures to certain regional equity markets, sectors or industries. **Equity Risk Factor** exposures are a result of active biases towards stocks with High Momentum, Low Volatility, cheap Valuations, etc. Equity Risk Factor exposures are defined to be independent of Traditional Beta. **Manager-Specific Risk** is attributable to the manager's discretionary selection and timing of stocks, sectors, country/regions and themes.

Figure 1: Drivers of Equity Portfolio Returns



Source: J.P. Morgan Quantitative and Derivatives Strategy.

In our classification of Equity Risk Factors, we employ a method similar to that used in our primer on Cross-Asset Risk Factors. In that report, we started with a theoretical model for returns of any asset class, and focused on the economic/ market rationale and risk properties of individual return drivers. We argued that Carry, Value, Momentum and Volatility are the main alternative Risk Factor styles that can be consistently defined and implemented across asset classes.[2] In the equity space, we could apply a similar classification while allowing for concepts that are specific to the equity asset class. For instance, a number of equity factors are based on analysts' expectations, and growth or quality of corporate earnings; these stock-specific concepts cannot be generalized to other asset classes such as commodities or currencies. This will result in a more granular classification of Equity Risk Factors compared to our broader cross-asset factor classification. Building on findings from our previous research,[3] we will argue that most Equity Risk Factors can be classified as **Value, Growth, Quality, Momentum and Volatility**.

The main difference between this equity factor classification and our cross-asset classification is the addition of two new categories – 'Quality' and 'Growth' – that are concerned with corporate financial statements/ratios, and companies' ability to maintain and grow earnings. Our equity factor style classification also does not include 'Carry'. A natural choice for equity **Carry** would be Dividend Yield (or alternatively Earnings Yield); however, the Dividend Yield factor often overlaps with **Value** (and during certain market regimes with Quality).

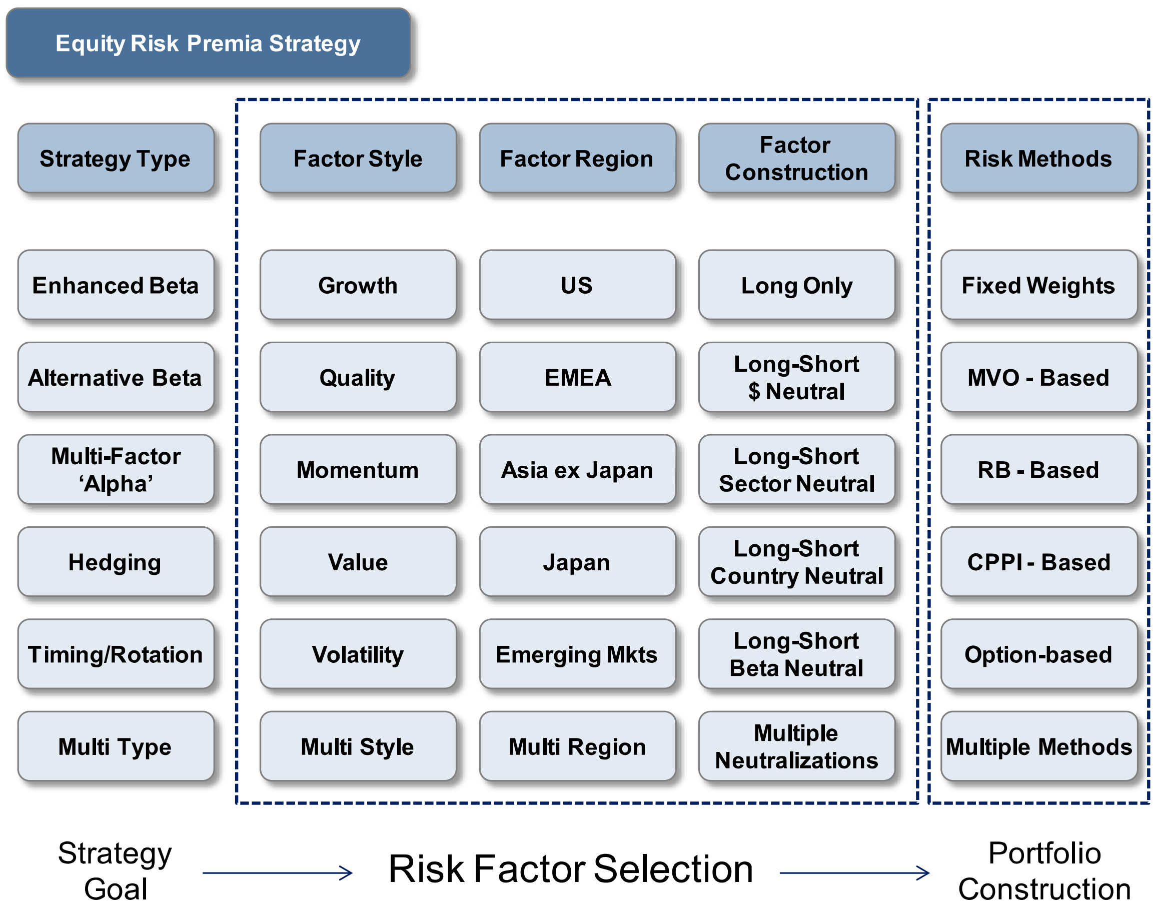
We have expanded the **Momentum** factor style to include other factors derived from price patterns, so that it reflects a broader Technical Style category. This group of Risk Factors includes Price Momentum, combination of Price Momentum and mean-reversion, as well as factors derived from stock price trends in non-consecutive time intervals such as a Seasonality factor. Finally, the **Volatility** style includes factors such as (low/high) stock Volatility, (low-high) stock Beta with respect to a broad equity benchmark, and (small-large) Capitalization Size.

[2] We created 20 prototype Models on Equities, Rate and Credit, Currencies and Commodities based on these four fundamental Risk Factor styles and examined their historical performance/risk properties during different regimes of macroeconomic growth, inflation, market volatility, funding liquidity and market liquidity.

[3] See our primer on Cross-Asset Risk Factors and Equity Factor Reference Handbooks.

To summarize, we will use **Value, Growth, Quality, Momentum, and Volatility** as the main Equity Risk Factor styles. This framework is illustrated in Figure 2 and elaborated in the rest of this report. The framework is also consistent with our cross-asset Risk Factor framework but is adjusted for specifics of the equity asset class and terminology often used by equity quant managers.

Figure 2: Classification of Equity Risk Factor Strategies



Source: J.P. Morgan Quantitative and Derivatives Strategy.

In this report, we test this Equity Risk Premia framework and study its correlation and portfolio properties. For that purpose, we designed a number of Equity Risk Factor benchmarks in each of the 5 factor Styles: Value, Growth, Quality, Momentum, and Volatility. We designed these simple factor benchmarks for the US, Europe, Japan and Asia-ex Japan (based on MSCI regional/country specifications). Selection of factors in each of these style categories is not unique and we have not selected the best-performing factor implementations, but rather the simplest, well-known examples that capture the main properties of the factor style. Figure 3 shows our choice of prototype Equity Risk Factors studied in this report.

Figure 3: Classification of Equity Risk Factor Styles, and Our Selection of Prototype Factors (Benchmarks)

Styles	Growth	Quality	Momentum	Value	Volatility
Prototype Factors	Earnings Momentum	Return on Equity	12 Month Price Momentum	Earnings Yield	Low Volatility
	Price Earnings Growth	Net Profit Margin	Enhanced Price Momentum	FCF Yield	Low Beta
	FCF/IC Growth	Debt to Equity	Seasonality	Dividend Yield	Size

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Our prototype factors are constructed by the following methodology: Every month-end we rank all the stocks listed in our universe.[4] The universe of stocks is the applicable MSCI regional index (e.g. MSCI US for US factors), excluding stocks that are undergoing corporate actions. Stocks are ranked according to the measure (or measures) used to construct the Risk Factor. For instance, the Value Risk Factor is constructed based on Earnings Yield (inverse of P/E). The factor is designed by selecting the top 40 names (in this case, the stocks with the highest earnings yields) as our Long basket and selecting the bottom 40 names (in this case the stocks with the lowest earnings yields) as our Short basket.[5] The stocks are equally weighted within the baskets and our portfolios are built to be sector neutral in all regions except Asia ex-Japan, where we used country-neutralization instead.[6] Sector/country neutrality is achieved by using a Z-score methodology to adjust the Risk Factor measure in each of the sectors.[7] For instance, Earnings Yield is normalized in each of the sectors before selecting the most attractive stocks across all sectors.

In this chapter we describe each of the Risk Factor Styles (Value, Quality, Growth, Momentum, and Volatility). For each of the Styles we introduce and test several specific Risk Factors. The second and third chapters study factor correlations, factor portfolios and multi-factor models.

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[4] We rank stocks 2 days before month-end and rebalance the factor on the close of the last trading day of the month.

[5] Unless noted otherwise, backtests do not include transaction costs, and the starting date for the backtests is December 31, 1993. Note: Past performance is not indicative of future results.

[6] Detailed analysis of neutralization methods is presented in the second chapter of this report.

[7] Z-Score methodology for sector neutrality applies the following standardization to each stock X in the sector Y:

$$\frac{\text{E/P Stock } X - \text{average E/P of all stocks in sector } Y}{\text{Standard deviation of E/P for all stocks in sector } Y}$$

It is important to note that this methodology does not give exactly "sector-neutral" factors, but it significantly limits the sector biases. Similar standardization can be applied to achieve country neutrality as well. See the section 'Factor Neutralization Methods' on page 37 for more discussion on neutralization methods.

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Value

In our primer on Cross-Asset Risk Factors (page 40), we classified Value strategies based on the valuation anchor on which they rely: fundamental value, market value, relative value and cross-asset value strategies. The most popular Value factors in the equity space are based on price multiples such as earnings, book value, free cash flow and dividends. Value factors are long stocks that appear cheap and short stocks that appear rich, and the metric is typically based on a ratio of price to a line item from the company's Financial Statements.

There are two types of market phenomena that can affect the performance of Value factors: cyclical and structural. The **cyclical** aspect of value investing relates to periods when Value comes in and out of favor, driven by the prevailing market risk sentiment. While this cyclicality can affect the performance of all valuation factors, it can have great influence on the performance of certain factors *within* the valuation family (i.e. Price/Book, Price/Earnings, Price/Sales, Price/Cash Flow, etc.). For example, we observed that investors tend to favor book value when they lose confidence in earnings in times of financial crises. As a result, P/B tends to act more as a crisis metric and is favored over P/E when earnings are very low or negative and in the first few months of a market recovery (see our report "Return on Equity"). This was the case for Japan in 2009 (note the large spike in P/B performance in March 2009), and in GEM in the aftermath of the 1997 Asian financial crisis. Price/Book will often falter after it has had its run, at which point Price/Earnings factors tend to begin outperforming. This can be seen as a temporary decline in correlation between the two Value factors. Performance of Value factors can also vary due to **region-specific and structural reasons**. For instance, in Japan, there hasn't been much confidence in earnings over much of the 'lost decade' – hence, the more tangible P/B (especially when combined with Return on Equity) has been the preferred valuation metric in Japan. The structural dominance of P/B can wane as confidence returns to earnings, but in Japan it has remained strong over the last 15 years.

In the next chapter we study in more detail the market exposure of Value factors and their correlation properties. In order to do so, we first define and backtest several Value factors:

Earnings Yield (i.e. the inverse of Price/Earnings ratio) measures how cheap or expensive a stock price is compared to its forecast (forward) earnings. Cheap companies (relative to earnings) should be more attractive and are expected to outperform expensive ones.

Figure 4 shows the performance of the 12-Month Forward Earnings Yield factor in the US, Europe, Japan and Asia ex-Japan over the past 20 years. One can see that the factor worked well in Asia ex-Japan. In Europe and Japan, the factor appears to have lost some of its effectiveness post the 2008 market crash. Additionally, performance of the factor in the US has been rather weak – likely evidence of a more efficient market and a broad awareness of the Earnings Yield Factor.

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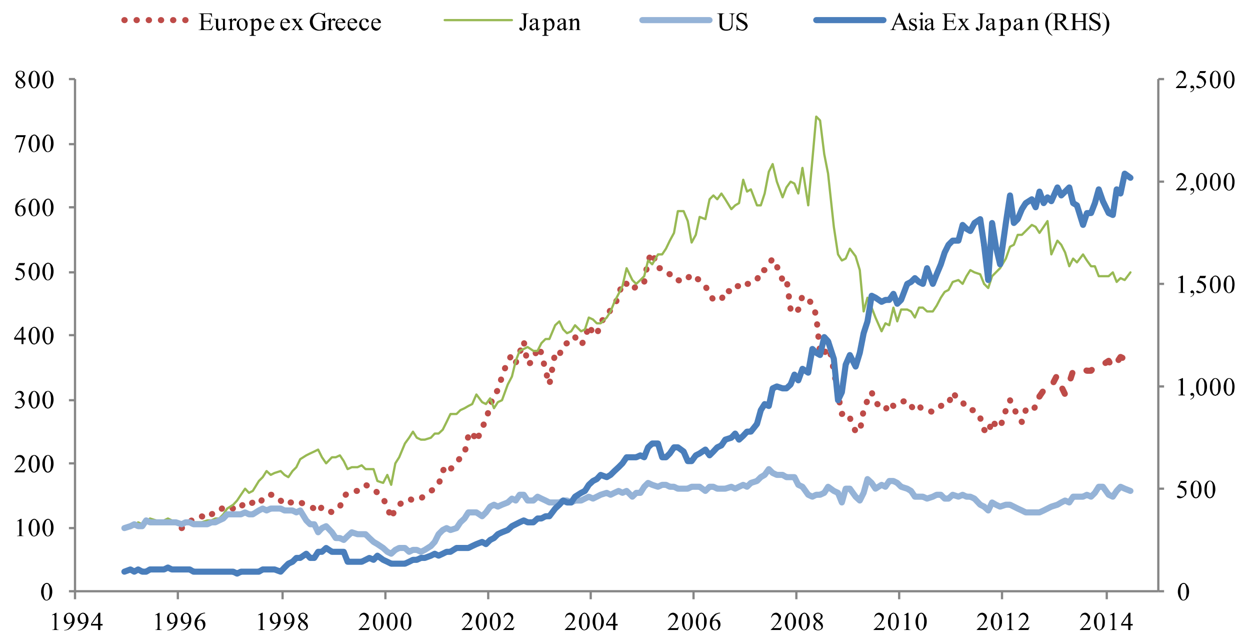
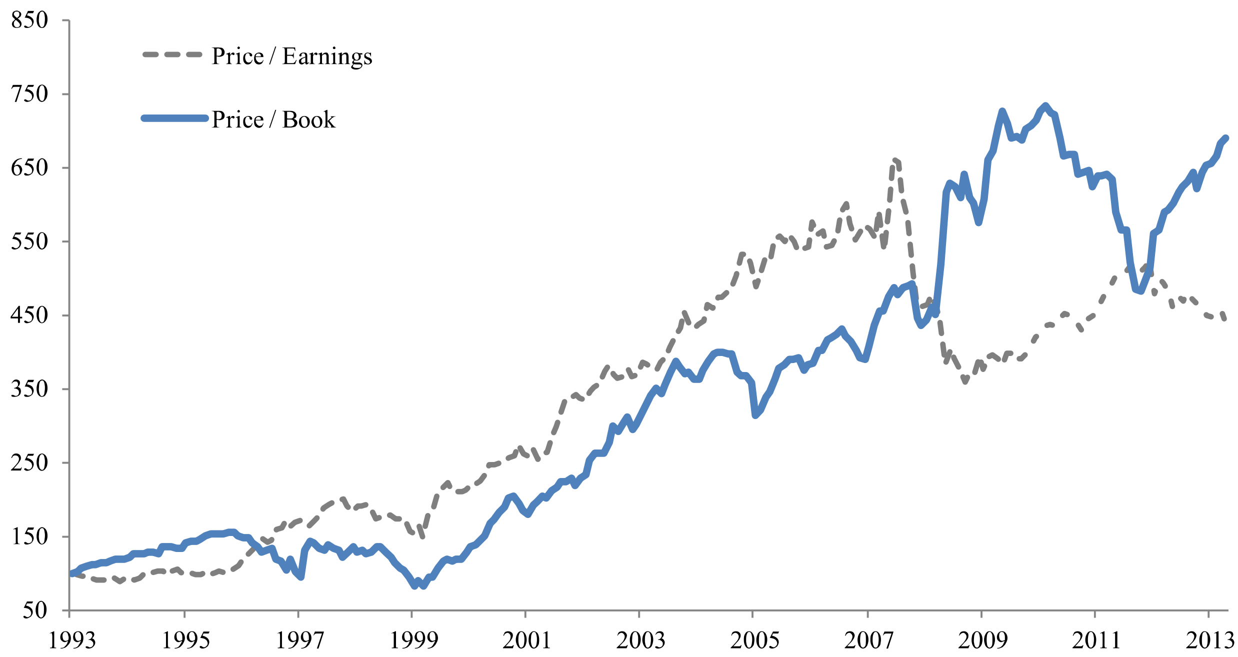
Figure 4: Performance of 12-Month Forward Earnings Yield Factors in the US, Europe, Japan and Asia-ex Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

While Earnings Yield worked reasonably well in Japan, a simple Price/Book factor appears to be more effective in the region (Figure 5) as we discussed above.

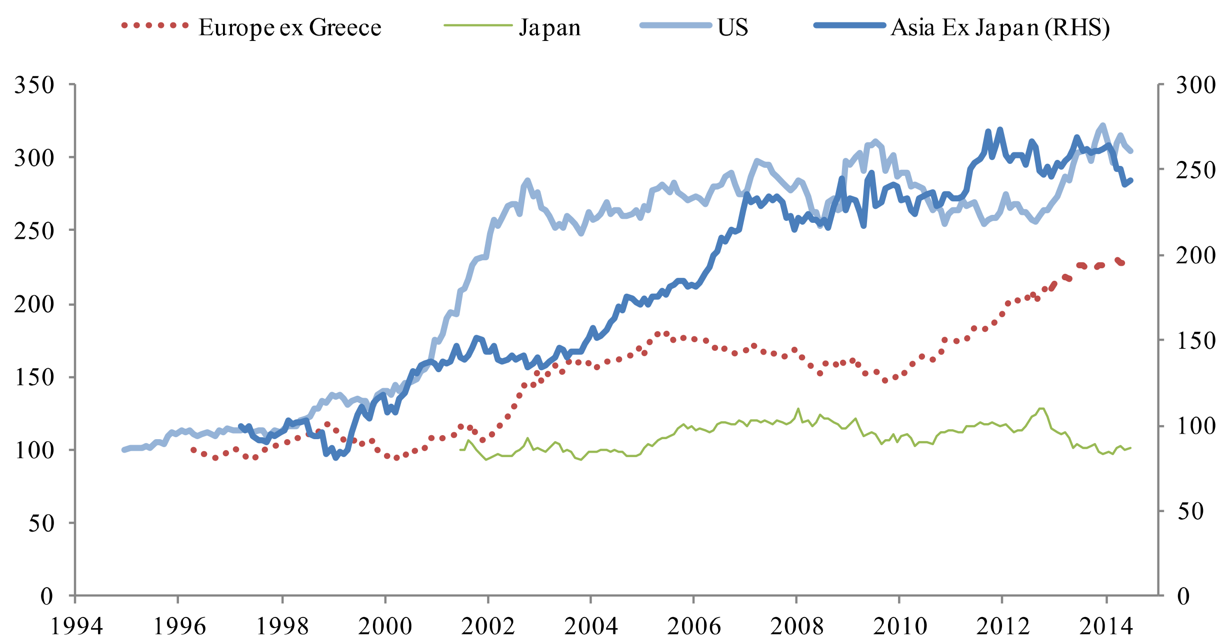
Figure 5: Price/Earnings vs. Price/Book in Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Free Cash Flow (FCF) Yield factor is long stocks that are cheap and short stocks that are rich based on the ratio of Price to Free Cash Flow.[8] A possible pitfall of the simple Price/Earnings ratio is that accruals accounting can affect the numerical value and mask true trends in earnings. FCF Yield mitigates this risk by relying on cash flow instead of accruals-impacted earnings measures. The use of a cash flow yield factor is more common in developed markets (the US and Europe) since the necessary accounting data is more readily available. Figure 6 shows that FCF Yield factor worked more consistently in the US, Europe, and Asia ex-Japan than in Japan.

Figure 6: Performance of Free Cash Flow Yield Factor in the US, Europe, Asia ex-Japan, and Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Dividend Yield Factor is often constructed based on forecast Dividend Yield. This factor assumes that a company rewarding shareholders with higher dividends should be more attractive to investors than a company that is, for example, unable to pay dividends. In the post-financial crisis period, the Dividend Yield factor has been more correlated to Quality factors, probably because the ability to pay dividends following the crisis was seen as an indicator of a higher-quality earnings stream. In the long run it does make sense, in our view, to look at Dividend Yield as a Value rather than Quality factor, as high Dividend Yields often result from depressed stock valuations.

Figure 7 shows the performance of the Dividend Yield factor in the US, Europe, Asia ex-Japan, and Japan. One can see that the Dividend Yield factor exhibited the most consistent performance in Asia ex-Japan, Japan, and Europe, while it was less effective in the US where one may want to also consider alternative forms of payout (i.e. buybacks) that can be quite significant.

[8] FCF is defined as: EBIT(1-Tax Rate) + Depreciation & Amortization – Change in Net Working Capital – Capital Expenditure

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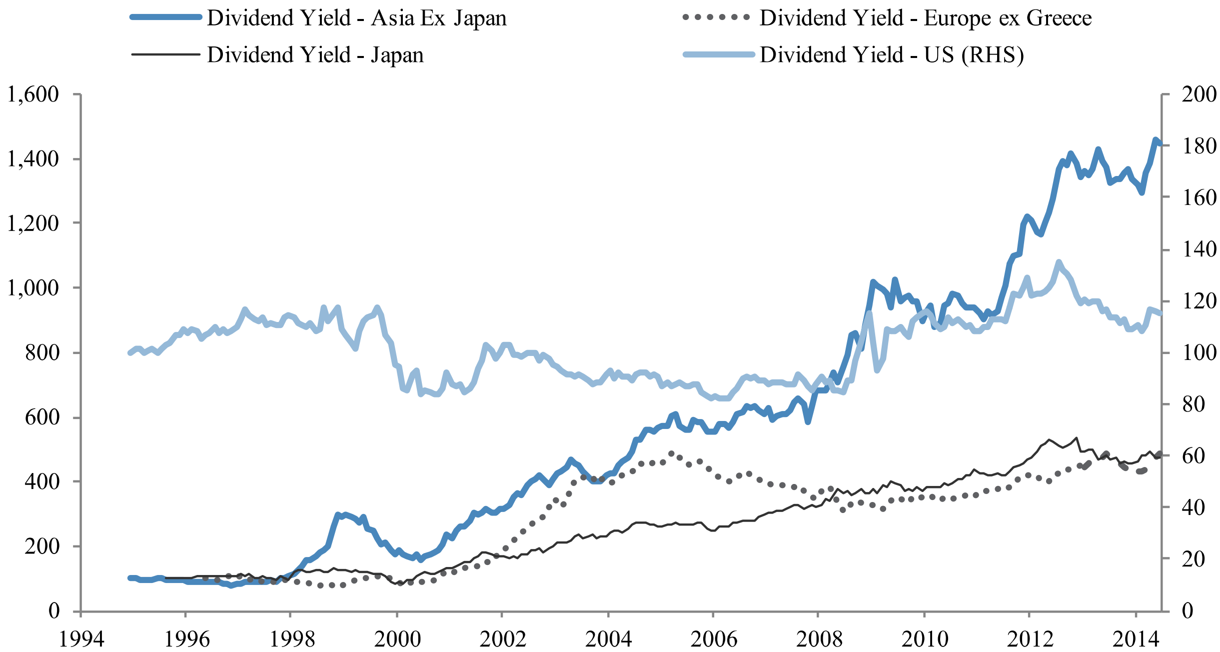
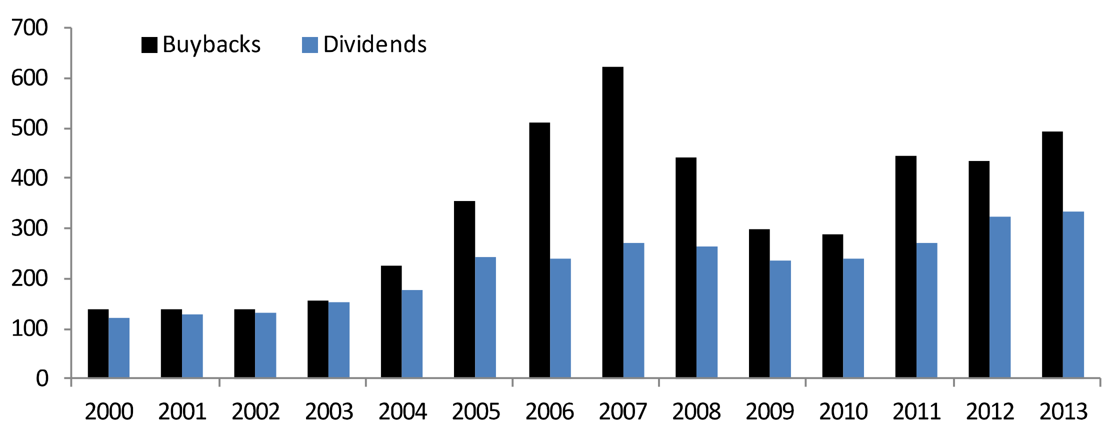
Figure 7: Performance of Dividend Yield Factor in the US, Europe, Asia ex-Japan, and Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES. * The US Dividend Yield Factor was based on trailing dividend data prior to May 2003.

Performance of the Dividend Yield factor can also be influenced by how investors perceive companies' dividend and buyback policies. Over the years, we have observed the US to be a more buyback-friendly market (compared to Europe, for example). As a result, we have seen several practitioners include Buybacks in constructing their Dividend Yield Models (e.g. "Quant Forensics Volume 5 – Replacing Dividend Yield with Shareholder Yield").

Figure 8: Gross Dividends and Buybacks in MSCI US since 2000 ($Bn)



Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.

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Expected behavior of Value Factors: Value Factors are expected to deliver positive risk premia over long time horizons. However, positive and negative Value cycles can be expected over time. In a market down cycle (e.g. 2008-9 global financial crisis), investors pay higher multiples for stocks they perceive as relatively "safe", i.e. those stocks they think can maintain or grow earnings. In that type of environment, Value underperforms Quality and Growth.

The historical performance of Value factors varies by region. In the US, Free Cash Flow Yield was one of the most effective factors. Dividend Yield was the best-performing Value factor in Europe. In Asia ex-Japan, the consensus forecasted Earnings Yield was the best-performing Value factor, and in Japan historically P/B has had the most consistent performance.

The table below shows the key performance and risk statistics for the Value Risk Factors in different regions. Statistics such as Information Coefficient (IC), Sharpe Ratio, etc. are shown both for Long/Short Factor portfolios as well as for Long-only portfolios. For definitions of the risk metrics we report, see the Appendix 'Performance-Risk Metrics' on page 115.

Table 1: Performance and Risk Summary for Value Factors in the US, Europe, Asia ex-Japan, and Japan

	Long / Short						Long Only				
	IC	Ann. Ret	Ann. Vol.	Hit-Rate	Sharpe	Max DD.	Ann. Ret	Ann. Vol.	Hit-Rate	Sharpe	Max DD.
Dividend Yield											
Asia Ex Japan	2.2%	12.0%	18.3%	61.1%	0.65	(60.0%)	10.9%	29.5%	57.5%	0.37	(67.3%)
Japan	2.7%	8.5%	11.2%	60.3%	0.76	(20.9%)	10.0%	24.6%	53.4%	0.40	(64.6%)
Europe	1.6%	8.8%	12.4%	56.7%	0.71	(25.9%)	13.4%	24.5%	61.9%	0.55	(74.1%)
US	0.0%	2.2%	9.8%	50.6%	0.22	(28.8%)	11.7%	18.5%	62.3%	0.63	(61.5%)
Earnings Yield											
Asia Ex Japan	2.9%	15.1%	17.6%	63.2%	0.86	(35.9%)	12.9%	35.1%	55.9%	0.37	(74.8%)
Japan	3.6%	7.9%	13.5%	58.2%	0.59	(45.0%)	8.1%	23.5%	56.1%	0.35	(53.7%)
Europe	2.1%	6.5%	14.9%	55.9%	0.44	(51.5%)	12.8%	25.8%	63.2%	0.50	(79.4%)
US	1.1%	1.9%	14.1%	51.8%	0.13	(56.4%)	13.7%	23.6%	63.2%	0.58	(70.7%)
FCF Yield											
Asia Ex Japan	1.0%	4.4%	11.3%	57.7%	0.39	(22.9%)	13.5%	33.1%	60.9%	0.41	(77.6%)
Japan	1.0%	0.8%	9.3%	53.8%	0.09	(22.5%)	7.9%	19.8%	55.0%	0.40	(40.5%)
Europe	1.6%	4.8%	7.5%	60.2%	0.64	(20.3%)	12.7%	23.3%	61.9%	0.55	(69.3%)
US	1.1%	5.9%	8.5%	58.3%	0.70	(18.8%)	15.9%	21.4%	64.8%	0.74	(69.3%)

Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Table 2 provides exact definitions of the 3 different metrics used to construct Value factors above.

Table 2: Value Risk Factors

Risk Factor	Technical Description
Earnings Yield	Consensus estimates of earnings for the next unreported fiscal year divided by stock price (negative earnings excluded)
Free Cash Flow Yield	Company's latest released free cash flow divided by current market capitalization
Dividend Yield	Consensus estimates of dividends for the next unreported fiscal year divided by stock price

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Other popular Value factors include Price to Cash Flow ratio, Price to Sales ratio, Free Cash Flow to Enterprise Value, Cash Flow to Total Assets, EBIT/EBITDA to Enterprise Value, Sales to Enterprise Value, etc. (see the Appendix 'Factor Reference Books' on page 133 for more details). Some practitioners may also 'normalize' a Value factor by its historical average and/or standard deviation over a certain time horizon, and correct for residual market exposures. These methods will be discussed in the second chapter.

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Similar to our analysis in the primer to Cross-Asset Risk Factors, we report below each Value Risk Factor's exposure to global economic Growth, Inflation, market Volatility and Funding Liquidity indicators.[9] Table 3 summarizes annualized average returns (and related *t*-statistics, in parentheses) of each Risk Factor[10] under "Low", "Mid" and "High" regimes of Growth, Inflation, Volatility and Liquidity, respectively.

Table 3: Performance (t-statistics*) of Value Risk Factors Under Different Macro/Market Regimes

	Growth			Inflation			Volatility			Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Fwd EY - Asia xJ	13.99	9.95	13.19	24.17	6.21	9.27	9.60	24.12	3.41	11.33	6.24	19.57
	(0.29)	(-0.44)	(0.15)	(1.98)	(-1.40)	(-0.47)	(-0.50)	(2.14)	(-1.63)	(-0.19)	(-1.11)	(1.30)
Fwd EY - Europe	2.18	6.55	6.58	6.50	6.16	2.17	3.94	14.96	-3.46	-2.04	11.39	6.83
	(-0.60)	(0.29)	(0.30)	(0.26)	(0.24)	(-0.54)	(-0.25)	(2.16)	(-1.92)	(-1.56)	(1.23)	(0.35)
Fwd EY - Japan	3.31	3.02	17.92	2.47	7.26	15.91	7.74	12.58	3.92	4.99	7.10	12.16
	(-1.10)	(-1.17)	(2.29)	(-1.20)	(-0.24)	(1.52)	(-0.08)	(1.04)	(-0.96)	(-0.71)	(-0.23)	(0.94)
Fwd EY - US	1.31	3.21	1.94	2.98	0.95	3.22	6.05	5.47	-5.06	-4.83	2.79	8.49
	(-0.20)	(0.24)	(-0.05)	(0.18)	(-0.35)	(0.21)	(0.90)	(0.77)	(-1.67)	(-1.62)	(0.15)	(1.47)
FCF Yield - Asia xJ	3.70	8.71	9.93	8.22	5.56	9.69	8.71	6.28	7.69	7.77	12.64	3.66
	(-1.00)	(0.31)	(0.66)	(0.18)	(-0.61)	(0.49)	(0.29)	(-0.33)	(0.04)	(0.06)	(1.18)	(-1.15)
FCF Yield - Europe	4.32	5.76	2.91	7.24	0.95	6.21	2.39	6.42	3.84	1.48	1.03	9.93
	(0.00)	(0.55)	(-0.55)	(1.06)	(-1.53)	(0.60)	(-0.66)	(0.82)	(-0.19)	(-1.09)	(-1.17)	(2.22)
FCF Yield - Japan	-3.27	5.32	2.55	3.98	-0.93	3.12	1.22	2.65	1.70	-0.94	2.19	2.76
	(-1.35)	(1.07)	(0.22)	(0.62)	(-0.90)	(0.33)	(-0.19)	(0.23)	(-0.03)	(-0.58)	(0.11)	(0.38)
FCF Yield - US	12.35	5.19	1.41	10.36	4.02	5.57	7.14	5.76	6.05	7.98	4.35	6.62
	(2.28)	(-0.42)	(-1.85)	(1.40)	(-1.08)	(-0.24)	(0.31)	(-0.21)	(-0.10)	(0.62)	(-0.74)	(0.11)
Div Yield - Asia xJ	24.92	15.08	-0.95	27.78	-2.43	22.16	7.76	13.44	17.85	14.37	13.06	11.62
	(2.46)	(0.42)	(-2.90)	(2.83)	(-4.08)	(1.57)	(-1.07)	(0.09)	(0.99)	(0.28)	(0.01)	(-0.28)
Div Yield - Europe	10.75	13.12	1.21	12.52	6.11	6.50	2.51	7.10	14.16	1.12	8.17	15.15
	(0.59)	(1.25)	(-1.82)	(1.03)	(-0.64)	(-0.37)	(-1.31)	(-0.30)	(1.55)	(-1.81)	(-0.02)	(1.81)
Div Yield - Japan	10.34	4.33	4.66	4.87	0.45	18.24	6.06	6.07	6.99	4.06	5.76	9.24
	(0.96)	(-0.51)	(-0.43)	(-0.36)	(-1.83)	(2.47)	(-0.08)	(-0.08)	(0.15)	(-0.59)	(-0.15)	(0.73)
Div Yield - US	9.79	-1.63	4.44	7.57	-3.57	8.70	1.21	0.19	12.59	7.58	1.94	2.82
	(1.24)	(-1.34)	(0.19)	(0.86)	(-1.97)	(1.18)	(-0.81)	(-0.77)	(1.75)	(0.77)	(-0.43)	(-0.27)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The *t*-statistic shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 4 summarizes the exposure of regional Value Risk Factors (Fwd Earnings Yield, FCF Yield and Dividend Yield) to macro/market regime indicators over the full backtest period from January 1995 to June 2014. We report both regression coefficients (Beta to the corresponding regime indicator) and related *t*-statistics.

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[9] Consistent with our primer to Cross-Asset Risk Factors, the macro/market regime indicators are defined as follows. Growth is defined as YoY change of OECD leading indicator; Inflation is defined as OECD global consumer price inflation indicator; Volatility is defined as the VIX indicator; Liquidity is defined as the difference between 3-month Treasury Bill rate and 3-month US$ Libor rate (the Ted spread defined as such is shown to be closely linked to both market and funding Liquidity). See more details in the Appendix 'Macro and Market Regimes' on page 112.

[10] To analyze Risk Factors' 'pure' macro and market exposures, we used 'beta-neutralized' versions of the long-short Risk Factors in each region (similar exercises are carried out in the following sections on other Risk Factor styles). See the section 'Factor Neutralization Methods' on page 37 for more discussion on factor neutralizations.

Table 4: Value Risk Factors' Exposures (t-stats*) to Macro/Market Regime Factors over the Full Sample Period

	Growth	Inflation	Volatility	Liquidity		Growth	Inflation	Volatility	Liquidity
Fwd EY - Asia xJ	0.02 (0.05)	-0.33 (-1.03)	-0.40 (-1.24)	0.40 (1.24)	**Fwd EY - Japan**	0.65 (2.57)	0.49 (1.97)	-0.46 (-1.82)	0.62 (2.51)
Fwd EY - Europe	0.27 (0.99)	-0.08 (-0.29)	-0.88 (-3.21)	1.07 (4.17)	**Fwd EY - US**	-0.24 (-0.95)	-0.07 (-0.29)	-0.62 (-2.46)	0.79 (3.20)
FCF Yield - Asia xJ	0.00 (0.01)	0.05 (0.24)	0.14 (0.64)	-0.21 (-1.02)	**FCF Yield - Japan**	0.16 (0.87)	0.14 (0.83)	-0.15 (-0.82)	0.23 (1.32)
FCF Yield - Europe	0.07 (0.48)	0.02 (0.14)	0.09 (0.54)	0.26 (1.74)	**FCF Yield - US**	-0.43 (-2.79)	-0.14 (-0.88)	0.01 (0.09)	0.13 (0.83)
Div Yield - Asia xJ	-0.59 (-2.07)	0.09 (0.33)	0.33 (1.14)	-0.18 (-0.62)	**Div Yield - Japan**	-0.11 (-0.48)	0.51 (2.23)	0.19 (0.82)	-0.04 (-0.19)
Div Yield - Europe	-0.20 (-0.84)	-0.15 (-0.64)	0.07 (0.31)	0.51 (2.27)	**Div Yield - US**	-0.23 (-1.13)	0.19 (0.97)	0.51 (2.37)	-0.57 (-3.01)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
*The *t*-statistic shown in parentheses is from regression of factor return versus respective macro/market regime indicator.

From the two tables, we can highlight a few simple observations:

- Low Liquidity and High Volatility regimes were negative for the Fwd Earnings Yield Risk Factor across all regions. High Liquidity and Low Inflation regimes were generally positive.
- FCF Yield Factor in the US was negatively correlated with Growth (i.e. a High Growth regime was negative for that factor). FCF Yield Factor in Europe performed best in a High Liquidity regime. Inflation and Volatility did not seem to bear a strong relationship with FCF Yield Factors.
- Low Growth and/or High Volatility was generally positive for the Dividend Yield factor as investors search for high-yielding assets and stocks that are perceived as relative safe havens.

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Momentum

Momentum Factors are derived from price time series by identifying trends and patterns.[11] Momentum theory for stock prices suggests that there is positive serial correlation between stock returns, in violation of efficient market hypothesis. There are many reasons for the existence of a momentum effect. In our primer on Cross-Asset Risk Factors (page 35) we argued that momentum can be driven by **Behavioral Biases** such as under- and over-reaction to news, and lagged time response to market news. Price momentum can also develop as a result of a **Positive Feedback Loop** between stock price performance and availability of capital to fund future corporate growth, or on a macro level, positive feedback between the economy and stock market performance. **Market Microstructure** can also drive momentum as trading rules such as "cut losses and let your profits run" can lead investors to commit in advance to selling assets that have underperformed and buying assets that have outperformed. When implemented via options, this behavior can lead to 'short gamma trading' that can further reinforce Price Momentum.

In addition to price momentum, over short time frames (less than one month) stock prices tend to exhibit reversion, most likely due to the relaxation of temporary market impacts. [12] While mean reversion on its own would be categorized as a Value effect, Equity Quant investors often improve Momentum signals by combining (or correcting) them for short-term mean-reversion effects.

The Momentum factor is fairly important as it often complements Value-based factors – investors want to buy 'cheap' stocks, but ideally when they have already bottomed. The combination of the two factors can be thought of as an effective way to help identify value names at the right time. In the second chapter of this report we will more formally demonstrate the negative correlation between Momentum and Value, as well as the hedging ability of Momentum during a market sell-off.

Our prototype Momentum factors are:

12-Month Price Momentum (PMOM) is a common Risk Factor employed by managers not just in Equities but across asset classes. To design a factor, stocks are ranked based on their total return over the past 12 months, and Z-scores calculated within each sector. A long-short portfolio is constructed by buying the top 40 and shorting the bottom 40 stocks as ranked by the momentum metric. Figure 9 shows the performance of 12M PMOM in the US, Europe, Asia ex-Japan and Japan.

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[11] This is in contrast to factors such as Growth, Value and Quality that are in most cases derived from stocks' fundamental data.
[12] See our Factor Reference Book series – in all regions we observe empirical evidence of 1-month price reversion. Also see our report on microstructure drivers of short-term mean reversion.

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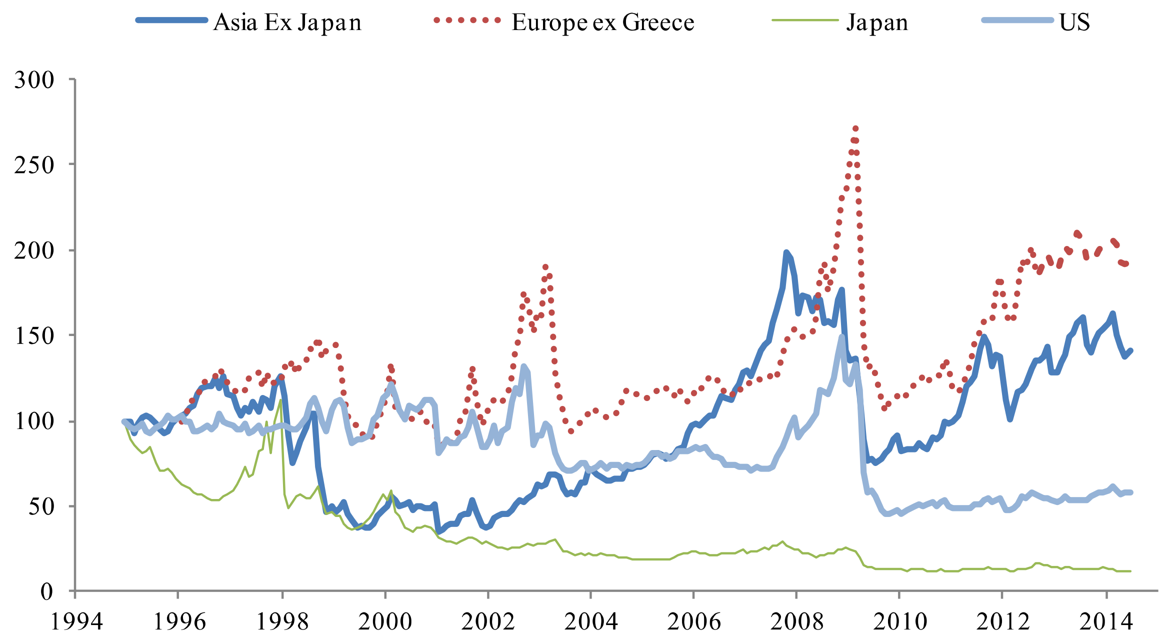
Figure 9: Performance of 12M PMOM Factor in the US, Europe, Asia ex-Japan, and Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

This simplest version of Price Momentum delivered positive returns in Asia ex-Japan and Europe, but exhibited relatively poor historical performance in Japan and the US. In fact, in Japan, there is little evidence that the momentum effect exists – it is likely the only market that does not seem to respond to this Risk Factor.[13] Despite poor performance in the US, Momentum has an attractive feature of providing a positive convex response to market sell-offs (such as in 2002 and 2008). In the US and Asia, incorporating *1-Month Price Reversion* significantly improved 12-Month Momentum (in fact, in Asia, 1-Month Reversion worked better than *12-Month Price Momentum*, although it is somewhat more difficult to implement as a standalone factor due to its high turnover).

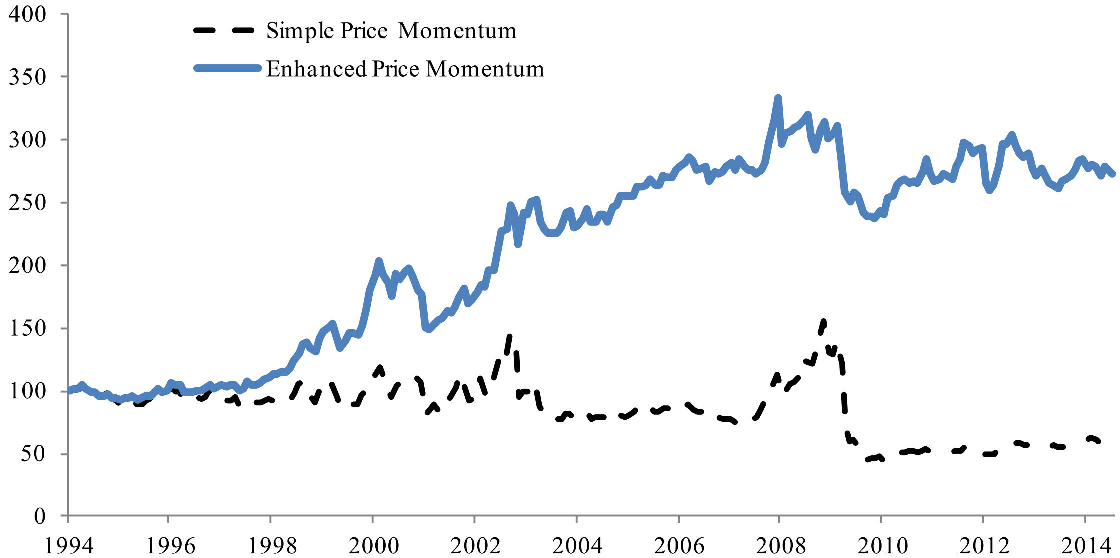
To improve on simple 12-Month Price Momentum in the US, we have designed a more effective Momentum factor that incorporates short-term reversion discussed below.

Enhanced Price Momentum is defined as 12-Month Price Momentum, taking a reversal view on the last month, adjusted for 3-month daily return volatility.[14] The rationale is to embed a simple risk neutralization technique through volatility adjustment while considering the short-term price reversal effect in the market. The main benefit is that the expected drawdown from the enhanced Price Momentum is smaller than a simple 12-Month Price Momentum factor. Further details can be found in our report Enhanced Price Momentum.

[13] As such, we are not maintaining a long-term Momentum investable benchmark for Japan.

[14] Mathematically this can be expressed as $Pmom_i(t) = \frac{1}{\sigma(t,t-3)_i}\left(\frac{Price_i(t-1)-Price_i(t-12)}{Price_i(t-12)} - \frac{Price_i(t)-Price_i(t-1)}{Price_i(t-1)}\right)$

Figure 10: Performance of 12M PMOM Factor vs. Enhanced Price Momentum Factor in US



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Other popular choices for Momentum/Technical factors include the Relative Strength Indicator for a certain horizon, Percent off 52-Week High, moving averages, etc. Momentum factors may also be 'standardized' by their (or the sector's) historical average and/or standard deviation over a particular time horizon. See the Appendix 'Factor Reference Books' on page 133 for more details.

The family of Momentum factors can be broadened to include other technical factors, i.e. factors that are based on historical price performance. One of these technical factors is Seasonality.

Seasonality is defined as how often a stock has historically outperformed (its benchmark index) in a specific calendar month. As we argued in our research piece Stock Seasonality Trading Model: How to Use Stock Periodic Seasonality to Improve Quant Model Performance, stocks that outperformed/underperformed in a particular period of the year tended to keep on doing so in future years. Investors should therefore favor stocks that have had a tendency to outperform in the month and avoid (or short) stocks with a tendency to underperform in the month (e.g. due to a company managing expectations before earnings announcement, benefiting from increased sales during holiday season, etc.). The rationale to include Seasonality in the Momentum family is as follows. The Momentum factor assumes trending of an asset price in consecutive time periods (e.g. if performance was positive for past 6 months, momentum assumes it will be positive in 7th month). Similarly, Seasonality assumes trending of asset prices in non-consecutive time periods. For instance, if the performance was positive in March, June, September and December, the stock is assumed to keep on outperforming in those months.

Figure 11 shows the performance of such a Seasonality strategy in the US, Europe, Asia ex-Japan and Japan.

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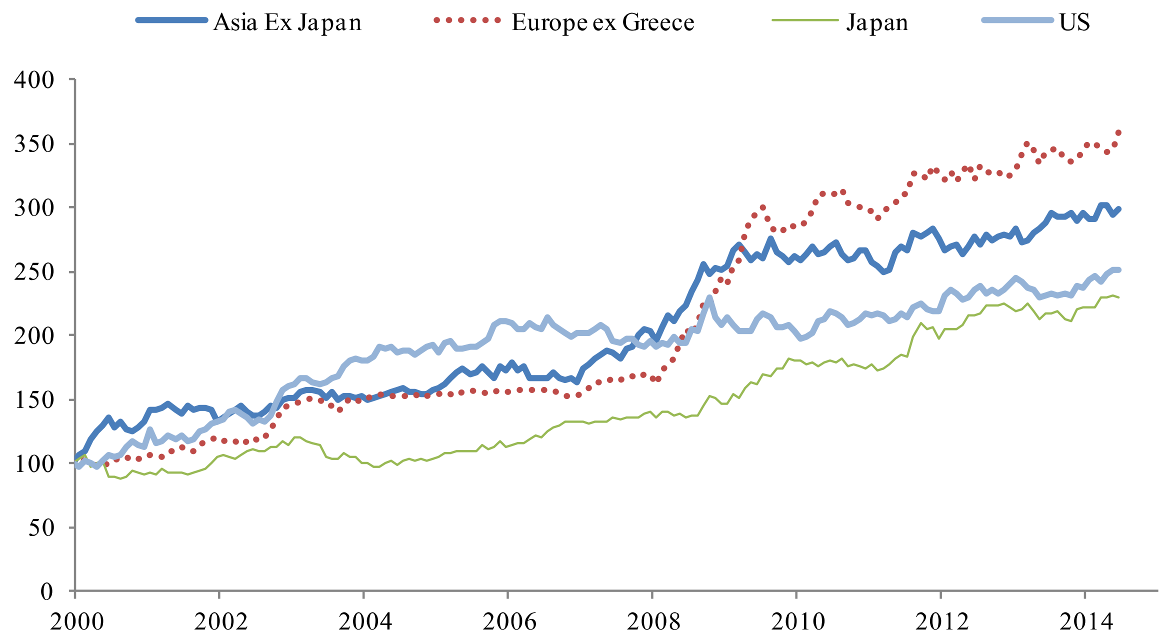
Figure 11: Performance of the Seasonality Factor in the US, Europe, Asia ex-Japan, and Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Expected behavior of Momentum Factors: Momentum (and more generally Technical Risk) Factors are expected to have positive long-term performance. In markets where Momentum performance is weak (such as the US), investors should assess the potential hedging benefits of the Momentum factor exposure against the opportunity cost of Factor's weak absolute performance.[15] While Price Momentum had positive performance in most of the markets, a notable exception is Japan where long-term Price Momentum was not observed.[16, 17]

Price Momentum has historically underperformed at market turning points, during market reversals and junk rallies as the weakest-momentum stocks that were being shorted exhibited the strongest relative correction (March 2009 is the most dramatic example). It is clear that a strategy based on *12-Month Price Momentum* was unable to weather the 1998/1999 and in 2008/2009 market turning points, with rolling 12-month losses exceeding 40% during these periods. It is therefore important to develop risk management procedures (such as stop-loss, factor diversification, etc.) to minimize Momentum drawdowns that can occur during market turning points. In the second chapter of this report, we demonstrate that even a simple beta neutralization of the Momentum factor can mitigate some of the drawdown risk related to market turning points.

Table 5 shows the key performance and risk statistics for the Momentum/Technical Risk Factors in different regions. Statistics such as Information Coefficient (IC), Sharpe Ratio, etc. are shown both for Long/Short Factor portfolios as well as for Long-only portfolios. Table 6 provides definitions of the metrics used to construct the Momentum factors.

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[15] See our Hedging Equity Risk Factor Model (HERF) in the third chapter of this report.
[16] "Does the Momentum Strategy Work Universally? Evidence from the Japanese Stock Market", Chunlin Liu, Yul Lee, Asia Pacific Financial Markets, December 2001.
[17] "International comparison of returns from conventional, industrial and 52-week high momentum strategies", Gupta Kartick, Journal of International Financial Markets, 2010.

Table 5: Performance-Risk Metrics for Momentum/Technical Risk Factors

	Long / Short						Long Only				
	IC	Ann. Ret	Ann. Vol.	Hit-Rate	Sharpe	Max DD.	Ann. Ret	Ann. Vol.	Hit-Rate	Sharpe	Max DD.
Momentum											
Asia Ex Japan	2.3%	2.3%	24.5%	61.5%	0.09	(70.9%)	7.1%	25.9%	60.3%	0.27	(68.5%)
Japan	(1.6%)	(9.8%)	23.3%	47.0%	(0.42)	(88.7%)	1.2%	19.5%	52.6%	0.06	(62.1%)
Europe	2.1%	2.3%	22.0%	57.1%	0.10	(60.9%)	12.3%	18.7%	60.7%	0.66	(56.1%)
US	0.6%	(2.4%)	21.1%	56.7%	(0.11)	(69.5%)	11.7%	16.5%	61.5%	0.71	(51.1%)
Seasonality											
Asia Ex Japan	1.8%	8.9%	9.6%	62.6%	0.93	(10.1%)	20.6%	24.4%	64.2%	0.85	(51.5%)
Japan	2.7%	6.8%	9.5%	58.8%	0.71	(19.5%)	10.1%	16.8%	56.1%	0.60	(39.8%)
Europe	2.5%	9.6%	8.1%	61.0%	1.19	(7.9%)	14.5%	21.3%	62.0%	0.68	(52.6%)
US	2.0%	7.1%	9.3%	57.2%	0.76	(14.2%)	12.5%	17.7%	63.6%	0.70	(55.0%)
Enhanced Price Momentum											
US	1.8%	5.0%	12.4%	60.2%	0.41	(28.7%)	13.3%	15.8%	64.2%	0.84	(53.4%)

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 6: Momentum Risk Factors

Risk Factor	Technical Description
Price Momentum	Total return, with dividends reinvested, over the last 12 months
Seasonality	Measure of how often a stock historically outperformed the benchmark (i.e. corresponding regional MSCI index) for the upcoming calendar month
Enhanced Price Momentum	12-Month Price Momentum less 1-Month Price Reversal, divided by three-month daily volatility

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Lastly, we report below the Momentum Factors' exposure to global economic Growth, Inflation, market Volatility and Funding Liquidity indicators. Table 7 summarizes annualized average returns (and related *t*-statistics, in parentheses) of each Risk Factor under different regimes of Growth, Inflation, Volatility and Liquidity.

Table 7: Performance (t-statistics*) of Momentum/Seasonality Risk Factors Under Different Macro/Market Regimes

	Growth			Inflation			Volatility			Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Momentum - Asia xJ	0.43	20.88	17.93	-1.65	23.69	12.06	21.22	6.84	11.17	3.61	9.79	25.83
	(-1.76)	(1.08)	(0.67)	(-1.90)	(1.86)	(-0.12)	(1.13)	(-0.87)	(-0.26)	(-1.32)	(-0.46)	(1.78)
Momentum - Europe	12.48	6.60	5.81	2.31	18.04	-0.72	11.72	7.76	5.51	2.67	-1.19	21.51
	(0.57)	(-0.22)	(-0.34)	(-0.78)	(1.68)	(-1.05)	(0.46)	(-0.05)	(-0.38)	(-0.78)	(-1.23)	(1.97)
Momentum - Japan	-17.58	-1.42	7.31	-14.89	9.20	-13.38	-6.00	1.45	-7.13	-0.19	-10.52	-0.97
	(-2.11)	(0.38)	(1.72)	(-1.56)	(2.54)	(-1.22)	(-0.32)	(0.82)	(-0.49)	(0.57)	(-1.01)	(0.45)
Momentum - US	-2.49	-0.78	1.77	-6.66	6.01	-4.43	-0.26	5.44	-6.69	1.33	-6.83	3.99
	(-0.34)	(-0.05)	(0.39)	(-0.97)	(1.40)	(-0.56)	(0.04)	(1.02)	(-1.06)	(0.31)	(-1.08)	(0.77)
Seasonality - Asia xJ	10.02	9.23	7.18	2.30	10.49	12.74	8.20	8.42	9.75	13.86	10.28	4.98
	(0.34)	(0.13)	(-0.47)	(-1.71)	(0.56)	(1.08)	(-0.18)	(-0.10)	(0.28)	(1.19)	(0.40)	(-1.40)
Seasonality - Europe	16.99	8.84	4.36	9.46	8.52	12.21	4.24	5.52	20.16	19.78	0.95	10.63
	(2.11)	(-0.34)	(-1.74)	(-0.13)	(-0.50)	(0.66)	(-1.84)	(-1.28)	(3.20)	(2.47)	(-2.61)	(0.27)
Seasonality - Japan	11.48	7.38	3.35	7.37	7.70	6.83	6.47	0.05	15.03	5.07	11.54	5.72
	(1.12)	(0.01)	(-1.12)	(0.01)	(0.12)	(-0.13)	(-0.25)	(-1.93)	(2.16)	(-0.51)	(1.09)	(-0.57)
Seasonality - US	9.65	9.71	2.72	1.88	9.83	9.26	2.68	13.40	6.62	6.13	7.96	7.54
	(0.59)	(0.62)	(-1.21)	(-1.28)	(0.74)	(0.47)	(-1.26)	(1.50)	(-0.18)	(-0.25)	(0.15)	(0.07)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The *t*-statistic shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 8 summarizes the exposure of regional Momentum/Seasonality Risk Factors to macro/market regime indicators over the full backtest period from January 1995 to June 2014. We report both regression coefficients and related *t*-statistics.

Table 8: Momentum/Seasonality Risk Factors' Exposures (t-stats*) to Macro/Market Regime Factors over the Full Sample Period

	Growth	Inflation	Volatility	Liquidity		Growth	Inflation	Volatility	Liquidity
Momentum - Asia xJ	0.71	0.42	-0.58	0.20	Momentum - Japan	0.79	0.29	-0.15	0.10
	(1.69)	(1.01)	(-1.39)	(0.49)		(2.06)	(0.77)	(-0.40)	(0.26)
Momentum - Europe	0.28	0.45	0.12	0.05	Momentum - US	0.89	0.58	-0.15	-0.30
	(0.67)	(1.11)	(0.29)	(0.13)		(2.62)	(1.72)	(-0.44)	(-0.90)
Seasonality - Asia xJ	-0.04	0.43	0.06	-0.43	Seasonality - Japan	-0.34	0.07	0.51	-0.29
	(-0.20)	(2.44)	(0.31)	(-2.39)		(-1.76)	(0.36)	(2.56)	(-1.53)
Seasonality - Europe	-0.48	0.24	0.72	-0.59	Seasonality - US	-0.09	0.32	0.25	-0.29
	(-2.80)	(1.42)	(4.10)	(-3.59)		(-0.41)	(1.63)	(1.15)	(-1.45)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
*The *t*-statistic shown in parentheses is from regression of factor return versus respective macro/market regime indicator.

From the two tables above, we can highlight a few observations: Price Momentum factors were positively correlated with Growth, while on average negatively correlated with Volatility. This indicates that while Momentum tends to outperform during market crises, the subsequent Momentum drawdown during the recovery rally usually wiped out its crisis gains. Despite the full sample negative correlation to the market (on account of sharp moves around market crises), Momentum has achieved positive performance on account of long stretches of positive growth and stock price appreciation.

Growth

Growth Risk Factors provide exposure to companies that are expected to deliver (or have delivered in the past) strong earnings growth. Growth factors are important as they often complement the performance of Value factors in a quant portfolio. The design of Growth factors can be based on historical earnings data or on sell-side analysts' earnings forecasts (usually aggregated consensus such as IBES).

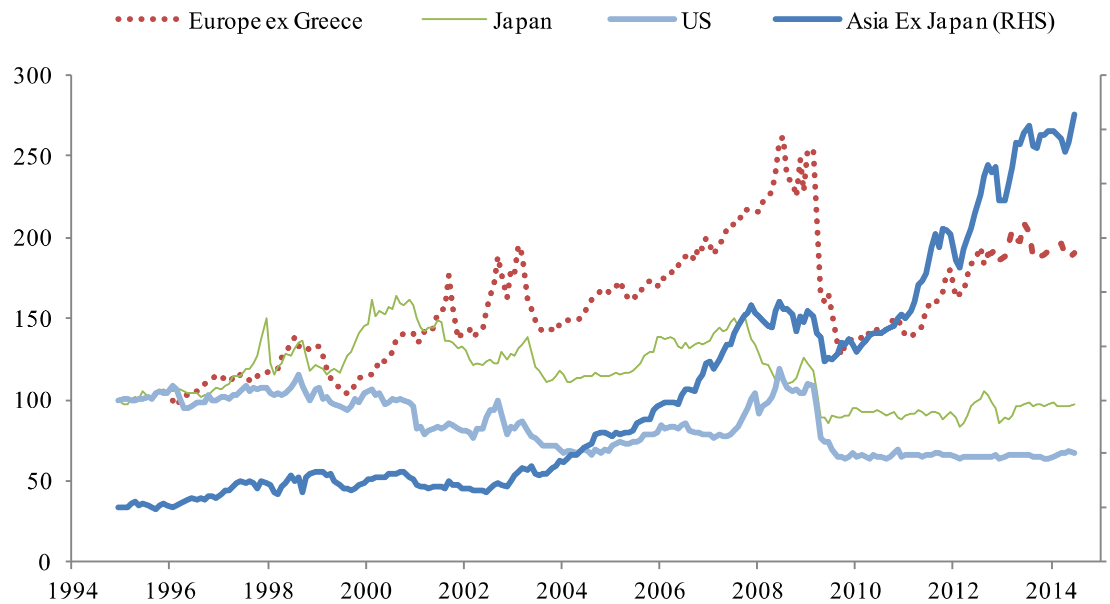
Earnings *Growth* and Earnings Momentum are both derived from analysts' earnings forecasts, but they attempt to exploit different behavioral biases. Earnings *Growth factor*s select stocks with significant upside earnings potential as estimated by sell-side analysts. A potential pitfall is that the forecast growth can be either overly optimistic or based on extrapolation. After a stretch of positive performance, this factor can correct sharply when earnings disappoint or macro trends reverse.

The Earnings *Momentum factor* exploits the herding and anchoring biases of sell-side analysts. A theory of why this type of Growth Factor delivers positive returns is that analysts tend to change their opinion about stocks incrementally. When new macroeconomic, industry or stock-specific information is released, analysts may be slow to fully incorporate the information in their earnings forecasts. These anchoring and herding behavioral biases of analysts may provide opportunities for quantitative investors.

The prototype Growth factors that we designed and tested include Earnings Momentum, Price Earnings Growth (PEG ratio), and Free Cash Flow/Investment Capital Growth (FCF/IC Growth). In the second chapter we show that the PEG factor more closely correlates to Value than Growth factors. The reason for this is the dominance of the more volatile Price/Earnings component for the PEG ratio vs. the Growth component. For this reason, we use only Earnings Momentum and FCF/IC when designing our Growth Style benchmarks.

The Earnings Momentum Factor is long stocks for which earnings estimates were increased by analysts and shorts stocks for which earnings expectations were reduced. The factor relies on the potential existence of fundamental momentum in corporate earnings, as well as the delayed response of analysts and investors. Our choice of earnings Momentum factor is based on the average of 1-month and 3-month changes in the consensus forecast earnings per share (EPS) for the next two fiscal years. Figure 12 shows the performance of this factor in the US, Europe, Asia ex-Japan and Japan since 1994. One can see that the Earnings Momentum factor worked well in Asia ex-Japan and to some extent in Europe.

Figure 12: Performance of Earnings Momentum Factor in the US, Europe, Asia ex-Japan, and Japan

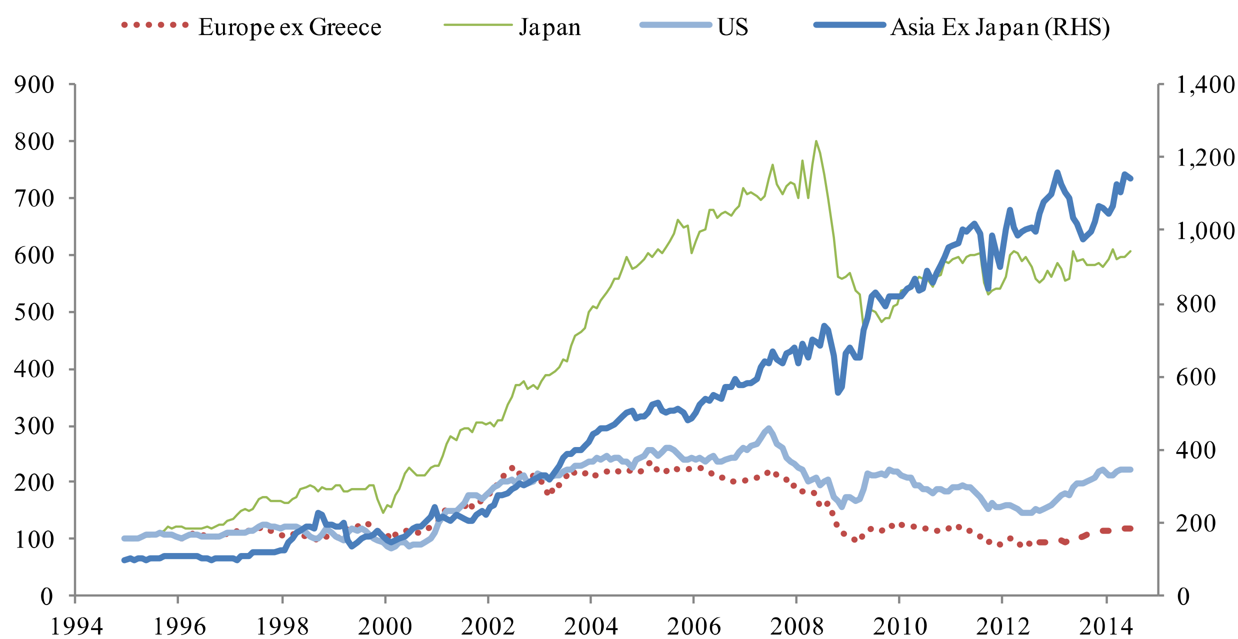


Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Performance in the US and Japan was overall muted, but positive during the market crises of 2002 and 2008.

Price Earnings Growth (PEG) is defined as forecasted Price/Earnings divided by the consensus estimate of long-term EPS Growth. Investors should favor stocks that are cheap according to their Price to Earnings but have higher consensus growth prospects. Figure 13 shows the performance of the PEG factor in the US, Europe, Asia ex-Japan and Japan.

Figure 13: Performance of PEG Factor in the US, Europe, Asia ex-Japan, and Japan



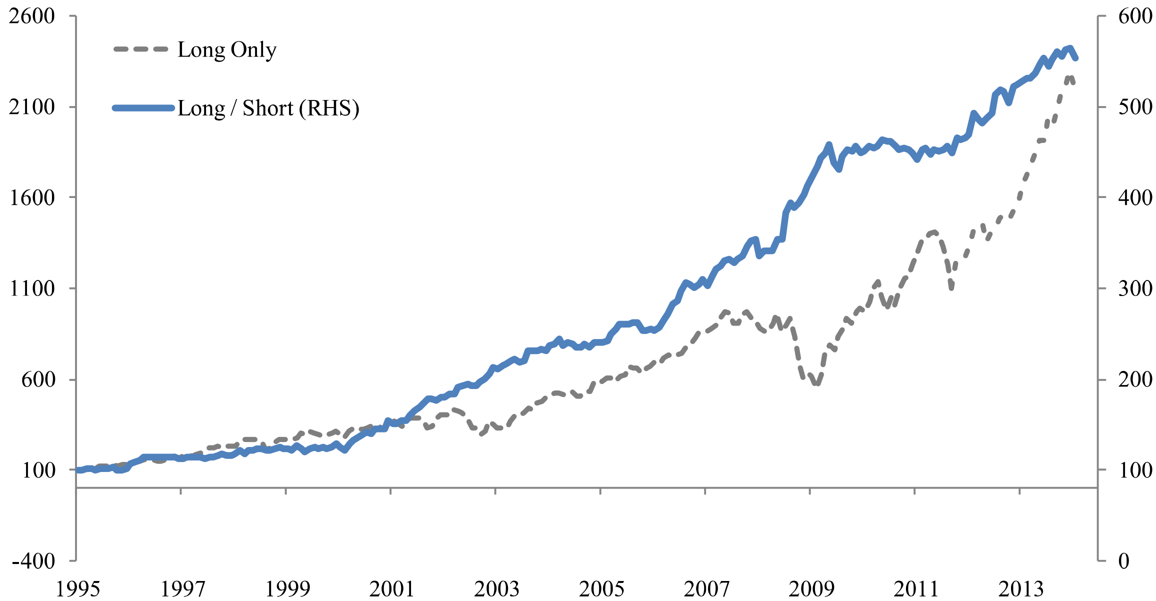
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Strictly speaking, PEG is not a pure Risk Factor as it combines the Value measure of P/E, with a Growth metric. Indeed, we later show that the covariance properties of PEG are more similar to Value than Growth factors.

Similar to Earnings Momentum, the PEG factor worked well in Asia ex-Japan. We believe that the Asia ex-Japan market is less efficient at incorporating new information, and a window of opportunity exists to exploit revisions in earnings and analyst recommendations. Another popular Growth factor in Asia is the 1-Month Change in Consensus Recommendations, which ignores analysts' actual EPS estimates and simply looks at changes in Buy/Sell ratings.

One can see that similar to Earnings momentum, the PEG factor was relatively ineffective in the US. For this reason in the US we use Free Cash Flow to Investment Capital growth as our prototype Growth factor. **FCF/IC Growth Factor** is based on year-on-year growth in free cash flow relative to invested capital. This Growth factor had relatively consistent performance in the US as shown in Figure 14.

Figure 14: Performance of FCF/IC Growth Long/Short Factor and Long-Only FCF/IG Portfolios in the US



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Expected behavior of Growth Factors: Growth-based Risk Factors are expected to deliver long-term positive risk premia. However, this needs to be qualified given the regional differences in factor performance, especially the poor performance of the simplest implementation of Earnings Momentum and PEG factors in the US.

Growth Risk Factors that rely on *changes* in analyst consensus (like Earnings Momentum) are expected to work regardless of the growth cycle as they are the result of analyst biases (such as delayed response or cyclical forecasts). This was discussed in one of our previous reports (How to Improve Earnings Momentum Strategies). Growth Factors that rely on growth forecasts (e.g. PEG) tended to perform better during bull markets, while the factors suffered in periods of contraction.

Table 9 shows key performance and risk statistics for the Growth Risk Factors in different regions. Statistics such as Information Coefficient (IC), Sharpe Ratio, etc. are shown both for Long/Short Factor portfolios as well as for Long-only portfolios. Table 10 provides definitions of the metrics used to construct the Growth factors.

Table 9: Performance and Volatility Summary for Growth Factors in the US, Europe, Asia ex-Japan, and Japan

	Long / Short						Long Only				
	IC	Ann. Ret	Ann. Vol.	Hit-Rate	Sharpe	Max DD.	Ann. Ret	Ann. Vol.	Hit-Rate	Sharpe	Max DD.
EMOM											
Asia Ex Japan	2.8%	11.4%	13.4%	57.9%	0.85	(26.3%)	9.6%	30.5%	57.1%	0.31	(71.6%)
Japan	0.4%	0.2%	12.0%	53.7%	0.02	(48.7%)	5.7%	21.1%	55.7%	0.27	(51.2%)
Europe	2.3%	4.5%	14.4%	65.2%	0.31	(51.0%)	11.6%	19.9%	62.3%	0.58	(61.5%)
US	0.0%	(1.8%)	12.4%	53.0%	(0.14)	(47.3%)	11.1%	18.3%	60.3%	0.60	(59.1%)
PEG											
Asia Ex Japan	2.4%	12.0%	17.3%	61.9%	0.70	(41.2%)	10.5%	34.2%	56.7%	0.31	(76.1%)
Japan	3.4%	9.3%	12.9%	61.9%	0.72	(41.2%)	9.7%	24.7%	57.4%	0.39	(54.2%)
Europe	1.0%	0.4%	13.7%	50.6%	0.03	(62.5%)	7.6%	26.0%	59.1%	0.29	(80.4%)
US	1.2%	3.2%	14.0%	53.4%	0.23	(52.0%)	12.3%	24.9%	61.9%	0.49	(75.9%)
FCF / IC Growth											
US	2.1%	7.1%	6.5%	60.4%	1.09	(6.6%)	14.1%	18.6%	65.3%	0.76	(47.8%)

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 10: Growth Risk Factors

Risk Factor	Technical Description
Earnings Momentum	Average 1-month and 3-month change in analyst consensus estimate of earnings per share for the next two fiscal years
Price Earnings Growth	Analyst consensus estimate of price/earnings divided by the consensus estimate of long-term growth
FCF/IC Growth	Year-on-year growth in free cash flow relative to invested capital

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Other potential choices for Growth factor design include: Historical Earnings Growth (e.g. EPS growth during the past 5 years), Consensus Earnings Growth over the 2 subsequent financial years, Net Revisions of Analyst Forecasts (number of positive revisions divided by number of negative revisions for a certain fiscal year), Internal Growth Rate, etc.

Lastly, we report below for each Growth Risk Factor its performance during economic Growth, Inflation, market Volatility and Funding Liquidity regimes. Table 11 summarizes annualized average returns (and related *t*-statistics, in parentheses) of each Risk Factor under "Low", "Mid" and "High" regimes of Growth, Inflation, Volatility and Liquidity, respectively. Table 12 summarizes the exposure of regional Growth Risk Factors (EPS Growth and PEG) to macro/market regime indicators over the full backtest period from January 1995 to June 2014. We report both regression coefficients (Beta to the corresponding regime indicator) and related *t*-statistics.

Table 11: Performance (t-statistics*) of Growth Risk Factors Under Different Macro/Market Regimes

	Growth			Inflation			Volatility			Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
EPS GR - Asia xJ	5.23	19.13	16.32	12.02	15.99	11.22	20.86	9.68	10.14	8.09	14.45	18.14
	(-1.85)	(1.23)	(0.61)	(-0.31)	(0.67)	(-0.43)	(1.61)	(-0.85)	(-0.75)	(-1.21)	(0.20)	(1.01)
EPS GR - Europe	-0.80	8.02	10.15	-1.27	9.78	8.89	11.29	6.61	1.12	0.95	5.16	11.72
	(-1.53)	(0.48)	(1.00)	(-1.67)	(1.06)	(0.57)	(1.13)	(0.14)	(-1.22)	(-1.22)	(-0.20)	(1.40)
EPS GR - Japan	-6.02	2.84	7.82	-4.28	11.44	-8.47	5.33	-1.39	0.70	2.10	2.00	0.54
	(-2.20)	(0.37)	(1.82)	(-1.56)	(3.68)	(-2.46)	(1.09)	(-0.85)	(-0.24)	(0.16)	(0.13)	(-0.29)
EPS GR - US	-9.15	3.23	-0.16	-7.10	1.73	-2.54	2.29	0.94	-9.31	-2.43	-5.18	1.53
	(-1.87)	(1.37)	(0.49)	(-1.23)	(1.23)	(-0.11)	(1.13)	(0.77)	(-1.91)	(-0.11)	(-0.82)	(0.93)
PEG - Asia xJ	10.91	6.43	15.99	20.87	7.54	5.94	6.43	20.57	6.33	15.83	4.85	12.66
	(-0.04)	(-0.93)	(0.97)	(1.80)	(-0.89)	(-0.86)	(-0.93)	(1.89)	(-0.95)	(0.94)	(-1.24)	(0.31)
PEG - Europe	-7.66	-1.57	2.27	4.69	-3.27	-8.44	-0.82	8.02	-13.30	-10.28	4.39	0.08
	(-1.15)	(0.12)	(1.00)	(1.44)	(-0.31)	(-1.18)	(0.26)	(2.35)	(-2.61)	(-1.83)	(1.35)	(0.50)
PEG - Japan	4.43	0.68	17.25	4.97	7.89	9.56	8.91	11.02	2.43	1.70	7.61	13.06
	(-0.70)	(-1.58)	(2.30)	(-0.53)	(0.13)	(0.41)	(0.34)	(0.83)	(-1.17)	(-1.34)	(0.04)	(1.31)
PEG - US	4.96	3.04	2.28	11.55	2.27	-3.94	5.49	5.82	-0.99	-1.83	2.97	9.15
	(0.35)	(-0.09)	(-0.26)	(1.73)	(-0.33)	(-1.42)	(0.47)	(0.55)	(-1.01)	(-1.21)	(-0.10)	(1.31)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The *t*-statistic shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 12: Growth Risk Factors' Exposures (t-stats*) to Macro/Market Regime Factors over the Full Sample Period

	Growth	Inflation	Volatility	Liquidity		Growth	Inflation	Volatility	Liquidity
EPS GR - Asia xJ	0.45	0.11	-0.61	0.27	EPS GR - Japan	0.60	-0.07	-0.23	0.17
	(1.69)	(0.41)	(-2.32)	(1.03)		(3.01)	(-0.33)	(-1.13)	(0.87)
EPS GR - Europe	0.61	0.61	-0.41	0.35	EPS GR - US	0.71	0.34	-0.55	0.28
	(2.50)	(2.58)	(-1.63)	(1.47)		(3.19)	(1.54)	(-2.49)	(1.25)
PEG - Asia xJ	0.15	-0.36	-0.18	0.34	PEG - Japan	0.70	0.21	-0.69	0.71
	(0.52)	(-1.23)	(-0.61)	(1.18)		(2.81)	(0.85)	(-2.77)	(2.92)
PEG - Europe	0.35	-0.42	-0.92	1.04	PEG - US	-0.44	-0.64	-0.47	1.04
	(1.32)	(-1.63)	(-3.53)	(4.23)		(-1.71)	(-2.58)	(-1.82)	(4.29)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
*The *t*-statistic shown in parentheses is from regression of factor return versus respective macro/market regime indicator.

From the two tables above, we can highlight a few simple observations:

- EPS Growth Factors were positively correlated with High Growth and High Liquidity regimes in all regions. In addition, EPS Growth Factors performed poorly during High Volatility regimes. Given these properties, we can conclude that EPS Growth Factors show strong pro-cyclical behavior.
- A High Growth regime also was positive for PEG factors in all regions apart from the US. Similar to EPS Growth, PEG factors performed poorly during High Volatility or Low Liquidity regimes. This counterintuitive behavior of the US PEG factor can be explained by the dominant Value (P/E) component of this factor.

Volatility

Traditional asset models such as the Capital Asset Price Model (CAPM) state that taking higher risk usually results in higher asset returns. What has puzzled researchers is that with equities, the opposite can quite often be true. In a number of different equity markets, and over extended time periods, stocks with Low Volatility (risk) significantly outperformed high-volatility stocks (e.g. see "*An Analytic Derivation of the Efficient Portfolio Frontier*", Merton, 1972). Since the global financial crisis, there has been increased interest in low-volatility investing.

There are a few reasons that could explain why lower-volatility and lower-beta stocks may command a premium. Historically, under normal market conditions, Low Volatility stocks have performed in line with (or even slightly better than) high-volatility stocks, However, during market crises, investors seek out safer assets and Low Volatility stocks tend to outperform. This 'option-like' behavior is often cited as a reason for the premium and hence outperformance of Low Volatility stocks. The effect is also known as the "Low Volatility Anomaly". Behaviorally, the Low Volatility anomaly can also be explained by the positive bias of many investors towards high-volatility stocks that are akin to 'lottery tickets'. It is well known that lottery tickets have negative average payoffs, but people nonetheless buy them for the chance of a big win (an example of the 'mental accounting' bias). In that regard, investors may overpay for what is in option language known as 'upside skew'. Other behavioral biases include 'crash aversion' (when investors are concerned about downside risk), 'representative bias' (when investors rely on appealing anecdotes – volatile names can be bid up on the stories they generate but ultimately disappoint investors), and 'overconfidence' of investors who are active in the high-volatility end of the market.[18]

Unless the market exhibits a strong up-trend, often there is not enough compensation for the higher risks attached to high-beta and high-volatility stocks. Low premium and high risk of higher-beta/volatility names results in subpar risk-adjusted performance. In all, it was documented that taking less risk did not sacrifice returns in a number of different equity markets (e.g. see "The Volatility Effect: Lower Risk without Lower Return", David Blitz, ERIM, July 2007). Low Volatility strategies have become popular in the last 5 years, especially in developed markets after the 2008-2009 financial crisis. Structurally, increased allocations into low-volatility strategies from insurance and the mutual fund industry may have also contributed to strong performance. As we will discuss in the next chapter, low Volatility/Beta long-short factors have significant negative market exposure (as stocks on the short side have higher beta than ones on the long side). In strong up markets, this negative beta will result in a performance drag. To properly understand and attribute performance of these factors, one often needs to work with factors that are neutralized for market exposure (beta).

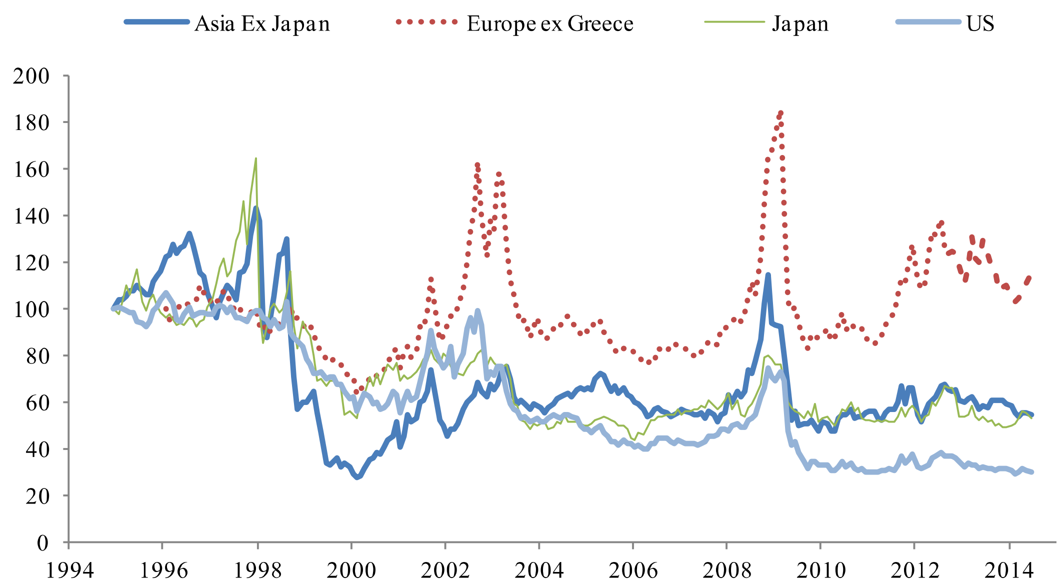
In addition to Low Volatility and Beta factors, we have classified Capitalization Size premia into the Volatility family of factors. Size premium is well researched and is one of the factors in the famous Fama-French three-factor model.[19] Various academic papers argue for the close link between Volatility premia and Small Size premia.[20] Intuitively, investors know that Small Capitalization stocks tend to be more volatile, more sensitive to equity market volatility and levels of credit spreads. In our correlation study in the second chapter we will also show that covariance properties of Low Volatility and Low Beta Factors are very similar to those of Large-Small Size factor.[21] Below we tested the performance of Low Volatility, Low Beta as well as Small Size Risk Factors across different regions.

The **Volatility** measure we use in our prototype factor is the standard deviation of daily stock returns over the last 90 days.[22] Historically, volatility tends to exhibit a negative correlation with equities (i.e. stocks with Low Volatility outperformed both the market and high-volatility stocks during market downturns). If there is not sufficient premia attached to High Volatility names, investors should favor Low Volatility stocks. Figure 15 shows historical performance of the Low

[18] "Explanation for the Volatility Effect – An Overview based on the CAPM Assumptions", Blits Falkenstein & Vliet, Working Papper SSRN, 2013.
[19] Fama, E. F.; French, K. R. (1992), "The Cross-Section of Expected Stock Returns," The Journal of Finance 47 (2): 427.
[20] See, for instance, Amihud, Y. (2002), "Illiquidity and stock returns: cross-section and time-series effects," Journal of Financial Markets 5 (1), 31-56; Chan, K. C., and Chen, Nai-fu (1991), "Structural and return characteristics of small and large firms," Journal of Finance 46, 1467-1484; Vassalou, M. and Y. Xing (2004), "Default Risk in Equity Returns," Journal of Finance 59, 831-868.
[21] Note that Low Volatility and Low Beta have strong positive correlation to Large-Small Size factor (and negative to Small-Large Size factor).
[22] The lower the better; our Risk Factor is Long a basket of *Low* Volatility stocks and Short a basket of *High* Volatility stocks.

Volatility factor across different regions (long Low Volatility and short High Volatility stocks). As this factor (in its basic long-short dollar-neutral form) has significantly negative market beta and given the positive market trend, one would expect a much weaker performance than the one illustrated in Figure 15. One can also notice the strong performance during the crises of 1997/1998, 2002, and 2008.

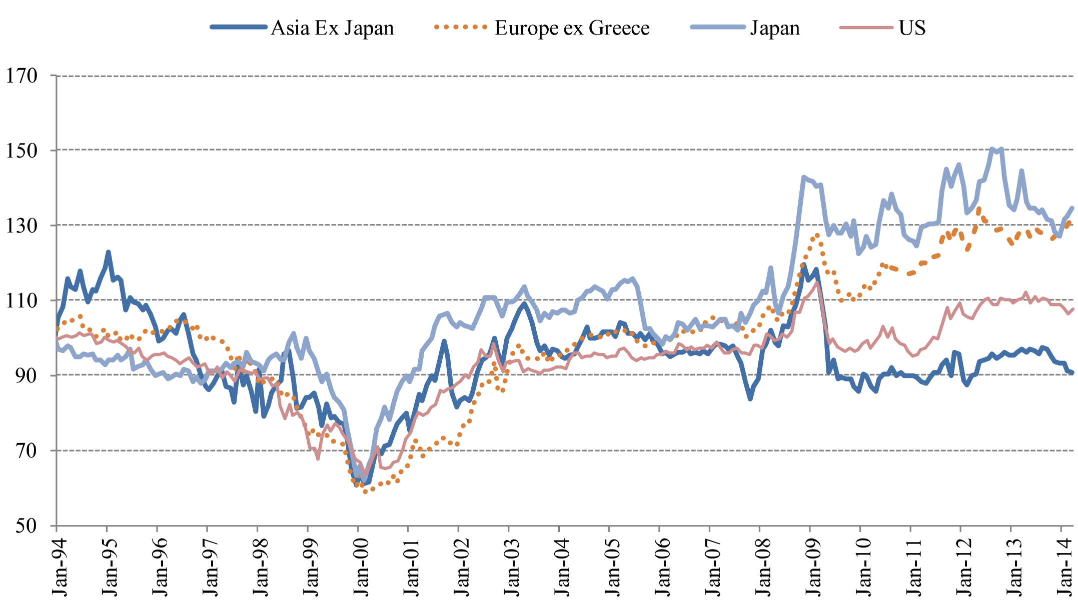
Figure 15: Long Low Volatility/Short High Volatility Factor in the US, Europe, Asia ex-Japan, and Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Figure 16 shows an implementation that is long Low Volatility stocks and short the market benchmark. This implementation is closer to being market neutral, and one can more clearly notice the outperformance of Low Volatility stocks (factor betas and neutralization methods are discussed in more detail in the second chapter).

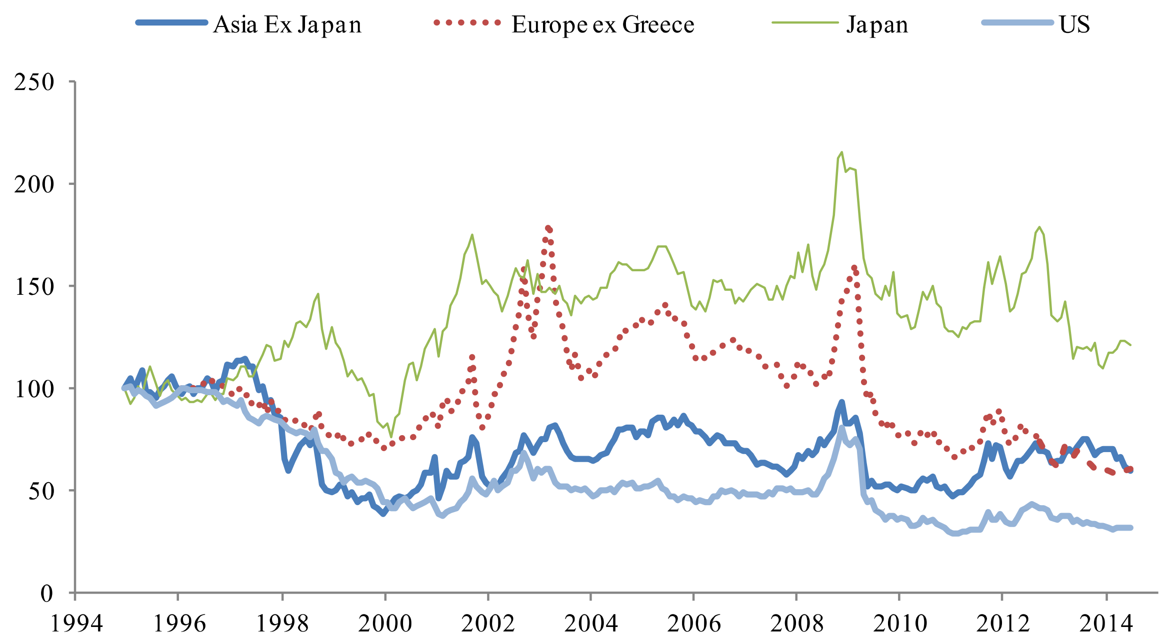
Figure 16: Long Low Volatility/Short Benchmark Factor in the US, Europe, Asia ex-Japan, and Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Beta is calculated as the regression slope between the trailing returns of the stock and its benchmark market. Equivalently, beta of a stock can be calculated as a product of the stock's correlation to the market, and the ratio of the stock's and market's volatility. Given that the Beta score is proportional to the Volatility score, a Low Beta factor will have very similar properties to a Low Volatility factor (i.e. Low Beta stocks outperformed the market and High Beta stocks).[23, 24] Volatility and Beta Factors (i.e. long *Low* Beta/Volatility and short *High* Beta/Volatility) have performed well during down markets when investors seek the relative safety of stocks with low volatility and low correlation (to the falling market). Figure 17 shows the performance of the Low Beta factor.

Figure 17: Long Low Beta/Short High Beta Factor in the US, Europe, Asia ex-Japan, and Japan



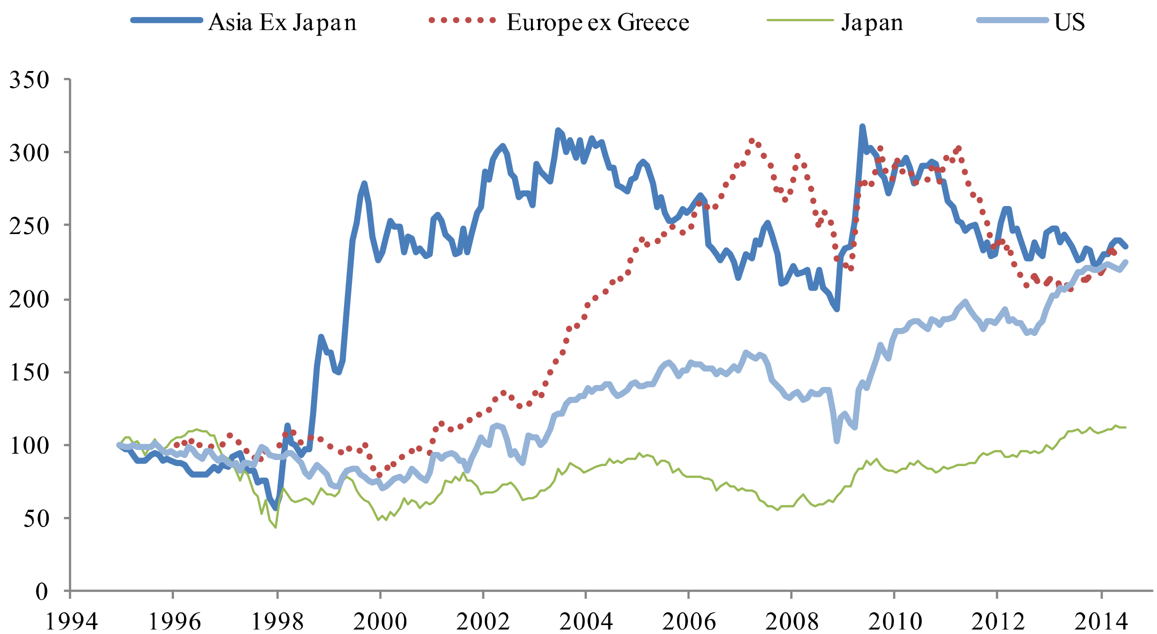
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Properly accounting for market exposure of the Low Beta factor reveals a more consistent outperformance over the cycle, but also a high sensitivity during market turns. In this regard, Low Volatility and Low Beta factors are similar to Momentum Factors. This will be confirmed in our correlation analysis in the second chapter.

The **Size** factor is constructed based on the market capitalization of the company (defined as current market price multiplied by the number of shares outstanding). Outperformance of Small Capitalization stocks has been well documented across regions.[25] Qualitatively, companies that are smaller in size tend to have a more favorable risk/reward profile that is often related to their higher growth rate. Smaller stocks do generally have higher information uncertainty and higher volatility and beta. Figure 18 below shows the historical performance of the Small-Large Size factor across regions. Please note that investors most often define the Size factor as Small-Large (this factor has positive premium). As we have categorized the Size factor into the Volatility Style, in our correlation studies we test properties of the Large-Small Size factor to more directly compare it to Low Volatility and Low Beta factors (i.e. we will effectively change the sign of factor returns).

[23] The difference between Beta and Low Volatility is that, in addition to Volatility, Beta score incorporates correlation (score penalizes high-volatility and highly correlated stocks).
[24] See for instance our report "Minimum-Variance Strategies: Frequently Asked Questions and Methods to Improve Min-Var strategies".
[25] Fama, E. F, French, K. R. (1993), "Common risk factors in the returns on stocks and bonds," Journal of Financial Economics 33: 3. Fama, E. F., French, K. R. (2012), "Size, value, and momentum in international stock returns," Journal of Financial Economics 105 (3): 457.

Figure 18: Size (Small vs. Large) Across Regions



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

The table below shows the key performance and risk statistics for Volatility Risk Factors in different regions. Statistics such as Information Coefficient (IC), Sharpe Ratio, etc. are shown both for Long/Short Factor portfolios as well as for Long-only portfolios. Table 14 provides definitions of the metrics used to construct the Volatility factors.

Table 13: Performance-Risk Metrics for Low Volatility/Beta and Small Size Risk Factors

	Long / Short						Long Only				
	IC	Ann. Ret	Ann. Vol.	Hit-Rate	Sharpe	Max DD.	Ann. Ret	Ann. Vol.	Hit-Rate	Sharpe	Max DD.
Low Volatility											
Asia Ex Japan	2.1%	(1.5%)	25.7%	56.3%	(0.06)	(79.0%)	5.0%	17.0%	60.3%	0.29	(66.7%)
Japan	1.2%	(3.8%)	21.6%	47.8%	(0.18)	(73.0%)	3.8%	15.5%	50.6%	0.24	(45.0%)
Europe	1.6%	2.1%	20.4%	53.4%	0.10	(54.2%)	10.5%	14.3%	64.4%	0.73	(46.2%)
US	(0.7%)	(5.6%)	18.7%	49.0%	(0.30)	(73.2%)	9.8%	12.7%	63.2%	0.77	(40.6%)
Low Beta											
Asia Ex Japan	1.9%	(1.5%)	21.7%	56.3%	(0.07)	(62.2%)	6.7%	21.2%	60.7%	0.32	(76.3%)
Japan	1.2%	0.1%	17.9%	52.2%	0.00	(51.3%)	4.5%	18.9%	53.0%	0.24	(46.0%)
Europe	0.5%	(2.1%)	19.1%	50.2%	(0.11)	(67.4%)	9.5%	15.1%	59.1%	0.63	(54.3%)
US	(0.3%)	(5.1%)	17.2%	45.7%	(0.29)	(70.7%)	7.7%	13.8%	63.6%	0.55	(48.4%)
Small Size											
Asia Ex Japan	(0.2%)	3.2%	21.4%	46.2%	0.15	(55.3%)	6.9%	36.1%	52.6%	0.19	(73.3%)
Japan	0.5%	0.9%	20.1%	51.4%	0.05	(61.5%)	3.0%	28.8%	51.0%	0.10	(73.3%)
Europe	0.5%	3.2%	12.5%	50.2%	0.25	(41.2%)	8.8%	23.9%	59.1%	0.37	(67.9%)
US	1.1%	3.9%	14.8%	50.6%	0.26	(37.0%)	12.8%	24.4%	59.5%	0.52	(65.1%)

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 14: Low Volatility/Low Beta and Small Size Risk Factors

Risk Factor	Technical Description
Volatility	Volatility of the stock price over the last 90 days
Beta	Beta of the stock relative to its local market based on the last 2 years of weekly returns
Size	Current price times the number of shares outstanding

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Similar to the previous Risk Factor style sections, we report below Low Vol/Low Beta/Small Size Risk Factors' exposure to global economic Growth, Inflation, market Volatility and Funding Liquidity indicators. Table 15 summarizes annualized average returns (and related *t*-statistics, in parentheses) of each Risk Factor under "Low", "Mid" and "High" regimes of Growth, Inflation, Volatility and Liquidity, respectively.

Table 15: Performance (t-statistics*) of Low Vol/Low Beta/Small Size Risk Factors Under Different Macro/Market Regimes

	Growth			Inflation			Volatility			Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Low Vol - Asia xJ	3.33	5.40	2.29	-2.07	3.98	9.75	8.15	2.03	0.85	-0.89	1.02	10.89
	(-0.09)	(0.48)	(-0.39)	(-1.48)	(0.11)	(1.43)	(1.25)	(-0.46)	(-0.79)	(-1.27)	(-0.74)	(2.03)
Low Vol - Europe	3.13	9.94	5.20	5.49	3.31	11.68	10.96	4.51	3.90	-1.20	4.11	15.12
	(-0.92)	(1.22)	(-0.33)	(-0.22)	(-1.11)	(1.48)	(1.39)	(-0.56)	(-0.76)	(-2.42)	(-0.63)	(3.03)
Low Vol - Japan	-5.32	-0.96	9.64	-1.97	-2.18	10.24	4.50	-3.67	2.54	-0.24	0.97	2.63
	(-1.62)	(-0.52)	(2.15)	(-0.71)	(-1.04)	(1.93)	(0.84)	(-1.20)	(0.35)	(-0.34)	(-0.04)	(0.38)
Low Vol - US	-0.67	-2.10	3.41	-2.51	-0.20	4.02	3.71	-0.03	-3.04	-5.39	1.64	4.39
	(-0.29)	(-0.75)	(1.04)	(-0.82)	(-0.17)	(1.04)	(1.14)	(-0.08)	(-1.06)	(-1.83)	(0.46)	(1.36)
Low Beta - Asia xJ	2.16	8.16	3.58	8.25	-1.52	10.88	7.45	0.90	5.56	-10.03	11.27	12.66
	(-0.66)	(0.94)	(-0.28)	(0.89)	(-2.07)	(1.40)	(0.75)	(-1.00)	(0.25)	(-4.04)	(1.78)	(2.16)
Low Beta - Europe	-4.87	8.57	7.75	7.25	0.67	5.99	10.55	2.53	0.43	-7.87	7.24	13.02
	(-2.87)	(1.51)	(1.24)	(0.99)	(-1.40)	(0.51)	(1.95)	(-0.56)	(-1.29)	(-4.19)	(0.97)	(3.13)
Low Beta - Japan	-0.83	3.83	5.83	-0.21	-1.88	14.70	1.26	5.71	1.87	0.72	1.96	6.15
	(-0.87)	(0.21)	(0.67)	(-0.67)	(-1.41)	(2.31)	(-0.39)	(0.64)	(-0.25)	(-0.51)	(-0.23)	(0.74)
Low Beta - US	-2.54	-0.10	1.50	-7.80	3.58	1.44	6.10	-1.08	-6.16	-9.31	1.53	6.64
	(-0.71)	(0.09)	(0.62)	(-2.29)	(1.65)	(0.50)	(2.16)	(-0.23)	(-1.92)	(-3.00)	(0.63)	(2.35)
Small Size - Asia xJ	7.56	5.52	-3.01	34.33	-8.86	-11.54	-5.03	7.63	7.48	7.76	4.78	-2.46
	(0.62)	(0.32)	(-0.94)	(4.37)	(-2.27)	(-1.85)	(-1.23)	(0.63)	(0.60)	(0.65)	(0.21)	(-0.86)
Small Size - Europe	-2.87	9.10	8.13	6.57	4.79	3.76	9.34	10.35	-3.74	-4.80	8.19	11.86
	(-1.79)	(0.98)	(0.75)	(0.34)	(-0.08)	(-0.26)	(0.92)	(1.31)	(-2.21)	(-2.41)	(0.70)	(1.69)
Small Size - Japan	11.89	4.49	-15.02	12.82	-9.05	2.31	-0.71	2.40	-0.33	-7.52	4.79	4.09
	(1.78)	(0.62)	(-2.42)	(1.77)	(-1.85)	(0.24)	(-0.18)	(0.30)	(-0.12)	(-1.23)	(0.67)	(0.56)
Small Size - US	5.20	8.63	1.54	5.56	5.89	3.32	2.09	10.25	3.03	1.58	5.29	8.49
	(0.02)	(0.75)	(-0.77)	(0.09)	(0.21)	(-0.32)	(-0.65)	(1.10)	(-0.45)	(-0.76)	(0.04)	(0.72)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The *t*-statistic shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 16 summarizes the exposure of regional Low Vol/Low Beta/Small Size Risk Factors to macro/market regime indicators over the full backtest period from January 1995 to June 2014. We report both regression coefficients (Beta to the corresponding regime indicator) and related *t*-statistics.

Table 16: Low Vol/Low Beta/Small Size Risk Factors' Exposures (t-stats*) to Macro/Market Regime Factors over the Full Sample Period

	Growth	Inflation	Volatility	Liquidity		Growth	Inflation	Volatility	Liquidity
Low Vol - Asia xJ	0.25 (1.18)	0.36 (1.77)	-0.43 (-2.04)	0.18 (0.86)	**Low Vol - Japan**	0.39 (1.65)	0.43 (1.88)	-0.05 (-0.22)	-0.26 (-1.12)
Low Vol - Europe	0.22 (1.22)	0.32 (1.82)	-0.09 (-0.50)	0.01 (0.04)	**Low Vol - US**	0.40 (2.21)	0.42 (2.39)	-0.33 (-1.81)	0.21 (1.18)
Low Beta - Asia xJ	0.24 (1.07)	-0.03 (-0.16)	-0.25 (-1.15)	0.65 (3.03)	**Low Beta - Japan**	0.18 (0.72)	0.46 (1.86)	-0.02 (-0.09)	-0.18 (-0.73)
Low Beta - Europe	0.38 (2.18)	0.07 (0.43)	-0.36 (-2.04)	0.44 (2.65)	**Low Beta - US**	0.33 (1.86)	0.55 (3.24)	-0.48 (-2.73)	0.36 (2.10)
Small Size - Asia xJ	-0.51 (-1.28)	-1.14 (-2.95)	0.35 (0.86)	0.25 (0.64)	**Small Size - Japan**	-0.76 (-2.00)	-0.36 (-0.96)	0.28 (0.74)	0.04 (0.11)
Small Size - Europe	0.05 (0.20)	-0.39 (-1.66)	-0.79 (-3.25)	0.74 (3.21)	**Small Size - US**	-0.26 (-0.93)	-0.42 (-1.55)	-0.37 (-1.34)	0.60 (2.25)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
*The *t*-statistic shown in parentheses is from regression of factor return versus respective macro/market regime indicator.

From the two tables above, we can highlight a few simple observations: High Growth, High Liquidity and Low Volatility generally benefited Low Volatility Risk Factors across regions. While Low Volatility/Beta factors tended to outperform during market crises, the subsequent drawdown during the recovery rally usually wiped out crisis gains. As a result, despite the full sample negative correlation to the market, Low Volatility/Beta factors have had positive correlation to Growth. We found the same to be true with the Momentum Factor. The Small Size Risk Factor has similar properties to Low Volatility and Low Beta (note that in the tables and charts we show the Small-Large Factor).

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Quality

Quality Risk Factors rely on balance sheet and income statement items that indicate a company's ability to sustain earnings over time. It is generally accepted that it is desirable to tilt portfolios towards businesses with high and sustainable profitability. The market also appears to reward relative earnings certainty and penalize those stocks that carry a large degree of earnings volatility. However, Quality factors as standalone investments tend to have on average weak and counter-cyclical performance, and often times trade at stretched valuations as investors pay a premium to minimize potential downside. For this reason, Quality factors are often combined with other Risk Factors using a multi-factor approach. The most popular combination with Quality is Value, resulting in the common investment philosophy of 'Quality at a Reasonable Price' (QARP).

One way of measuring Quality, i.e. the sustainability of profits, is to decompose the profitability ratio ROE into Profit Margin (Net Income/Sales), Asset Turnover (Sales/Assets) and Leverage (Assets/Equity). Each of these ratios can serve as a Quality Factor. Other popular choices of Quality factors are Interest Coverage, Capital Expenditure to Depreciation, Current Ratio, Dividend Payout Ratio, Earnings Risk (Coefficient of variation for consensus earnings), number of covering analysts, etc. The predictive power of each of these standalone Quality factors is not strong, and they are usually combined into a Quality factor composite (e.g. combining Profitability, Earnings Quality, Credit Risk measures). Composite signals are more reliable signals and examples include the Altman Z-Score and Piotroski's F-Score.[26]

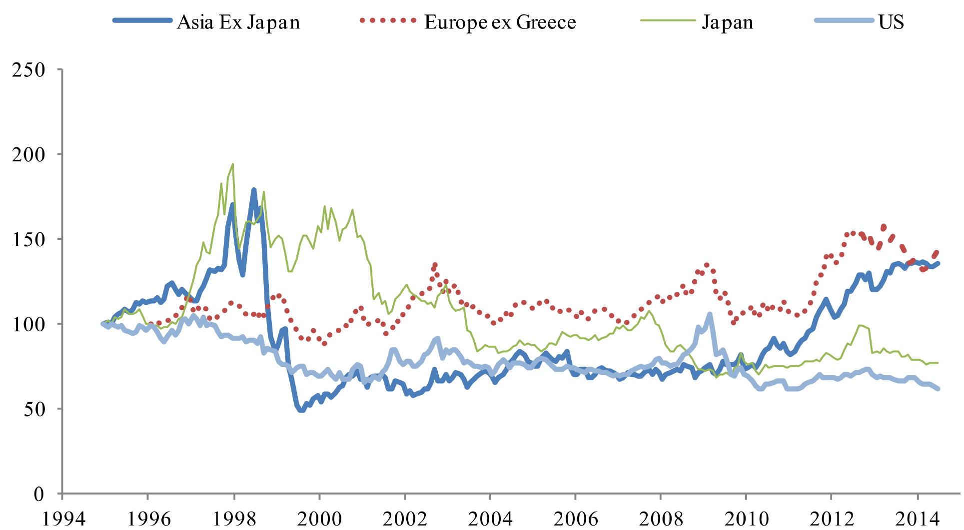
Quality factors will often have negative market exposure (negative beta). Negative beta is a result of long exposure to high-quality stocks that also tend to be less volatile, and short exposure to more volatile, low-quality names. For this reason, Quality factors are often positively correlated with Volatility, Growth and Momentum factors, and negatively correlated with Value and broad market exposure. The negative beta of Quality factors needs to be taken into account when evaluating and attributing performance of this factor. In the next chapter we will show that neutralizing beta can improve the performance of Quality factors. Because of their counter-cyclical behavior, Quality factors can be used to construct a portfolio of factors to hedge broad equity exposure (see 'Hedging with Risk Factors' section on page 92).

Practitioners often adjust Quality metrics to a sector or universe, and normalize by standard deviation. Also common is the use of changes in Quality factors such as Asset Turnover growth, ROE growth, etc. For an extensive list of Quality factors, see the Appendix 'Factor Reference Books' on page 133. Below we define and test three simple Quality factors that we intend to use as prototype Style benchmarks in each of the regions.

Return on Equity is defined as Net Income divided by the company's Equity. Companies with higher ROE (i.e. generating a larger amount of profits compared to the shareholders' equity) should be more attractive to investors than companies with lower ROE. Detailed analysis of the ROE factor can be found in our report "Return on Equity – Is it useful for stock picking?" Figure 19 below shows the performance of a long-short ROE factor in US, Europe, Asia ex-Japan, and Japan.

[26] The Importance of Financial Strength for Value Investing, Revisiting and Reviving the Altman-Z Score

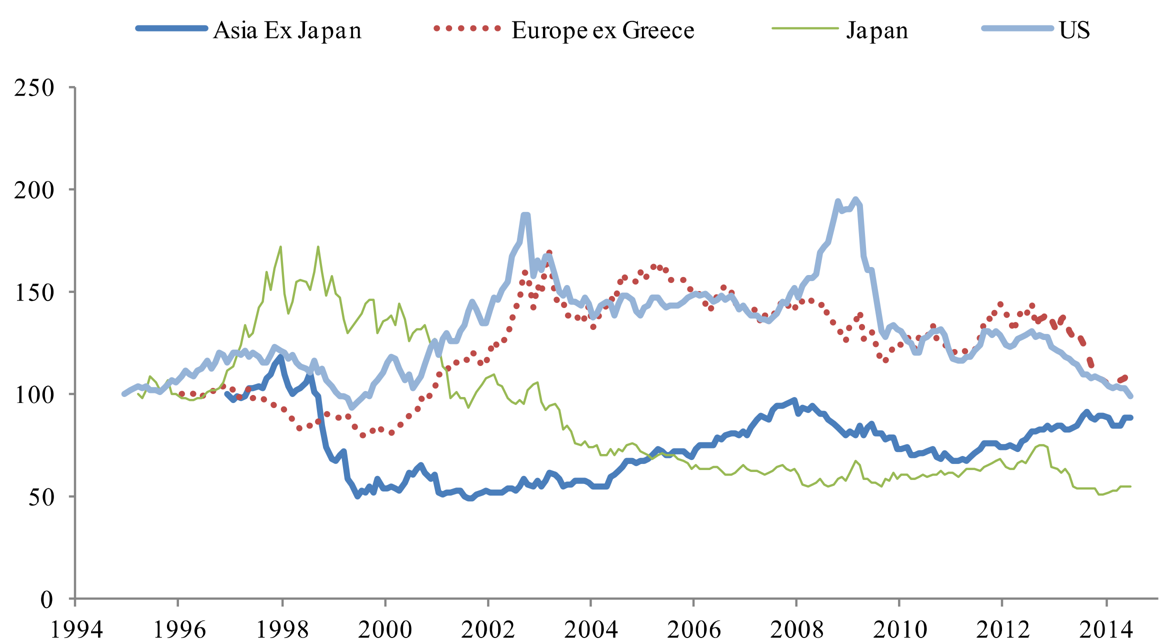
Figure 19: Performance of Return on Equity Factor in the US, Europe, Asia ex-Japan, and Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Net Profit Margin is defined as Net profit (after tax) divided by revenue. Companies with higher margins (i.e. generating a larger amount of profits per unit of sales) should be more attractive to investors than companies with low margins. Similar to ROE, this factor has performed positively during times of market stress (due to its average negative market beta), and has generally underperformed during market recoveries. Figure 20 below shows the performance of a long-short Net Profit Margin factor in US, Europe, Asia ex-Japan, and Japan.

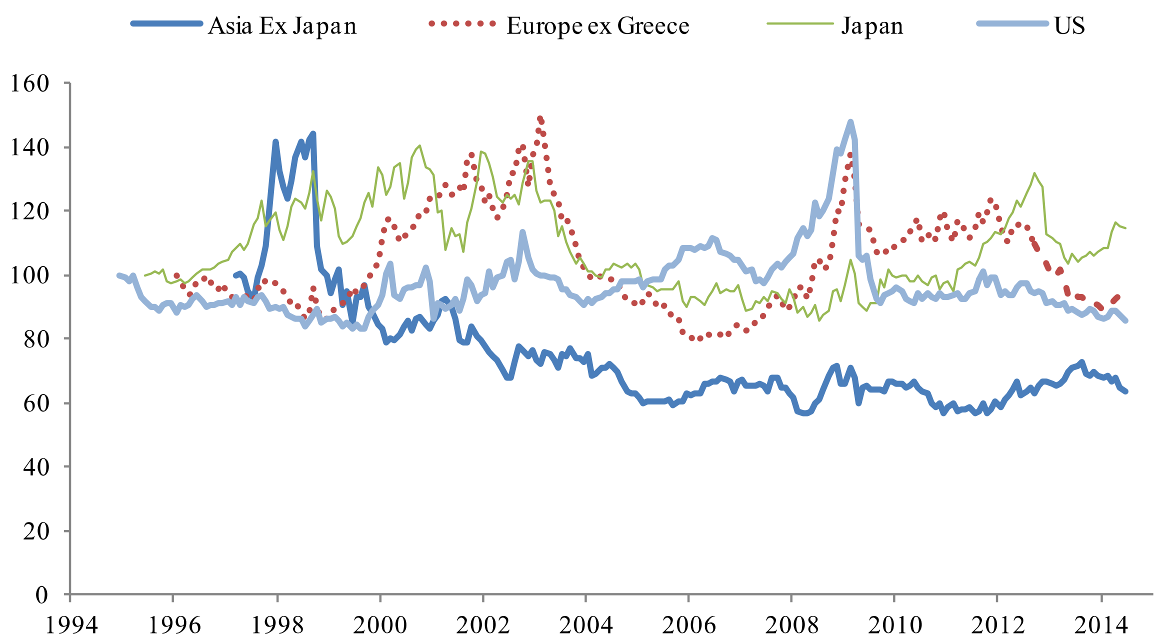
Figure 20: Performance of the Net Profit Margin Factor in the US, Europe, Asia ex-Japan, and Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Debt to Equity Ratio is defined as a company's liabilities divided by its balance sheet shareholder equity. Companies with a low level of debt to equity should be more attractive to investors than companies with a higher level of leverage. As with other Quality factors, performance charts indicate counter-cyclical behavior that we will analyze in more detail in the second chapter of this report. Figure 21 below shows performance of a long-short Debt to Equity factor in US, Europe, Asia ex-Japan, and Japan.

Figure 21: Performance of the Debt/Equity Factor in the US, Europe, Asia ex-Japan, and Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Accruals are defined as the difference between the reported (Accrual) earnings and cash earnings divided by total assets (to normalize the factor).[27] While there is debate among researchers about what determines the size of Accruals – for example, whether it can be prone to potential earnings manipulation or is a rational response of firm management to changes in investment opportunities available to the firm – empirical analysis over the long run is fairly clear: the higher the Accruals for a firm, the more it is likely to underperform its peers with lower Accruals. Accruals is considered a Quality Risk Factor because firms with low (high) Accruals are expected to show greater (lower) persistence in reported earnings in the long run. More details can be found in "Game of Accruals: What Approach Maximizes Alpha? (March 2014)." Figure 22 below shows performance of a long-only and long-short Accruals factor in the US.

[27] The commonly used calculation of Accruals based on balance sheet data is as follows: Accruals factor = Δ (Total Assets – Cash and Cash Equivalent) – Δ (Total Liabilities – Short-Term Debt – Long-Term Debt) divided by the average Total Assets. The change (Δ) in Balance Sheet items is calculated over one year.

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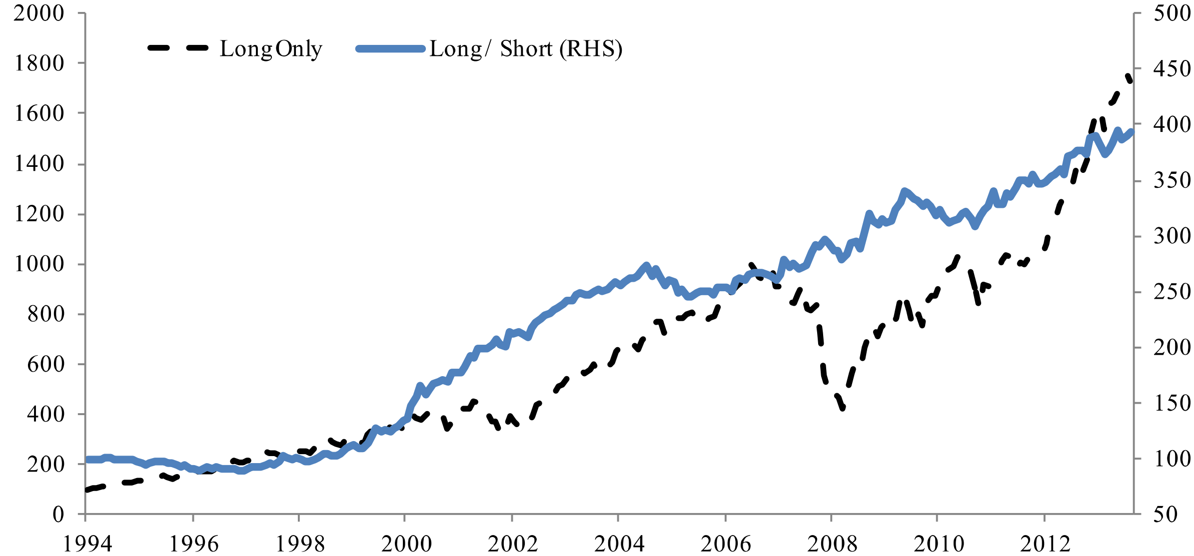
Figure 22: Accruals Performance – Long Only vs. Long/Short in US



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

Table 17 provides definitions of the metrics used to construct the Quality factors.

Table 17: Quality Risk Factors

Risk Factor	Technical Description
Return on Equity	Net income divided by total shareholders' equity
Net Profit Margin	Ratio of net profit after tax to revenue
Debt/Equity Ratio	Total liabilities divided by total shareholders' equity
Accruals	Difference between the reported (accrual) earnings and cash earnings, divided by total assets

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Expected behavior of Quality Factors: While the performance of simple Quality factors has not been very strong, this was largely due to their negative market exposure. In that regard, we think these factors should be evaluated based on their performance net of market beta (see next chapter), or based on their ability to lower portfolio correlations (counter-cyclical behavior). Quality factors can also be combined in a multi-factor model with other factors such as Value, to build 'Quality at a Reasonable Price (QARP)' strategies, for example.

The table below shows the key performance and risk statistics for Quality Risk Factors in different regions. Statistics such as Information Coefficient (IC), Sharpe Ratio, etc. are shown both for Long/Short Factor portfolios as well as for Long-only portfolios.

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Table 18: Performance-Risk Metrics for Quality Risk Factors

	Long / Short						Long Only				
	IC	Ann. Ret	Ann. Vol.	Hit-Rate	Sharpe	Max DD.	Ann. Ret	Ann. Vol.	Hit-Rate	Sharpe	Max DD.
Return On Equity											
Asia Ex Japan	1.4%	1.7%	18.4%	57.5%	0.09	(73.3%)	4.8%	25.1%	55.9%	0.19	(66.0%)
Japan	0.5%	(1.6%)	14.8%	51.4%	(0.11)	(63.0%)	2.9%	20.0%	55.5%	0.14	(58.8%)
Europe	1.1%	2.6%	12.1%	55.5%	0.21	(28.7%)	10.1%	18.8%	61.9%	0.54	(61.1%)
US	0.0%	(1.9%)	11.5%	49.4%	(0.17)	(41.5%)	12.3%	16.8%	62.8%	0.73	(51.7%)
Profit Margin											
Asia Ex Japan	1.0%	(1.3%)	14.0%	53.8%	(0.10)	(60.0%)	4.5%	28.1%	58.3%	0.16	(76.6%)
Japan	0.2%	(2.7%)	13.8%	50.0%	(0.20)	(69.7%)	2.2%	17.1%	54.1%	0.13	(56.0%)
Europe	0.6%	1.4%	10.8%	52.6%	0.13	(34.2%)	10.6%	18.6%	61.5%	0.57	(66.8%)
US	(0.1%)	(0.1%)	10.8%	51.4%	(0.01)	(49.3%)	10.7%	15.5%	62.3%	0.69	(56.9%)
Gearing											
Asia Ex Japan	0.1%	(3.2%)	14.1%	48.2%	(0.23)	(64.9%)	6.5%	26.3%	56.4%	0.24	(68.0%)
Japan	0.6%	0.9%	11.6%	53.1%	0.08	(38.0%)	3.9%	18.2%	54.4%	0.22	(46.6%)
Europe	0.3%	0.3%	10.8%	50.6%	0.02	(45.4%)	9.8%	17.9%	60.3%	0.55	(56.6%)
US	0.3%	(0.7%)	10.8%	52.6%	(0.07)	(42.4%)	11.9%	16.5%	62.3%	0.72	(52.8%)
Accruals											
US	2.0%	7.2%	7.5%	58.7%	96.4%	(11.4%)	15.7%	18.6%	65.1%	0.84	(57.7%)

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Lastly, we report below Quality Risk Factors' exposure to global economic Growth, Inflation, market Volatility and Funding Liquidity indicators.[28] Table 19 summarizes annualized average returns (and related *t*-statistics, in parentheses) of each Risk Factor under "Low", "Mid" and "High" regimes of Growth, Inflation, Volatility and Liquidity, respectively.

Table 20 summarizes the exposure of regional Quality Risk Factors to macro/market regime indicators over the full backtest period from January 1995 to June 2014. We report both regression coefficients (Beta to the corresponding regime indicator) and related *t*-statistics.

[28] See Appendix: Macro and Market Regimes. Consistent with our primer to Cross-Asset Risk Factors, the macro/market regime indicators are defined as follows: Growth is defined as YoY change of OECD leading indicator; Inflation is defined as OECD global consumer price inflation indicator; Volatility is defined as the VIX indicator; Liquidity is defined as the difference between 3-month Treasury Bill rate and 3-month US$ Libor rate (the Ted spread defined as such is shown to be closely linked to both market and funding Liquidity).

Table 19: Performance (t-statistics*) of Quality Risk Factors Under Different Macro/Market Regimes

	Growth			Inflation			Volatility			Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
ROE - Asia xJ	1.22	12.61	8.62	-0.60	15.32	3.52	9.04	6.89	6.53	6.85	4.95	10.65
	(-1.18)	(0.96)	(0.21)	(-1.41)	(1.86)	(-0.62)	(0.29)	(-0.11)	(-0.18)	(-0.12)	(-0.48)	(0.59)
ROE - Europe	6.19	6.83	2.68	2.18	5.10	8.96	6.36	0.05	9.36	3.95	5.45	6.15
	(0.27)	(0.48)	(-0.74)	(-0.83)	(-0.03)	(0.91)	(0.30)	(-1.54)	(1.25)	(-0.36)	(0.07)	(0.29)
ROE - Japan	-7.17	1.17	13.74	2.00	8.62	-6.96	5.21	3.01	-0.48	1.48	6.41	-0.15
	(-2.28)	(-0.33)	(2.62)	(-0.12)	(1.76)	(-1.86)	(0.61)	(0.10)	(-0.71)	(-0.25)	(0.89)	(-0.63)
ROE - US	-1.76	0.68	-3.71	-2.44	-2.06	0.15	0.32	-2.23	-2.88	-6.19	-1.22	2.62
	(-0.05)	(0.72)	(-0.66)	(-0.24)	(-0.18)	(0.46)	(0.60)	(-0.20)	(-0.40)	(-1.45)	(0.12)	(1.33)
Net PM - Asia xJ	-8.00	10.05	7.85	-7.51	12.28	4.28	12.42	-0.94	0.64	-0.46	5.50	6.02
	(-2.61)	(1.49)	(1.04)	(-2.61)	(2.38)	(0.13)	(1.89)	(-1.05)	(-0.74)	(-0.98)	(0.39)	(0.61)
Net PM - Europe	3.29	4.57	4.46	-0.73	4.55	9.36	3.47	3.75	5.07	1.32	1.01	9.57
	(-0.26)	(0.14)	(0.11)	(-1.54)	(0.16)	(1.44)	(-0.20)	(-0.13)	(0.32)	(-0.93)	(-0.96)	(1.86)
Net PM - Japan	-3.57	-0.09	5.92	2.38	4.22	-6.86	0.27	0.64	1.28	3.57	-0.30	-1.10
	(-1.17)	(-0.22)	(1.39)	(0.41)	(1.16)	(-1.74)	(-0.12)	(-0.03)	(0.15)	(0.77)	(-0.27)	(-0.50)
Net PM - US	-0.41	2.57	0.71	-4.09	1.93	5.10	0.83	0.91	1.12	0.58	2.16	0.12
	(-0.46)	(0.54)	(-0.08)	(-1.58)	(0.41)	(1.18)	(-0.04)	(-0.01)	(0.06)	(-0.13)	(0.41)	(-0.28)
Debt/Equity - Asia xJ	-0.40	8.61	-3.59	-0.09	0.64	4.86	-2.10	-1.10	6.58	4.87	1.43	-1.62
	(-0.44)	(1.73)	(-1.27)	(-0.39)	(-0.24)	(0.68)	(-0.80)	(-0.61)	(1.35)	(0.85)	(-0.01)	(-0.83)
Debt/Equity - Europe	2.14	1.93	5.95	2.10	6.53	-0.06	-0.93	-2.41	12.81	5.40	-1.20	5.48
	(-0.38)	(-0.48)	(0.85)	(-0.40)	(1.21)	(-0.94)	(-1.27)	(-1.96)	(3.23)	(0.65)	(-1.40)	(0.70)
Debt/Equity - Japan	1.86	1.66	6.65	6.10	3.61	-0.18	1.70	1.78	6.62	5.43	3.26	1.55
	(-0.44)	(-0.51)	(0.95)	(0.73)	(0.07)	(-0.86)	(-0.47)	(-0.48)	(0.95)	(0.59)	(-0.04)	(-0.55)
Debt/Equity - US	-2.64	-0.84	4.75	-0.88	-0.09	2.80	-0.91	0.57	1.61	-2.18	0.18	3.28
	(-0.99)	(-0.41)	(1.40)	(-0.39)	(-0.21)	(0.64)	(-0.43)	(0.05)	(0.38)	(-0.84)	(-0.08)	(0.92)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The *t*-statistic shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 20: Quality Risk Factors' Exposures (t-stats*) to Macro/Market Regime Factors over the Full Sample Period

	Growth	Inflation	Volatility	Liquidity		Growth	Inflation	Volatility	Liquidity
ROE - Asia xJ	0.36	0.11	0.07	0.10	ROE - Japan	0.46	-0.25	-0.31	0.42
	(1.16)	(0.37)	(0.23)	(0.31)		(1.81)	(-1.00)	(-1.24)	(1.71)
ROE - Europe	0.05	0.36	0.37	-0.22	ROE - US	-0.06	0.31	0.09	0.02
	(0.24)	(1.85)	(1.81)	(-1.14)		(-0.30)	(1.71)	(0.50)	(0.11)
Net PM - Asia xJ	0.29	0.38	-0.35	0.01	Net PM - Japan	0.03	-0.14	0.32	-0.25
	(1.18)	(1.62)	(-1.39)	(0.06)		(0.14)	(-0.67)	(1.49)	(-1.19)
Net PM - Europe	0.13	0.25	0.17	0.15	Net PM - US	0.22	0.61	0.00	-0.14
	(0.75)	(1.46)	(0.96)	(0.87)		(1.27)	(3.66)	(0.03)	(-0.84)
Debt/Equity - Asia xJ	-0.16	0.08	0.37	-0.19	Debt/Equity - Japan	-0.02	-0.12	0.30	-0.20
	(-0.66)	(0.36)	(1.54)	(-0.85)		(-0.10)	(-0.62)	(1.46)	(-1.02)
Debt/Equity - Europe	0.02	0.07	0.57	-0.12	Debt/Equity - US	0.34	0.29	0.15	-0.08
	(0.12)	(0.41)	(3.14)	(-0.66)		(1.87)	(1.60)	(0.83)	(-0.45)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
*The *t*-statistic shown in parentheses is from regression of factor return versus respective macro/market regime indicator.

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Factor and Style Correlations

Similar to Risk Factors in other asset classes, Equity Risk Factors are expected to deliver positive performance over market cycles. Ideally, factors should outperform a broad market benchmark on a risk-adjusted basis. Perhaps an even more important advantage of Risk Factors is their lower and more stable correlation, compared to the correlation between traditional market segments such as industry sector, or country benchmarks. Lower correlations will allow investors to build a factor portfolio with significantly lower volatility (and hence higher information ratio) than a broad market or sector benchmark. The lower and more stable correlation of factors also allows for the use of Equity Risk Factors to enhance performance or hedge traditional equity benchmarks.

In this section, we study the correlation properties of Equity Risk Factors and compare them to sector and country correlations. However, before we can analyze factor correlations, we need to understand different approaches in factor construction and biases factors can acquire as a result of a construction methodology. This brings us to the topic of factor neutralization – the process in which a 'raw' factor is to a certain degree stripped of broad market, sector or country exposures. Once we understand factor neutralization, we will proceed to analyze the correlations of long-only factors, long-short factors, and beta-neutral long-short factors across styles and geographic regions.

Factor Neutralization Methods

To illustrate the importance of factor neutralization, take for example a long-only Dividend Yield Factor. Without normalizing this factor for sector biases, most likely the factor would give a long exposure to Utility companies that historically have paid high dividends. The correlation of this 'raw' Dividend factor would in turn largely reflect its correlation to the Utility sector. Long-only factors (also called 'enhanced beta' exposure) obviously have much larger exposure to the broad market than long-short factors. However, market normalization is also important for long-short factors. For instance, the Low Beta factor (long low-beta stocks, short high-beta stocks) almost by definition will have significant short exposure to the equity market benchmark (i.e. negative correlation) without normalization (i.e. non-normalized factors will be a mix of a 'pure' low-beta factor and short market exposure). The short market exposure may be the main driver of the factor's returns if the factor is not normalized.

As our goal is to understand correlation properties of Risk Factors – rather than correlation properties of residual market, sector, or country exposures in a factor – we always aim to work with normalized factors. In this section we examine different neutralization techniques and their effect on Equity Risk Factors.

In practice, neutralization of market, sector or country exposures of a multi-factor portfolio can be done as a final stage of portfolio construction by using an optimizer. However, this approach may not be helpful to gain insights about individual Equity Risk Premia (ERPs). In our approach, we prefer performing normalization on individual factors. This will enable us to accurately study the correlation properties of individual factors. These properties are then used as inputs to select factors in a multi-factor portfolio (e.g. those with complementary correlation properties), or to test various portfolio construction models (e.g. by using ex-ante factor covariance as an input).

The types of neutralization we will investigate in this section are:

- **Market Beta**: Beta-neutralized Risk Factors are constructed to remove broad market exposure of a long-short factor. Beta neutralization can be implemented in different ways. For instance, one can use trailing (historical) beta of the long and short sides to obtain a long-short factor with (ex-post) zero beta. Another way is to work with forecasted betas for individual stocks.
- **Sector**: Sector-neutralization is often done according to GICS sector (level 1) classifications. This approach is often used for developed markets where the sector is a larger driver of risk than country-specific risk, for example. As we will discuss later in the section, the choice of sector normalization method may force a specific sector allocation of a long-only Risk Factor.

- **Country**: Country normalization is often done according to geographic location of the primary exchange where the stock is traded. Country normalization is more common in emerging markets, or in developed market situations when the country-specific (e.g. geopolitical) risks are dominating sector risks.

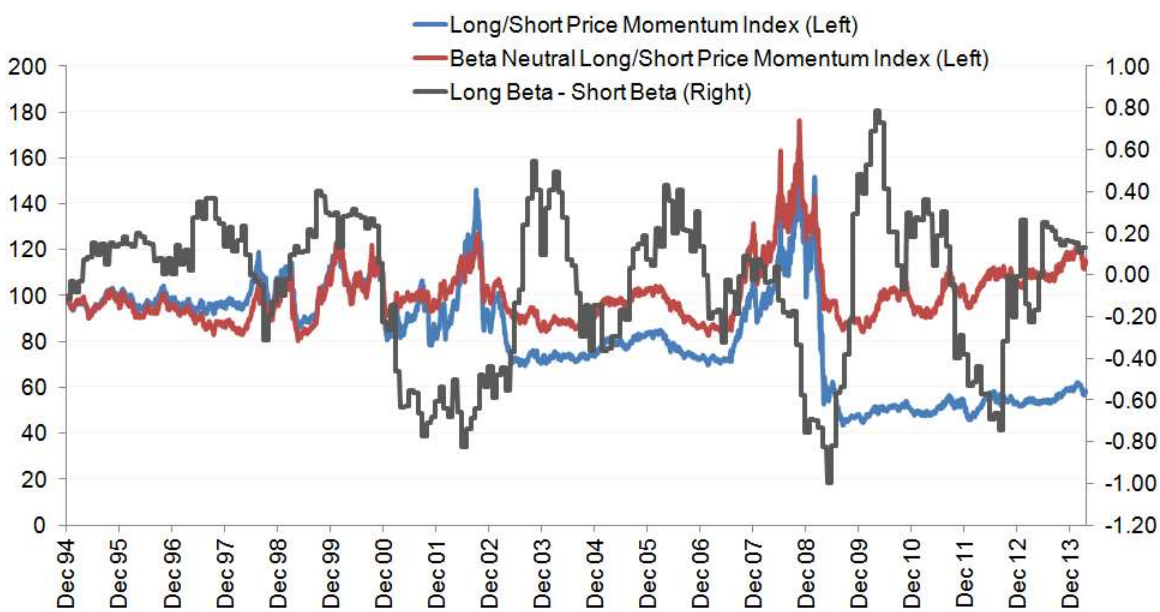
In the rest of the section we will go through each of these neutralization methods to illustrate their effects on the raw factors.

Beta Neutralization

So far in the report, we have analyzed long-only Risk Factors (enhanced beta) and long-short factors that were designed as dollar-neutral (but not market beta neutral) long-short portfolios. Beta neutralization is usually applied to these long-short dollar-neutral factors. While construction of dollar-neutral long-short factors implies some level of market neutrality, actual beta of these long-short portfolios may swing from large positive to large negative values, introducing significant market risk into a factor's performance.

For instance, Figure 23 shows the beta of a long-short (dollar-neutral) Momentum factor. One can see that in 2008 and the beginning of 2009, the beta of this factor dropped from 0 to -1 right before the March 2009 rally (gray line). The shift in beta exposure of momentum happened as the factor was long defensive stocks that performed well early in the crisis (Low Beta stocks) and short high-beta stocks (e.g. financials) that performed poorly in 2008. As the market started to rally in 2009, this caused a large drawdown of the Momentum factor, drawing down years of performance (blue line). Even a simple beta neutralization (based on a trailing beta) would have prevented the large market bias and drawdown of the Momentum factor (red line).

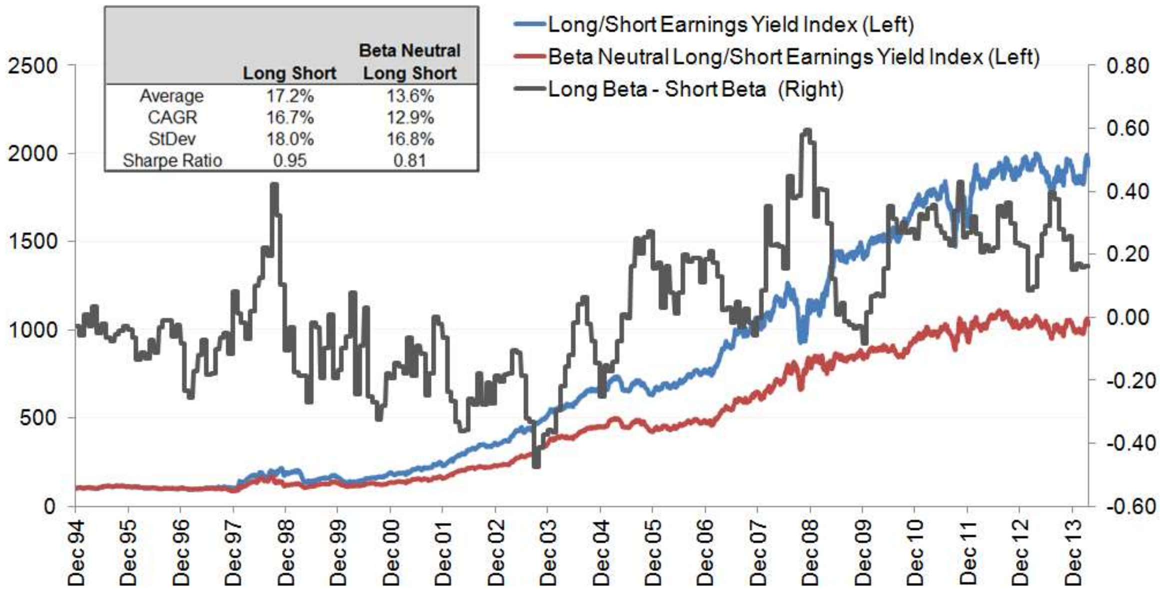
Figure 23: Price Momentum in US with and without Beta Neutralization



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI Barra, Thomson Reuters.

However, beta neutralization does not always improve factor performance. A good example is Value factors (which often behave opposite to momentum). Figure 24 shows that as beta neutralization is applied to the Earnings Yield factor, performance is reduced. This is because, on average, Value stocks tend to pick up higher beta after a prolonged period of market weakness and show stronger recovery in the early stages of a bull market. Neutralizing the beta of a Value factor changes its inherent nature somewhat – dampening the returns, albeit on slightly lower volatility. For example, the average return of the Earnings Yield factor for a beta-neutral long-short index was 13.6%, lower than the return of 17.2% for a non-neutralized long-short index for the Asia-Ex Japan region, while volatility was reduced only slightly (from 18% to 16.8%) resulting in lower risk-adjusted returns due to beta neutralization.

Figure 24: Earnings Yield (forward) in Asia (ex Japan) with and without Beta Neutralization



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI Barra, Thomson Reuters.

There are a number of ways to perform beta neutralization of a raw long-short factor.

One possible approach is to use an **optimizer**. This might involve setting the target beta of the long and short sides to be 1. The advantage is that dollar neutrality can be maintained for a full allocation of funds. Using an optimizer allows other constraints to be simultaneously applied, such as controlling country or sector exposures, limiting maximum weights for individual stocks, or incorporating transaction cost and market impact assumptions.

A simple and more transparent way is to use **stratified sampling** by breaking the stock universe into sub-groups that have similar market beta. One can then select the stocks with the best and worst factor scores from these beta sub-groups for long and short portfolios, respectively. This approach has the advantage of being very simple (e.g. can be done in a spreadsheet), and allowing the factor to maintain dollar neutrality.

If we eliminate the need for dollar neutrality, an even simpler option of **levering the long and/or short side** is available. One can simply fix the ratio of long and short exposure such that the long-short beta is zero (based on trailing betas). This is the approach we use in the charts and tables below.

To analyze the beta exposure in long-short dollar-neutral factors, we have calculated average, minimum, and maximum beta exposure for each long-only and dollar-neutral long-short factor discussed in the previous section. Additionally, we have calculated the 'beta instability' (standard deviation of beta exposure of long-short dollar-neutral factors), as well as largest draw-downs and draw-ups in factor beta (Table 21-Table 25). These data should help develop intuition about the market risk embedded in long-only and long-short ERPs that are not beta neutralized.

From the table and charts, we make the following observations:

- The average long-only Risk Factor beta for Asia (~0.8) is lower than that for the US and Europe (~1) due to the heterogeneous country nature of the Asia-Ex market. US long-only factors show the most stable beta (standard deviation ~0.14), while Japan factors have the highest instability (standard deviation ~0.24). On average, long-short factor betas are negative (-0.2) and have a standard deviation of 0.2. Negative average long-short beta is largely the result of a handful of factors (Low Beta, Low Volatility) that have high negative beta (by construction). Most of the other long-short factors are on average beta neutral.

- Low Volatility and Low Beta factors have statistically significant low (for long-only)/negative (for long-short) beta values. The long-only Beta factor has beta of 0.4, and long-short -1.2 (~5 standard deviation significance). The long-only Volatility factor has a beta of 0.65, and long-short -0.5 (~2 standard deviation significance). Because of their low/negative beta, these factors will underperform in a prolonged bull market. Hence, beta neutralization of the Low Volatility and Low Beta factors has improved their performance as shown in the US charts below.
- Quality factors (long High Quality and short Low Quality) on average also have low long-only beta, and negative long-short beta. The reason is that these factors are short Low Quality names that often have higher beta. However, the beta bias of Quality factors is not as strong as for Beta and Volatility factors. For instance ROE, Gearing and Profit margin factors have beta of ~0.9 for long-only, and -0.15 for long-short factors. The significance of Quality factors' low/negative beta is ~1 standard deviation.
- Among the Value factors, the Dividend Yield factor tends to have a low/negative beta – 0.87 for long-only factor, and -0.2 for long-short (significance ~1.3 standard deviations). Earnings Yield and FCF Yield on average have been close to beta neutral with fairly stable beta exposure.
- PEG (Growth) is one of the few factors that has shown a positive beta tilt, while earnings Momentum factors have close to neutral beta.
- 12-Month Price Momentum has shown a negative beta tilt, and it is the most volatile in terms of beta shift. For instance, shifts from minimum to maximum beta of a long-short (dollar-neutral) Momentum factor were 1.8, 1.6, 1.35, and 1.25 in the US, Europe, Asia-ex, and Japan, respectively. Beta neutralization of momentum and management of risk around market turning points is of great importance with this factor.

Table 21: Beta Exposure for Value Factors in US, Europe, Asia ex-Japan, and Japan

	Long Only						Long/Short					
	Avg	Std Devn	Min	Max	Max DD.	Max DU.	Avg	Std Devn	Min	Max	Max DD.	Max DU.
Dividend Yield												
Asia Ex Japan	0.77	20.1%	0.28	1.32	0.78	1.04	-0.23	22.6%	-0.80	0.26	0.98	1.06
Japan	0.79	25.6%	0.15	1.47	1.32	1.07	-0.11	14.7%	-0.51	0.34	0.81	0.85
Europe	0.91	21.5%	0.45	1.33	0.67	0.88	-0.23	16.0%	-0.64	0.18	0.82	0.75
US	0.99	7.0%	0.84	1.27	0.38	0.43	-0.26	11.1%	-0.62	-0.03	0.59	0.47
Earnings Yield												
Asia Ex Japan	0.94	23.9%	0.34	1.50	0.83	1.16	0.03	21.3%	-0.47	0.59	0.90	1.07
Japan	0.84	25.5%	0.25	1.39	1.14	1.10	-0.04	17.2%	-0.35	0.49	0.73	0.84
Europe	1.06	27.6%	0.38	1.59	0.79	1.21	-0.01	29.7%	-0.78	0.63	0.89	1.41
US	1.17	18.2%	0.74	1.56	0.49	0.81	-0.07	20.2%	-0.62	0.35	0.88	0.97
FCF Yield												
Asia Ex Japan	0.89	17.0%	0.45	1.20	0.46	0.75	-0.02	8.2%	-0.24	0.20	0.44	0.39
Japan	0.80	22.8%	0.23	1.22	0.55	0.99	-0.05	8.8%	-0.28	0.13	0.41	0.29
Europe	1.08	22.0%	0.48	1.50	0.69	1.01	0.01	11.9%	-0.23	0.30	0.53	0.53
US	1.14	19.9%	0.71	1.62	0.51	0.90	-0.06	11.0%	-0.53	0.16	0.66	0.68

Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI.

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Table 22: Beta Exposure for Growth Factors in US, Europe, Asia ex-Japan, and Japan

	Long Only						Long/Short					
	Avg	Std Devn	Min	Max	Max DD.	Max DU.	Avg	Std Devn	Min	Max	Max DD.	Max DU.
EMOM												
Asia Ex Japan	0.91	18.7%	0.39	1.28	0.67	0.89	-0.06	14.6%	-0.54	0.33	0.85	0.86
Japan	0.87	26.8%	0.23	1.64	1.41	1.04	-0.01	14.0%	-0.46	0.39	0.85	0.72
Europe	1.04	18.9%	0.42	1.43	0.81	1.01	-0.06	21.9%	-0.60	0.49	1.04	1.09
US	1.18	17.7%	0.79	1.73	0.70	0.95	-0.01	16.6%	-0.60	0.45	1.05	0.91
PEG												
Asia Ex Japan	0.96	21.4%	0.37	1.51	0.74	1.14	0.07	17.7%	-0.30	0.60	0.60	0.90
Japan	0.89	25.9%	0.24	1.52	1.28	1.16	0.04	17.3%	-0.35	0.59	0.85	0.94
Europe	1.11	25.1%	0.47	1.55	0.68	1.08	0.10	23.1%	-0.49	0.63	0.64	1.11
US	1.20	19.5%	0.73	1.58	0.49	0.85	0.00	21.7%	-0.67	0.46	0.92	1.13

Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI.

Table 23: Beta Exposure for Momentum/Technical Factors in US, Europe, Asia ex-Japan, and Japan

	Long Only						Long/Short					
	Avg	Std Devn	Min	Max	Max DD.	Max DU.	Avg	Std Devn	Min	Max	Max DD.	Max DU.
Momentum												
Asia Ex Japan	0.84	19.7%	0.37	1.25	0.83	0.88	-0.11	26.2%	-0.70	0.65	1.25	1.36
Japan	0.83	27.4%	0.10	1.54	1.44	1.18	-0.07	27.8%	-0.71	0.53	1.12	1.24
Europe	1.00	22.2%	0.43	1.59	0.87	1.17	-0.09	36.8%	-0.89	0.73	1.57	1.62
US	1.17	21.6%	0.60	1.87	0.96	1.27	-0.05	35.0%	-1.00	0.79	1.54	1.79
Seasonality												
Asia Ex Japan	0.84	17.0%	0.42	1.25	0.71	0.83	-0.01	17.6%	-0.56	0.40	0.94	0.96
Japan	0.78	22.0%	0.25	1.31	0.83	1.06	0.00	17.9%	-0.54	0.46	1.00	0.92
Europe	1.03	17.1%	0.59	1.59	0.95	1.00	0.02	23.6%	-0.88	0.69	1.52	1.57
US	1.11	15.2%	0.71	1.62	0.84	0.90	0.05	25.8%	-0.61	1.03	1.64	1.32

Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI.

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Table 24: Beta Exposure for Low Volatility/Beta and Small Size Risk Factors in US, Europe, Asia ex-Japan, and Japan

	Long Only						Long/Short					
	Avg	Std Devn	Min	Max	Max DD.	Max DU.	Avg	Std Devn	Min	Max	Max DD.	Max DU.
Low Volatility												
Asia Ex Japan	0.58	18.6%	0.18	0.96	0.71	0.78	-0.47	22.2%	-0.94	0.07	1.01	0.88
Japan	0.60	21.6%	0.11	1.17	1.06	0.85	-0.40	15.3%	-0.88	-0.05	0.75	0.83
Europe	0.71	12.9%	0.41	1.02	0.61	0.47	-0.52	29.9%	-1.04	0.10	1.14	0.83
US	0.83	8.1%	0.63	1.02	0.40	0.34	-0.58	25.6%	-1.05	0.00	1.05	0.81
Low Beta												
Asia Ex Japan	0.23	18.8%	-0.31	0.55	0.86	0.86	-1.32	20.4%	-1.75	-0.85	0.90	0.84
Japan	0.36	22.0%	-0.11	0.82	0.93	0.84	-0.97	18.2%	-1.47	-0.59	0.85	0.87
Europe	0.39	18.8%	-0.02	0.69	0.65	0.71	-1.35	30.2%	-2.07	-0.75	1.29	1.32
US	0.60	7.7%	0.43	0.81	0.31	0.38	-1.14	27.9%	-1.76	-0.51	1.26	1.02
Small Size												
Asia Ex Japan	0.85	19.0%	0.32	1.27	0.80	0.96	-0.03	14.8%	-0.46	0.43	0.60	0.89
Japan	0.83	25.7%	0.24	1.66	1.42	0.93	-0.08	16.5%	-0.36	0.32	0.68	0.47
Europe	0.91	22.9%	0.39	1.37	0.65	0.98	-0.22	22.8%	-0.71	0.24	0.78	0.96
US	1.13	16.6%	0.78	1.52	0.49	0.74	0.09	18.3%	-0.39	0.56	0.53	0.95

Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI.

Table 25: Beta Exposure for Quality Risk Factors in US, Europe, Asia ex-Japan, and Japan

	Long Only						Long/Short					
	Avg	Std Devn	Min	Max	Max DD.	Max DU.	Avg	Std Devn	Min	Max	Max DD.	Max DU.
Return on Equity												
Asia Ex Japan	0.81	16.4%	0.37	1.23	0.63	0.87	-0.18	20.0%	-0.59	0.32	0.91	0.82
Japan	0.85	21.5%	0.48	1.53	1.05	0.80	-0.02	17.6%	-0.36	0.38	0.73	0.75
Europe	0.96	9.0%	0.70	1.18	0.41	0.48	-0.20	23.9%	-0.67	0.24	0.91	0.65
US	1.08	11.5%	0.78	1.35	0.57	0.55	-0.17	24.5%	-0.70	0.33	1.03	0.83
Profit Margin												
Asia Ex Japan	0.86	15.4%	0.50	1.23	0.51	0.73	-0.05	15.0%	-0.37	0.38	0.71	0.75
Japan	0.77	18.5%	0.45	1.29	0.84	0.65	-0.10	18.6%	-0.42	0.42	0.83	0.84
Europe	0.90	14.7%	0.57	1.28	0.45	0.71	-0.22	28.4%	-1.02	0.21	1.23	1.12
US	1.01	11.0%	0.72	1.23	0.49	0.51	-0.22	24.8%	-0.81	0.21	1.02	0.76
Gearing												
Asia Ex Japan	0.81	15.2%	0.41	1.21	0.52	0.79	-0.10	14.2%	-0.51	0.18	0.67	0.69
Japan	0.80	18.9%	0.46	1.51	1.05	0.65	-0.09	12.2%	-0.33	0.31	0.64	0.53
Europe	0.93	12.8%	0.58	1.16	0.41	0.58	-0.17	13.1%	-0.54	0.17	0.58	0.71
US	1.04	11.1%	0.76	1.40	0.50	0.64	-0.13	13.7%	-0.56	0.15	0.71	0.53

Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI.

Figure 25-Figure 37 show the performance of long-short as well as beta-neutralized long-short factors in the US. The charts also show time series of beta exposure of long-short factors. These charts can illustrate the performance impact of removing the beta exposure, and help identify time periods when the factors were especially vulnerable to market risk.

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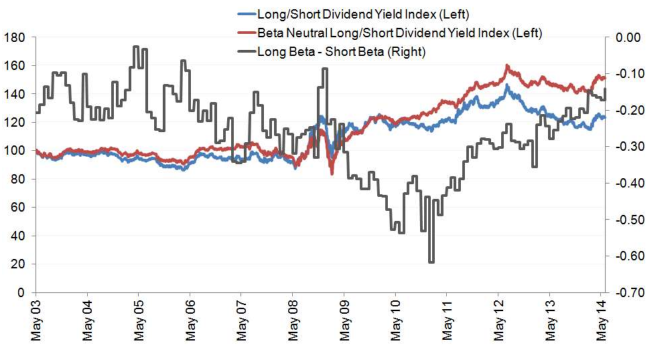
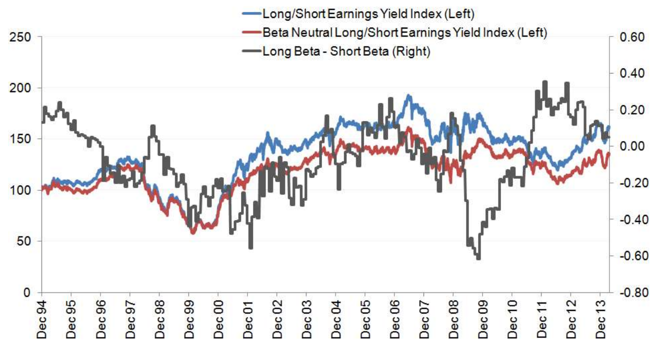
Figure 25: Dividend Yield



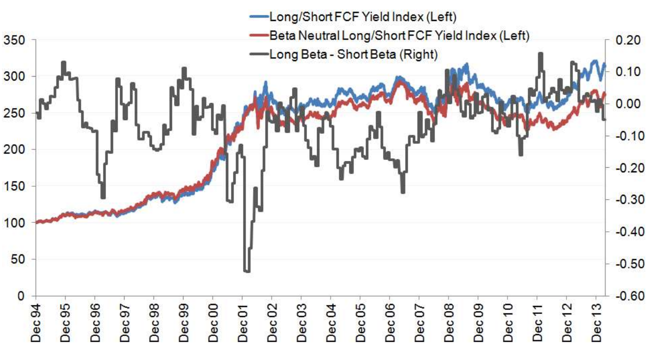
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 26: Earnings Yield



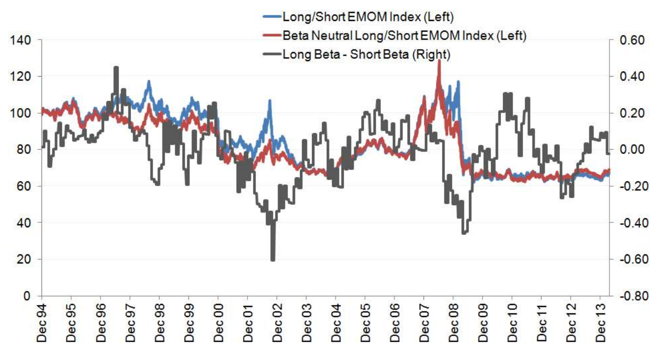
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 27: FCF Yield



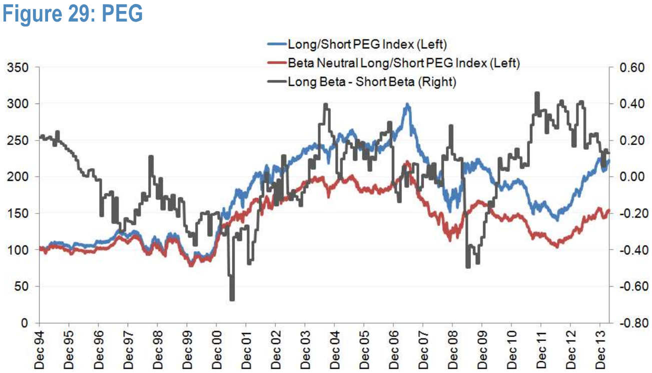
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 28: Earnings Momentum



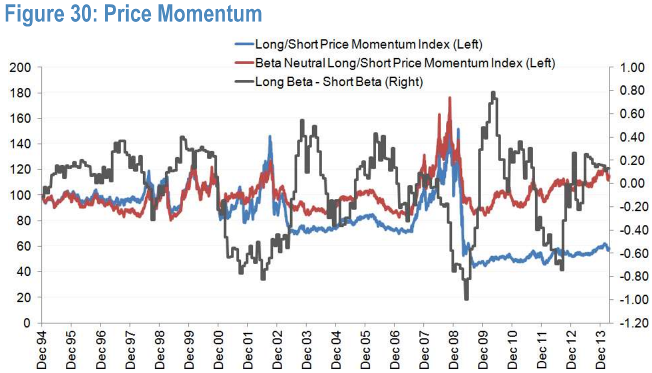
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 29: PEG



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 30: Price Momentum



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

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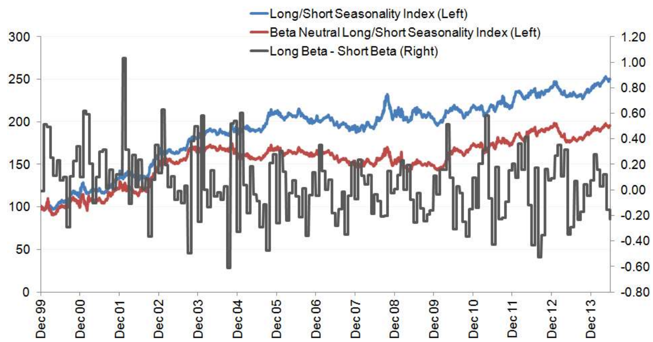
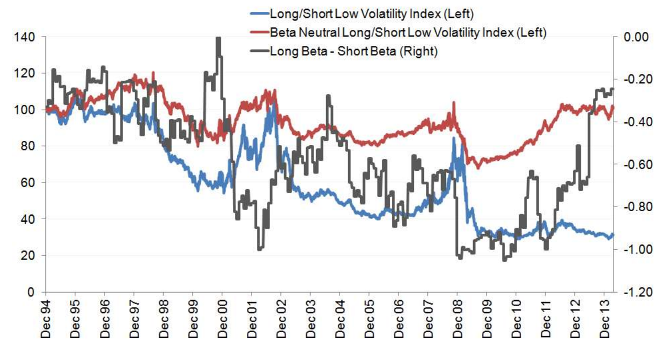
Figure 31: Seasonality



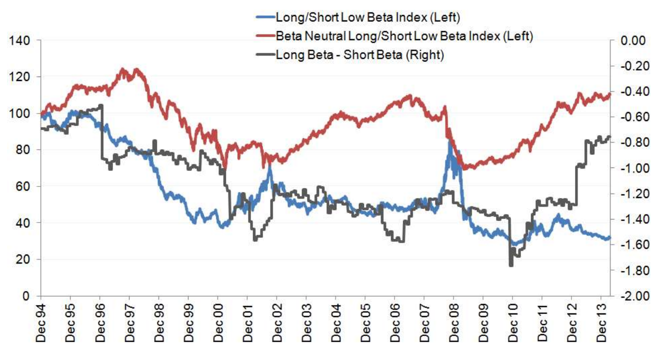
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 32: Low Volatility



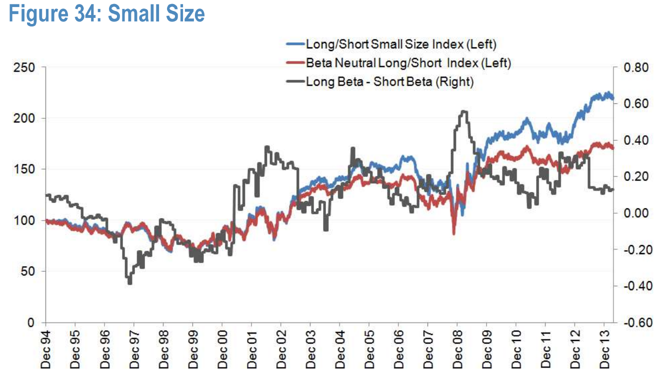
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 33: Low Beta



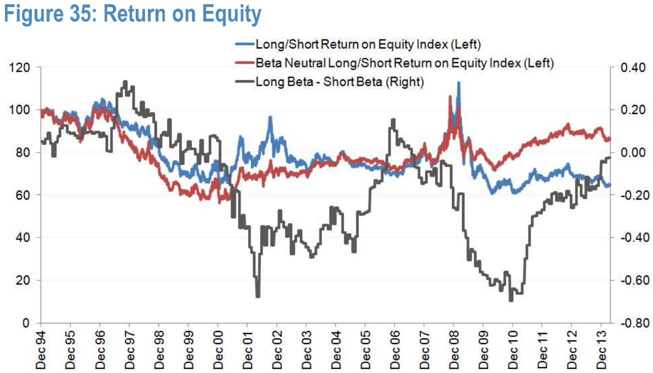
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 34: Small Size



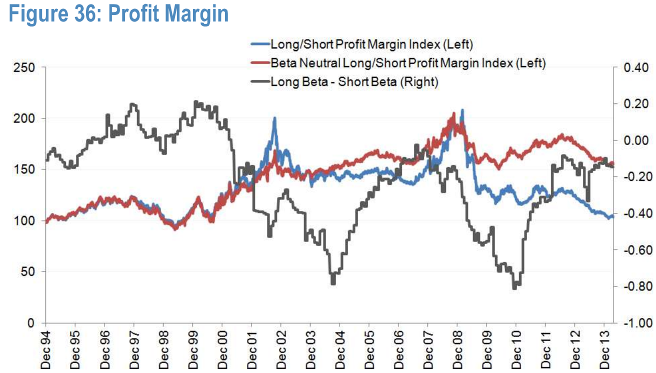
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 35: Return on Equity



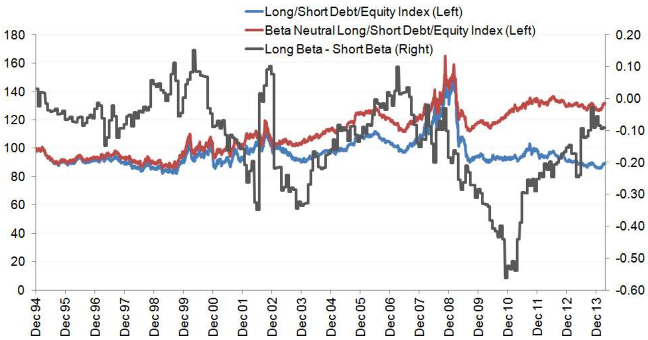
Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 36: Profit Margin



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Figure 37: Debt/Equity



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Thomson Reuters.

Sector Neutralization

If there is no mechanism in place to control sector allocation, Equity Risk Factors may acquire significant sector biases and exposures to sector-specific risks. This is certainly true for long-only ERPs, where Risk Factor metrics can select virtually all stocks from one sector. Sector normalization can also alter the properties of long-short Risk Factors. The current composition of the US Dividend Yield factor has 31% weight in Utilities which is ~10 times higher than market capitalization of the sector. Similarly, the factor does not have any exposure to Technology, which is currently the largest sector by market capitalization, and the large Financials exposure is mainly attributed to high-dividend-paying REITs.

Table 26 shows the current sector weights in long-only US ERPs which can be compared to market capitalization sector weights. In addition to Dividend Yield, one can notice other biases such as Value factors being tilted significantly towards financials, ROE factor biased towards consumer stocks, etc. The last row in the table shows the absolute ERP sector bias defined as the sum of absolute sector weight differences from the market capitalization benchmark in each of the factors.

Table 26: Sector Composition of Long-Only ERP for the US Universe

		Value			Growth		Quality			Momentum		Volatility		
	Market Cap	Fwd EY	FCF Yield	Div Yield	EPS GR	PEG	ROE	Net PM	Debt/Equity	Momentum	Seasonality	Low Vol	Low Beta	Small Size
Cons. Disc.	12%	8%	10%	8%	6%	19%	**31%**	8%	18%	16%	18%	26%	24%	11%
Cons. Staples	9%	3%	5%	8%	0%	5%	**20%**	7%	10%	6%	5%	8%	3%	11%
Energy	11%	10%	2%	10%	19%	13%	3%	5%	6%	23%	7%	3%	13%	8%
Materials	4%	5%	2%	2%	3%	8%	7%	2%	6%	6%	2%	0%	5%	0%
Industrials	10%	10%	5%	2%	15%	8%	10%	2%	13%	6%	4%	10%	13%	11%
Health Care	13%	3%	3%	0%	18%	3%	10%	10%	8%	18%	11%	18%	2%	18%
Technology	19%	15%	11%	0%	15%	11%	13%	25%	5%	18%	15%	27%	10%	23%
Utility	3%	3%	0%	31%	0%	3%	0%	0%	5%	0%	9%	0%	0%	0%
Telecom	3%	0%	0%	8%	2%	0%	2%	0%	6%	6%	0%	3%	3%	3%
Financials	16%	**44%**	**62%**	**31%**	23%	29%	5%	43%	23%	0%	29%	5%	27%	15%
Absolute ERP Sector Bias	0%	57%	92%	96%	49%	53%	65%	64%	48%	53%	50%	54%	58%	24%

Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI.

These large sector biases of long-only factors are often a reason to introduce a sector-neutralization scheme in the design of ERP benchmarks. A common approach is to normalize Risk factor metrics (e.g. ROE, P/E, or Dividend Yield) within each sector. This can be accomplished by adjusting the metric by the sector's average, and dividing by the standard deviation, and will result in giving Risk Factor metric z-scores within a sector (e.g. typically ranging from -2 to 2). After this process one can take the best (highest) scores for the long-only factor (and long highest, short lowest for a long-short factor).

Table 27 shows the effect of such sector neutralization on the current US long-only ERPs. After sector neutralization, factor portfolios are more evenly distributed across the sectors. This can also be noted by the Absolute ERP sector bias measure (shown in the last row). This measure averaged ~60% for raw factors, and dropped to ~30% on average for sector-normalized factors.

Table 27: Sector Composition of Long-Only ERPs for the US Universe After Sector Normalization

		Value			Growth		Quality			Momentum		Volatility		
	Market Cap	Fwd EY	FCF Yield	Div Yield	EPS GR	PEG	ROE	Net PM	Debt/Equity	Momentum	Seasonality	Low Vol	Low Beta	Small Size
Cons. Disc.	12%	19%	11%	18%	10%	18%	15%	28%	18%	18%	18%	16%	18%	16%
Cons. Staples	9%	6%	8%	8%	6%	6%	8%	11%	6%	10%	5%	2%	5%	8%
Energy	11%	8%	10%	7%	8%	11%	8%	8%	11%	15%	7%	11%	8%	8%
Materials	4%	10%	5%	5%	3%	2%	8%	0%	6%	6%	2%	11%	0%	6%
Industrials	10%	11%	7%	10%	16%	11%	10%	16%	11%	6%	4%	19%	15%	13%
Health Care	13%	6%	13%	11%	13%	10%	10%	8%	8%	15%	11%	11%	10%	6%
Technology	19%	11%	20%	21%	15%	16%	10%	10%	15%	11%	15%	15%	11%	18%
Utility	3%	6%	5%	0%	6%	5%	10%	3%	5%	3%	9%	3%	5%	6%
Telecom	3%	0%	3%	2%	2%	2%	2%	2%	3%	2%	0%	2%	3%	3%
Financials	16%	21%	18%	18%	21%	19%	20%	13%	16%	15%	29%	10%	26%	15%
Absolute ERP Sector Bias	0%	46%	12%	22%	28%	24%	35%	49%	23%	29%	50%	40%	45%	25%

Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI.

One may ask why sector normalization has not resulted in long-only factors that more closely match the sector weights of a capitalization benchmark. The answer to that is the choice of a particular normalization scheme. In our approach, we have normalized Risk Factor metrics in each of the 10 industry sectors. By selecting a fixed cutoff in terms of z-score, we have effectively imposed an equal weighting of sectors. While we have reduced very large sector biases in which a factor would largely select stocks from one or two sectors (such as the example of Dividend Yield factor selecting largely Utilities and REITs), we have also removed market capitalization bias from our selection.

A simple method of normalizing Risk Factor metrics (calculating z-scores) is in effect enforcing equal weighting between categories used to split the universe (in this case sector, but could be country or geographic region, for example). If the goal of an investor is to design Risk Factors that will more closely resemble a particular benchmark, one should modify the normalization method, for example, to select stocks with highest z-score within a sector up until a target sector weight is matched. In this approach, the ERP will more closely resemble the sector composition of the market (i.e. have less sector bias), but as a tradeoff will 'dilute' exposure to factor risk metric.

Sector normalization is also very important for long-short factors. Taking again the example of the Dividend Yield factor, a non-normalized long-short factor would be long Utilities and REITs and short stocks that typically do not pay dividends such as Technology or Biotech stocks. This will bias the factor with a specific long-short sector view. After performing normalization as described above (selecting the highest factor risk metric z-scores for long leg, and lowest for the short leg), the long-short factor will generally be free of sector bias (i.e. note that for every long stock in one sector, we have selected one short stock). As with long-only factors, note that this normalization method will treat each sector equally, i.e. will give equal number of constituents to the smallest and largest sectors by market capitalization. Some investors may not feel comfortable with this approach (e.g. liquidity concerns, idiosyncratic risk concerns), and can constrain the normalization to select a larger number of long-short stock pairs from larger sectors and a smaller number of long-short stock pairs from smaller sectors.

In our analyses we have sector-normalized ***the US, Japan, and Europe ERPs.*** Sector neutralization is the most common approach when designing ERPs in developed markets where the country risks are less important than sector risk (of course for single-country regions such as the US and Japan, there is no country risk). Because of the heterogeneous mix of countries in Asia (e.g. different emerging vs. developed market status, no single currency like the Euro zone, varying political regimes, etc.), the macroeconomic and political risks are usually higher than the sector risks. Hence, we prefer country neutralization in Asia.

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Country Neutralization

In most cases, ERPs are designed to focus on one particular country (e.g. US) or a relatively homogenous region (e.g. European Monetary Union). If one is designing an ERP benchmark from stocks belonging to very different markets, there is a risk the ERP will be biased towards certain countries. For instance, if there is a country-specific crisis (e.g. Greece in 2011, or Argentina in 2001), Risk Factor metrics for stocks in those countries may reach extreme levels (e.g. Earnings Momentum) and factors may select most of the stocks from that country for either a long or short leg. This would result in a factor performance that is heavily influenced by developments in the specific country.

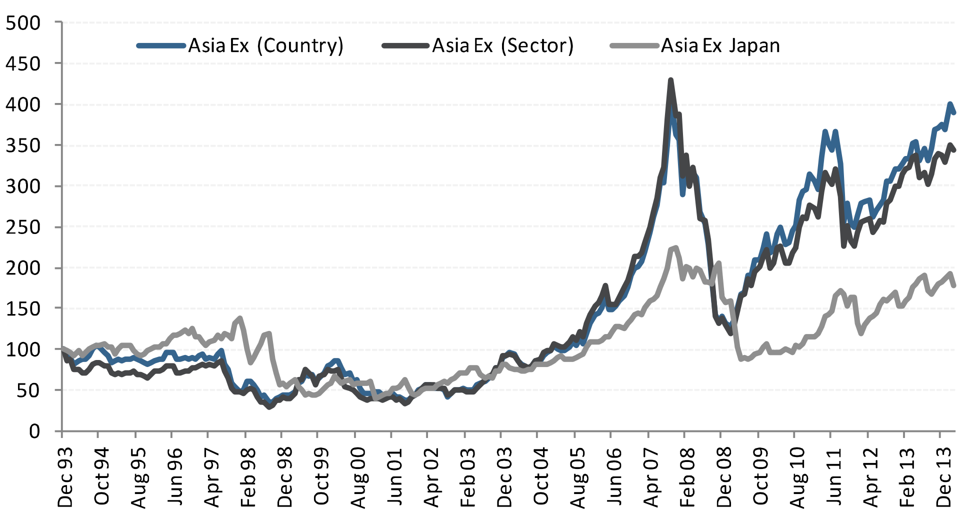
Similarly, historical country-specific trends in dividend yields, corporate buybacks, or inflation rates may introduce biases if one does not consider country normalization. For instance, companies in certain countries pay higher dividends than those in others due to the preference of local investors, tax regulations, etc. (e.g. the Dividend Yield of stocks in MSCI country indices averages 4.9% for the UK and 2.3% for the US). Constructing a Dividend Yield factor without regard to long-term historical trends in the Risk Factor metric may introduce persistent country biases.

Similar to sector normalization, country biases can be reduced by a simple procedure. One can divide the stock universe into 'country' sub-groups. For each country we calculate z-scores (take the raw metric, subtract the country average and divide by the country universe standard deviation). The country-neutralized long side will comprise the best scores from each country, while the country-neutralized short side will comprise the worst scores from each country.

Country neutralization can effectively reduce exposure to country-associated macro risks and often reduces factor draw-downs due to country-specific crises. Country normalization has been our preferred method of neutralization in Asia (ex-Japan) and Emerging Markets. Our risk premia factors for Asia ex-Japan have all been neutralized for country risk.

Historically, country-neutralized ERPs in Asia performed better than sector-neutralized ERPs, and the correlation of stocks to their country benchmarks has been consistently higher than the correlation of stocks within a sector (see our report "How does reducing Country bias impact Risk and Return?"). More recently, in Asia and Emerging Markets, there has been an increased importance of global sectors on stocks (intra-sector correlations have been rising, see "Revisiting Country versus Sector in EM"). Figure 38 shows the impact of country and sector normalization on the Price Momentum factor in Asia ex-Japan.

Figure 38: Sector and Country Neutralization on Price Momentum in Asia (ex-Japan)



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI.

Country normalization is not without its own potential pitfalls. By selecting factor components based on country-normalized z-scores, one is effectively assigning equal (or similar) weights to each of the countries. In an extreme example of the MSCI Emerging Markets universe, there is the chance that the simple country normalization would result in an equal number of stocks from China (currently ~20% of the index) and Egypt (currently ~0.2% of the index). The simplistic implementation of country normalization can thus introduce various risks including liquidity risk, turnover, as well as country- and company-specific biases. An investor can refine country neutralization by taking into account those risks and, for example, limiting the universe by liquidity, limiting country exposures to match weights in market capitalization benchmark, etc.

Other Neutralization Approaches

Finally, we would like to mention that most investors apply a customized normalization process to fit their needs. This may include combining country and sector normalization, and/or normalization for other macro exposures such as interest rates, commodity prices or inflation. While most normalization schemes include z-score calculations, investors can combine z-scores with absolute levels of Risk Factor metrics (e.g. trailing Dividend Yield greater than 1% and z-score greater than 1). Also a common approach is to eliminate outliers, e.g. z-scores greater than ~3 or 4 that would indicate idiosyncratic situations, or a problem with the data. For instance, in this way, the Low Volatility factor would not select a company that is being taken over and for which volatility has been close to zero due to a pending deal.

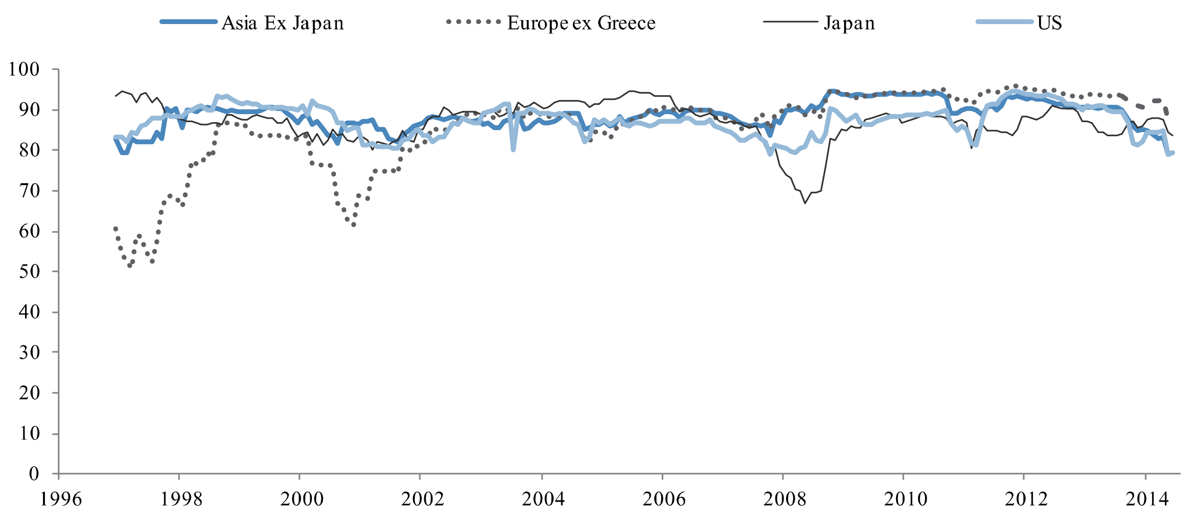
Correlation of Long-Only Factors

Now that we have discussed neutralization of various factor biases, we can start investigating the correlation between Equity Risk Factors. Understanding the correlation between Risk Factors is essential for building a factor portfolio, multi-factor model, or a factor rotation strategy (these topics will be discussed in the last chapter of this report).

Theoretically, Risk Factors are defined as 'independent' risk dimensions and their correlations are expected to be close to zero. In reality, this is often not the case and factors will have time varying (positive or negative) correlations. If one can achieve low average correlations across a group of factors and over an extended time period, a portfolio of 'real' Risk Factors may behave similar to a portfolio of idealized Risk Factors (e.g. principal components).

We start by analyzing the correlation of long-only factors that are sector normalized. Strictly speaking, long-only Risk Factors are 'enhanced betas' rather than Risk Factors (see our classification of ERP strategy type in Figure 2 on page 8 and our discussion of 'Smart Beta' in the Appendix on page 120). As such, they carry significant long market exposure (beta), and are expected to be highly correlated (both within a certain region, and across different regions). In fact, Figure 39 below shows that that the average correlation among the 13 long-only Risk Factors in each region was between 80% and 90% most of the time during the past two decades.

Figure 39: Average Correlation of 13 Long-Only Risk Factors in Each of the Geographic Regions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Given the high level of correlation between long-only factors, there is limited diversification benefit of designing a portfolio of long-only Risk Factors within one region. Long-only risk factors should therefore be selected primarily based on their expected performance (e.g. outperformance vs. their benchmark). The correlation of factors across different regions is lower than the correlation of factors within a region. In fact, the correlation of factors across regions is comparable to the levels of correlation of sectors across regions, and to the correlation of sectors within a region, as shown in Figure 40 below.

The reason why sector or regional correlations are lower than the correlation of factors within a region can be found in the factor design. Long-only factors have significant market beta exposure which is often close to 1, and the stocks are selected across sectors (sector normalization). Selecting stocks in a long-only factor thus closely mimics the country benchmark. On the other hand, the correlation of sectors in one region can be fairly low as defensive sectors (e.g. bond-like Utilities) can have very low or even negative correlation to cyclical sectors.

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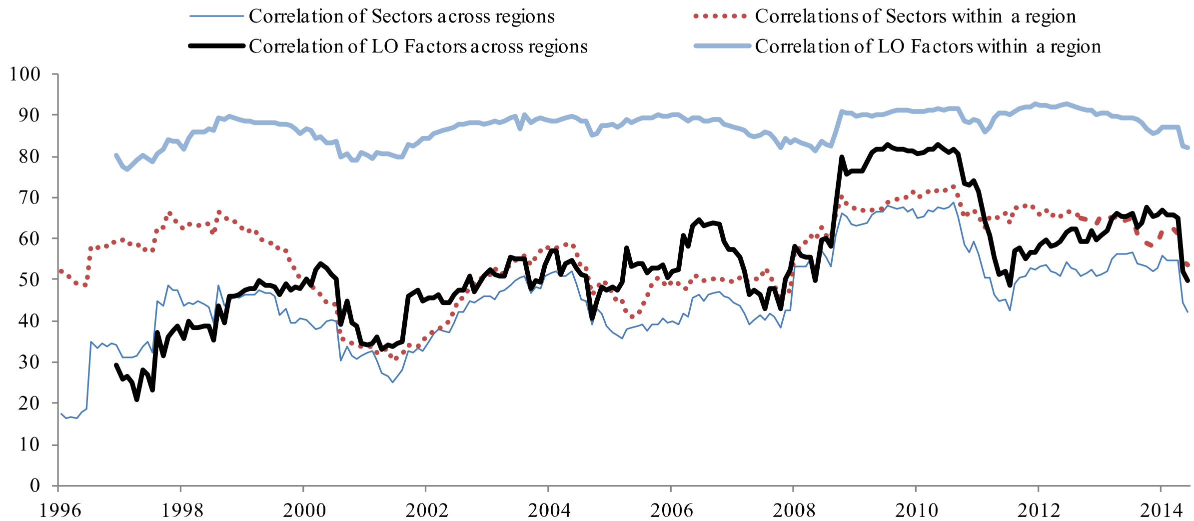
Figure 40: Correlation of Long-Only Factors Within a Region Is Higher than Correlation of Long-Only Factors Across Regions, Correlation of Sectors Across Regions, or Correlation of Sectors Within a Region



Source: J.P. Morgan Quantitative and Derivatives Strategy.

These findings suggest that individual factor selection (i.e. factor performance) is often more important when investing in long-only factors within a region.[29] On the other hand, relatively low correlation of long-only factors across regions highlights the value of designing global factor style benchmarks or global multi-factor portfolios.

[29] In the section 'Portfolio of Regional Factors' on page 74, we discuss a case study of a portfolio of long-only European Risk Factors, in which individual factor performance plays a more significant role than factor diversification.

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Correlation of Long-Short Factors

Long-only Risk Factors combine market (beta) risk and active Risk Factor tilts (and hence are a form of 'enhanced beta'). Given that market exposure is the main driver of returns, one cannot learn much about the Factor correlation structure by studying long-only Factors.

For this reason we will study the correlation of long-short ERPs. There are various ways one can define long/short Risk Factors. In our introductory sections, we applied the simplest 'cash neutral' hedged portfolio method. While this simple cash-neutralization removes some of the market exposure from all factors, it does not do that uniformly for all factors (for instance cash-neutral Low Volatility and Low Beta factors are still left with significant short market exposure). Beta-neutral long-short ERPs are often better in removing market bias from the ERP. In this section, we will study the correlation properties of both cash-neutral and beta-neutral Risk Factors.

Table 28 below shows the correlation between long-short (cash-neutral) Equity Risk Factors. We have included a broad market benchmark (MSCI AC World) into the matrix to illustrate the residual exposure of long-short factors to the market. For simplicity, we equally weighted regional Risk Factors to obtain a 'global' Risk Factor performance time series for each of the factors (e.g. Dividend Yield time series is equally weighted Dividend Yield in US, Europe, Asia ex-Japan, and Japan). Later in the section we will also analyze the correlation matrix of regional factor styles.

Table 28: Correlation between Cash-Neutral Long/Short Equity Risk Factors (equally weighted avg of regional Risk Factors, %)

		Beta	Value			Growth		Quality			Momentum		Volatility		
		Traditional	Fwd EY	FCF Yield	Div Yield	PEG	EPS GR	ROE	Net PM	Debt/Equity	Momentum	Seasonality	Low Vol	Low Beta	Large Size
Beta	Traditional		76	-42	-15	75	14	4	-22	-71	-36	-19	-83	-90	-19
Value	Fwd EY	22		-28	9	97	1	-1	-28	-70	-62	-28	-87	-88	-53
	FCF Yield	-26	19		32	-28	-18	8	-6	30	-24	-2	36	43	-24
	Div Yield	-26	41	27		2	-38	-40	-46	-27	-47	-5	24	26	-38
Growth	PEG	38	88	8	28		7	11	-28	-66	-55	-30	-86	-88	-43
	EPS GR	-22	-14	20	-12	-27		61	45	33	54	-11	1	-14	42
Quality	ROE	-37	-1	26	-5	-18	59		54	38	50	24	-3	-13	45
	Net PM	-41	-1	28	0	-22	52	78		54	52	33	9	6	37
	Debt/Equity	-53	-25	25	-12	-38	45	59	61		65	30	67	63	49
MOM	Momentum	-37	-33	18	-21	-44	80	61	59	58		32	53	42	81
	Seasonality	-18	-23	-10	-6	-25	-9	10	14	13	-1		25	22	7
Volatility	Low Vol	-71	-11	32	21	-32	55	62	62	63	65	2		97	45
	Low Beta	-76	-14	34	30	-34	47	50	55	58	57	5	89		33
	Large Size	-24	-24	6	-30	-34	62	67	57	52	75	1	60	37	

	Traditional	Fwd EY	FCF Yield	Div Yield	PEG	EPS GR	ROE	Net PM	Debt/Equity	Momentum	Seasonality	Low Vol	Low Beta	Large Size
Full Sample Average	-29	2	16	3	-9	26	32	31	23	26	-4	30	26	24
Crisis Average	-17	-3	8	-4	-4	20	25	23	16	20	-11	23	15	23
Ave During GFC	-17	-20	-2	-12	-18	13	18	12	15	16	6	8	3	12

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods. Crisis periods we include for the correlation calculations are July 1997 to August 1998 (Asian Financial Crisis, Russian Default and LTCM), January 2000 to September 2001 (Tech Bubble), and June 2007 to February 2009 (Global Financial Crisis).
** The traditional Beta Risk Factor is regional MSCI All-Country World excess return indices; Equity Risk Factors are based on equal averages within a certain factor style cross the four regions (the US, Europe, Japan and Asia ex Japan).

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Looking at the correlation structure of cash-neutral long-short ERPs, we can see that most ERPs have negative correlation to the market. As discussed, the reason for that is the ERP construction methodology in which stocks in the long leg of the portfolio (Low Beta, Low Volatility, High Quality, Large Size) often have lower market beta than stocks in the short portfolio (High Beta, High Volatility, Low Quality, Small Size). For instance, without beta neutralization, the sample correlation between the market and Low Volatility/Low Beta Risk Factor is significantly negative at -71%/-76%, respectively. Despite the correlation matrix of cash-neutral ERPs being 'tainted' by residual market exposure, one can start seeing correlation patterns that are not a result of market exposure, but rather of the fundamental properties of the ERP.

For instance, Quality factors tend to be positively correlated between themselves. This correlation is significantly higher than what would be expected just from their residual market exposure (correlation to market). Similarly, the high correlation of Quality, Momentum and Volatility factors also indicates that these ERPs are related to each other.

One can notice that the PEG factor (originally classified as Growth style) is highly correlated with Forward Earnings Yield factor (+88%) and has a negative correlation another with EPS Growth Factor (-27%). This indicates that the P/E is a much more important driver of PEG than the growth component. From its correlation to other factors, the PEG would be more appropriately classified as a 'Value' factor rather than a 'Growth' factor.[30] Similarly, momentum and seasonality – both categorized as 'Technical' factors – have little in common as indicated by the lack of correlation.[31]

To further reduce the impact of market exposure to correlations, and get closer to 'true' ERP correlations, we have calculated the correlation matrix for 'beta-neutralized' long-short Equity Risk Factors in Table 29 below.[32]

One can see that beta neutralization reduced market exposure for most of the factors. For instance, we find much smaller ex-post market exposures of Low Volatility/Low Beta factors, and some of the cross-factor correlations that were to an extent driven by residual factor beta are lower (e.g. correlation between Low Volatility and Quality factors).

However, we see that even after beta-neutralization, the full sample correlation of factors is still on average negative to market, and various correlation patterns we observed with cash-neutral long-only factors persist. Our understanding is that this is a result of non-linear properties of many factor returns. Let's consider the Low Volatility Factor – as discussed before, this factor is long Low Volatility and short High Volatility stocks and will hence have a negative market exposure. Beta adjusting this factor will eliminate market exposure during normal market conditions. However, during a market crisis, the beta of High Volatility stocks may increase disproportionally more than the beta of Low Volatility stocks, leading to a convex short market exposure of this factor. This would result in a negative beta for the Low Volatility factor even after 'linear' beta neutralization.

[30] For this reason, we used regional Earnings Growth factors in the section 'Global Style Benchmarks' on page 103.
[31] In our approach we have started with ERP style classification and Risk Factors most commonly used by equity quant investors. In some instances, this classification may not be fully justified by correlation properties of these factors.
[32] Neutralization of Risk Factors' ex-ante market (beta) risks was discussed in more detail in the section 'Factor Neutralization Methods' on page 38.

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Table 29: Sample Correlation Between Traditional Beta and Long/Short (After Beta Neutralization) Equity Risk Factors

		Beta	Value			Growth		Quality			Momentum		Volatility		
		Traditional	Fwd EY	FCF Yield	Div Yield	PEG	EPS GR	ROE	Net PM	Debt/Equity	Momentum	Seasonality	Low Vol	Low Beta	Large Size
Beta	Traditional		68	-19	-19	61	27	5	-36	-50	-16	-37	-15	-5	-41
Value	Fwd EY	25		-5	4	95	20	8	-32	-39	-47	-40	-50	-44	-62
	FCF Yield	-19	18		31	-9	-7	8	-7	10	-40	-3	8	23	-30
	Div Yield	-5	46	19		-1	-31	-35	-33	-34	-43	6	34	40	-21
Growth	PEG	32	87	13	36		23	24	-33	-31	-42	-39	-48	-49	-47
	EPS GR	-11	-7	11	-19	-14		53	29	37	51	-28	20	-3	18
Quality	ROE	-22	0	19	-20	-9	56		49	50	43	22	-8	-38	36
	Net PM	-26	0	23	-7	-14	42	65		62	47	41	-17	-39	36
	Debt/Equity	-31	-18	15	-26	-22	35	46	46		49	29	4	-24	48
MOM	Momentum	-26	-38	4	-33	-40	67	54	47	38		24	47	21	71
	Seasonality	-27	-27	-10	-16	-29	-5	12	12	19	7		10	-2	20
Volatility	Low Vol	-26	12	19	19	0	41	36	35	23	29	-12		87	45
	Low Beta	-19	12	21	27	0	25	16	24	15	18	-11	72		18
	Large Size	-35	-27	3	-36	-31	54	66	52	43	66	16	42	6	
Full Sample Average		-15	6	10	-1	1	21	25	23	14	15	-5	22	16	17
Crisis Average		-7	-2	4	-10	0	16	16	12	7	8	-11	14	7	12
Ave During GFC		-6	-10	-3	-8	-8	16	17	5	8	13	0	9	-1	7

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods. Crisis periods we include for the correlation calculations are July 1997 to August 1998 (Asian Financial Crisis, Russian Default and LTCM), January 2000 to September 2001 (Tech Bubble), and June 2007 to February 2009 (Global Financial Crisis).
** The traditional Beta Risk Factor represents regional MSCI All-Country World excess return indices; Equity Risk Factors are based on equal averages within a certain factor style across the four regions (US, Europe, Japan and Asia ex Japan).

Table 29 gives important insights into the correlation structure of (beta-neutral) Equity Risk Factor styles. In particular, we note the following:

- Factors within an ERP style are positively correlated (as discussed before, we have treated PEG as a 'Value' factor, despite its original classification as one of the 'Growth' factors).
- The average correlation between the market (MSCI AC World) and all the other Factors was on average negative (-15%) over the tested time period (January 1995 to June 2014)[33], and remained negative during market crises. This confirms that Equity Risk Factors can effectively diversify or even hedge a traditional long-only equity portfolio.
- On average, Value factors are negatively correlated to Momentum, Quality and Growth Risk Factors. The strongest negative correlation is between Value and Momentum – a result we found not just in equities but across asset classes. The negative correlation of Value to most of the other ERP styles highlights the important role Value factors should have in any factor portfolio.
- Growth, Quality, Momentum and Volatility factors tend to be positively correlated.[34] This indicates that there is a fundamental link between these factors. For instance, one can see how stocks with high Earnings Momentum (positive Growth) or high ROE (Quality) may develop positive Price Momentum. Price appreciation may in turn result in lower Volatility for these stocks. These stocks may become part of long legs of Growth, Quality, Momentum and Low Volatility factors – resulting in positive correlation between these styles. The opposite would be the case for stocks with, for example, unfavorable Debt to Equity ratio (low Quality) or negative Earnings Momentum (low Growth). These stocks may experience price depreciation (negative momentum) and thus higher volatility. Again, these stocks would likely be found in short legs of Growth, Quality, Momentum and Low Volatility factors, leading to positive correlation between these styles.
- The ERP correlation structure indicates that it is not unreasonable to think of risk driven by 2 factors: 1) Value and 2) 'Generalized Momentum' (Momentum, Growth, Quality, Low Volatility). This concept was discussed in work by Asness et al (2013). However, we note that the Growth, Quality, Momentum, and Volatility factors each have their own specific properties and that the average correlation of these factors was only 33%. This indicates a significant benefit of diversifying across Growth, Quality, Momentum and Volatility. Moreover, during periods of market stress, the correlation between these factors dropped to 26%.
- A very attractive feature of ERPs is that the average factor correlation during market crises was lower than over the full time history. This is a very unusual behavior as correlations of stocks or other risky assets tend to increase during periods of market turmoil. Specifically, during market crises the average correlation of Value to other styles dropped from -7% to -19%, and the average correlation between Growth, Quality, Momentum and Volatility factors dropped from 33% to 25%.

In our analysis of correlation between long-only factors (Figure 40), we found that there was a limited diversification benefit of investing in long-only factors within a region. This was largely a result of the dominant market exposure of long-only factors and sector normalization of each factor. In contrast to long-only factors, the average correlation of long-short factors within a region was very low. Figure 41 below shows that average correlation of Risk Factors in the US, Europe, Asia, and Japan has been fairly low (0-20%) and stable over market cycles. As a result, equity managers can effectively diversify a portfolio by investing in a set of long/short Equity Risk Factors within the region.[35]

[33] According to Table 28 on page 53, the average correlation between Traditional Beta (MSCI AC World) and all the other (non-neutralized) Equity Risk Factors style was comparatively lower at -29%.
[34] An exception is the Low Beta factor which has negative correlation to growth and quality, and positive correlation to some Value factors.
[35] See our case study of overlaying long/short Risk Factors with market benchmarks on page 82.

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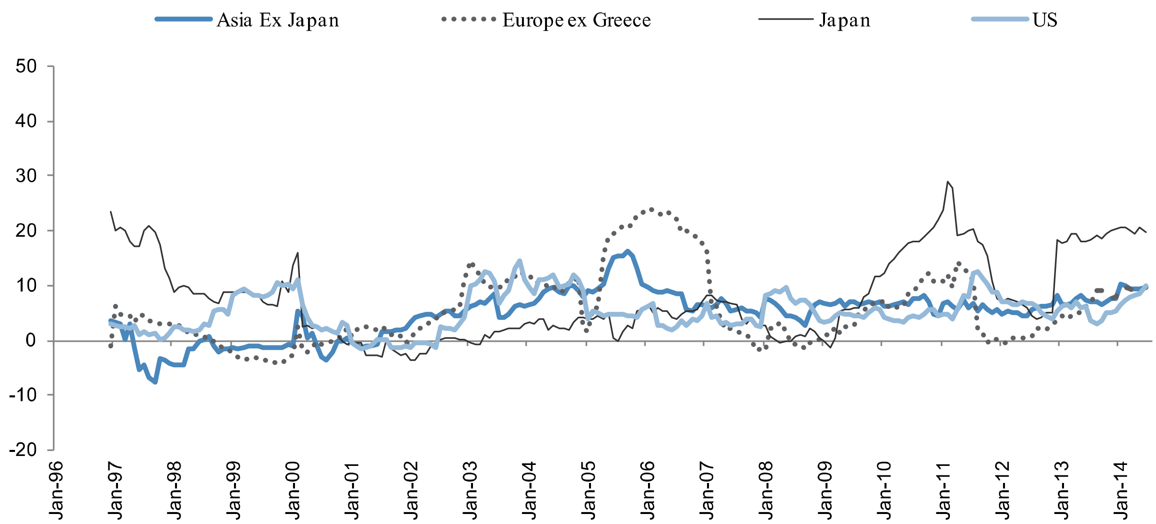
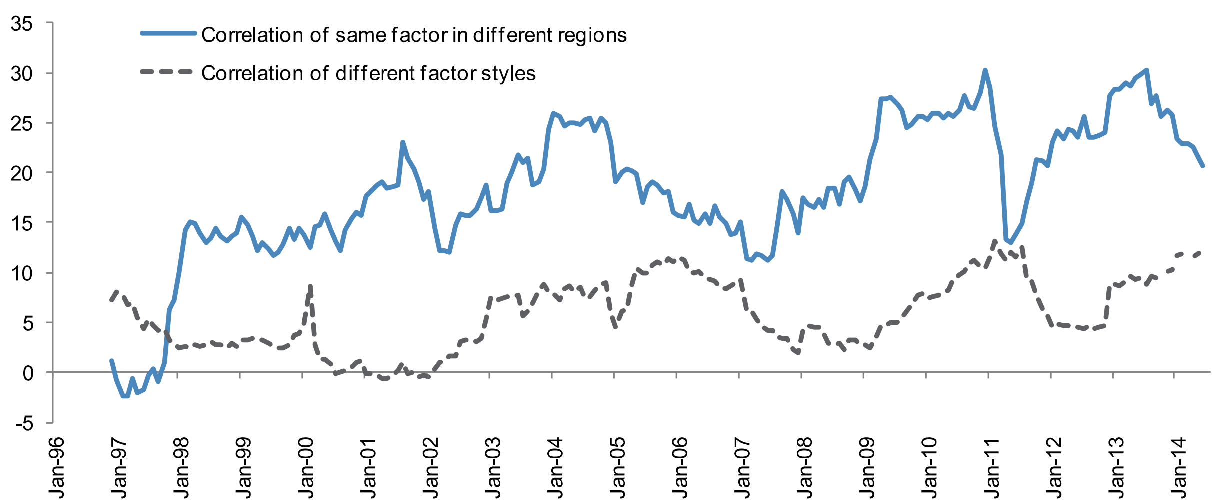
Figure 41: Average Correlation Among (Beta-Neutralized) Risk Factor Styles in Different Global Regions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 42 shows the average correlation of different factors within one region (averaged for all regions), and average correlation of one factor across different regions (averaged for all styles). One can see that diversification across factor styles is more important than diversification of a single factor between regions.

Figure 42: Factor Style Diversification Is More Effective than Cross-Region Diversification on a Simple Factor



Source: J.P. Morgan Quantitative and Derivatives Strategy.

However, diversification across factor styles and diversification across regions are largely independent, so a multi-factor portfolio will benefit from both style and regional diversification. This makes a strong case for global Equity Risk Factor investing. In the section titled 'Multi-Factor Portfolios' on page 71, we will examine different applications of Global Long/Short Equity Risk Factor portfolios including investing, hedging and active trading.

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Correlation of Factor Styles

In the previous section, we studied correlations of individual long-short factors. Specifically, we averaged the performance of a single factor across regions and calculated a historical correlation matrix for the universe of factors (e.g. Dividend Yield factor was an average of Dividend Yield in the US, Europe, Asia ex-Japan, and Japan). Next we would like to study the correlation of factor styles. For this purpose, we average the performance of factors belonging to one particular style within a geographic region and calculate the correlation between styles (e.g. Value in US would be the average of US Dividend Yield, FCF Yield, and forward Earnings Yield).

The aim of this analysis is to deepen our understanding of style correlations, and also to understand how factor styles are correlated between different regions (e.g. Value in US correlates with Quality in Japan, etc.). An understanding of style and regional correlations is important when designing a Global Multi-Factor Model.[36]

Table 30 and Table 31 below (on the next two pages) show the correlation matrix among regional equity indices and selected Value, Quality, Growth, Momentum and Low Volatility Risk Factors[37] during the sample period from January 1995 to June 2014, before and after beta neutralization.

We make the following observations from the correlation matrices:

- During the full sample period, **regional equity benchmarks** (traditional factor 'style') have significant positive correlation and their **correlations tend to increase during crises**. As expected, factor styles are also positively correlated between different regions (e.g. Value in Europe is positively correlated to Value in Japan), but much less than regional equity benchmarks. In contrast to the correlation of regional benchmarks, **the correlation of a factor style in different regions tends to be lower during market crises** (e.g. Volatility factors in Europe and Asia had 36% correlation over full sample and only -3% during market crises).
- On Average, the **correlation of Traditional Equity benchmarks to all other Risk Factors was negative before beta neutralization and close to zero after neutralization**. Including all Factor styles in an equity portfolio has the ability to significantly reduce average correlations.
- As we noted in the last section, Value tends to have positive correlation to Equity benchmarks in all regions, while **Quality, Growth, Momentum and Low Volatility Risk Factors generally have negative correlation with Equity benchmarks**. While market exposure of Risk Factors is lower after applying beta neutralization, it does not disappear completely.
- **Value had negative correlations with most of the other Risk Factors** (Growth, Quality, Momentum, Low Volatility). An exception is Value in Japan which had on average positive correlation with Risk Factors in other regions.
- **Quality, Growth, Momentum and Low Volatility on average had positive correlation**, and were negatively correlated to Value and the Traditional Equity benchmark. The strongest negative correlation was between Momentum and Value.
- The diversification ability of Quality Factors (as measured by average correlation to other factors) tends to be somewhat lower than for other styles, which is more pronounced during crises when diversification is most needed. We will also see that in the analysis of our multi-factor model in the next chapter. Given the negative correlation of Value and other Risk Factors, Value has the highest diversification ability according to this metric.

[36] Examples of such models are given in the next chapter in which we study a portfolio of global style benchmarks, and two different multi-factor models.
[37] We used the average of Fwd Earnings Yield, FCF Yield and Dividend Yield Factors to represent 'Value', EPS Growth Factor to represent 'Growth', the average of ROE, Net Profit Margin and Debt/Equity Factors to represent 'Quality', Price Momentum Factor to represent 'Momentum' and the average of Low Volatility, Low Beta and Large Size Factor to represent 'Volatility'.

Table 30: Sample Correlation Between Traditional, Value, Quality, Growth, Momentum and Volatility Non-Neutralized Long/Short Risk Factors

Color Scheme	Less than -50%	-50% to -20%	-20% to 0%	0% to +20%	+20% to +50%	Greater than +50%

		Traditional				Value				Quality				Growth				Momentum				Volatility			
		Asia xJ	Europe	Japan	USA	Asia xJ	Europe	Japan	USA	Asia xJ	Europe	Japan	USA	Asia xJ	Europe	Japan	USA	Asia xJ	Europe	Japan	USA	Asia xJ	Europe	Japan	USA
Traditional	Asia xJ		90	81	78	29	31	28	11	26	0	-1	30	7	-25	-19	-50	1	-25	-30	-26	-78	-69	-76	-55
	Europe	69		89	92	29	29	30	15	25	-7	-12	31	4	-46	-32	-56	-5	-39	-38	-26	-65	-76	-68	-58
	Japan	56	55		82	45	22	46	29	32	0	1	21	-10	-40	-38	-61	-23	-35	-36	-45	-67	-59	-70	-62
	USA	69	83	53		28	37	25	19	24	-16	-20	17	7	-58	-27	-66	-11	-52	-36	-29	-51	-79	-53	-57
Value	Asia xJ	-7	-4	-6	-6		28	14	13	29	26	4	-6	27	-12	-27	-20	-54	-24	-19	-34	-45	-9	-46	-21
	Europe	5	2	8	1	27		-10	25	-20	-39	-35	-52	-15	-40	-50	-59	-18	-83	-34	-53	-28	-53	-30	-26
	Japan	-4	-4	-8	-7	25	4		-16	34	28	-39	37	-16	10	6	-39	-7	-8	-54	-21	-24	-36	-41	-55
	USA	13	17	10	13	16	33	0		-27	-57	26	-30	-30	-39	-28	-29	-50	-30	18	-57	-44	-1	4	-31
Quality	Asia xJ	-6	1	9	4	5	-10	13	-26		63	16	45	35	26	23	6	31	24	-1	19	5	-6	-28	5
	Europe	-33	-34	-18	-33	18	-10	28	-26	34		14	40	32	71	18	30	22	61	-6	35	18	27	-23	23
	Japan	-19	-6	-16	-9	-14	-21	5	2	15	28		14	-2	21	29	36	3	42	78	6	0	39	22	25
	USA	-21	-19	-13	-24	3	-21	29	-24	23	55	33		30	25	29	29	43	41	1	51	-8	-14	-19	-8
Growth	Asia xJ	-45	-24	-23	-27	9	-2	15	-5	8	24	30	20		25	36	45	30	18	5	54	2	15	-15	39
	Europe	-36	-55	-30	-48	14	-5	24	-14	15	62	16	36	30		37	47	31	67	20	32	21	51	7	33
	Japan	-14	-5	-38	-1	-6	-21	28	-9	9	15	44	19	25	10		37	23	40	37	36	19	23	29	15
	USA	-37	-45	-29	-50	10	-8	22	-12	19	55	27	56	19	56	8		39	68	45	74	47	65	29	71
Momentum	Asia xJ	-32	-14	-11	-21	-16	-8	10	-34	47	41	39	40	43	22	16	40		29	16	74	46	6	12	54
	Europe	-33	-41	-27	-42	3	-32	17	-27	22	77	29	55	18	57	16	57	40		37	55	25	64	19	43
	Japan	-15	-10	-23	-12	-15	-16	6	-10	18	26	72	33	30	15	58	30	40	33		21	25	40	63	37
	USA	-38	-38	-24	-39	-1	-24	11	-47	24	64	31	73	25	51	15	74	52	71	36		58	37	27	72
Volatility	Asia xJ	-70	-46	-36	-50	-6	2	12	-31	33	39	30	30	57	35	18	41	70	33	34	48		46	68	71
	Europe	-56	-68	-38	-63	13	-1	13	-7	19	71	29	45	27	72	15	62	35	72	32	62	53		50	73
	Japan	-38	-26	-50	-26	-4	-9	28	5	6	24	46	26	36	24	68	28	28	21	65	31	46	40		46
	USA	-56	-62	-42	-63	8	-5	13	-16	20	59	24	47	25	57	10	77	40	57	24	73	55	74	36	
Full Sample Average		-15	-12	-10	-13	3	-5	12	-8	13	25	18	22	14	18	12	22	20	21	20	23	17	22	18	20
Crisis Average		-7	-4	-5	-5	-1	-5	-6	-13	17	15	13	17	13	7	10	12	19	10	17	16	14	13	11	10
Ave During GFC		-2	-4	-4	-6	-2	-21	-5	-13	17	16	12	15	14	11	10	13	13	15	8	16	2	6	-4	10

Source: J.P. Morgan Quantitative and Derivatives Strategy.

* Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods.

** Crisis periods we include for the correlation calculations are July 1997 to August 1998 (Asian Financial Crisis, Russian Default and LTCM), January 2000 to September 2001 (Tech Bubble), and June 2007 to February 2009 (Global Financial Crisis or GFC).

*** Traditional Risk Factors are regional MSCI excess return indices; Alternative Risk Factors of Value, Quality, Growth, Momentum and Low Volatility are Long/Short excess return indices we constructed in previous sections.

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Table 31: Sample Correlation Between Traditional, Value, Quality, Growth, Momentum and Volatility Beta-Neutralized Long/Short Risk Factors

Color Scheme	Less than -50%	-50% to -20%	-20% to 0%	0% to +20%	+20% to +50%	Greater than +50%

		Traditional				Value				Quality				Growth				Momentum				Volatility			
		Asia xJ	Europe	Japan	USA	Asia xJ	Europe	Japan	USA	Asia xJ	Europe	Japan	USA	Asia xJ	Europe	Japan	USA	Asia xJ	Europe	Japan	USA	Asia xJ	Europe	Japan	USA
Traditional	Asia xJ		90	81	78	34	23	3	18	-10	12	6	49	-5	-19	-25	-10	-34	3	-14	7	-45	-24	-53	-9
	Europe	69		89	92	29	17	-1	23	1	9	0	54	-5	-37	-38	-9	-28	0	-17	15	-28	-24	-37	0
	Japan	56	55		82	42	11	12	36	13	17	13	42	-18	-32	-43	-22	-41	0	-12	-8	-35	-9	-34	-13
	USA	69	83	53		28	27	-5	28	6	1	-7	40	0	-50	-32	-21	-29	-14	-13	9	-18	-36	-21	4
Value	Asia xJ	6	3	2	2		29	-5	4	37	54	11	12	31	3	-25	6	-57	0	-6	-12	-37	20	-45	5
	Europe	11	12	12	12	25		-25	23	-23	-23	-31	-42	-15	-30	-45	-49	-34	-79	-28	-48	-15	-51	-29	-2
	Japan	-11	-13	-8	-13	21	1		-35	29	36	-41	38	-9	38	25	0	0	16	-46	7	-5	-23	-26	-38
	USA	20	28	17	26	9	31	-10		-22	-51	28	-23	-25	-45	-26	-43	-34	-28	25	-50	-46	6	17	-30
Quality	Asia xJ	1	2	12	10	7	-10	14	-24		69	9	36	36	30	18	35	22	40	10	26	29	26	3	23
	Europe	-27	-21	-13	-21	21	-7	31	-24	30		12	41	29	65	8	34	-5	57	-7	24	12	31	-35	15
	Japan	-14	3	-6	-3	-17	-16	-4	8	9	22		10	-4	9	23	19	7	35	81	0	3	44	31	12
	USA	-15	-9	-8	-19	0	-22	31	-22	16	41	28		24	15	13	47	24	54	0	65	-1	-4	-19	1
Growth	Asia xJ	-34	-17	-14	-18	1	-7	13	-7	7	26	25	17		22	36	62	26	23	2	52	-4	32	-17	46
	Europe	-25	-36	-22	-36	15	-4	33	-17	16	53	8	19	26		33	25	19	46	4	8	0	31	-17	-9
	Japan	-6	1	-22	7	-10	-17	22	-13	13	17	34	16	13	6		34	28	28	29	23	3	9	15	-7
	USA	-21	-25	-18	-34	7	-7	29	-12	14	37	20	47	17	41	1		41	56	18	75	29	26	-14	45
Momentum	Asia xJ	-27	-12	-9	-18	-21	-14	3	-29	38	30	28	31	33	17	13	34		21	20	61	65	15	41	51
	Europe	-25	-27	-20	-32	0	-36	21	-26	10	55	23	43	16	33	13	41	38		28	51	10	50	3	11
	Japan	-6	1	-10	-3	-17	-14	-2	1	16	18	64	28	19	7	48	22	29	30		5	12	23	62	10
	USA	-31	-24	-17	-32	-9	-31	12	-47	11	41	27	69	27	27	9	63	48	59	30		47	16	9	63
Volatility	Asia xJ	-36	-22	-14	-27	-16	4	18	-30	33	29	17	22	41	22	11	22	61	17	21	31		-3	47	64
	Europe	-33	-34	-18	-38	12	8	19	0	22	58	25	30	23	54	9	39	27	37	22	33	36		14	35
	Japan	-20	-8	-15	-9	-14	-4	22	8	10	16	35	18	22	14	54	10	22	1	51	17	35	29		19
	USA	-36	-33	-25	-30	-1	-6	14	-12	22	43	18	34	20	37	6	56	33	30	15	48	36	51	24	
Full Sample Average		-6	-1	-1	-3	1	-3	11	-5	12	20	14	17	11	13	10	17	15	13	16	16	13	18	14	15
Crisis Average		-2	2	1	1	-3	-9	-5	-11	15	15	12	17	12	5	6	9	15	10	14	13	11	12	10	9
Ave During GFC		7	8	7	6	7	-19	-2	-11	19	18	12	21	14	5	4	17	8	18	8	19	4	9	-4	13

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods.
** Crisis periods we include for the correlation calculations are July 1997 to August 1998 (Asian Financial Crisis, Russian Default and LTCM), January 2000 to September 2001 (Tech Bubble), and June 2007 to February 2009 (Global Financial Crisis or GFC).
*** Traditional Risk Factors are regional MSCI excess return indices; Alternative Risk Factors of Value, Quality, Growth, Momentum and Low Volatility are Long/Short excess return indices we constructed in previous sections.

As we noted with individual Risk Factors, correlation between factor styles and factor regions becomes weaker during market crises (an exception is the Quality factors, which saw increased correlation amongst the constituent factors and became positively correlated with traditional markets during crises). This is an attractive feature that can be used to mitigate the tail risk exposure of a traditional risky asset portfolio.

Finally, we can combine regional Risk Factors into a global style benchmark (as defined in the section 'Global Style Benchmarks' on page 110) and calculate the correlation of global ERP styles. The correlation matrix is shown in Table 32 below.

Table 32: Correlation Among Global Equity Risk Factor Styles and Traditional Assets (Global Equities and Bonds)

	Equity	Bond	Value	Quality	Growth	MOM	Low Vol
Equity		**-24**	3	**-25**	-19	**-28**	**-67**
Bond	**-22**		8	11	-5	-2	**26**
Value	5	0		-7	-7	**-52**	-4
Quality	**-34**	16	-7		15	**34**	**34**
Growth	**-20**	12	-4	**27**		**37**	**27**
Momentum	**-28**	14	**-38**	**42**	**42**		**37**
Low Volatility	**-68**	**29**	-10	**52**	**32**	**48**	
Full Sample Ave	**-28**	8	-9	16	15	14	14
Crisis Average	**-27**	2	-10	10	8	4	9
Ave During GFC	**-34**	-1	**-21**	11	10	7	6

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* We used MSCI AC World Index (in excess returns) for "Equity" and J.P. Morgan Global Government Bond USD Index (hedged, in excess returns) for "Bond".
** Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods.
*** Crisis periods we include for the correlation calculations are July 1997 to August 1998 (Asian Financial Crisis, Russian Default and LTCM), January 2000 to September 2001 (Tech Bubble), and June 2007 to February 2009 (Global Financial Crisis or GFC).
**** Correlation is calculated during the backtesting period from February 1995 to January 2014 based on weekly excess returns.

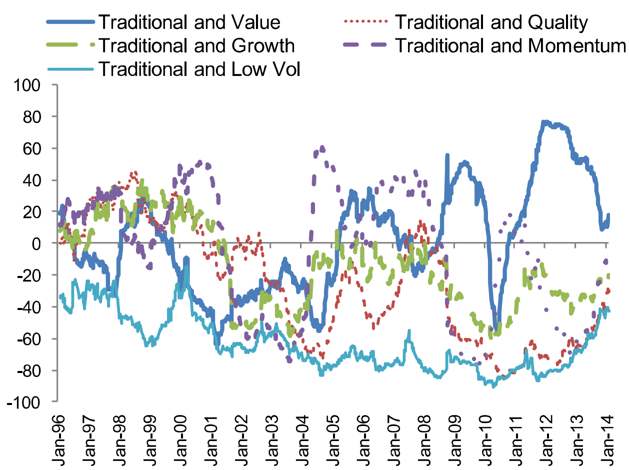
Similar to our correlation analysis of long-short factors and regional factor styles, we find that the Value Factor was negatively correlated to all other factor styles, and Quality, Growth, Momentum and Volatility were positively correlated. Factor correlations were lower during the crises compared to the full sample period. As explained in the previous section, this positive correlation cannot be fully explained by their common market exposures as a similar conclusion is reached from beta-neutralized Risk Factors.

Trends in Factor and Style Correlations

In the previous sections we examined the correlation of long-only, long-short and long-short beta-neutral factors, as well as the correlation between factor styles and regions. Our conclusions were based on correlations over the full sample time period of the past 20 years. During market crises we found that factor correlations preserved their main relationships, but correlation levels typically declined.

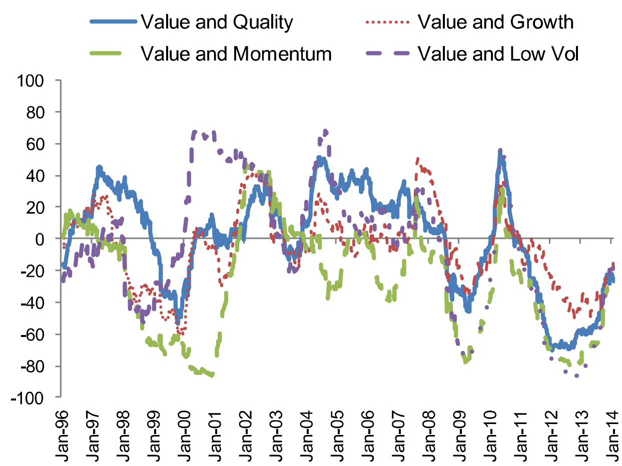
While our analysis was static (looking at correlation over the full time period, or during crises), factor correlations often change quite a bit over time. Figure 43-Figure 48 show the time-varying correlations among global style benchmarks, Value, Quality, Growth, Momentum and Low Volatility Risk Factors (including the Traditional equity benchmark i.e. MSCI ACWI).[38]

Figure 43: Correlation Between Global Equities and Factor Styles



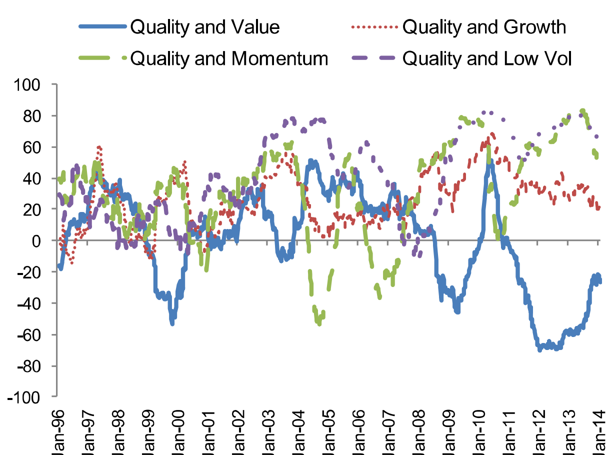
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 44: Correlation of Global Value to Other Factor Styles



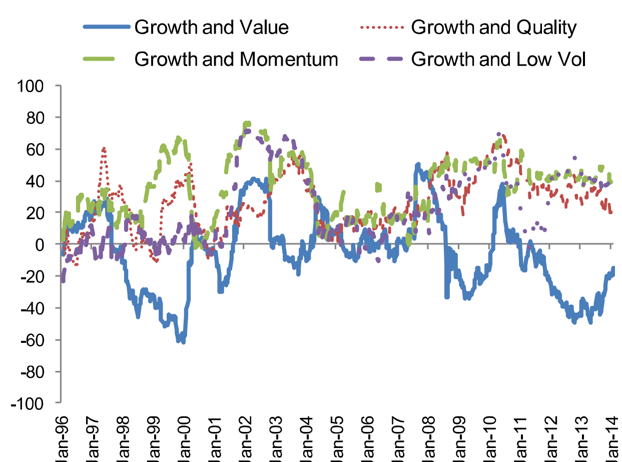
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 45: Correlation of Global Quality to Other Factor Styles



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 46: Correlation of Global Growth to Other Factor Styles



Source: J.P. Morgan Quantitative and Derivatives Strategy.

[38] These correlations were calculated based on trailing 1 year of factor returns.

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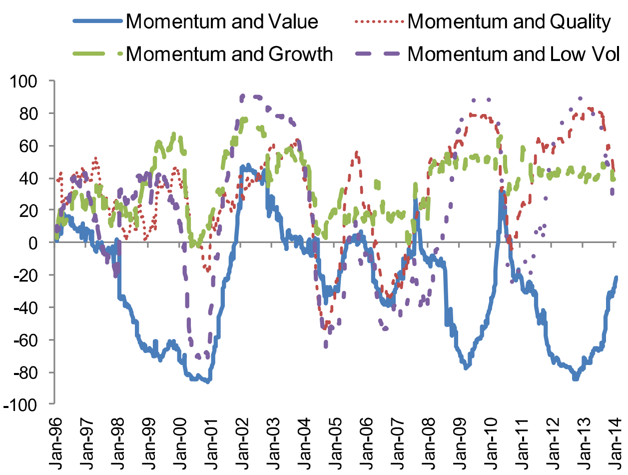
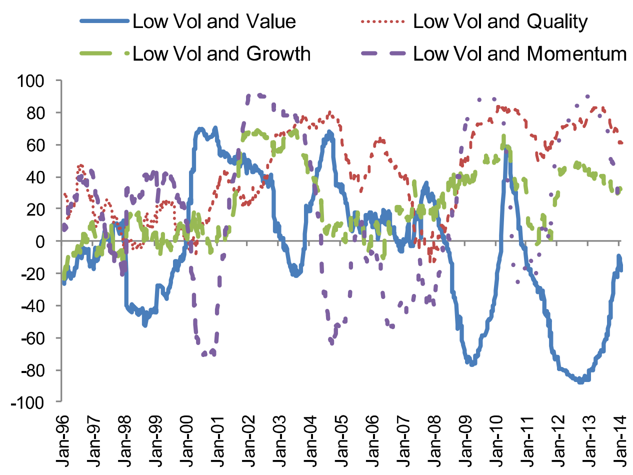
Figure 47: Correlation of Global Momentum to Other Factor Styles



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 48: Correlation of Global Low Volatility to Other Factor Styles



Source: J.P. Morgan Quantitative and Derivatives Strategy.

We make the following observations on the dynamics of correlations among the five Global Risk Factor Styles:

- **Traditional Equity** benchmarks were always negatively correlated to Low Volatility factors, whereas the negative correlation to Growth/Quality Factor was more pronounced over the past 5 years. The correlation of Traditional Equities to Momentum was fairly volatile, bottoming at -80% in 2009 and 2012. Most recently correlation of Traditional equity benchmarks to all factor styles started converging towards zero (decreasing for Value, and increasing for all other styles).
- **Value:** The correlation of Value to all other factor styles has been on a declining trend over the past 10 years. Correlation plummeted in 2009 and 2012 to -80%, but recently started increasing towards -20% to -30% range.
- **Quality:** The correlations between Quality and all other Risk Factors except Value were positive most of the time. Over the past 5 years, the correlation of Quality to Low Volatility, Momentum, and Growth has been above long-term historical averages.
- **Growth:** The correlation between Growth and all other Risk Factors except Value has gradually increased from ~10% to ~40% over the past 10 years.
- **Momentum:** The correlation between Momentum and other factor styles was fairly volatile. This is a result of the large (positive or negative) beta exposures Momentum tends to acquire. Averaged over the cycles of Momentum beta, correlation to Value has been declining and correlation with all other factors has been increasing over the past 10 years.
- **Low Volatility:** Over the past 5 years, the correlation of Low Volatility factors to Quality factors has been fairly high (60-70%), and correlation to Growth was above long-term averages (at 30-40%). Correlation to Momentum peaked above 80% when Momentum acquired large short market exposure in 2009 and 2012.

Figure 49 below shows the rolling 52-week average correlation of regional Equity benchmarks (MSCI indices for the US, Europe, Japan and Asia ex-Japan regions), and correlation between Global Factor Styles (Value, Quality, Growth, Momentum and Low Volatility Global Equity Risk Factors).

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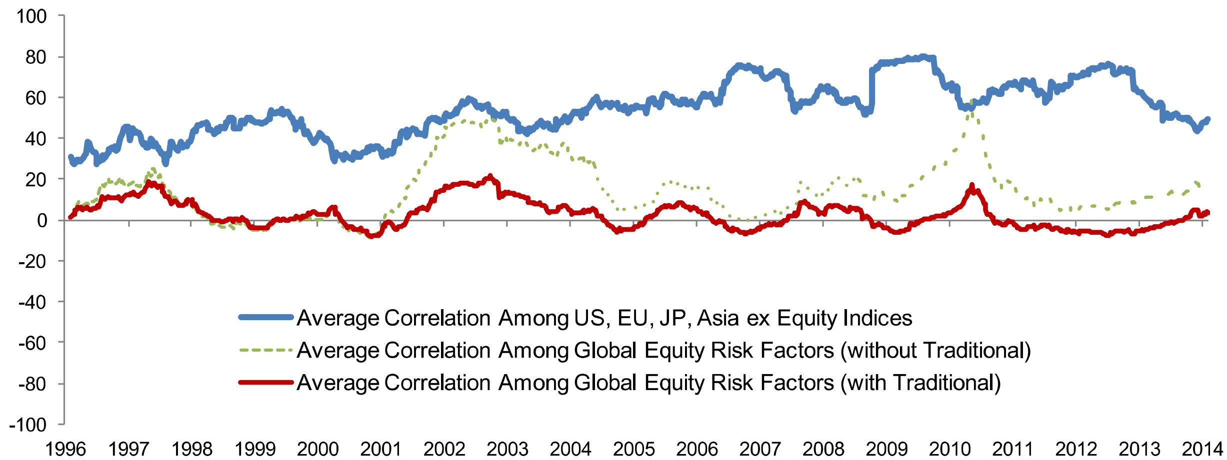
One can see that the average correlation of equity markets is consistently much higher than the average correlation of Equity Risk Factor Styles. Interestingly, the average correlation of a portfolio of Traditional Equity Market plus five Factor styles was close to zero during the whole back-testing period from January 1996 to January 2014.[39]

Figure 49: Rolling 52-Week Average Correlation Among Global Equity Indices and Long/Short Equity Risk Factors

(%)

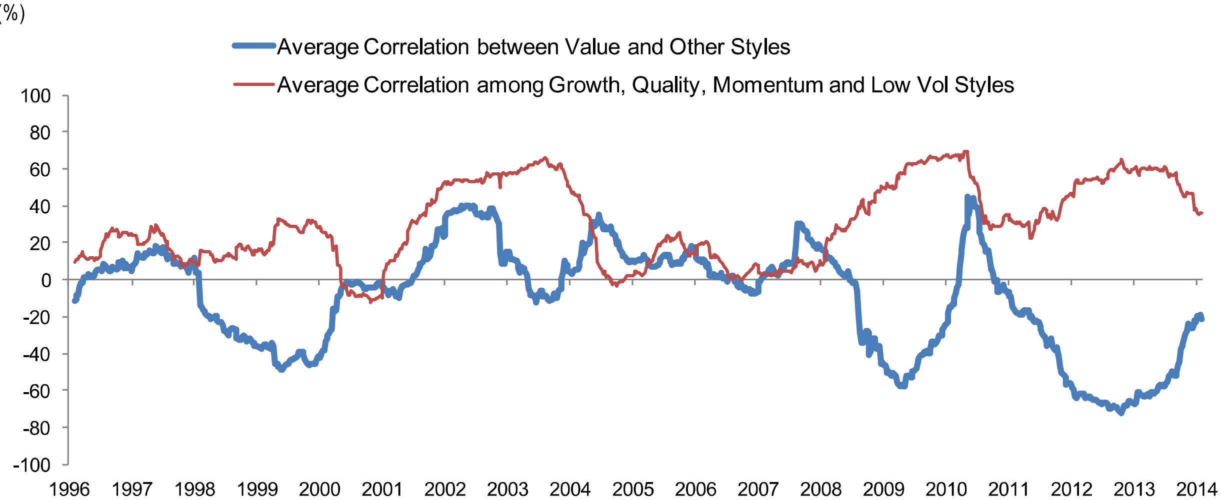


Source: J.P. Morgan Quantitative and Derivatives Strategy. * Global Equity Risk Factors include Value, Quality, Growth, Momentum and Low Volatility Style composites.

Figure 50 below shows the average correlation of Momentum, Quality, Growth and Low Volatility, as well as the correlation of the Value style to other styles. One can see that these correlations often have been moving in opposite directions, indicating a potentially simple correlation structure of equity factor styles: Value on one hand, and 'Momentum-like' factors of Growth, Momentum, Quality and Low Volatility.

Figure 50: Average Correlation Between Value and Other Factor Styles, and Among Growth, Quality, Momentum, Low Volatility Styles

(%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

[39] This effect of cross-style orthogonalization is similar to our finding in the Cross-Asset Risk Factor space (Chart 24 on page 53).

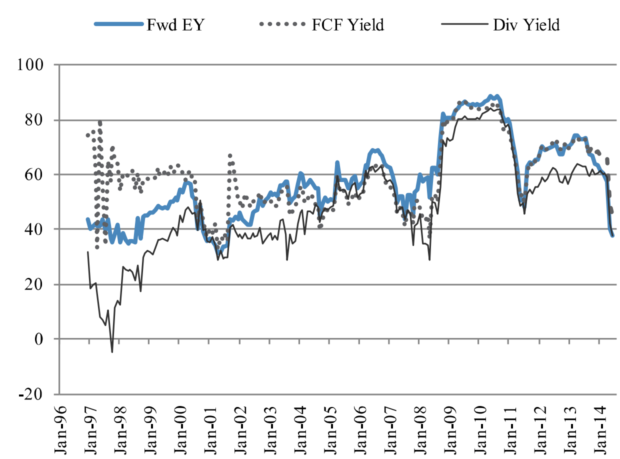
Over the past 10 years, the correlation of Value to other styles has been on average declining, while correlation among other factor styles has been increasing. While it seems that equity factor styles increasingly show bifurcation into Value and Momentum-like styles, average correlation of a factor portfolio including both Value and non-Value factors has been relatively low.

Clients often ask us how popular or perhaps even crowded certain factor styles seem to be. One way to assess the popularity of a trading strategy is to look at the correlations between various components of a strategy. Market capitalization benchmarks and global equity investing are almost by definition 'crowded' (as most investors follow this strategy). This can be seen from the relatively high correlation of regional market capitalization benchmarks (and compared to much lower factor style correlations).

One way to assess the potential crowding of a particular factor is to look at the correlation of the same factor in different regions. The premise is that if there is a substantial amount of global assets following a factor, the behavior of this factor will be similar across different regions.

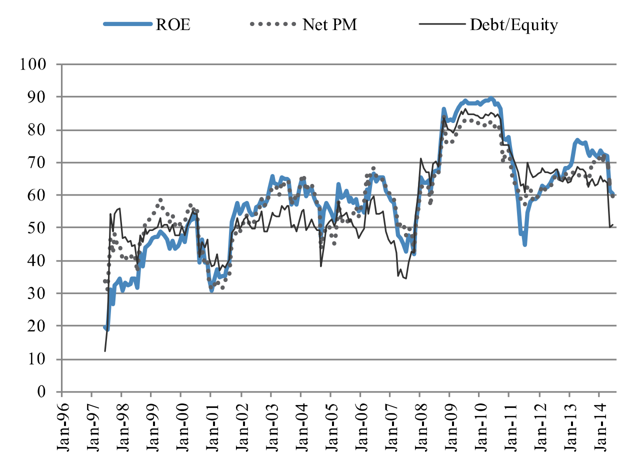
Figure 51-Figure 52 show the cross-regional correlation for Value and Quality factors, respectively. One can see that these correlations have been increasing over time. As we established that the risk of long-only factors is dominated by market beta, this was fully expected given the overall increase of stock correlations over the same time period. In fact, almost all of the cross-regional correlation increase for long-only factors can be attributed to the increase of global stock correlations.

Figure 51: Average Trailing 24-Month Correlation Among Value Risk Factors (Long-Only) Across Regions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 52: Average Trailing 24-Month Correlation Among Quality Risk Factors (Long-Only) Across Regions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Long-short (beta-neutral) factors can give much better insights about the popularity (and potential crowdedness) of certain factor styles. Figure 53-Figure 57 show cross-regional correlations of beta-neutralized long-short factors over the past two decades. One can see that certain factors have higher cross-regional correlations than others.

Value factors have fairly low regional correlation (Dividend Yield and FCF Yield have lower and more stable correlation than Forward Earnings Yield). **Quality** factor cross-regional correlations increased during the crisis (demand for relative safe haven stocks), and are currently very high for ROE (indicating the factor is potentially crowded) and are relatively modest for Debt/Equity and Net PM factors.

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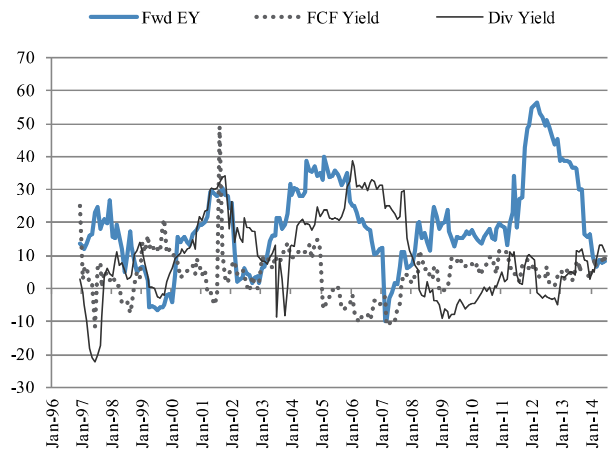
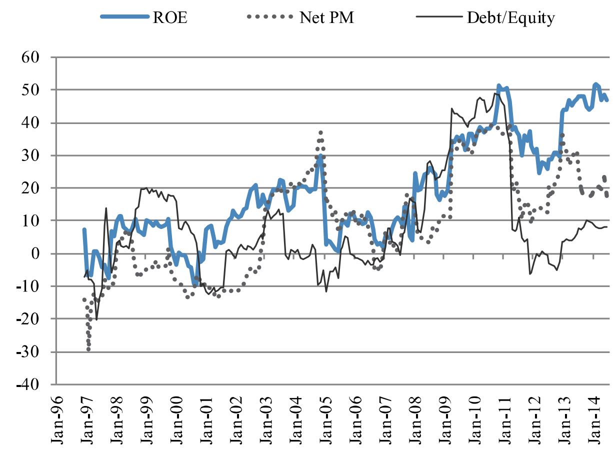
Figure 53: 2Y Correlation of Value Risk Factors Across Regions



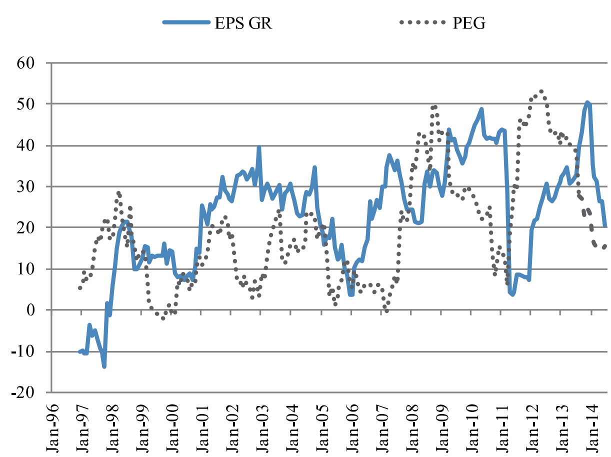
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 54: 2Y Correlation of Quality Risk Factors Across Regions



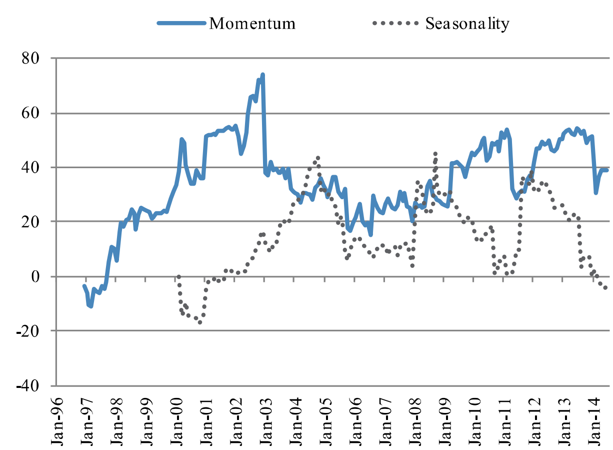
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 55: 2Y Correlation of Growth Risk Factors Across Regions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

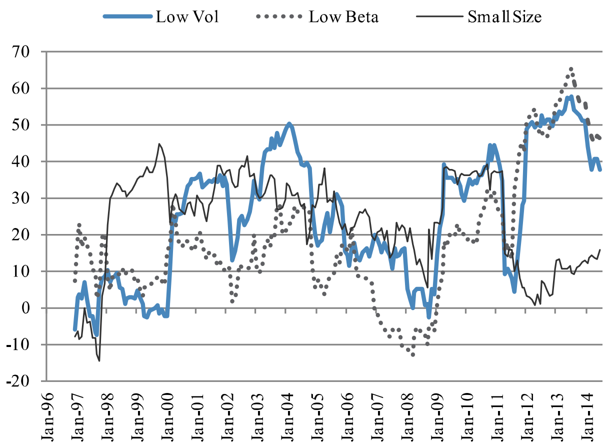
Figure 56: 2Y Correlation of Momentum/Technical Risk Factors Across Regions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Growth factor cross-regional correlations have been trending higher over the past 10 years, and exhibited some volatility. The cross-regional correlation of **Momentum** has been increasing as well, and has stayed high (in a 40-50% range). This indicates broad popularity of this factor and some crowding risk, in our view. On the other hand, the cross-regional correlation of the **Seasonality** factor has been very low, which is understandable for this less common, region-specific (rather than macro-driven) factor. **Among Low Volatility factors**, Low Beta and Low Volatility factors experienced substantial increases in correlation over the past 2-3 years. This reflects an increase in assets following Low Volatility strategies across the globe. The correlation of Small Cap factors across regions (old-fashioned small cap investing) is still fairly low. The correlation of all Volatility factors increased during the Global Financial crisis and Eurozone crisis (relative safe haven demand, widening of credit spreads that impact small caps globally). However, after the crises Small Cap correlations declined, while Low Beta/Volatility correlations stayed very high.

Figure 57: 2Y Correlation of Low Vol/Beta and Small Size Risk Factors Across Regions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Multi-Factor Portfolios

In the first chapter of this report we introduced factor styles and examined the performance and risk properties of individual Risk Factors. In the second chapter we discussed the correlation properties of individual factors, factor styles and regional/global factor benchmarks. Our main findings are that factors often deliver positive performance, and the correlation of different factors styles tends to be low and stable.

To take advantage of these attractive properties of Risk Factors, one needs to build a multi-factor portfolio. One way of building a **multi-factor portfolio** is to simply invest in several Risk Factor benchmarks. An example would be a portfolio of global Value and Momentum factor benchmarks. An alternative to building a portfolio of factors is to design a multi-factor model. A **multi-factor model** selects stocks based on how they rank according to several factor metrics at the same time. An example would be a Value and Momentum model that selects stocks that rank highly on a combined score of Value and Momentum. While a portfolio of Value and Momentum factors will tend to contain stocks with the highest rank on one of these two metrics separately (but may rank poorly on the other), a multi-factor model will tend to have stocks that rank favorably on both metrics (i.e. highest combined ranking).

We will start with discussing a **portfolio of global factor style benchmarks**. In particular, we will test various portfolio construction methodologies such as mean-variance optimization, risk parity, etc. Then we will study a sample **portfolio of long-only regional Risk Factors**. As examples of Multi-Factor Models, we will analyze the **J.P. Morgan Q-score Multi-Factor Model**, and introduce a new **J.P. Morgan Global Multi-Factor Model**. We will then demonstrate how Equity Risk Factors can be used to design a **hedge for traditional equities**, and finish with a discussion of several **active factor trading** strategies.

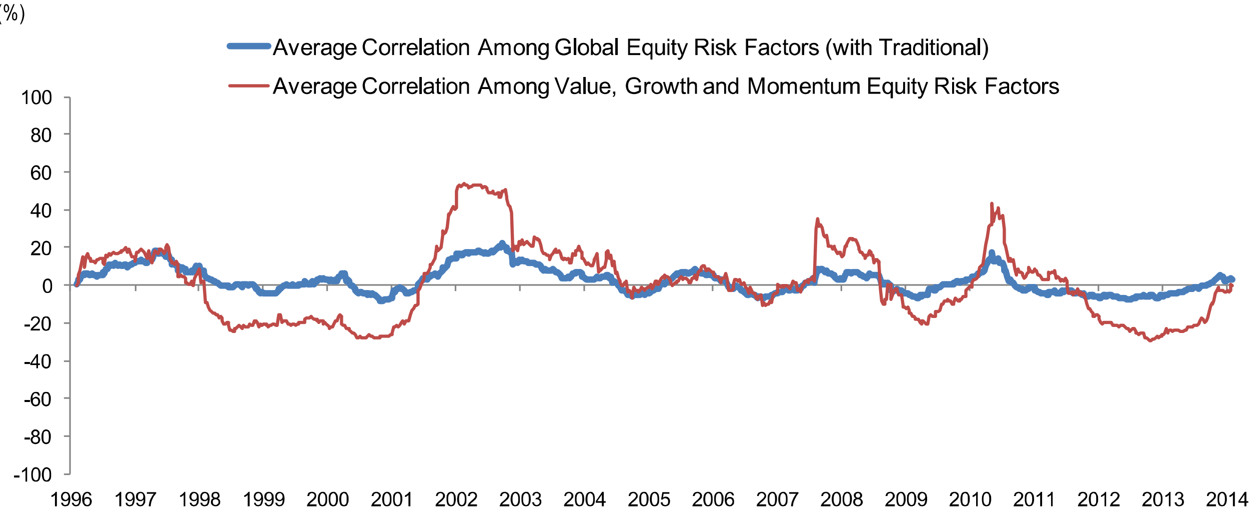
Portfolio of Global Factor Styles

A simple example of combining factors into a portfolio is a **J.P. Morgan Global Risk Factor Portfolio** containing Value, Growth and Momentum style benchmarks. The style benchmarks we use are the ones we constructed from regional Risk Factors in the section 'Global Style Benchmarks' in the Appendix. As the portfolio consists of long-short style benchmarks, it represents an "absolute return" strategy that aims to harvest Equity Risk Premia.

The main reason for our selection of Value, Growth and Momentum is the low and stable average correlation between these three styles as shown in Figure 58 below.

Figure 58: Rolling 52-Week Average Correlation Among Value, Growth and Momentum Equity Risk Factors

(%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

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For a portfolio of Global Value, Global Growth and Global Momentum Styles, we tested the following dynamic weight allocation methodologies, where style weights are rebalanced on a monthly basis:

1. Equal Weighted portfolio (EW),
2. Equal Marginal Volatility portfolio (EMV),
3. Mean-Variance Optimized portfolio with expected returns estimated by the average of past 6-month returns (MVO),
4. Global Minimum Variance portfolio (GMV),
5. Most Diversified portfolio (MDP),
6. Risk Parity portfolio (RP).

Readers can refer to our primer on Cross-Asset Risk Factors for technical explanations on each of these allocation methods (pages 59-118). To calculate the model weights at each of the month-end rebalances, we use the trailing 63-day sample volatility of Style benchmarks and use trailing 26-week correlation matrix.[40] For MVO return estimates, we used the annualized average of past 6-month returns.

Table 33 below shows the ex-post performance and risk of the six portfolio construction methods over the full time period (from January 1996 to January 2014). Figure 59 on the next page plots the excess return indices (in US$) for each of the six allocation methods.

Table 33: Performance-Risk Metrics for Different Portfolio Methods on Global Value, Growth and Momentum Risk Factors

	EW	EMV	MVO	GMV	MDP	RP
Ann. Ex Ret (%)	8.0	8.4	11.0	8.2	8.1	8.2
CAGR (%)	8.1	8.5	11.2	8.3	8.2	8.4
STDev (%)	6.7	6.2	8.3	5.9	6.1	6.0
MaxDD (%)	-15.7	-14.3	-8.8	-10.3	-10.4	-11.4
MaxDDur (in yrs)	3.3	2.8	1.4	4.2	3.8	2.6
***t*-Statistic**	**5.1**	**5.8**	**5.7**	**5.9**	**5.7**	**5.9**
Sharpe Ratio	**1.20**	**1.35**	**1.33**	**1.38**	**1.33**	**1.38**
Hit Rate (%)	71.9	70.5	66.4	65.9	68.7	68.2
Skewness	-0.24	0.11	0.12	0.39	0.34	0.36
Kurtosis	3.60	2.86	1.60	2.59	2.64	2.69
Correl w/Equity*	-0.24	-0.18	-0.12	-0.06	-0.12	-0.13
Correl w/Bond*	0.07	0.06	0.02	0.02	0.02	0.04

Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.
* We used MSCI AC World Excess Return Index for "Equity" and J.P. Morgan Global Government Bond USD Index (hedged) for "Bond".
** Performance is calculated during the backtesting period from January 1996 to January 2014.

Based on the historical backtest, we can observe the following:[41]

- EW had the lowest Sharpe ratio (1.20), lowest return (CAGR at +8.1%), and worst drawdown (-15.7%). As illustrated in our primer on Cross-Asset Risk Factors, the Equal-Weight (EW) method randomly allocates risk and is expected to underperform optimization and risk-based allocation models. The Sharpe ratios of other portfolio methods were closely clustered (1.33 to 1.38).

[40] These simplistic volatility and correlation assumptions could be enhanced by using more elaborated models such as GARCH.
[41] These results are similar to our findings for Cross-Asset Risk Factor portfolios. See pages 101-107 in our primer report on Cross-Asset Risk Factors.

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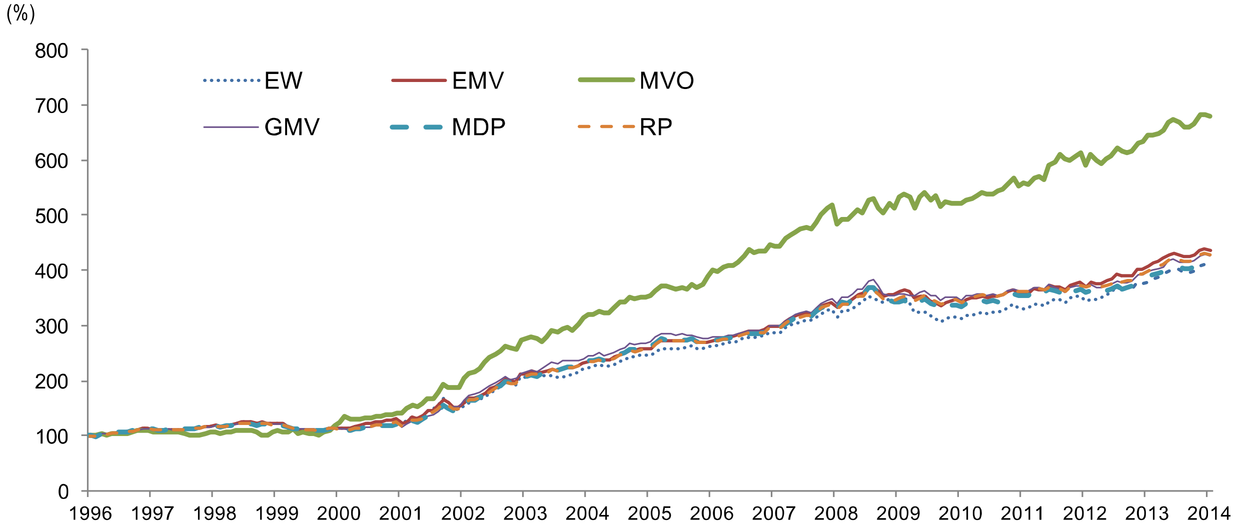
- EMV improved upon EW in overweighting less volatile Factor Styles and achieved better performance. However, its drawdown (-14.3%) was still relatively large compared with returns (CAGR at +8.5%). RP further improved upon EMV in reducing portfolio drawdown and increasing portfolio Sharpe ratios.
- MVO generated the highest return (CAGR at +11.2%) and lowest drawdown (-8.8%)/drawdown duration (1.4 years) among the six asset allocation models. MVO also had the lowest Kurtosis among all methods. The strong performance of MVO was achieved because of stable risk premia returns and covariance. In effect, MVO outperformed due to trending (momentum) behavior of Factor Styles.[42] GMV and MDP, which are special cases of MVO, generated lower CAGRs, lower volatility and higher drawdowns compared to MVO.
- Except EW, all the other five allocation methods achieved positive skewness. All portfolio construction methods had close to zero correlation with global Bonds and negative correlation with global Equities.

Figure 59: Historical Performance of Portfolio Construction Methods for Global Value, Growth and Momentum Factor Styles



Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.

Overall, we find that the risk-based methods (GMV, MDP, EMV, RP) delivered similar returns and volatility profiles. As a result, the ex-post performances closely match one another (Figure 59). On the other hand, MVO delivered stronger returns (+11% per annum) at a higher volatility without resorting to leverage. From a tail-risk perspective, MVO actually performed much better than a leveraged risk-based allocation method, given its maximum drawdown and drawdown duration were only -8.8% and 1.4 years, respectively. To better understand how this performance was achieved considering the underlying Risk Factors each returned less than +9% per annum (Table 58 on page 110), we performed a factor weight and performance attribution of the six risk models.

Figure 60-Figure 65 show the monthly factor weights for different models. For instance, GMV (Figure 62) is closely related to MDP (Figure 63) – both try to minimize ex-ante portfolio variance with the former penalizing higher-volatility assets. In addition, EMV (Figure 64) is a special case of Risk Parity (Figure 65) which disregards asset correlation. Since our portfolio of Value, Growth and Momentum Risk Factors had roughly zero average correlation, these two methods produced roughly similar portfolio weights. Similar to GMV, the Risk Parity method also tries to manage portfolio risk by overweighting assets with lower systematic risk (lower average correlation with other assets and lower marginal volatility).

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[42] We discussed the topic of "Factor on Factor" on pages 55-58 in our primer report on Cross-Asset Risk Factors.

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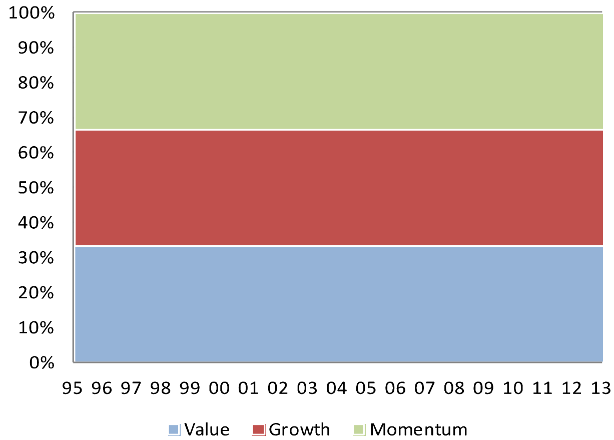
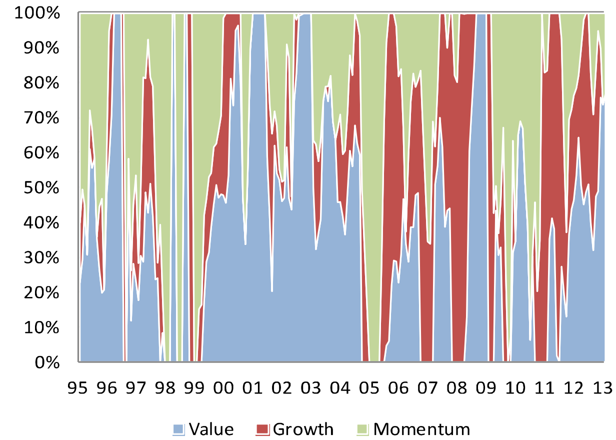
Figure 60: Portfolio Weights of EW



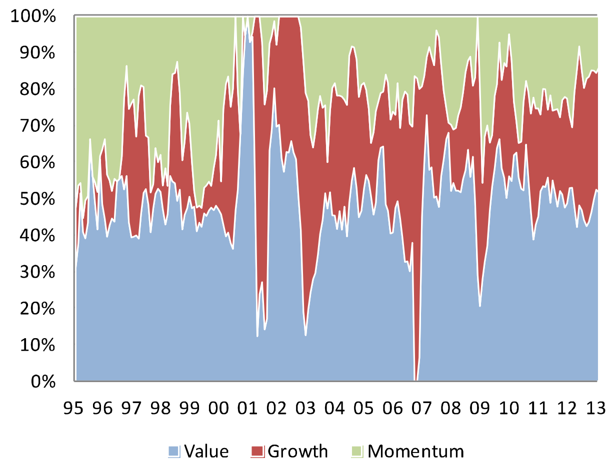
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 61: Portfolio Weights of MVO



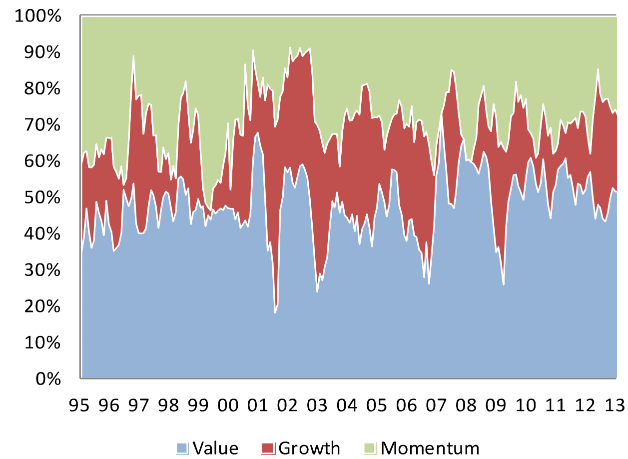
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 62: Portfolio Weights of GMV



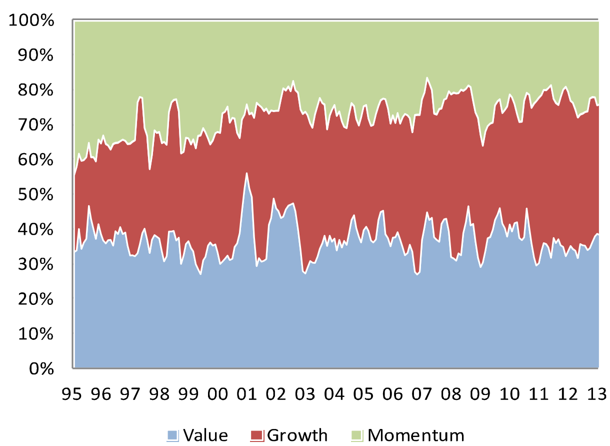
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 63: Portfolio Weights of MDP



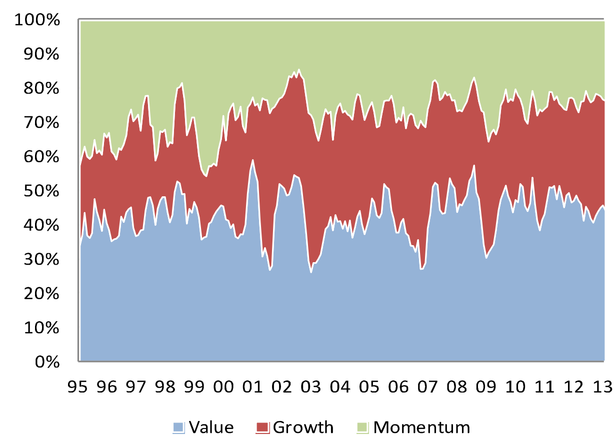
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 64: Portfolio Weights of EMV



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 65: Portfolio Weights of Risk Parity



Source: J.P. Morgan Quantitative and Derivatives Strategy.

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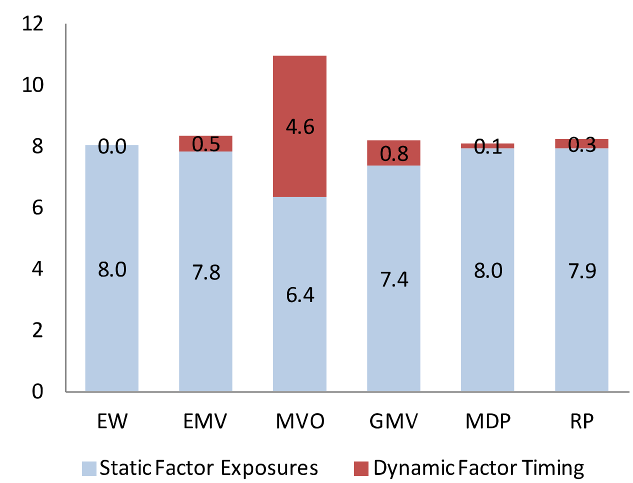
Compared with the risk-based methods that focus purely on certain aspects of 'risk reduction', the momentum-based MVO (Figure 61) is a more aggressive algorithm that tries to time the underlying assets tactically, as can be seen from the high turnover of portfolio weights: it substantially overweighted Value during Value's outperforming period in 2001-2004 and became more tactical in recent years given more frequent style rotations.

Overall, MVO's 'market timing' seems to generate significant Alpha after controlling for the strategy's static Risk Factor beta exposures. To see this, Figure 66 below breaks down the annualized returns for each of the six risk methods into a component that is attributable to static exposures to the three global Risk Factors (Value, Growth, and Momentum) and a component that is due to dynamic style timing.[43] We find that while dynamic timing only makes marginal contributions to the returns of risk-based methods, it contributed +4.6% per annum to the return of MVO. This enhanced return doesn't come without additional risk. Figure 67 shows the risk contribution from the static and dynamic components, from which we find the increase in return volatility of MVO compared with other models largely comes from the dynamic component.

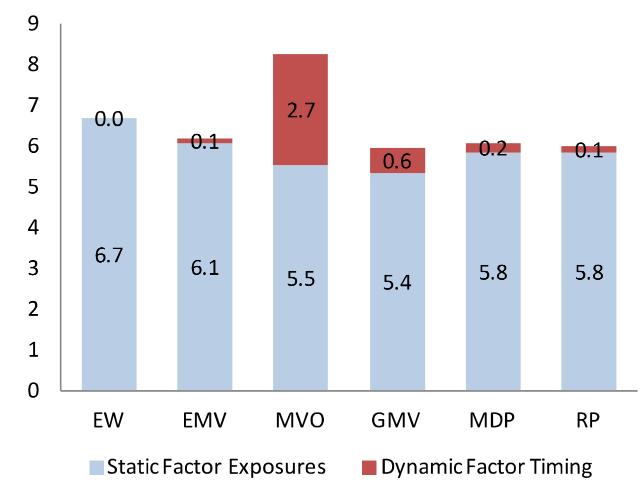
Figure 66 and Figure 67 also offer additional insights into the macro behaviors of different risk methods. For instance, we find that the dynamic component of MDP and RP doesn't contribute to meaningful differences in returns and risks and hence their return/risk profiles closely resemble certain fixed-weight portfolios. On the other hand, the dynamic component of GMV contributed 0.8% per annum to the returns as compensation for the return drags from its structural overweight to lower-volatility Factors (Growth Factor). This enhancement in return, however, comes at a roughly proportional increase in portfolio volatility.

Figure 66: Attribution of Risk Method Returns to Static (Factor Beta) and Dynamic (Factor Timing) Components



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 67: Attribution of Risk Method Risk to Static (Factor Beta) and Dynamic (Factor Timing) Components



Source: J.P. Morgan Quantitative and Derivatives Strategy.

To further evaluate the historical performance of these models, we compare the six portfolio construction methods at each year-end by looking at their performances over the past three years. Figure 68 shows the best- and Figure 69 the worst-performing allocation methods according to different reward/risk metrics such as Sharpe, Sortino, Calmar, CVaR ratios, etc. as defined in the Appendix 'Performance-Risk Metrics' on page 115.

[43] Specifically, we conduct linear regressions of the ex-post returns of the six models on the three global Risk Factors. The static return contribution comes from beta components of these regressions and the dynamic contribution comes from the Alphas. Interested readers could refer to our primer report on Cross-Asset Risk Factors for more discussions on return and risk attributions.

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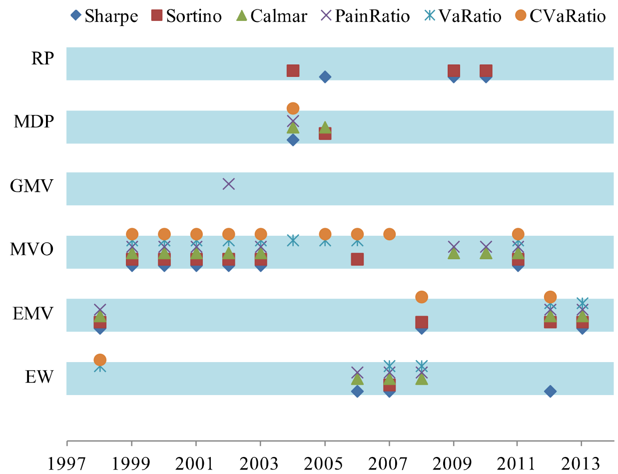
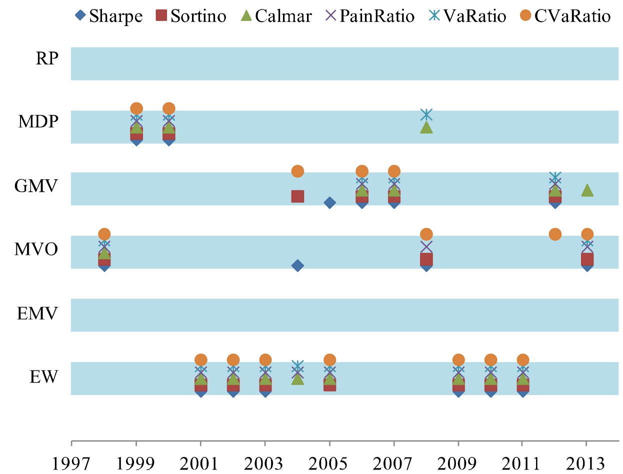
Figure 68: Best-Performing Portfolio Allocation Method Based on Trailing 3-Year Reward/Risk Ratios



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 69: Worst-Performing Portfolio Allocation Method Based on Trailing 3-Year Reward/Risk Ratios



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Similar to our findings in evaluating Cross-Asset Risk Factor portfolio performance, no single allocation method appeared to be best under all market regimes. More detailed observations about risk model performances are listed below:

- **MVO was the best-performing model from 1998 to 2011.** However, it was also the worst-performing strategy during market sell-offs in 1998 and 2008. Its performance also deteriorated over the past 3 years, with the most recent performance (2013) being the worst among all models. The performance of MVO hinges crucially on the success of using the underlying Risk Factor momentum to predict future performances and stable factor covariance. Recent deterioration of MVO performance suggests a potentially less stable factor correlation and return environment.
- **Equal Marginal Volatility** (EMV) was one of the top-performing models during crises of 1998 and 2008 (and most recently in 2012-2013). Strong performance in 1998 and 2008 may be a result of increased factor volatility and correlation shifts that typically occur during market crises. Given the poor performance of MVO in these years when EMV excelled, one could derive portfolio weights through some "**Model Averaging**"[44] mechanism to reduce the negative impact of model risk. For example, an equal average of MVO and EMV models could improve the portfolio Sharpe ratio to 1.46 (from 1.33 for MVO and 1.35 for EMV).
- **EMV and RP never ranked as the "worst" performing model** during the whole backtesting period, suggesting Risk-Parity based models are relatively robust across different market regimes.
- The **Equal Weight** (EW) model was one of the worst-performing models throughout the whole backtesting period (it did rank as one of the best-performing models in 2006-07 and 2012). The reason for its underperformance was that **(1)** EW ignored risk by making an overly simplistic assumption of "everything is equal" in asset allocations, and **(2)** EW is theoretically inconsistent in allocating between underliers with potential leverage and/or "redundant assets".[45]

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[44] Model Averaging works for the same model with different parameters as well. For instance, an equally weighted MVO model with 1-month and 6-month momentum assumptions would produce a compounded annual return, maximum drawdown, and Sharpe ratio of 12%, -8.1% and 1.45, respectively.
[45] See pages 86-88 of our primer report on Cross-Asset Risk Factors for "Robustness of Asset Allocation Models."

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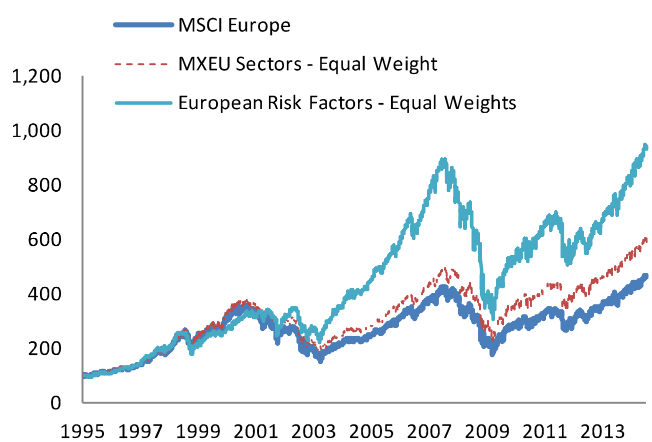
Portfolio of Regional Factors

In the previous section we studied an example of a portfolio of global long-short factor styles. Our next example of a multi-factor portfolio is a basket of long-only European Risk Factors. The portfolio consists of 13 Risk Factor benchmarks introduced in the previous chapters. [46]

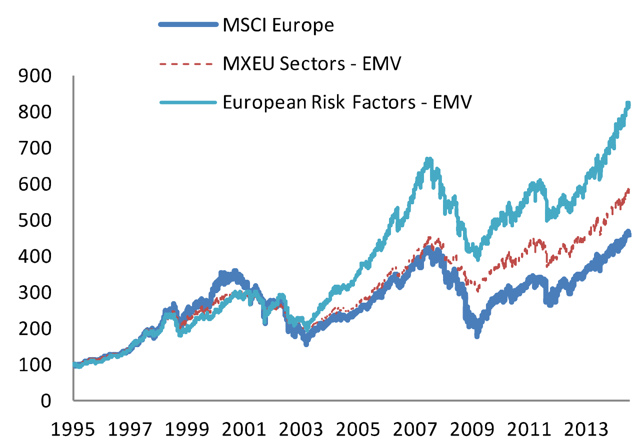
The simplest portfolio construction method is to equally weight factors which are rebalanced each month-end. Figure 70 shows performance of an equally weighted portfolio and compares it to MSCI Europe and an equally weighted portfolio of MSCI Europe industry sectors. Despite the outperformance of the Risk Factor portfolio (information ratio for factor portfolio was 0.6, vs. 0.39 for MSCI Europe and 0.47 for equally weighted MSCI Europe sectors), equal-weighting is not optimal method for constructing a portfolio. The reason is its simplistic allocation of risk which ignores the volatility of the underlying assets. A simple improvement over equal-weighting scheme is equal risk weighting.[47] Figure 71 shows the historical performance of an EMV portfolio of 13 Equity Risk Factors with month-end rebalances, compared with MSCI Europe index and portfolio of 10 GICS sector indices of MSCI Europe based on the same EMV methodology.

Figure 70: European Risk Factor vs Sector Portfolio (Equal Weight)



Source: J.P. Morgan Quantitative and Derivatives Strategy.
Past performance is not indicative of future returns.

Figure 71: European Risk Factor vs Sector Portfolio (EMV)



Source: J.P. Morgan Quantitative and Derivatives Strategy.
Past performance is not indicative of future returns.

Table 34 and Table 35 summarize the performance/risk profiles of equal-weighted and EMV (risk-weighted) portfolios during the full sample period from January 1995 to March 2014 as well in the more recent period (after the tech bubble) from January 2002 to March 2014.

One can see that the capitalization-weighted benchmark had the lowest Sharpe ratio both during the full time period as well as in the more recent period since 2002. Equal weighting of sectors outperformed the capitalization-weighted benchmark by avoiding concentration in technology and financial sectors during the tech and financial bubbles in 2000 and 2008, respectively.

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[46] The 13 Equity Risk Factors are implemented as J.P. Morgan ERP tradable benchmarks from five style categories including Value Factors: Fwd Earnings Yield (QTJPEYEL), FCF Yield (QTJPFYEL), Dividend Yield (QTJPDYEL); Growth Factors: EPS Growth (QTJPEMEL), PEG (QTJPPGEL); Quality Factors: ROE (QTJPROEL), Net Profit Margin (QTJPNIEL), Debt/Equity Ratio (QTJPEDEL); Momentum Factors: Price Momentum (QTJPPMEL), Seasonality (QTJPSYEL); and Volatility Factors: Low Volatility (QTJPLVEL), Low Beta (QTJPLBEL) and Small Size (QTJPLSEL).
[47] At each rebalancing date, we calculate each asset's trailing 21-day annualized volatility and determine the weights based on the following formula: $\min\,(100\%, 15\%/\text{Annualized Vol})/\text{Number of Assets}$. Essentially, we make an Equal-Marginal Volatility weighting scheme with a marginal volatility target of 15%/Number of Assets. It is a version of risk parity that ignores the correlation structure of the underlying assets.

Table 34: European Risk Factor vs MSCI Europe Sector Portfolio Performance/Risk – January 1995 to June 2014

	MSCI	MXEU Sectors		Risk Factors	
	Europe	EW	EMV	EW	EMV
Annualized Ret (%)	9.7	10.9	9.7	13.2	11.6
CAGR (%)	8.1	9.6	9.4	12.1	11.3
STDev (%)	19.2	18.6	12.3	18.4	13.0
MaxDD (%)	-58.2	-54.6	-37.7	-65.5	-42.0
MaxDDur (in yrs)	6.3	5.8	5.4	6.8	5.9
***t*-Statistic**	**2.2**	**2.6**	**3.5**	**3.2**	**3.9**
Sharpe Ratio	**0.39**	**0.47**	**0.63**	**0.60**	**0.73**
Hit Rate (%)	54.5	54.7	54.9	55.5	55.6
Skewness	-0.04	-0.04	-0.35	-0.28	-0.44
Kurtosis	5.87	5.78	2.69	6.66	3.14
Correl w/ MXEU	100.0	99.4	92.4	87.1	81.1

Source: J.P. Morgan Quantitative and Derivatives Strategy.
Past performance is not indicative of future returns.

Table 35: European Risk Factor vs MSCI Europe Sector Portfolio Performance/Risk – January 2002 to June 2014

	MSCI	MXEU Sectors		Risk Factors	
	Europe	EW	EMV	EW	EMV
Annualized Ret (%)	6.2	7.3	7.2	10.9	10.0
CAGR (%)	4.2	5.5	6.6	9.1	9.5
STDev (%)	20.3	19.7	12.4	20.7	13.8
MaxDD (%)	-58.2	-53.6	-33.6	-65.5	-42.0
MaxDDur (in yrs)	6.3	5.8	5.4	6.8	5.9
***t*-Statistic**	**1.1**	**1.3**	**2.0**	**1.8**	**2.6**
Sharpe Ratio	**0.23**	**0.29**	**0.46**	**0.45**	**0.62**
Hit Rate (%)	53.7	53.8	53.8	54.4	54.4
Skewness	0.07	0.06	-0.23	-0.17	-0.27
Kurtosis	6.53	6.34	2.32	5.66	2.42
Correl w/ MXEU	100.0	99.5	91.9	89.9	82.6

Source: J.P. Morgan Quantitative and Derivatives Strategy.
Past performance is not indicative of future returns.

The equally weighted portfolio of Risk Factors generated a Sharpe ratio that was ~50% higher than that of the capitalization benchmark, and ~20% higher than the Sharpe ratio of an equal-weighted sector portfolio.

Implementing the EMV portfolio construction further improved the performance of an Equity Risk Factor portfolio. Table 34 and Table 35 show that the EMV Risk Factor portfolio had a full-sample Sharpe ratio of 0.73 and post-2001 Sharpe ratio of 0.62. The EMV factor portfolio achieved lower risk with comparable absolute performance compared to the equally weighted portfolio. For instance, the compounded annual total return of the EMV factor portfolio was +9.5% during January 2002 to June 2014, slightly higher than for the equally weighted portfolio, while the volatility was reduced by a third. Lastly, full-sample correlation between the risk parity factor portfolio and MSCI Europe (81%) was lower than correlation between the EMV sector portfolio and MSCI Europe (92%).

To track the performance of an EMV European Risk Factor portfolio, the J.P. Morgan Structuring Desk created the **J.P. Morgan Risk Parity ERP Long-Only Index** (**QTJPERPL** <Index> on Bloomberg), which allocates weights to 13 long-only European Equity Risk Factors according to a similar risk-weighting scheme as the one we implemented in the EMV model shown above. Consistent with our analysis and findings, the risk-weighted portfolio outperformed MSCI Europe after inclusion of all rebalancing costs. Figure 72 below shows that during the recent two years (June 2012 to June 2014), the index delivered 52% return, outperforming the total return delivered by MSCI Europe.

Due to its exposure to the equity benchmark, the risk of a long-only Risk Factor portfolio will be primarily driven by market risk. An alternative to a basket of long-only factors is a portfolio of long/short Factors (similar to the Global Style Portfolio from the previous section). **J.P. Morgan Risk Parity ERP Long-Short Index** (**QTJPERPF** <Index> on Bloomberg) applies the same risk-weighting methodology to 13 long/short European Equity Risk Factors. As shown in Figure 73, the portfolio outperformed Global Hedge Funds (the broad HFRX index, an absolute term benchmark).

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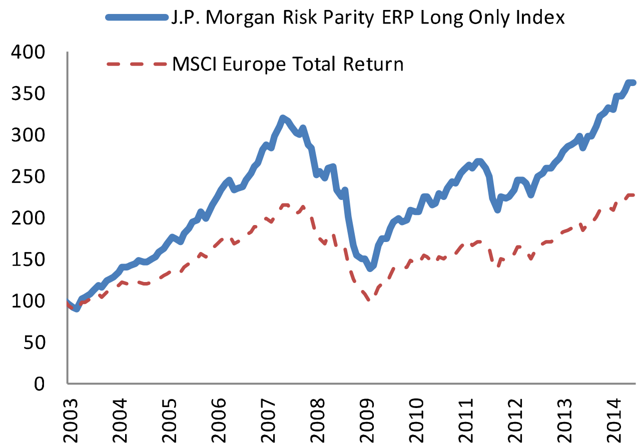
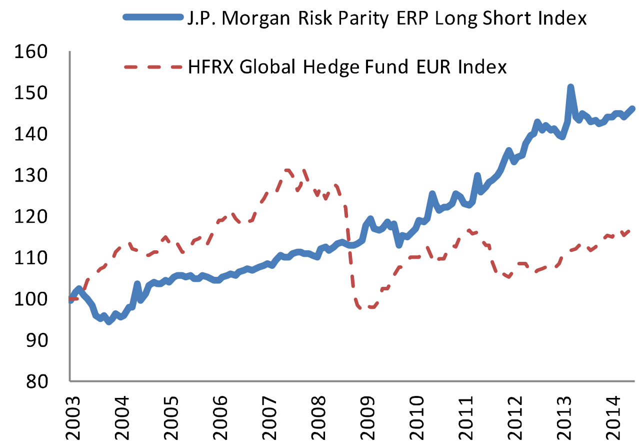
Figure 72: Performance of J.P. Morgan Risk Parity ERP Long-Only Index Compared with MSCI Europe (in EUR total return)



Source: J.P. Morgan. Past performance is not indicative of future returns.
* Returns are in EUR, with dividends reinvested, net of a 0.04% rebalancing factor.
** Indices are rebased to 100 on December 31, 2002 for comparison purposes.

Figure 73: Performance of J.P. Morgan Risk Parity ERP Long-Short Index Compared with MSCI Europe (in EUR total return)



Source: J.P. Morgan. Past performance is not indicative of future returns.
* Returns are in EUR, with dividends reinvested, net of a 0.04% rebalancing factor and an adjustment factor of 1% p.a.
** Indices are rebased to 100 on December 31, 2002 for comparison purposes.

Multi-Factor Models

In the previous section we constructed a basket of factor benchmarks in order to create a multi-factor portfolio. Given the offsetting correlations of individual factors, the portfolio Sharpe ratio was significantly higher than the Sharpe ratios of the individual factors. Building a portfolio of factors is the most direct way to take advantage of low factor correlations. A different approach is to build a **multi-factor model**. Multi-factor models directly select stocks into a portfolio (rather than selecting factors) based on stocks' combined ranking on a number of different factor metrics.

To illustrate the difference between a factor portfolio and multi-factor model, let's look at the example of a Momentum and Value portfolio. In a factor portfolio approach, an investor would separately design a Momentum long-short factor and a Value long-short factor. These two factors would then be combined into a portfolio. A portfolio of these two factors should benefit from the negative correlation between the Momentum and Value factors. A multi-factor approach would rank all the stocks in the universe according to Value and Momentum metrics. Value and Momentum scores would then be averaged and stocks ranked according to the combined score. The final portfolio would consist of stocks with the highest combined scores (and in a long-short model, there would be a short leg with stocks with the lowest combined scores).

While a factor portfolio directly benefits from the negative price correlation of stocks with the highest Value scores (which may rank poorly on Momentum scores) to those with the highest Momentum scores (which may rank poorly on Value), a multi-factor model benefits from an offsetting effect of Value and Momentum attributes in each of the stocks. In other words, a stock that is selected by multi-factor model will have above-average ranking in both metrics and may appeal to Value investors and Momentum investors at the same time.

In this section we introduce two multi-factor models developed by our team. The JPM Q-score model is based on four factor styles – Value, Momentum, Growth, and Quality – and has shown historically strong performance in Emerging Markets and Asia, but less so in developed markets. The second model we introduce and analyze in depth is the J.P. Morgan Global 5-Factor Model. This model incorporates Volatility factors (Small-Large Size and Low Volatility), in addition to the Q-score styles of Value and Momentum. The model delivered more consistent performance in Developed Markets than the Q-score model.

JPM Q-Score Model

The JPM Q-Score model blends factors from four major styles: Value, Momentum, Growth and Quality. The model consists of ten common factors shown in the table below. Each factor is assigned the specified weight, and scores (sector-normalized Z-scores) are weighted averaged to calculate the composite score. The model selects the top 20% ranking stocks for the long leg and the bottom 20% ranking stocks for the short leg and rebalances every month-end (i.e. the monthly L/S quintile returns). The model is updated weekly and is available online. For all the details of calculating the Q-Score, please see our report, The JPM Q-Score for Emerging Market Stock Selection, February 2012.

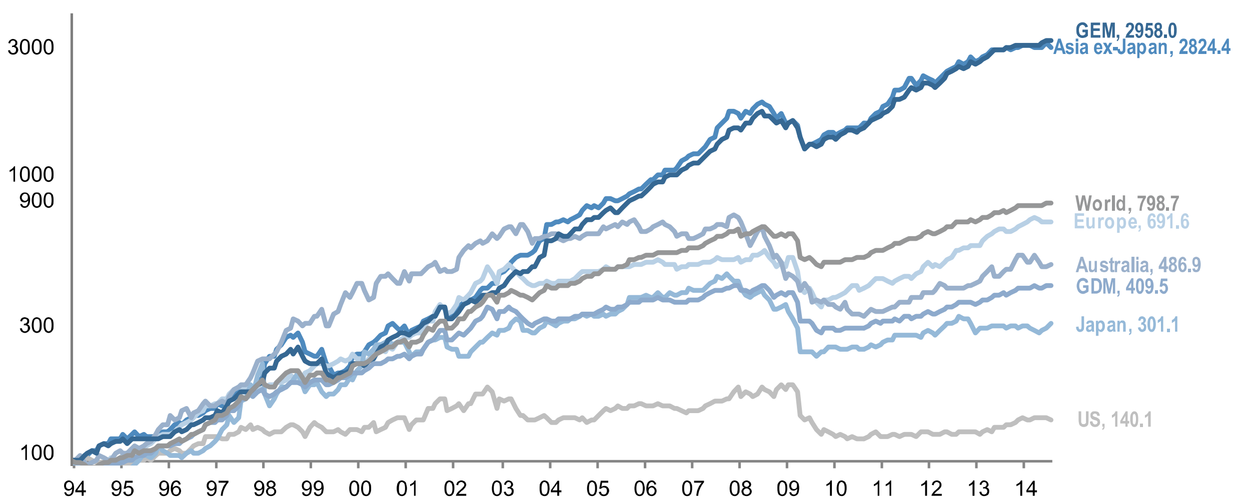
Figure 74 below shows the performance of our Q-score methodology over the past 20 years. Model performance was tested separately for the US, Europe, Asia ex-Japan, Japan, Australia and Global Emerging Markets (GEM). One can notice that the model delivered the strongest performance in Asia ex-Japan and GEM, while the performance in Global Developed Markets (GDM) and the US in particular has been relatively poor. The reason is that some of the relatively simple factors such as P/E, Earnings Momentum and Simple 12M Price Momentum have not been performing well in the US, while the stronger-performing factors from the Volatility style were not included. The Global Financial Crisis caused most of the component Risk Factors to underperform in 2008 and 2009, but the performance recovered over the last 5 years.

Table 36: JPM Q-Score Styles, Factors and Weights

VALUE *[30%]*	MOMENTUM/Technical *[20%]*
P/E vs Market (12M Fwd EPS) *[34%]* P/E vs Country Sector (12M Fwd EPS) *[33%]* EPS Growth (FY1 Mean to FY2 Mean) *[33%]*	12M Price Momentum *[75%]* 1M Price Reversion *[25%]*
GROWTH *[30%]*	**QUALITY *[20%]***
Earnings Momentum 3M (Risk Adj.) *[34%]* Net Revisions to Mean FY2 EPS *[33%]* 1M Change in Consensus Recs *[33%]*	Historical ROE *[50%]* Earnings Certainty (Var. in Forecast EPS) *[50%]*

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 74: Q-Score Regional Performance – stronger performance in GEM and Asia ex Japan, weaker performance in the US and GDM



Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.

Introducing Global 5-Factor Model

In addition to JPM Q-score model, our research team developed a Global 5-Factor Model that selects stocks based on their Value, Momentum, Quality, Volatility and Size scores. The advantage of this model is its relative simplicity (small number of factors) and inclusion of Low Volatility and Small Size factors that improved model performance and risk properties in Developed Markets.

Below we analyze this model in some detail, focusing on portfolio construction methods such as stock and factor weighting, normalization, liquidity and beta management, etc.

The five **Risk Factor metrics** that will be used to rank and select stocks for the portfolio are:

- **Momentum:** Simple 12-month Total Return momentum. Due to the lack of a Momentum effect in Japan, in that region we chose a 1-month Price Reversal factor.
- **Value:** Our 'Value' factor is 1-year forward Earnings Yield for stocks outside Japan, and Book to Price ratio for stocks in Japan.

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- **Size:** Small-Large factor is calculated based on market capitalization of each company in its respective normalization universe.
- **Volatility:** Low Volatility score is calculated based on 1-year realized volatility of daily total returns.
- **Quality:** Company's reported Return on Equity.

In our analysis we find that for certain stock weighting schemes, the addition of a Quality factor did not improve overall performance of the model. For this reason, in some of the tests we dropped the Quality factor and reduced our model to 4 factors as indicated in Table 37 below:

Table 37: J.P. Morgan Multi-Factor Composites – 4-Factor and 5-Factor Models

Factor Style	Momentum	Value	Size	Volatility	Quality
Factor Description	PM 12M (1M reversal for JP)	Earning Yield (Book to Price for JP)	Market Cap	Realized 1Y Vol	Return on Equity
5-Factor Model	●	●	●	●	●
4-Factor (Reduced) Model	●	●	●	●	

Source: J.P. Morgan Quantitative and Derivatives Strategy.

The starting universe for our global model is the MSCI All-Country World Index. After ranking the stocks according to equally weighted Factor scores outlined above, we select Top-Quintile (top 20% ranked) stocks for the long leg and Bottom-Quintile stocks for the short leg.

The MSCI All-Country World universe currently has 2,446 stocks (as of end of July 2014) and a quintile portfolio would have 489 stocks in the long and short legs, respectively. The number of stocks in the MSCI All-Country World index has varied from ~2,000 to ~2,800 in the past, and hence the size of long/short legs varied over time as well.

In our analysis we separately analyzed the performance of a Long-Only portfolio, LongShort composite indices that are cash-neutral, and at the end discuss beta neutralization that involves time-varying leverage.

Portfolio rebalancing at each month-end is rather straightforward: stocks are ranked according to a composite factor score constructed from a linear combination of scores.[48] For instance, our 5-factor model uses a composite factor score that combines normalized scores of 12M Momentum (1-month mean-reversion for Japan), Forward Earnings Yield (Book to Price for Japan), Market Cap, Trailing 1-Year Volatility and ROE. For each factor score underneath the composite, we apply a normalization process based on 'Z-Score Transformation with Winsorization'.[49]

Normalization of Factor Scores

Combining scores for each of the factors into the composite factor score is done according to a particular weight prescription. To start with, we assign equal weights to individual factors (and test different factor weighting schemes later).

Normalization of raw factor scores into normalized Z-sores can be done in different ways, so we test and discuss a number of commonly employed normalization methods:

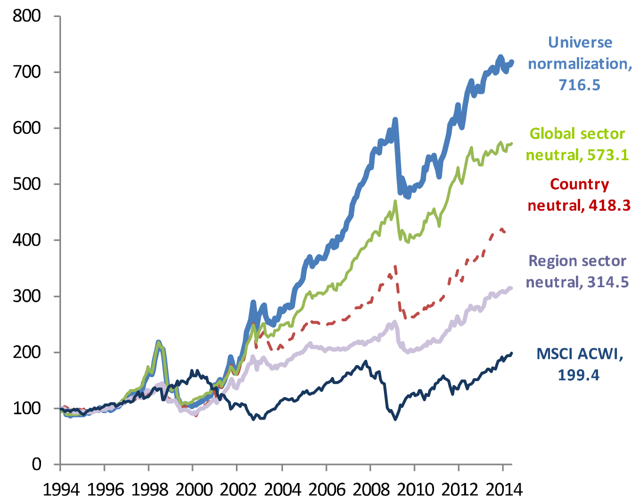
- Full universe normalization: Z-Score is computed based on the full stock universe;
- Country neutralization: Z-score is computed within each country according to MSCI classifications;

[48] The factor scores are calculated as of 1 business day before month-end rebalance dates since May 2013 and as of month-end before.
[49] We first calculate the Z-Score for each individual stock and apply Winsorization which replaces extreme data (e.g. Z-Score greater than 3 or less than -3) values with boundary values. The Z-Scores can be neutralized for certain buckets such as sectors/countries, market cap, country sector combinations, etc. For robustness, we apply the Z-Score normalization and Winsorization iterative process 10 times before we aggregate individual scores into a composite score.

- Global sector neutralization: Z-score is computed within each GICS sector according to MSCI classifications;
- Regional sector neutralization: Z-score is computed within GICS sectors separately from the following regions – North America, Europe, Emerging Asia Pacific, Developed Asia Pacific ex-Japan, Japan, LatAm America and EMEA ex-Dev EU.

Figure 75 below shows the performance of the 5-factor model (long/short) during the period from January 1994 to May 2014 based on the four normalization schemes above. Performance and risk metrics for these models are reported in Table 38.

Figure 75: Performance of the 5-Factor Long/Short model under different normalization schemes



Source: J.P. Morgan. Past performance is not indicative of future returns.
* MSCI ACWI is US$ excess return index after deducting US$ cash return from total returns.

Table 38: Performance comparison of MSCI ACWI with 5-Factor composites under different normalization schemes

	MSCI ACWI	Universe Normal	Country Neutral	Global Sector Neutral	Region Sector Neutral
Ann. Ex Ret (%)	4.6	10.8	7.7	9.4	6.1
CAGR (%)	3.5	10.2	7.3	9.0	5.8
STDev (%)	15.6	14.5	11.2	12.4	9.7
MaxDD (%)	-57.0	-52.1	-37.3	-51.6	-37.7
MaxDDur (in yrs)	7.3	3.8	3.2	4.0	3.0
t-Statistic	**1.3**	**3.4**	**3.1**	**3.4**	**2.8**
Sharpe Ratio	**0.30**	**0.75**	**0.69**	**0.76**	**0.63**
Hit Rate (%)	58.6	64.8	63.9	65.6	64.3
Skewness	-0.79	-0.91	-0.41	-1.37	-0.91
Kurtosis	1.95	4.16	2.78	7.15	3.24
Correl w/ ACWI	100.0	-48.4	-61.0	-45.2	-60.4

Source: J.P. Morgan. Past performance is not indicative of future returns.
* MSCI ACWI is US$ excess return index after deducting US$ cash return from total returns.

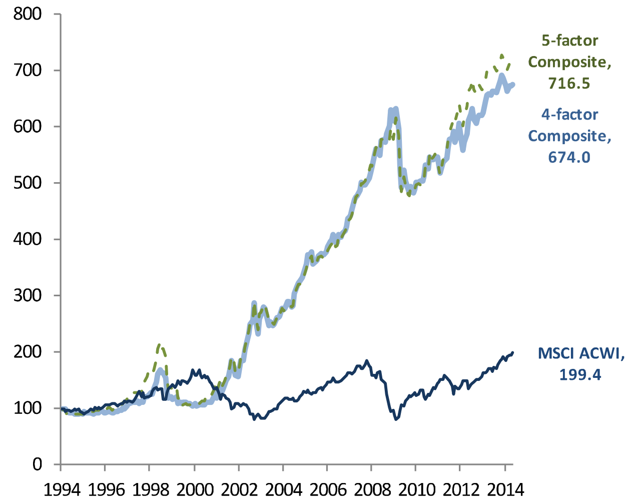
We find that all long/short composites outperformed the MSCI All-Country Index (MSCI ACWI) in risk-adjusted terms. Over the full sample, Sharpe ratios of the model were more than 2 times higher than the MSCI ACWI Sharpe ratio.

One can also notice that the model (with all normalization schemes) had negative correlation with MSCI ACWI suggesting it could be used as a hedge or a complement to a long equity exposure. We address performance of beta-neutralized models separately in our analysis on page 89.

Among the four alternative normalization schemes, the full-universe normalization and global-sector normalization delivered the highest Sharpe ratios (0.75 and 0.76, respectively), albeit with larger maximum drawdowns (-52.1% and -51.6%, respectively). The country-neutralized composite had more negative exposure to the market beta (-61% ex-post correlation) and hence underperformed the full-universe normalization method during 2003-2007. In addition, the more granular regional-sector neutralization scheme seems to dilute factor scores, resulting in the lowest return (and Sharpe ratio).

As a next step, one can investigate the role played by each of the factors. This can be done by comparing the performance of a reduced model by removing one factor. In our example, we illustrate this process by removing the Quality factor i.e. reducing our 5-factor model to a 4-factor model under the full-universe normalization scheme. Results are shown in Figure 76 and Table 39. Under an equal-weighted stock scheme, we find the 4-factor model performed nearly identically to the 5-factor model, with an annualized compounded excess return of 10%. In fact, the 4-factor model had a lower drawdown than the 5-factor model during the 1997-1999 Asian Financial Crisis/Russia Default/LTCM Crisis as high-ROE stocks performed poorly around the globe (see Figure 19 on page 35). Adding the ROE factor in the construction of a multi-factor portfolio doesn't seem to improve performance in the full-universe equally weighted stock methodology.

Figure 76: Performance of the 5-Factor and 4-Factor Composites (Long/Short) with Full-Universe Normalization



Source: J.P. Morgan. Past performance is not indicative of future returns.
* MSCI ACWI is US$ excess return index after deducting US$ cash return from total returns.

Table 39: Performance Comparison of MSCI ACWI (Excess Return) with 5-Factor and 4-Factor Composites (Long/Short) Under Full-Universe Normalization

	MSCI ACWI	5-Factor Model	4-Factor Model
Ann. Ex Ret (%)	4.6	10.8	10.3
CAGR (%)	3.5	10.2	9.8
STDev (%)	15.6	14.5	13.6
MaxDD (%)	-57.0	-52.1	-37.6
MaxDDur (in yrs)	7.3	3.8	3.3
***t*-Statistic**	**1.3**	**3.4**	**3.4**
Sharpe Ratio	**0.30**	**0.75**	**0.76**
Hit Rate (%)	58.6	64.8	65.2
Skewness	-0.79	-0.91	-0.36
Kurtosis	1.95	4.16	2.78
Correl w/ ACWI	100.0	-48.4	-52.8

Source: J.P. Morgan. Past performance is not indicative of future returns.
* MSCI ACWI is based on US$ excess return index.

Attribution of performance to Quality can also be done for long and short legs of the model separately. Table 40 shows that the performance of the long-only model is not reduced significantly by removing Quality under various normalization schemes. Later in the section we will show that adding the Quality factor does improve performance in some of the other construction methods such as market-capitalization weighting of the stocks in the model (as opposed to equal weighting of stocks we considered so far).

Table 40: Performance Comparison of MSCI ACWI with 5-Factor and 4-Factor Composites (Long-Only) Under Different Normalization Schemes

		5-Factor ERP Composites				4-Factor ERP Composites			
	MSCI ACWI	Universe Normal	Country Neutral	Global Sector Neutral	Region Sector Neutral	Universe Normal	Country Neutral	Global Sector Neutral	Region Sector Neutral
Ann. Ex Ret (%)	4.6	11.2	8.5	10.5	8.3	10.9	8.4	10.3	8.6
CAGR (%)	3.5	10.0	7.4	9.3	7.2	9.8	7.2	9.1	7.5
STDev (%)	15.6	17.6	16.2	17.8	16.3	17.6	16.2	17.6	16.3
MaxDD (%)	-57.0	-56.9	-54.8	-56.1	-55.8	-54.5	-55.3	-53.8	-55.1
MaxDDur (in yrs)	7.3	3.3	6.0	3.3	6.0	5.8	8.8	3.3	6.1
***t*-Statistic**	**1.3**	**2.9**	**2.4**	**2.7**	**2.3**	**2.8**	**2.3**	**2.6**	**2.4**
Sharpe Ratio	**0.30**	**0.63**	**0.52**	**0.59**	**0.51**	**0.62**	**0.51**	**0.59**	**0.53**
Hit Rate (%)	58.6	65.2	59.4	63.9	60.2	61.9	57.8	60.7	59.8
Skewness	-0.79	-1.06	-1.02	-0.93	-0.96	-0.92	-0.98	-0.89	-0.90
Kurtosis	1.95	3.48	3.52	3.14	3.33	2.73	3.33	2.80	3.29
Correl w/ ACWI	100.0	85.9	88.7	86.7	89.4	84.1	87.8	85.5	88.2

Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.

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Stock-Weighting Methods

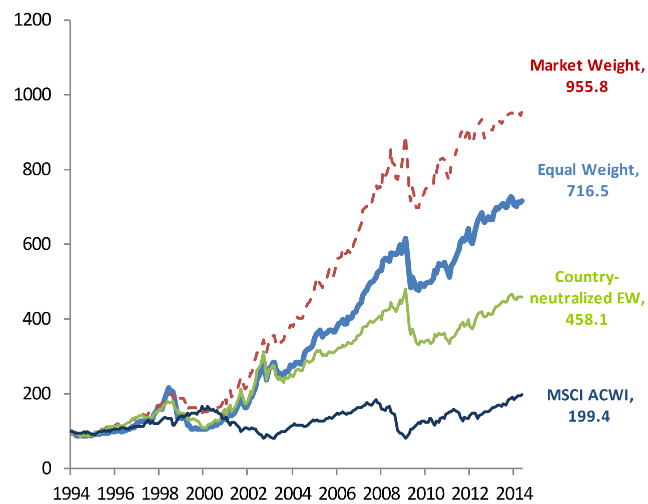
So far we have used a simple equal weighting of stocks in the long and short baskets. One can certainly test performance under other weighting schemes such as market-capitalization weights, and equal weights within a country with capitalization weights for the total country exposure (country-neutral equal weight). Pursuing alternative weighting schemes can be driven by, for example, manager's goal of using the long leg to enhance a benchmark, or risk limits for exposure to particular country. We will also show that selection of stock weights strongly correlates with selection of factor. The reason is that different weighting schemes (equal weights and market-cap weights) may effectively re-weight factor styles such as Size, Volatility, and Quality.

For the 5-factor and 4-factor ERP composite models based on full-universe normalization, we consider three weighting methods below:

- Equal weight: Stocks in the long and short baskets are rebalanced to have equal weights;
- Market-cap weight: Stocks in the long and short baskets are rebalanced to reflect their market capitalization;
- Country-Neutral Equal weight: We assign equal weights to the stocks within a country such that their sum is equal to the respective country's weight in the MSCI All-Country World Index.[50]

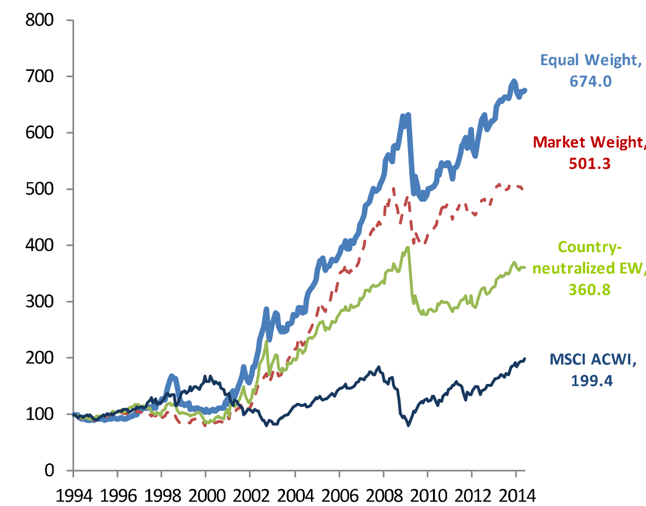
Figure 77 and Figure 78 show historical performances of 5-factor and 4-factor long/short models under different stock weighting schemes. Related performance/risk metrics are summarized in Table 41.

Figure 77: Performance of the 5-Factor Composites (Long/Short) Under Different Stock Weighting Schemes



Source: J.P. Morgan. Past performance is not indicative of future returns.
* MSCI ACWI is US$ excess return index after deducting US$ cash return from total returns.

Figure 78: Performance of the 4-Factor Composites (Long/Short) Under Different Stock Weighting Schemes



Source: J.P. Morgan. Past performance is not indicative of future returns.
* MSCI ACWI is US$ excess return index after deducting US$ cash return from total returns.

[50] In the case no stocks from a country are present in our portfolio then we rescale the stock weights so that the portfolio country weights (summation of stock weights in a country) are proportional to the country weights in MSCI ACWI. For example, suppose there are only two countries, A and B, represented in the long portfolio and the respective MSCI ACWI weights are 5% and 15%. Then the 'country-neutralized equal-weight method' will assign a total weight of 25% to stocks in country A and 75% to stocks in country B. Within countries A and B, we assign equal weights to the stocks.

Table 41: Comparison of MSCI ACWI with 5-Factor and 4-Factor Composites (Long/Short) Under Different Stock Weighting Schemes

		5-Factor ERP Composite			4-Factor ERP Composite		
	MSCI ACWI	Equal Weight	Market Weight	Country Neutral EW	Equal Weight	Market Weight	Country Neutral EW
Ann. Ex Ret (%)	4.6	10.8	12.0	8.6	10.3	8.6	7.4
CAGR (%)	3.5	10.2	11.7	7.8	9.8	8.3	6.5
STDev (%)	15.6	14.5	13.0	14.8	13.6	11.7	14.8
MaxDD (%)	-57.0	-52.1	-27.8	-40.0	-37.6	-25.4	-30.5
MaxDDur (in yrs)	7.3	3.8	2.4	5.3	3.3	4.6	5.3
***t*-Statistic**	**1.3**	**3.4**	**4.2**	**2.6**	**3.4**	**3.3**	**2.3**
Sharpe Ratio	**0.30**	**0.75**	**0.92**	**0.58**	**0.76**	**0.74**	**0.50**
Hit Rate (%)	58.6	64.8	63.9	61.9	65.2	59.4	58.6
Skewness	-0.79	-0.91	-0.06	-0.34	-0.36	0.42	-0.08
Kurtosis	1.95	4.16	2.07	2.85	2.78	1.69	2.85
Correl w/ ACWI	100.0	-48.4	-35.9	-51.3	-52.8	-24.8	-48.4

Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.

We first note (as demonstrated before) that for the Equal-Weighting scheme, the impact of removing Quality from the 5-factor models is minimal. However, we can identify a few other observations:

- The market-capitalization weight method performed much better in the 5-factor model, significantly outperforming the equally weighted method, but underperformed in the 4-factor model (i.e. model without Quality). This indicates the importance of Quality (ROE factor) in the selection of stocks with larger capitalization. As a result, removing Quality from consideration (4-factor model) caused market-weight to underperform the equal-weight method.
- In both cases (with or without Quality), the country-neutral equal-weight method underperformed. The reason is that the country weighting may significantly overweight stocks with a lower composite score (and underweight ones with a higher score) in order to achieve country target weights.

Number of Stocks in the Portfolio

So far we have used quintile portfolios in all of our backtests for the global 5-factor model. The quintiles in our analysis had 400-500 stocks in each of the long and short baskets (currently 489). We now want to address how changing the number of stocks impacts performance and risk of the model. Intuitively, a larger basket of stocks should result in higher diversification and lower performance volatility. Another benefit of using a larger basket is higher capacity and potentially lower market impact. However, using a large basket can also result in less concentrated factor exposures which can lead to lower returns.

Table 42 and Table 43 show performance statistics for the 5-factor model (and 4-factor model) for different numbers of stocks in the portfolio – N = 50, 100, 200, and 300 for both market-cap weights (MW) and equal stock weights (EW).

We find that the returns of the market-cap weighted models generally decrease as N increases. For instance, compounded annual return for the 5-factor long/short model (market-cap weight) was +12.7% when N = 300 and +19.8% when N = 100.

Even though returns decrease with N, volatility and drawdowns significantly improve (decrease) at larger values of N. For instance, the annualized volatility of the equally weighted 5-factor model decreased from 28% to 18% as the number of stocks was increased from 100 to 300. Generally, the Sharpe ratio for various models increased for larger baskets, as can be seen from Table 42, Table 43 and Table 41 (original Quintile portfolio).

Table 42: Performance 5-Factor Composites (Long/Short) with Different Number of Stocks in the Portfolio

	MSCI ACWI	5-Factor Long-Short ERP (EW)				5-Factor Long-Short ERP (MW)			
		N = 50	*N* = 100	*N* = 200	*N* = 300	*N* = 50	*N* = 100	*N* = 200	*N* = 300
Ann. Ex Ret (%)	4.6	14.2	14.7	13.2	12.2	19.8	20.9	15.2	13.3
CAGR (%)	3.5	6.3	10.8	11.3	11.0	15.1	19.8	14.4	12.7
STDev (%)	15.6	36.7	28.4	21.7	18.2	33.2	23.3	18.4	15.6
MaxDD (%)	-57.0	-93.8	-84.6	-71.5	-62.9	-74.4	-46.6	-33.5	-34.8
MaxDDur (in yrs)	7.3	10.3	6.7	4.2	3.9	5.3	5.3	3.1	3.1
***t*-Statistic**	**1.3**	**1.7**	**2.3**	**2.8**	**3.0**	**2.7**	**4.0**	**3.7**	**3.8**
Sharpe Ratio	**0.30**	**0.39**	**0.52**	**0.61**	**0.67**	**0.60**	**0.90**	**0.82**	**0.85**
Hit Rate (%)	58.6	60.7	63.9	65.2	63.5	58.6	60.7	61.1	62.3
Skewness	-0.79	-1.58	-1.44	-1.22	-1.03	-0.29	0.15	0.04	0.06
Kurtosis	1.95	8.11	6.87	5.62	4.76	2.30	1.28	2.45	2.69
Correl w/ ACWI	100.0	-35.8	-40.9	-46.8	-48.0	-37.9	-38.2	-40.7	-42.2

Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.

Table 43: Performance 4-Factor Composites (Long/Short) with Different Number of Stocks in the Portfolio

	MSCI ACWI	4-Factor Long-Short ERP (EW)				4-Factor Long-Short ERP (MW)			
		N = 50	*N* = 100	*N* = 200	*N* = 300	*N* = 50	*N* = 100	*N* = 200	*N* = 300
Ann. Ex Ret (%)	4.6	17.7	16.4	12.6	12.2	13.7	17.4	13.5	11.2
CAGR (%)	3.5	12.3	13.7	11.0	11.4	10.2	16.3	12.8	10.7
STDev (%)	15.6	33.1	25.7	20.3	16.6	28.0	21.1	16.9	14.3
MaxDD (%)	-57.0	-81.6	-70.3	-64.9	-52.1	-73.4	-31.9	-36.1	-29.8
MaxDDur (in yrs)	7.3	4.2	3.8	3.9	3.6	8.0	5.3	2.5	4.3
***t*-Statistic**	**1.3**	**2.4**	**2.9**	**2.8**	**3.3**	**2.2**	**3.7**	**3.6**	**3.5**
Sharpe Ratio	**0.30**	**0.54**	**0.64**	**0.62**	**0.74**	**0.49**	**0.82**	**0.80**	**0.79**
Hit Rate (%)	58.6	61.9	62.3	65.2	64.3	57.0	61.9	61.5	61.1
Skewness	-0.79	-1.08	-0.87	-0.99	-0.60	-0.29	0.11	0.15	0.33
Kurtosis	1.95	5.94	4.42	5.11	3.62	1.89	1.63	1.99	1.91
Correl w/ ACWI	100.0	-45.4	-51.7	-52.1	-52.2	-31.9	-33.8	-32.2	-26.6

Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.

Alternative Factor Weighting

So far, our Global 5-factor scores (as well as 4-factor scores) were obtained by equally weighting individual factor scores. Equal weighting may not be optimal given that the performance and correlation structure between these factors is not uniform. For instance, if 4 out of 5 factors are highly correlated to each other, there may be a limited diversification benefit to equally weighting factor scores. Similarly, if one factor has had consistently better performance, an investor may decide to overweight the corresponding factor score when calculating the composite score.

In order to investigate the impact of changing the composite weights, we have performed a simple analysis in which we vary the weight of a specified anchoring factor while equally weighting all the others factors. The result of this analysis can give us estimated sensitivities of model performance to the change in weights of each of the factors. We have applied this exercise to a four-factor model containing Value, Momentum, Size and Volatility. For instance, equally weighting will assign 25% weight to each of the factors, resulting in Sharpe ratio of 0.76 (0.76 for equal stock weights, and 0.74 for market-capitalization stock weights, Table 41). Now we can ask what the Sharpe ratio would be if we increase the weight of Value to 40% and assign 20% weight to each of the other factors.

Table 44 shows the model Sharpe ratios of the 4-factor models under different assumptions of weights for the anchoring factors, for the equally weighted model. Comparing to the base case Sharpe ratio of 0.76 (in Table 41), we find that increasing the weight of 'Value' to 50% would increase the portfolio Sharpe ratio to 0.96 under an equally weighted stock scheme. On the other hand, increasing the weight of the Momentum, Size or Low Volatility factor in the composite factor score would have generally resulted in a reduction in Sharpe ratio. Table 44 is color coded to indicate factors for which an increase in weight leads to higher Sharpe ratio (green), and factors for which an increase in weight leads to lower Sharpe ratios (red).

One can see that an increased weight in Value leads to higher Sharpe ratios, while an increase in Momentum, Size and Volatility exposures generally leads to lower Sharpe ratios. This is consistent with our findings from the previous chapter that (equally weighted) Value factors tend to be negatively correlated to all other factors, while Momentum and Volatility factors tend to be positively correlated. As a result, increased exposure to Value led to a lower average correlation of stocks in the portfolio.

Table 44: Sharpe Ratios under alternative weighting schemes – 4-Factor Model with equal stock weights

Anchor	Anchoring Factor			
Weight	Value	Momentum	Size	Volatility
30%	0.86	0.77	0.79	0.65
40%	0.94	0.70	0.75	0.44
50%	0.96	0.63	0.63	0.27
60%	0.97	0.54	0.50	0.20
70%	0.91	0.50	0.40	0.12

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 45: Sharpe Ratios under alternative weighting schemes – 4-Factor Model with market-cap stock weights

Anchor	Anchoring Factor			
Weight	Value	Momentum	Size	Volatility
30%	0.71	0.76	0.73	0.69
40%	0.69	0.71	0.67	0.50
50%	0.67	0.68	0.56	0.37
60%	0.68	0.66	0.49	0.29
70%	0.60	0.60	0.40	0.18

Source: J.P. Morgan Quantitative and Derivatives Strategy.

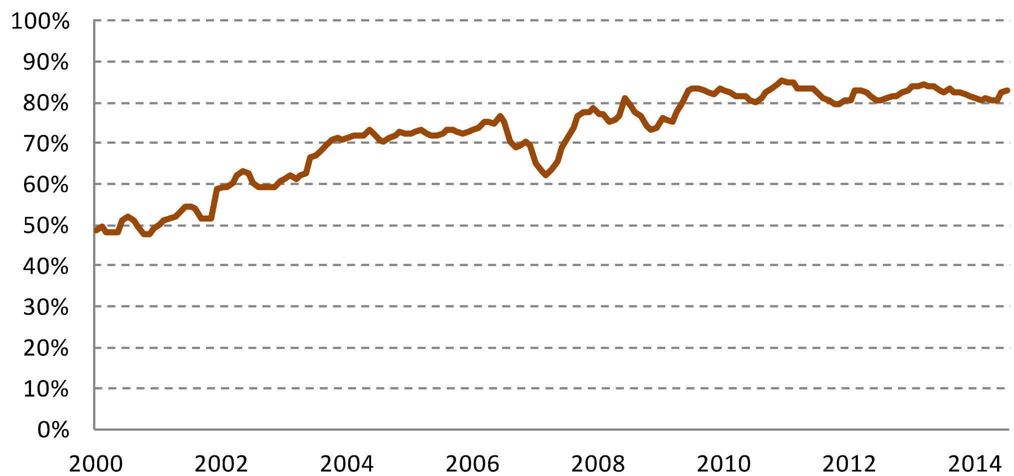
Table 45 shows the same analysis for the market-capitalization weighted model. One can see that the market-capitalization model favors more evenly distributed factor weights, i.e. increasing Value focus did not have an incremental effect on the selection of large-capitalization stocks. This observation further highlights how construction of factors can affect optimal factor allocation (in this case the capitalization weighting scheme introduced significant Size factor biases).

Liquidity Filters

So far we have constructed long and short baskets from the full universe of MSCI All-Country World stocks assuming no liquidity constraints. To conduct more realistic backtests, we next examine the impact of imposing a liquidity filter on the stocks entering the portfolios.

There are various ways to impose liquidity constraints on the stock universe. For instance, one may remove the bottom-decile (10%) stocks with the lowest average traded value (in US$) over the past three months. In our tests below, we use a slightly stricter liquidity filter, which removes stocks for which 3-month average traded value is less than 10% of the universe average. Given that the distribution of stock trading value is positively skewed (the largest stocks dominate the trading volume), this requirement usually removes more than 10% of the stocks in the universe. Figure 79 below shows that roughly 82% of the constituents of MSCI ACWI were selected since 2009. Before 2003, the proportion of liquid stocks according to this criterion was lower, reflecting a more skewed distribution of average daily volume.

Figure 79: Percentage of Stocks Selected (from the Constituents of MXWD) After Applying Liquidity Filter



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 46 shows performance and risk metrics before applying the liquidity filter and Table 47 shows the same metrics after applying the liquidity filter.[51] We find that the risk-adjusted performance of models was reduced by applying the filter (exception is 5-factor equal-weighting model). The reduction of the Sharpe ratio was largely a result of lower annualized returns as a result of the omission of the least liquid stocks (1-2% per annum), but that was to some extent balanced by the lower volatility of 'liquidity-filtered' models.

Table 46: Performance of 5-Factor and 4-Factor Long-Short Models (No Liquidity Filter)

	MSCI	5-Factor ERP		4-Factor ERP	
	AC World	Equal Weight	Market Weight	Equal Weight	Market Weight
Annualized Ret (%)	4.6	10.8	12.0	10.3	8.6
CAGR (%)	3.5	10.2	11.7	9.8	8.3
STDev (%)	15.6	14.5	13.0	13.6	11.7
MaxDD (%)	-57.0	-52.1	-27.8	-37.6	-25.4
MaxDDur (in yrs)	7.3	3.8	2.4	3.3	4.6
***t*-Statistic**	**1.3**	**3.4**	**4.2**	**3.4**	**3.3**
Sharpe Ratio	**0.30**	**0.75**	**0.92**	**0.76**	**0.74**
Hit Rate (%)	58.6	64.8	63.9	65.2	59.4
Skewness	-0.79	-0.91	-0.06	-0.36	0.42
Kurtosis	1.95	4.16	2.07	2.78	1.69
Correl w/ MXWD	100.0	-48.4	-35.9	-52.8	-24.8

Source: J.P. Morgan Quantitative and Derivatives Strategy.
Past performance is not indicative of future returns.

Table 47: Liquidity Filtered Performance of 5-Factor and 4-Factor Long-Short Models

	MSCI	5-Factor ERP		4-Factor ERP	
	AC World	Equal Weight	Market Weight	Equal Weight	Market Weight
Annualized Ret (%)	4.6	10.3	10.0	8.7	7.0
CAGR (%)	3.5	9.9	9.6	8.0	6.6
STDev (%)	15.6	13.0	12.5	13.5	11.3
MaxDD (%)	-57.0	-32.0	-21.7	-27.7	-22.3
MaxDDur (in yrs)	7.3	3.2	2.8	5.3	5.9
***t*-Statistic**	**1.3**	**3.6**	**3.6**	**2.9**	**2.8**
Sharpe Ratio	**0.30**	**0.79**	**0.80**	**0.64**	**0.62**
Hit Rate (%)	58.6	65.2	63.5	65.6	61.5
Skewness	-0.79	-0.33	-0.35	-0.26	0.03
Kurtosis	1.95	2.28	2.65	3.14	2.44
Correl w/ MXWD	100.0	-48.1	-38.6	-50.9	-32.0

Source: J.P. Morgan Quantitative and Derivatives Strategy.
Past performance is not indicative of future returns.

Beta-Neutralization

So far we compared different factor-normalization and stock-weighting schemes for cash-neutral long/short models. All of these models had negative exposures (beta) to the market. As we discussed before, the main reason for the negative beta is

[51] We show performance for 5-factor and 4-factor models, both for equal weighting of stocks and market-capitalization stock weights.

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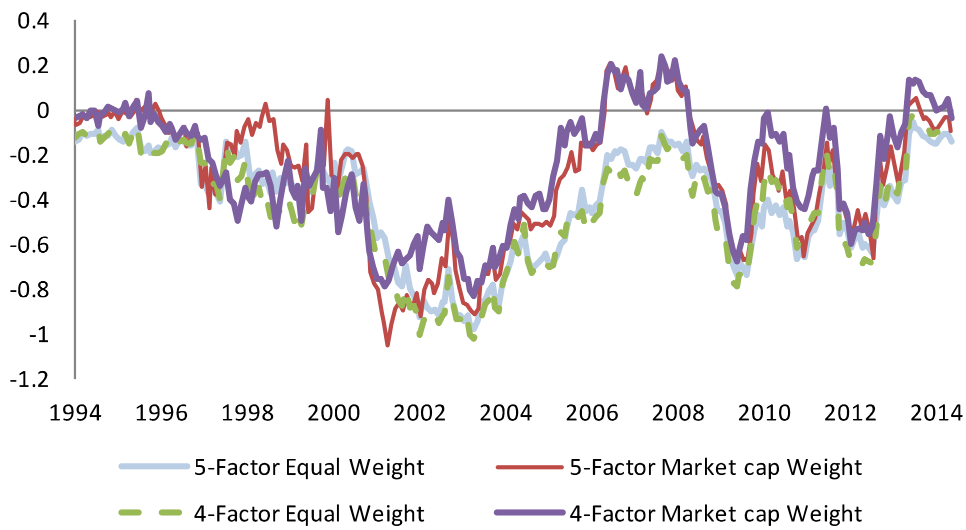
the inherently short market exposure of Momentum, Volatility and Quality factors. Now we want to more closely examine the time-varying model beta and test beta-neutral composites.

Figure 80 below shows the month-end portfolio beta of our 5-factor and 4-factor models. We find that the cash-neutral models almost always had negative market beta (beta values were largely bounded within a range of -1 to 0.1).

Figure 80: Ex-Ante Beta of Multi-Factor Cash Neutral Long/Short ERP Models (Full-Universe Normalization)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

This systematic negative market bias can present a drag on returns as equity markets deliver long-term positive risk premia. To mitigate this problem, an investor may construct a beta-neutral model.[52] Table 48 and Table 49 show the performance of beta-neutralized models for the full universe and liquidity-filtered universe, respectively.[53]

Table 48: Performance of Multi-Factor Models after Beta-Neutralization – full universe

	MSCI AC World	5-Factor ERP		4-Factor ERP	
		Equal Weight	Market Weight	Equal Weight	Market Weight
Annualized Ret (%)	4.6	12.0	12.6	11.5	9.4
CAGR (%)	3.5	12.2	12.8	11.6	9.3
STDev (%)	15.6	9.6	9.8	8.8	10.0
MaxDD (%)	-57.0	-36.8	-21.9	-22.3	-16.6
MaxDDur (in yrs)	7.3	3.8	2.3	3.6	3.3
***t*-Statistic**	**1.3**	**5.7**	**5.8**	**5.9**	**4.2**
Sharpe Ratio	**0.30**	**1.25**	**1.28**	**1.30**	**0.94**
Hit Rate (%)	58.6	68.9	67.2	66.0	61.9
Skewness	-0.79	-0.90	-0.11	-0.22	0.12
Kurtosis	1.95	3.98	0.69	1.17	0.26
Correl w/ MXWD	100.0	12.3	7.0	17.7	18.8

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 49: Performance of Multi-Factor Models after Beta-Neutralization – after liquidity filtering

	MSCI AC World	5-Factor ERP		4-Factor ERP	
		Equal Weight	Market Weight	Equal Weight	Market Weight
Annualized Ret (%)	4.6	11.1	10.6	9.1	7.5
CAGR (%)	3.5	11.3	10.7	9.1	7.4
STDev (%)	15.6	8.5	9.2	8.2	8.6
MaxDD (%)	-57.0	-25.2	-17.0	-19.8	-17.1
MaxDDur (in yrs)	7.3	3.2	1.9	2.5	2.1
***t*-Statistic**	**1.3**	**5.9**	**5.2**	**5.0**	**4.0**
Sharpe Ratio	**0.30**	**1.30**	**1.15**	**1.10**	**0.88**
Hit Rate (%)	58.6	67.6	65.2	63.9	63.9
Skewness	-0.79	0.01	-0.29	0.02	-0.10
Kurtosis	1.95	0.41	1.32	0.58	0.32
Correl w/ MXWD	100.0	4.7	0.3	6.9	8.6

Source: J.P. Morgan Quantitative and Derivatives Strategy.

[52] Alternatively, non-neutralized Risk Factors could be employed to hedge a long-only equity portfolio.
[53] Beta-neutralization is done by leveraging the short basket to match its beta with that of the long basket at each rebalancing.

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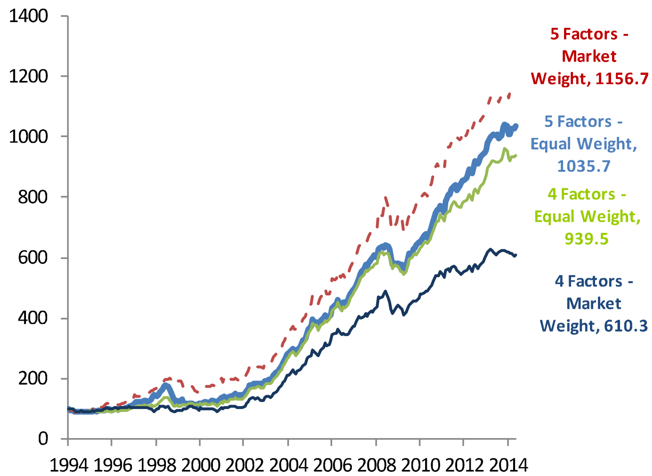
Comparing these results with non-neutralized models in Table 41 (full universe) and Table 47 (after liquidity filtering), we find beta-neutralization significantly improved returns (by 1-2% per annum), and reduced volatility and maximum drawdowns. For example, an equally weighted 5-factor model delivered a Sharpe ratio of 0.75 (10.2% return and 14.5% volatility); after beta-neutralization, the Sharpe ratio increased to 1.25 (12.2% return and 9.6% volatility).

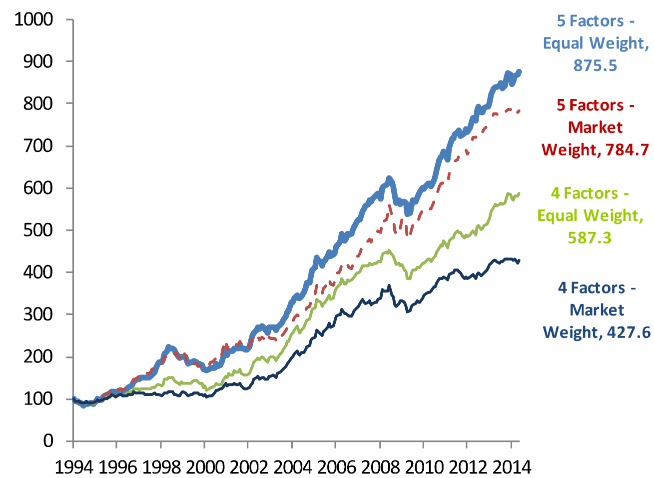
Figure 81 and Figure 82 plot the historical performance of beta-neutralized models. We note the strong performance of these models over the past two decades.

Figure 81: Performance of Beta-Neutralized Models – full universe



Source: J.P. Morgan Quantitative and Derivatives Strategy.
Past performance is not indicative of future returns.

Figure 82: Performance of Beta-Neutralized Models – after liquidity filtering



Source: J.P. Morgan Quantitative and Derivatives Strategy.
Past performance is not indicative of future returns.

Hedging with Risk Factors

Given low or negative correlation to market, Risk Factors can be used to hedge a long equity portfolio. In this section we will examine how one can hedge a broad equity benchmark with static and dynamic factor portfolios. Investors can also use factors to hedge a custom portfolio that does not resemble a broad benchmark. Custom hedging can be done by eliminating portfolio exposure to factors with negative performance trends.

Static Hedge for Equity Benchmark

The negative correlations between several Risk Factors and the standard equity benchmarks shown in Table 28 (page 56) suggest that these factors can be potentially used as hedging tools. Of the Risk Factor Styles considered, Volatility (with Size defined as Large-Small), Momentum and Quality factors show significant negative correlation with the market. Intuitively this makes sense – a portfolio of Low Volatility stocks is likely to outperform a portfolio of High Volatility stocks when the market declines, while the reverse is likely to happen when the market is rising. Similarly, a Low Beta basket of stocks is likely to outperform a High Beta basket during a bear market and underperform in a bull market. Quality factors like Return on Equity, Net Profit Margin and Debt-to-Equity ratio are also likely to display a comparable relationship with the market direction – investors are likely to gravitate to the relative safety of Higher ROE, Higher Margin and Lower Debt-to-Equity firms in turbulent times. When the market is rising, investors may become less risk averse and more likely to embrace Lower Quality and potentially cheaper stocks. As a result, Quality factors' performance may move in a direction opposite to the market.

Table 50: Percentage Correlation Between the Equity Market and Long-Short Risk Factors – In All, Rising and Falling Market Conditions

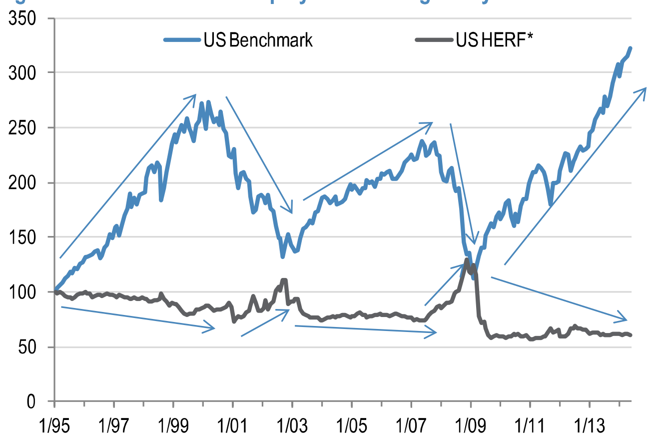
	Value			Growth		Quality			Momentum		Volatility		
All Periods	Fwd EY	FCF Yield	Div Yield	EPS GR	PEG	ROE	Net PM	Debt/Equity	Momentum	Seasonality	Low Vol	Low Beta	Small Size
US	2	-12`	-6	-25```	17```	-41```	-45```	-43```	-39```	2	-63```	-65```	36```
Europe	20```	-13``	-8	-32```	37```	-38```	-39```	-45```	-39```	-8	-63```	-71```	9
Japan	-8	-15``	-7	-16``	9	-27```	-42```	-35```	-23```	-28```	-53```	-45```	20```
Asia x Japan	17```	-17``	-23```	-6	21```	-39```	-21```	-47```	-30```	-9	-73```	-67```	35```
Rising Market													
US	1	1	13	-28```	15`	-22```	-23```	-22```	-30```	8	-43```	-53```	18``
Europe	8	1	8	-35```	17``	-33```	-29```	-21``	-29```	8	-50```	-54```	17``
Japan	-8	4	12	-14	1	-24```	-30```	-22``	-22``	-18`	-32```	-14	20``
Asia x Japan	14	0	4	-18``	10	-41```	-34```	-41```	-49```	-3	-69```	-68```	51```
Falling Market													
US	9	-1	-1	-21``	12	-34```	-36```	-47```	-40```	-6	-48```	-45```	34```
Europe	29```	1	2	-12	46```	-22``	-3	-41```	-38```	-16	-48```	-50```	12
Japan	8	-4	-13	-9	16``	-1	-18``	-20``	-3	-30```	-27```	-28```	1
Asia x Japan	15	-18`	-7	4	26```	-7	12	-34```	-5	3	-56```	-32```	19``

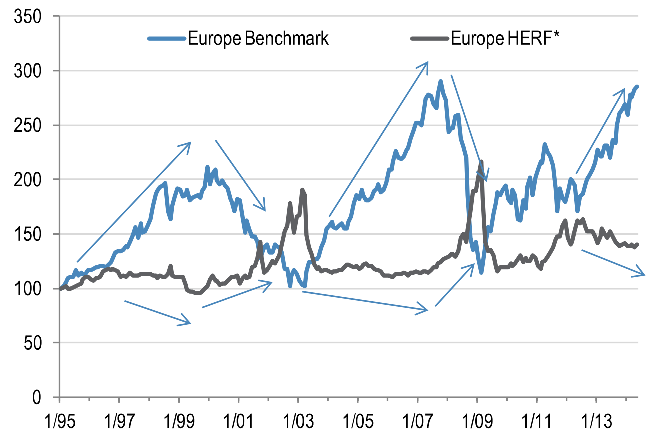
Source: J.P. Morgan Quantitative and Derivatives Strategy.
Correlation is for total dollar excess returns of MSCI US, MSCI Europe, MSCI Japan and MSCI Asia ex Japan versus the total dollar returns of the respective regional Long-Short Risk Factor portfolios over the period 1994-2014.
```: The T-statistic of the correlation is significant at less than 1% level (two-tail hypothesis).
``: The T-statistic of the correlation is significant between 1% and 5% level.
`: The T-statistic of the correlation is significant between 5% and 10% level.
```

Table 50 substantiates the above intuition of *symmetric* negative correlation between several Risk Factor returns and market returns. Notably, Low Volatility and Low Beta Risk Factors show almost the same correlation with market returns, conditioned on market direction in all four regions. Quality Risk Factors appear to be symmetric in the US, Europe and Japan though the negative correlation with the market is slightly weaker in a declining market especially for Japan. In Asia ex Japan, the negative correlation between Quality Risk Factors and the market is primarily confined to rising markets; though even in this region the relationship is symmetric for the Debt/Equity ratio. For the Momentum factor the correlation symmetry is convincing for the US and Europe but weak for Japan and Asia ex Japan.

Since the correlations are statistically meaningful, a Hedging Equity Risk Factor (HERF) composed of long-short regional portfolios of Beta (with weight = 1/6), Volatility (weight = 1/6), Momentum (weight = 1/3) and Debt-to-Equity (weight = 1/3) was built for the US and Europe. Figure 83 plots the market index (MSCI US and MSCI Europe, USD excess returns) against the respective country HERF. The charts visually confirm the negative correlation between each equity benchmark and its corresponding HERF.

Figure 83: The Benchmark Equity Index Is Negatively Correlated with the Hedging Equity Risk Factor





Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.
Benchmarks are excess return MSCI US USD and MSCI Europe USD (benchmark return = total return less USD short-term interest rate, i.e. return from unfunded benchmark holdings).
`Hedging Equity Risk Factor (HERF) is an index based on weighted sum of long-short regional portfolio returns of Beta, Volatility, Momentum and Debt-to-Equity Factors.

Static Hedge: The simplest type of hedge is a static approach. In a static hedge the market portfolio is combined with a hedging instrument in a **fixed** proportion. For this case study we show the result of combining the market index with HERF in four proportions: 90% market/10% HERF (90/10), (70/30), (60/40) and 50% market/50% HERF (50/50).

Table 51: Static Hedging – Fixed Weights of Benchmark and HERF

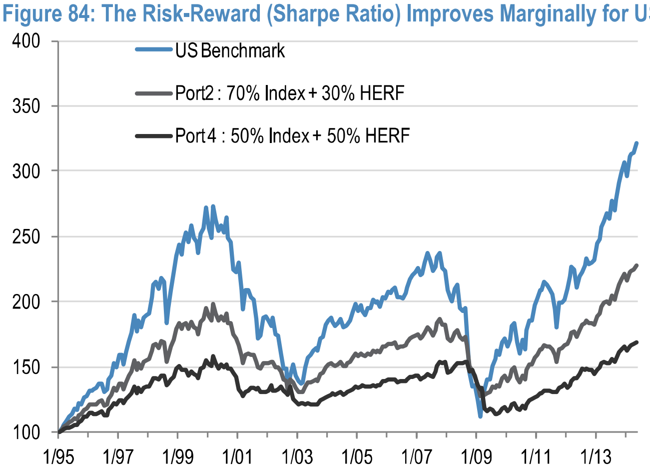
	US					Europe				
Portfolio	Sharpe Ratio	Ann. Return	Ann. Stdev	Hit Rate (%)	Max. Drawdn	Sharpe Ratio	Ann. Return	Ann. Stdev	Hit Rate (%)	Max. Drawdn
Benchmark (B)	0.47	7.3%	15.5%	63%	-59%	0.39	7.1%	18.2%	59%	-61%
HERF (H)`	-0.09	-1.4%	14.8%	51%	-56%	0.19	2.9%	15.2%	60%	-47%
Static B/H (90%/10%)	0.49	6.4%	13.1%	62%	-52%	0.43	6.7%	15.5%	61%	-54%
Static B/H (70%/30%)	0.52	4.7%	9.1%	61%	-35%	0.56	5.9%	10.5%	60%	-36%
Static B/H (60%/40%)	0.50	3.8%	7.6%	63%	-30%	0.63	5.5%	8.6%	61%	-28%
Static B/H (50%/50%)	0.42	3.0%	7.0%	63%	-28%	0.68	5.0%	7.4%	60%	-21%

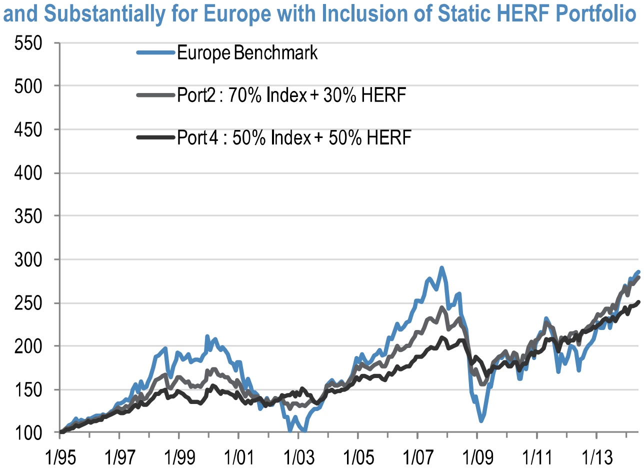
Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.
HERF is the Hedging Equity Risk Factors portfolio composed of Beta (1/6), Volatility (1/6), Momentum (1/3) and Debt-to-Equity (1/3).

Table 51 shows the benefit of a static hedge in improving the Sharpe ratio in Europe, and to a lesser degree in the US. There are few observations we can make: the annualized return of the hedged portfolio is less than the benchmark as the HERF return was below benchmark (in fact, the US HERF return is negative); the benefit of adding the HERF to the benchmark is in the reduced volatility of the combined portfolio due to the negative correlation between the two. For the US, the annualized benchmark volatility of 15.5% (zero weight for HERF) falls to less than half (7.0%) when 50% of the weight is allocated to the HERF. The drop in volatility is more dramatic for Europe where the volatility drops from 18.2% to 7.4%. In the US, the maximum Sharpe ratio (of the mixes considered above) is achieved at a lower HERF allocation (70%/30% mix), while in Europe the Sharpe continues rising to a maximum 0.68 at a 50%/50% mix.

Figure 84 shows the performance of $100 invested in the benchmark, 70%/30% and 50%/50% mixed portfolios. As discussed above, the volatility of the mixed static portfolios was much smaller than the benchmark and the drawdowns during major bear markets were lower. A comparison of the percentage drop in volatility and percentage reduction in drawdown suggests that the static hedge worked better in Europe compared to the US.

Figure 84: The Risk-Reward (Sharpe Ratio) Improves Marginally for US and Substantially for Europe with Inclusion of Static HERF Portfolio





Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.
Benchmarks are excess return MSCI US USD and MSCI Europe USD (benchmark return = total return less USD short-term interest rate, i.e. return from unfunded benchmark holdings).
`Hedging Equity Risk Factor (HERF) is an index based on weighted sum of long-short regional portfolio returns of Beta, Volatility, Momentum and Debt-to-Equity Factors.

Dynamic Hedge with a Switching Model

While the static hedges are able to reduce volatility of the combined portfolio without reducing the average return as much, they don't take advantage of the time-varying nature of the hedging portfolios and the benchmark. The HERF portfolio can be thought of as insurance that pays when the market declines, while requiring steady payment in normal times since its expected return is lower than the benchmark return.

A 90%/10% mix of benchmark/HERF portfolio would be appropriate for normal market environment, but if there is a substantial risk of market selloff, it may be sensible to switch to a 50%/50% mix. To implement a strategy that would switch between various HERF allocations, we look at a simple timing signal based on 3-month momentum of the HERF return. The switching rule is as follows:

If 3-month HERF return > 0, go long 50% benchmark and 50% HERF portfolio;
If 3-month HERF returns < 0, stay close to benchmark by going long 90% benchmark and 10% HERF.

The intuition is that the momentum of the Hedging Equity Risk Factor could act as a leading indicator of market direction. Other approaches like using the Price Momentum of the benchmark itself or crossover of the correlations of the benchmark and HERF also work, but we found HERF momentum to be a better, and a more consistent timing indicator.

Table 52 shows that when the strategy of switching between 90%/10% and 50%/50% allocations based on the sign of HERF momentum is followed in the US, there is a 53% improvement in the Sharpe ratio compared to that of the benchmark. Moreover, the Sharpe ratio more than doubles in Europe under this dynamic strategy (~126% higher than the benchmark's Sharpe). The improvement is also significant for a strategy that switches between 70%/30% and 50%/50% mixes, with 36% and 115% Sharpe ratio improvements in the US and Europe, respectively.

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Table 52: Two Variations of Dynamic Hedge – Considerable Improvement in Risk-Reward Profile Compared to the Benchmark

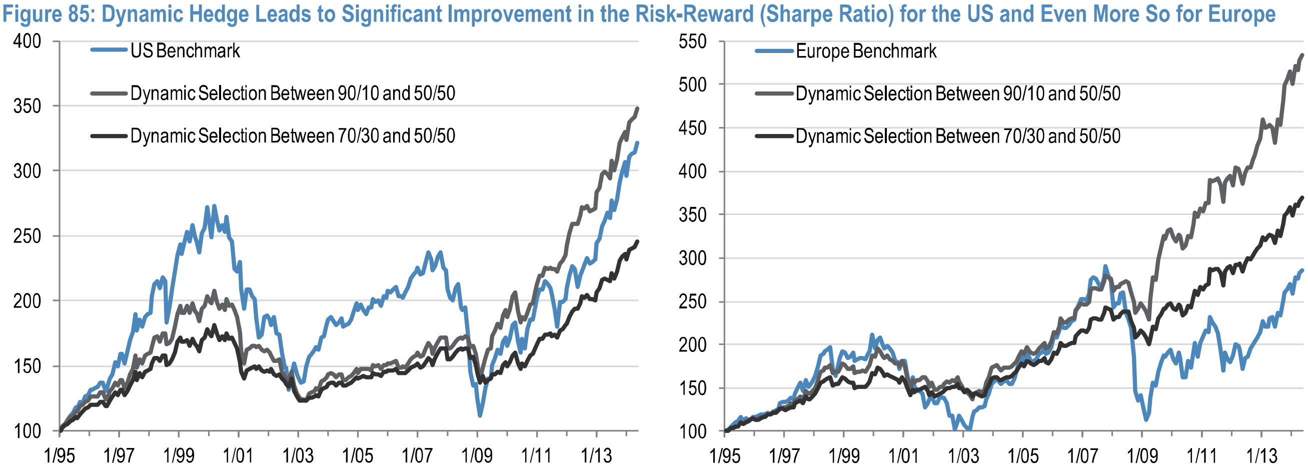
	US					Europe				
Portfolio	Sharpe Ratio	Ann. Return	Ann. Stdev	Hit Rate (%)	Max. Drawdn	Sharpe Ratio	Ann. Return	Ann. Stdev	Hit Rate (%)	Max. Drawdn
Benchmark	0.47	7.3%	15.5%	63%	-59%	0.39	7.1%	18.2%	59%	-61%
When 3-month momentum of Hedging Equity Risk Factor is Positive, then										
Switch from 90/10 to 50/50	0.72	6.9%	9.6%	65%	-41%	0.88	8.9%	10.0%	62%	-30%
Switch from 70/30 to 50/50	0.64	4.9%	7.6%	64%	-32%	0.84	6.9%	8.2%	63%	-19%

Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.
HERF is the Hedging Equity Risk Factors portfolio composed of Beta (1/6), Volatility (1/6), Momentum (1/3) and Debt-to-Equity (1/3).

Figure 85 shows the time series performance of the dynamically hedged portfolio strategy (90%/10% to 50%/50%). For the US, the hedging strategy was less successful in the aftermath of the Tech bubble (March 2000 to September 2002). While the US benchmark declined 52% during this episode, the dynamically hedged portfolios fell 26% (for 70/30 to 50/50 strategy) and 33% (for 90/10 to 50/50 strategy). The decline in the hedged portfolios was about in line with their volatility relative to the benchmark. However, during the Financial Crisis bear market (May 2007 to February 2009) the benchmark fell 53% while the hedged portfolios fell just 13% and 17%.

In Europe, the dynamically hedged portfolio delivered protection in both bear markets. The European benchmark fell 51% after the Tech bubble burst, while the hedged portfolios fell just 12% (70/30) and 17% (90/10). During the Financial Crisis, the benchmark fell 59% while the hedged portfolios fell just 9% and 10%, respectively.

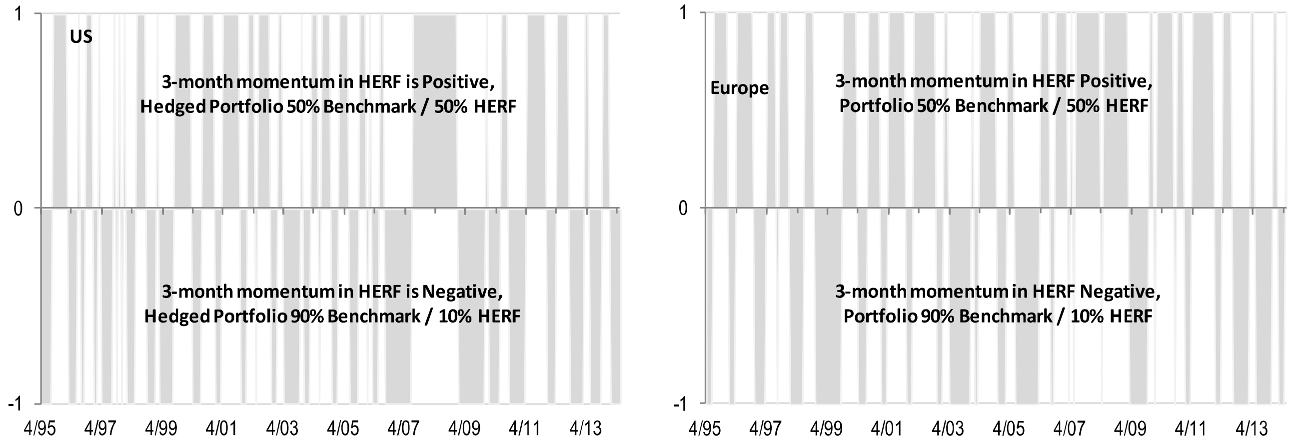
Figure 85: Dynamic Hedge Leads to Significant Improvement in the Risk-Reward (Sharpe Ratio) for the US and Even More So for Europe



Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.

Next we analyze the switching signal which shifts the portfolio from the benchmark to the HERF. It is important that the switching rule is not narrowly episodic, i.e. that it works only in one or two major crises. Figure 86 shows that a 3-month momentum rule is fairly dynamic. In the US, the strategy tilts towards the benchmark 54% of the months versus 46% of the months towards hedging. In Europe, the strategy's tilt towards the benchmark is 46% while 54% of the months are tilted towards hedging. On average, the duration of tilts is 4 to 5 months.

Figure 86: Switching Signal – Get away from Benchmark (use a 50%/50% Mix) when 3-month Return Momentum of the HERF is positive



Source: J.P. Morgan Quantitative and Derivatives Strategy.
`Hedging Equity Risk Factor (HERF) is an index based on weighted sum of long-short regional portfolio returns of Beta, Volatility, Momentum and Debt-to-Equity Factors.

In conclusion, we have shown that selected Risk Factors can be used as equity market hedges. The static hedge example offers significant protection during market downturns while incurring a reasonable cost, in our view. Dynamically hedging the portfolio based on the hedging factor momentum can add further value.

Hedging a Custom Portfolio

Risk factors can also be used to hedge a custom equity portfolio that does not resemble a broad equity benchmark. In the previous example of dynamic factor hedging, the switching signal relied on the momentum of hedging factors. In other words, when the HERF factors had positive momentum, we increased allocation to HERF, and when they had negative momentum we decreased its allocation. We will rely on the same concept of factor momentum in our custom hedging approach.

One can analyze the custom portfolio by attributing portfolio performance to a comprehensive set of factors. For instance, one can regress portfolio returns against 13 Risk Factors belonging to the Value, Momentum, Quality, Growth and Volatility styles (introduced in the second chapter). If the performance of the portfolio is suffering because of negative contribution from a group of factors, investors can decide to hedge out these factor exposures. The premise is that factors often show trending behavior and performance drag due to a specific factor may persist.

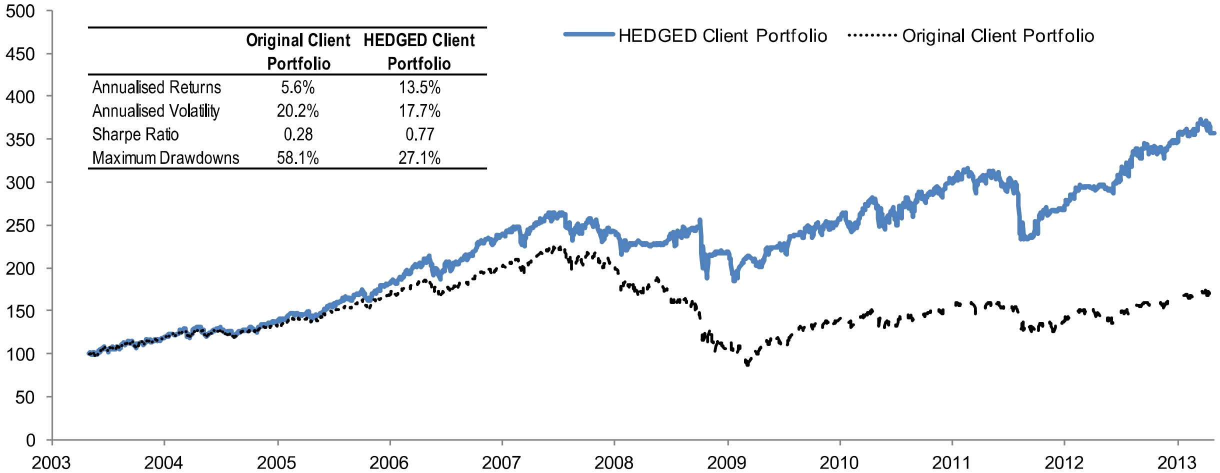
For example, if the portfolio has an exposure to the Dividend Yield factor, and Dividend Yield had a recent negative performance, an investor can short the Dividend Yield factor to prevent a negative impact of the factor trend.

A simple prescription for this hedging approach would be to regress the portfolio against the 13 Risk Factors every month (e.g. by using 60-day regression, calculate the portfolio beta to each of the factors). One then identifies, for example, 5 Factors that had the highest negative contribution to the portfolio returns over the past month (note these may be long or short factor exposures). Under the assumption that factor performance over the past month will persist (trend) in the next month, the investor can hedge out the portfolio's exposure to these 5 factors.

The example below illustrates this custom hedging approach. We have used a sample investor portfolio and calculated factor exposures by using our in-house Portfolio Analyzer (for detailed description of this tool see The Equity Risk Studio – Introducing the J.P. Morgan Risk Platform).

Figure 87 below shows the performance of sample investor portfolio, as well as a portfolio that is hedged by the above outlined prescription.

Figure 87: Example of Hedging a Custom Portfolio by Using Risk Factors

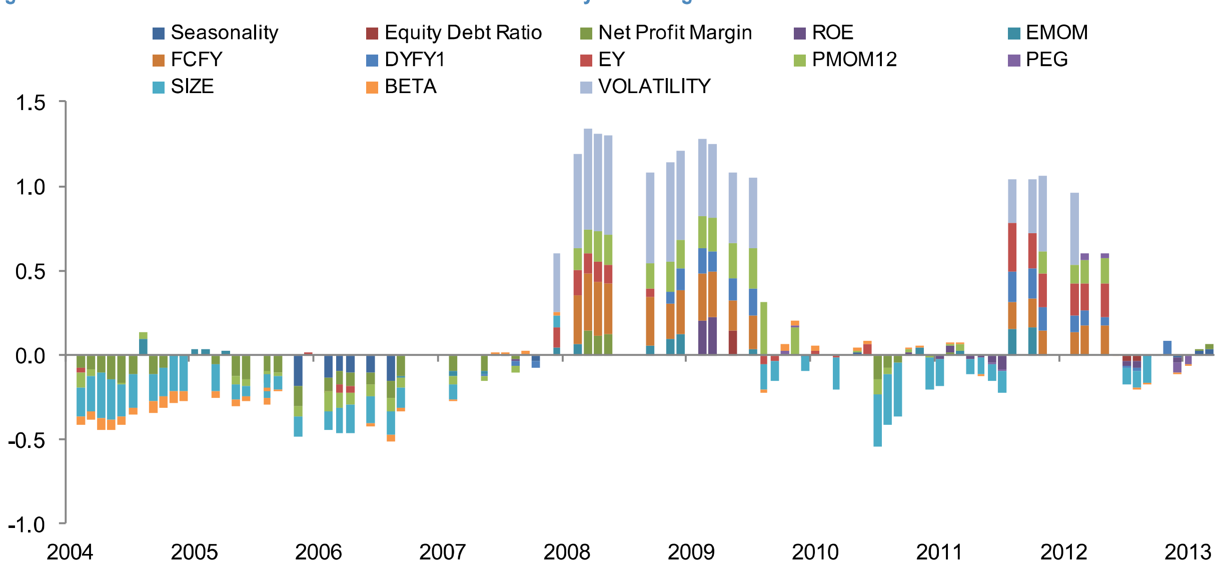


Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, Bloomberg, IBES. Past performance is not indicative of future returns.

As the figure shows, hedging the Risk Factors with negative return contributors significantly improved the portfolio's returns and reduced its risk. Specifically, the portfolio Sharpe Ratio increased from 0.28 to 0.77 and the maximum drawdown was reduced by ~50%.

To more closely examine how the factor hedging worked, below we show the factor composition of monthly hedges. Figure 88 shows the number of Risk Factors as well as factor weights (positive or negative) employed. One can note that hedges are required 60% of the time, and that the turnover of factors is not very high. The table shows the percentage of time a particular Risk Factor is used as a Hedge.

Figure 88: Number and Amount of Risk Factors Used Historically as a Hedge



Factor Name	Seasonality	Debt/ Equity	Net PM	ROE	Earnings MoM	FCF Yield	Dividend Yield	Earnings Yield	12M Price MoM	PEG ratio	Small Size	Low Beta	Low Volatility
% of Time Picked as Hedge	5%	1%	12%	5%	8%	4%	6%	8%	13%	4%	15%	16%	4%

Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, Bloomberg, IBES.

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Active Factor Allocations

In the previous section we discussed static (fixed-weight) factor models as well as portfolio construction methods with dynamic factor weights. These portfolio construction methodologies used historical covariance to design an optimal risky portfolio (e.g. Risk Parity, Equal Marginal Volatility, etc.).[54] In recent years, there has been increased interest in dynamic factor models. These models use various signals to time factor performance cycles (also referred to as factor switching, factor rotation, or active models). The timing signal can be based on historical price patterns (implying the existence of factor momentum and/or reversion), valuation of factors (e.g. assessing if the factor is currently 'cheap' or 'rich') or macro variables such as inflation, growth, liquidity, correlation levels, etc.

In this section we illustrate the concepts of active, signal-based factor rotation using 3 relatively simple models:

1. Using factor Momentum to select factor weights;
2. Factor of Factors approach – specifically using Value and Momentum to rank and select Factors;
3. Macro Factor Rotation – using macro variables to forecast factor performance.

Factor Momentum Approach

Factor performance often reflects macroeconomic trends and patterns of investor behavior. These trends can persist over extended time periods and hence one can expect factors to develop Price Momentum. For instance, falling interest rates may create demand for high-yielding stocks and the cyclical outperformance of the Dividend Yield factor over several quarters. Strong macroeconomic growth and positive feedback between the economy and stock market may lead to persistent outperformance of the Price Momentum factor. Given the macro nature of factor cycles, one would expect the existence of factor momentum that can be captured in a dynamic factor rotation model.

In one of our previous reports, we investigated a multi-factor model that used factor price performance to allocate factor weights (Dynamic Factor Rotation – Using Momentum and Price Overreaction). Here we will test the effectiveness of Price Momentum for the selection of global factors/factor styles. Specifically, we test whether dynamically allocating to Equity Risk Factors ranked by Price Momentum could lead to meaningful enhancement of risk-adjusted returns. Given that long/short Risk Factors displayed the most dispersion within different regions (see Figure 41 on page 60), we first test the momentum-based factor rotation strategies in each region. We also illustrate an example of a Global Risk Factor rotation strategy by combining regional factor momentum strategies.

There are various ways to implement a Factor Momentum strategy. For instance, the Mean-Variance Optimized (MVO) portfolio method often uses past price returns as future expected returns. MVO could be regarded as a special case of a Factor Momentum strategy combined with risk optimization (see the section 'Portfolio of Global Factor Styles' on page 71 for more analysis). A more direct factor momentum approach is to rank a set of Risk Factors by past price returns (e.g. at every month-end) and invest in a specified number of the top-ranked factors. To see how this simplified factor momentum strategy worked in different regions, we report below the returns (Table 53) and Sharpe ratios (Table 54) based on the number of top-ranked factors selected (K) as well as several momentum metrics used to rank the factors. Momentum metrics are based on the number of months over which we calculate the factor Price Momentum (denoted as N).

Using the equally weighted regional Risk Factor portfolio (K = 13) as a benchmark, we find that a factor-rotation strategy based on Price Momentum generates a higher return with all combinations of N (momentum window size) and K < 13 (number of top-performing factors). For instance, an equally weighted long/short Equity Risk Factor strategy in Europe has an average annualized return of +4.3%, whereas a factor rotation strategy based on the past 1-month return and selecting the top-6 performing factors could more than double the return to +9.8%. As the percentage increase in return is more than the increase in strategy volatility, the strategy Sharpe ratio improved from 0.63 (equal weight) to 1.0 (factor momentum).

[54] In addition to covariance, MVO is using recent price return as a forecast of future return (thus relying on momentum as a timing signal).

Table 53: Annualized Returns (%) for Factor Rotation Strategies Based on *N*-Month Price Momentum and *K* Top-Performing Factors

United States:

Number of Risk Factors (*K*)	Top Risk Factors Based on *N*-mth Momentum: 1	2	3	4	5	6	9	12
1	**14.0**	**5.8**	1.4	4.6	**6.4**	**6.0**	3.1	4.9
2	**9.3**	**6.0**	4.9	**7.2**	3.7	4.5	3.0	3.1
3	**7.9**	3.9	**5.6**	**6.1**	3.9	4.2	3.0	2.0
4	**6.0**	3.4	**5.6**	**6.0**	3.3	2.6	2.7	1.7
5	**5.6**	2.8	4.1	4.6	3.4	2.1	2.6	2.3
6	4.9	2.5	3.2	3.3	3.2	2.1	2.2	1.8
9	3.0	1.4	2.6	2.4	2.6	2.5	2.1	1.9
13	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2

Europe:

Number of Risk Factors (*K*)	Top Risk Factors Based on *N*-mth Momentum: 1	2	3	4	5	6	9	12
1	**14.9**	**10.5**	**10.1**	**12.5**	6.5	7.3	**11.9**	**14.0**
2	**11.2**	**10.3**	**9.1**	**8.2**	**8.1**	7.6	7.5	**11.3**
3	**9.9**	**8.6**	7.4	7.8	7.6	7.7	**8.7**	**9.2**
4	**10.1**	**8.0**	7.3	7.8	**9.0**	7.8	**8.9**	**8.8**
5	**9.8**	7.1	7.3	7.8	**8.2**	**8.2**	7.8	7.3
6	**9.8**	7.3	7.4	6.7	6.8	7.2	6.9	6.0
9	7.5	7.0	6.6	5.9	6.3	6.0	5.3	5.2
13	4.3	4.3	4.3	4.3	4.3	4.3	4.3	4.3

Japan:

Number of Risk Factors (*K*)	Top Risk Factors Based on *N*-mth Momentum: 1	2	3	4	5	6	9	12
1	-1.1	**7.6**	**6.6**	5.0	**6.3**	4.4	4.2	2.1
2	2.2	**7.1**	**7.6**	**6.8**	**6.3**	3.7	3.8	2.7
3	2.9	**6.0**	**6.1**	**6.7**	4.8	3.0	3.5	4.7
4	3.1	**6.0**	**6.2**	**5.5**	4.8	3.7	4.2	3.8
5	3.3	**7.0**	**5.6**	4.8	3.8	3.9	4.3	4.0
6	3.7	**6.3**	**6.2**	4.9	4.4	4.4	4.4	4.4
9	2.7	4.9	4.7	4.8	4.6	4.2	3.9	3.8
13	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4

Asia ex-Japan:

Number of Risk Factors (*K*)	Top Risk Factors Based on *N*-mth Momentum: 1	2	3	4	5	6	9	12
1	**20.8**	**17.2**	**16.7**	**12.6**	10.9	**13.2**	**16.8**	**17.2**
2	**18.0**	**16.6**	**16.7**	11.9	**12.3**	11.6	**14.6**	**14.0**
3	**14.8**	**13.4**	**16.0**	11.1	9.7	10.8	11.9	**12.8**
4	**12.9**	**13.4**	**12.8**	11.5	9.6	10.3	**12.4**	**12.9**
5	11.7	**12.3**	**12.6**	9.7	9.7	9.9	10.9	11.5
6	11.7	11.6	10.8	9.8	8.4	8.4	10.5	9.9
9	8.5	8.3	8.5	8.2	7.5	7.4	7.8	7.8
13	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Intuitively, the larger the N (momentum window size) is, the more stable the momentum signals, leading to less frequent factor portfolio turnover. Meanwhile, larger K (number of selected factors) values correspond to more factor diversification. On the other hand, a factor momentum strategy with large N could respond in a less timely manner to regime switches and large K values could dilute the factor momentum signal. As a result, there is generally a balance in the selection of the parameter pair (N, K) for a factor momentum strategy, and the selection could be region-specific.

From Table 54, one can observe that a 1-month momentum strategy generally worked well in the US and Europe, while Asia (including Japan) seems to favor a momentum window size of 2-3 and 9-12 months. For instance, a strategy that selected the 2 top-performing US factors based on the previous month's returns could generate a Sharpe ratio of 0.68 during January 1996 to June 2014, almost quadrupling that of an equally weighted US Equity Risk Factor strategy (0.19). On the other hand, a sector rotation strategy that selected the 3 top-performing Asia (ex-Japan) factors based on past 3-month returns could generate a Sharpe ratio of 1.03.

Table 54: Sharpe Ratios for Factor Rotation Strategies Based on *N*-Month Price Momentum and *K* Top-Performing Factors

United States:

Number of Risk Factors (*K*)	Top Risk Factors Based on *N*-mth Momentum: 1	2	3	4	5	6	9	12
1	**0.91**	0.35	0.08	0.26	0.36	0.33	0.17	0.30
2	**0.68**	0.42	0.35	**0.52**	0.25	0.30	0.19	0.20
3	**0.70**	0.31	0.46	0.48	0.31	0.33	0.22	0.16
4	**0.56**	0.29	**0.50**	**0.54**	0.28	0.21	0.22	0.15
5	**0.59**	0.27	0.41	0.45	0.31	0.19	0.23	0.21
6	**0.55**	0.24	0.35	0.36	0.32	0.20	0.22	0.16
9	0.41	0.15	0.34	0.31	0.33	0.30	0.25	0.23
13	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19

Europe:

Number of Risk Factors (*K*)	Top Risk Factors Based on *N*-mth Momentum: 1	2	3	4	5	6	9	12
1	**0.82**	0.58	0.52	0.66	0.33	0.39	0.59	0.67
2	0.79	0.68	0.59	0.53	0.53	0.49	0.44	0.73
3	0.76	0.60	0.52	0.53	0.56	0.59	0.65	0.65
4	**0.88**	0.62	0.55	0.60	0.75	0.64	0.70	0.71
5	**0.92**	0.59	0.64	0.65	0.71	0.71	0.67	0.62
6	**1.00**	0.68	0.72	0.63	0.66	0.68	0.64	0.55
9	**0.90**	**0.83**	**0.80**	0.71	0.72	0.70	0.59	0.56
13	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63

Japan:

Number of Risk Factors (*K*)	Top Risk Factors Based on *N*-mth Momentum: 1	2	3	4	5	6	9	12
1	-0.05	0.36	0.36	0.22	0.28	0.21	0.20	0.11
2	0.12	0.40	0.46	0.41	0.34	0.21	0.25	0.18
3	0.19	0.40	0.40	0.43	0.31	0.20	0.24	0.33
4	0.23	0.45	0.46	0.39	0.35	0.28	0.32	0.30
5	0.28	**0.57**	0.46	0.37	0.31	0.32	0.36	0.35
6	0.34	**0.58**	**0.59**	0.42	0.40	0.40	0.41	0.41
9	0.31	**0.56**	**0.54**	**0.54**	**0.51**	0.48	0.46	0.46
13	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37

Asia ex-Japan:

Number of Risk Factors (*K*)	Top Risk Factors Based on *N*-mth Momentum: 1	2	3	4	5	6	9	12
1	0.92	0.79	0.71	0.53	0.48	0.60	0.75	0.75
2	0.99	**1.00**	0.98	0.65	0.65	0.67	0.83	0.79
3	1.00	0.92	**1.03**	0.71	0.62	0.75	0.77	0.92
4	0.91	**1.03**	0.90	0.80	0.70	0.82	0.91	**1.05**
5	0.91	**1.03**	0.98	0.78	0.80	0.89	0.96	**1.07**
6	**1.05**	**1.08**	0.94	0.86	0.78	0.81	**1.02**	**1.01**
9	0.93	0.91	0.91	0.90	0.84	0.86	0.93	0.96
13	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93

Source: J.P. Morgan Quantitative and Derivatives Strategy.

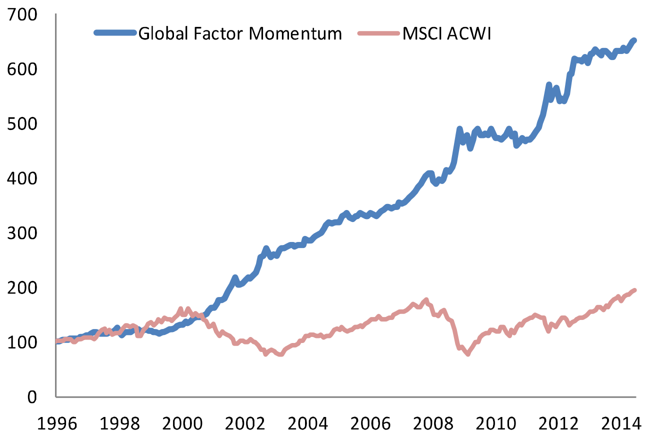
While regional factor momentum strategies displayed favorable risk/reward profiles compared with regional equity indices and equally weighted factor portfolios, they still suffered from relatively large drawdowns. To illustrate a further cross-regional diversification benefit, we selected representative strategies in each region (specific pairs of *N*, *K*) [55] and created a **global factor momentum strategy** by assigning equal weights to each regional strategy. Figure 89 shows the performance of such a strategy, which we note outperformed MSCI All-Country World over the past two decades.

Table 55 reports performance/risk statistics for regional factor momentum strategies and the equally weighted global composite. From the table, we find the global factor momentum strategy delivered +10.7% excess returns per annum with 8.1% annualized return volatility (translating to a Sharpe ratio of 1.3) and a -9.9% maximum drawdown. This attractive risk-reward profile could qualify it as an absolute return strategy for global investors. The strategy had a -46% correlation with the MSCI All-Country World index, suggesting it could be potentially used as an effective portfolio overlay/hedge[56] for long-only global equity investors.

[55] Specifically, we used (*N*, *K*) = (1, 2) in the US, (*N*, *K*) = (1, 6) in Europe, (*N*, *K*) = (2, 5) in Japan and (*N*, *K*) = (3, 3) in Asia ex-Japan. To minimize hindsight bias, we didn't select the ex-post best-performing pairs (*N*, *K*) within each region. Selecting (*N*, *K*) = (1, 1) in the US instead of (1, 2) in our base case, for instance, could further improve the return and Sharpe ratio of a regional equal-weighted factor rotation strategy to +11.7% per annum and 1.41, respectively (from +10.7% per annum and 1.30).

[56] Also see the section on 'Hedging with Risk Factors' on page 94 for more examples and illustrations of portfolio hedging applications of our regional Equity Risk Factors.

Figure 89: Performance of Global Factor Momentum Strategy vs MSCI All-Country World Index (ACWI)



Source: J.P. Morgan Quantitative and Derivatives Strategy.
* MSCI ACWI is US$ excess return index after deducting US$ cash return from total returns.

Table 55: Performance/Risk of Regional Factor Momentum Strategies and an Equally Weighted Global Composite

	US (1, 2)	Europe (1, 6)	Japan (2, 5)	Asia (3, 3)	Global
Ann. Ex Ret (%)	9.3	9.8	7.0	16.0	10.5
CAGR (%)	8.7	9.7	6.4	15.8	10.7
STDev (%)	13.7	9.8	12.1	15.5	8.1
MaxDD (%)	-22.4	-13.6	-35.8	-25.2	-9.9
MaxDDur (in yrs)	2.8	2.8	3.7	1.5	1.8
***t*-Statistic**	**2.9**	**4.3**	**2.5**	**4.4**	**5.6**
Sharpe Ratio	**0.68**	**0.99**	**0.57**	**1.03**	**1.30**
Hit Rate (%)	57.2	66.7	61.3	66.7	68.5
Skewness	-0.15	-0.17	-2.37	-0.48	-0.38
Kurtosis	2.31	3.46	20.50	4.06	2.16
Correl w/ ACWI	-31.6	-49.7	-22.3	-18.6	-45.9

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* MSCI ACWI is US$ excess return index after deducting US$ cash return from total returns.
** Regional Factor Momentum Strategies are denoted by 'Region (*N*, *K*)'. For instance, US (1,2) stands for a US Equity Risk Factor Momentum Strategies selecting 2 top-performing factors based on past 1-month returns.

Factor of Factors Approach

One can generalize a momentum approach, by using any factor or multiple factors to rank the performance of all other factors. This is called a 'Factor of Factors' approach (the momentum example is a specific case in which we selected one factor – momentum – to rotate between factors). A simple illustration of the Factor of Factors approach presented below is the Value and Momentum model. This model ranks factors according to Value and Momentum, averages the ranking and score and selects the factors with the highest combined rank. The Valuation and Momentum signals could be generated either by aggregating momentum and value scores from a stock level to a factor level (bottom-up) or by assessing Value and Momentum directly from the performance of the factor time series (top-down).

We can illustrate a direct (bottom-up) approach, with an example of a Value and Momentum model. For the Value signal we used Price to Book, and we used the average of total returns over 1, 3, 6 and 12 months as the Momentum signal. First, we calculate the average stock P/B in each of the factors. Once the P/B of each Risk Factor is calculated, we assign a P/B Z-Score to each of the factors. [57] The next step is to compute Price Momentum for each factor, and compute the Factors' Momentum Z-Score. Finally, we select a number of factors N (e.g. 1, 2, 3, 4, etc.) with the highest combined Z-Score. The process is repeated every month-end to select a Factor on Factor portfolio. Table 56 shows the Sharpe ratio for the Value and Momentum model where the portfolio consists of the top N = 1, 2, 3, and 4 ranked European Equity Risk Factors.

[57] To do so, we simply used a Z-Score methodology by applying the following to every Risk Factor:

$$\frac{\text{PB of a Risk Factor} - \text{average PB of all Risk Factors}}{\text{the standard deviation of PB}\quad\text{s for all Risk Factors}}$$

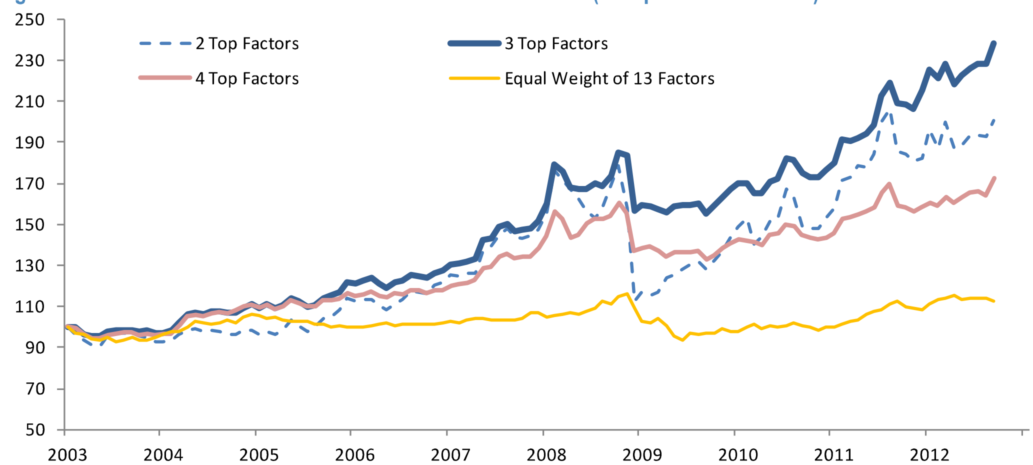
Table 56: Value- and Momentum-Based Factor Selection – Statistics

	Selecting Top: 1 Factor	2 Factors	3 Factors	4 Factors	Equal Weight of 13 Risk Factors
Annualized Return	10.2%	7.5%	9.5%	5.9%	1.2%
Annualized Volatility	25.1%	16.3%	10.1%	8.3%	5.7%
Sharpe Ratio	**0.41**	**0.46**	**0.94**	**0.70**	**0.21**
Max Drawdown	-58%	-37%	-16%	-17%	-19%

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Stats are calculated during May 2003 to December 2012. Past performance is not indicative of future returns.

Figure 90 shows the performance of this Factor on Factor model. From the figure (as well as Table 56) we can see that selecting the top factors ranked by a combined value and momentum score can significantly outperform an equally weighted benchmark of all factors.

Figure 90: Value and Momentum Factor on Factor Performance (European Risk Factors)



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, Bloomberg, IBES. Past performance is not indicative of future returns.

Another implementation of Factor of Factors is to directly look at factor-level performance/risk statistics to derive valuation and momentum scores. It is straightforward to define a momentum score based on the factor performance time series. However, it is not possible to define P/B Value based on a factor performance time series, so we use reversion to define the time series based Value measure. Specifically, we first define the factor's 'fair value' by extrapolating the average factor monthly performance (e.g. over the past 5 years). This can be done by running a 60-month regression of the factor index level versus number of months passed.[58] After deriving the fair factor value at each month-end rebalance date, we define the factor valuation Z-score as a spread between the factor's fair value and the current factor value divided by the trailing 60-month factor volatility:

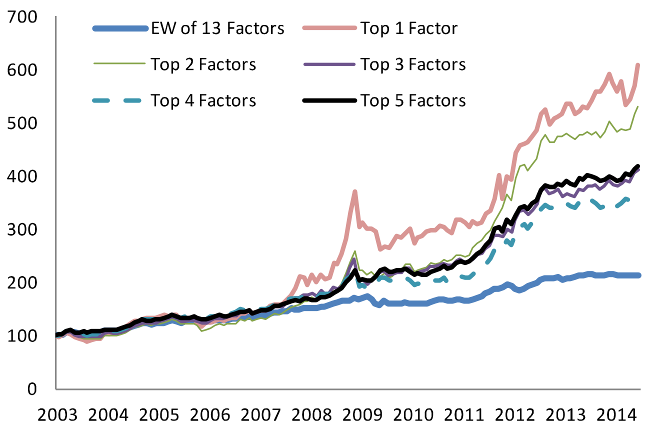
$$\text{Risk Factor Valuation Score} = \frac{\text{Regression Fair Value} - \text{Current Index Value}}{\text{Standard Deviation of Factor Returns}}$$

A Momentum/Value factor on factor approach then averages the factor momentum and valuation Z-scores, and takes a long position in the top-*N* ranked Factors. Figure 91 below shows the historical performance of this model for different values of *N* in Asia ex-Japan, and Table 57 presents related performance/risk metrics.

[58] For instance, the index is 1 as of 59 months ago, and is 60 as of current rebalancing. This rolling regression exercise is similar to the estimation of EPS trends or GDP trends in macroeconomic analysis. Strictly speaking, one should run a non-linear regression and include market/macro variables to better incorporate non-normality of Risk Factor returns and inter-market correlations.

We find that the strategy risk (volatility and max drawdown) decreases as N and portfolio diversification increase. The reduction in strategy volatility is larger than the reduction in returns, so the Sharpe ratio increases with N as well. While an aggressive strategy that selects only the top ranked factor ($N = 1$) generates a high return of +17.0% per annum (compared with a return of +6.8% per annum for the equally weighted Risk Factor strategy), it also led to significant volatility (17.2%) and a large drawdown (-29.2%). A strategy that selects the top-5 Risk Factors generated strong returns (+13.3%), low volatility (8%) and a mild drawdown (-8.8%).

Figure 91: Performance of Momentum/Value Models on Asia (ex-Japan) Risk Factors and Equally Weighted Risk Factor Benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy.
Past performance is not indicative of future returns.

Table 57: Performance/Risk of Factor on Factor Models on Asia (ex-Japan) Risk Factors by Selecting Top-N Factors (Equal Weight)

	Top 1 Factor	Top 2 Factors	Top 3 Factors	Top 4 Factors	Top 5 Factors
Ann. Ex Ret (%)	17.2	15.4	13.0	11.9	12.8
CAGR (%)	17.0	15.6	13.1	12.1	13.3
STDev (%)	17.2	12.5	10.6	9.4	8.0
MaxDD (%)	-29.2	-20.0	-19.2	-15.8	-8.8
MaxDDur (in yrs)	2.8	2.3	2.3	2.4	1.1
***t*-Statistic**	**3.4**	**4.2**	**4.2**	**4.3**	**5.4**
Sharpe Ratio	**1.01**	**1.23**	**1.23**	**1.27**	**1.60**
Hit Rate (%)	66.7	68.8	69.6	68.1	67.4
Skewness	-0.03	-0.39	-1.20	-1.01	-0.21
Kurtosis	2.28	3.03	7.59	6.80	1.81

Source: J.P. Morgan Quantitative and Derivatives Strategy.
Past performance is not indicative of future returns.

Macro Factor Rotation

Macro regimes such as inflation, economic growth, market volatility and liquidity often influence factor performance cycles (e.g. see Cross-Asset Risk Factors as well first chapter of this report). As macro environments tend to persist, investors can create factor rotation models that select factors based on macro regimes. In addition to regime persistence, investors can take advantage of potential lead/lag relationships between regimes and factor performance. In our previous research we have investigated several macro regime models. Below we discuss one specific model that has exhibited solid performance in the Asia-Pacific region.

In our first report on the macroeconomic effects on factors[59], we classified historical periods according to the 'state' (rising/falling, high/low, etc.) of the different macro time series (such as market indices, oil, gold, interest rates, currencies, etc.). We then identified which stock selection styles/factors investors preferred (or avoided) during these states historically. In our second report[60], we took this analysis one step further and developed a dynamic stock selection model that uses 'macro-driven' factor rotation.

The factor study was partitioned using the states of the following 14 macroeconomic or market time series:

- MSCI Index levels
- Market Volumes
- Asian Dollar Index
- TED Spread
- US Yield Curve
- Copper Prices
- Crude Oil to Gold Price Ratio
- US Federal Funds Rate
- Global Manufacturing Index (normalized by Inventory levels)
- VIX Index Levels
- Value Spreads (using Price to Book quartile aggregates)
- Market Dividend Yield Levels
- US 10-Year Bond Yield
- Baltic Dry Index

Each macro series above was classified into six potential states: Rising/Falling, High/Low and Post-Peak/Post-Trough. For each defined macro variable state we determined which factors performed the best (or worst). We summarized the results into a general 'rulebook' of factors to use (or avoid) during each of these macro states.

We found strong evidence that macro states have an impact on future factor performance. In particular, we believe that there is a strong link between macro states and *risk appetite,* and one conclusion is to classify factors as *defensive* or *aggressive*. When investors are confident and bullish, the factors that worked better were more *forward*-looking or *growth*-related factors with implicit leverage to the economic positive outlook. When investors are unsettled or bearish, we observe they tended to favor factors that offer downside market protection. This distinction between factor performance in risk-embracing and risk-averse market conditions is clearly evident in our rulebook.

Factors that generally did better in **defensive** or **risk-averse** environments were Forecast P/E relative to history (3 years), Historical Earnings Yield to P/E, Historical Dividend Yield, and ROE/ROA. Meanwhile, factors that tended to work better in **aggressive** or **risk-embracing** environments were Price to Book, Forecast Earnings Yield to P/E, Forward Earnings Momentum (3-month change), Historical Beta, Price Acceleration (6 month), Price Momentum (12 month), High Volatility and Small Caps.

The investigation up to this point had the benefit of hindsight when identifying when an environment state occurs (look-ahead bias), and it did not address the key question of what the macro state is currently. In our second report we developed a more 'tradable' macro regime model. To do so required a methodology for identifying 'tradable states' i.e. states that are identified by only using backward-looking information. For example, we used a 'rolling 12-month peak followed by two down months' to identify a falling state; and we defined months as 'high' or 'low' when the macro series breached its high or low Bollinger band, respectively. (Please see the full report for more details.)

[59] Measuring the Macro Impact on Factor Performance : A 'Rulebook' for choosing Factors in different macro environments
[60] Style timing using Macro Indicators: Testing a dynamic factor approach driven by macro environment signals

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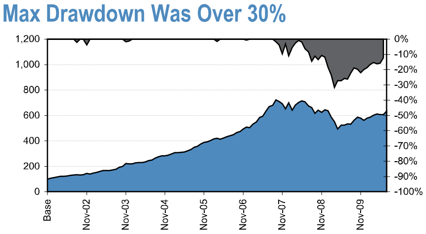
By considering each macro series and making a prediction as to which state it was in, we were able to form an overall ‘state table’ for every month. While we expect some states may give ‘false starts’ or incorrect signals, the number of macro series being used is relatively large and on average there should be some benefit from the breadth of this signal – an example of an ‘ensemble method’ (in which a set of weak signals is combined to form a strong one).

To test the idea of rotating factors according to a ‘rulebook’, we split the data and created an *in-sample* ‘rulebook’ using data from 1993 to 2001. Then every macro indicator/state employed this rulebook *out-of-sample* (i.e. after 2001). With this broad set of inputs being considered we needed a method to rationalize all of these factor suggestions which we did using a ‘voting booth’ approach. Every time a macro variable’s state was estimated, the most appropriate factor for that state (from the ‘rulebook’) was given one vote. Each factor can be ‘voted’ for multiple times by any macro variable that considered it the most effective for its current state. The top four voted factors were used to build a stock-selection model that we call our Macro Factor Rotation (MFR) model.

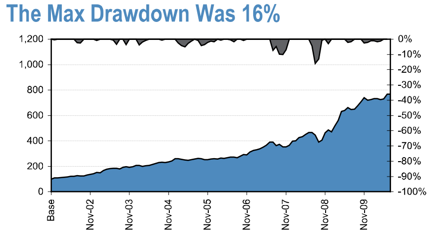
When backtesting the MFR model during the out-of-sample period we saw a marked improvement in the model’s handling of the ‘macro years’ – the period after 2007 when typical models struggled. Our Q-Score is one such ‘typical’ model – using static factors and weights at all times. By being able to dynamically move to more defensive and offensive factors the MFR Model did much better. Finally, in combination with the Q-Score the performance was better than either approach alone.

Figure 92: Our Q-Score in MSCI AxJ – The Max Drawdown Was Over 30%



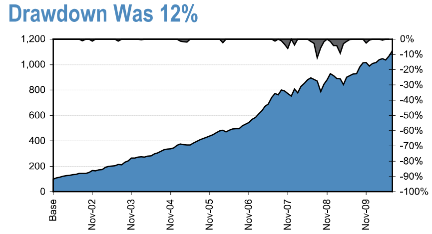
Source: J.P. Morgan Quantitative and Derivatives Strategy MSCI, Thomson Reuters.

Figure 93: The Macro Factor Rotation Model– The Max Drawdown Was 16%



Source: J.P. Morgan Quantitative and Derivatives Strategy MSCI, Thomson Reuters.

Figure 94: Combined 50:50 Model– The Max Drawdown Was 12%



Source: J.P. Morgan Quantitative and Derivatives Strategy MSCI, Thomson Reuters.

In conclusion there is evidence that different factors can be more or less relevant during certain macro regimes and we see these regimes being strongly influenced by investor risk appetites – classifying them as either *risk-embracing* or *risk-averse*. A broad set of macro ‘states’ can then be used to select factors better suited for the current risk appetite. Finally, if the risk appetite can be at all predicted (which we called the ‘tradable’ states) then there is further evidence that rotating between the appropriate factors can improve a quantitative factor model.

Appendices

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J.P. Morgan Investable ERP Indices

Our Structuring Desks around the globe created a suite of investable Equity Risk Premia (ERP) indices for the US, Europe, Japan and Asia ex-Japan regions. The design of individual investable ERP indices with a certain region/style mix are based on our discussion of regional Risk Factor styles in Chapter 2 of this report. In addition, a customized portfolio can be created on the back of these regional Risk Factors (see for instance our discussion of EMV portfolio of European Risk Factors on page 79). The table below lists Bloomberg tickers[61] along with the names of investable Equity Risk Premia Indices created.

J.P. Morgan US ERP Investable Indices					
Long/Short Tickers	**Long-Only Tickers**	**Factor Name**	**Factor Style**	**Region**	**Currency**
RPJPFYUT	QTJPFLUT	Free Cash Flow Yield	Value	U.S.	USD
RPJPFIUT	QTJPILUT	Free Cash Flow / Invested Capital	Value	U.S.	USD
RPJPFDUT	QTJPWLUT	Forward Dividend Yield	Value	U.S.	USD
RPJPFEUT	QTJPPLUT	Forward Earnings Yield	Value	U.S.	USD
RPJPDVUT	QTJPDLUT	Dividend Yield	Value	U.S.	USD
RPJPFTUT	QTJPYLUT	Free Cash Flow / Invested Capital Trend	Growth	U.S.	USD
RPJPNTUT	QTJPALUT	Net Operating Asset Trend	Growth	U.S.	USD
RPJPMTUT	QTJPMLUT	Price Momentum	Momentum	U.S.	USD
RPJPXMUT	QTJPXLUT	Extended Price Momentum	Momentum	U.S.	USD
RPJPREUT	QTJPELUT	ROE	Quality	U.S.	USD
RPJPVLUT	QTJPVLUT	Low Volatility	Volatility	U.S.	USD
RPJPSZUT	QTJPZLUT	Size	Volatility	U.S.	USD
RPJPSSUT	QTJPSLUT	Seasonality	Volatility	U.S.	USD
RPJPSTUT	QTJPTLUT	Short Interest Trend	Other	U.S.	USD
RPJPRTUT	QTJPRLUT	Short Interest Ratio Trend	Other	U.S.	USD

J.P. Morgan European ERP Investable Indices					
Long/Short Tickers	**Long-Only Tickers**	**Factor Name**	**Factor Style**	**Region**	**Currency**
RPJPEYEU	QTJPEYEL	Forward Earnings Yield	Value	Europe	EUR
RPJPFYEU	QTJPFYEL	Free Cash Flow Yield	Value	Europe	EUR
RPJPDYEU	QTJPDYEL	Dividend Yield	Value	Europe	EUR
RPJPPGEU	QTJPPGEL	Low PEG	Growth	Europe	EUR
RPJPEMEU	QTJPEMEL	Earnings Momentum	Growth	Europe	EUR
RPJPPMEU	QTJPPMEL	Price Momentum	Momentum	Europe	EUR
RPJPSYEU	QTJPSYEL	Seasonality	Momentum	Europe	EUR
RPJPROEU	QTJPROEL	Return On Equity	Quality	Europe	EUR
RPJPNIEU	QTJPNIEL	Net Income Margin	Quality	Europe	EUR
RPJPEDEU	QTJPEDEL	Equity Debt Ratio	Quality	Europe	EUR
RPJPLVEU	QTJPLVEL	Low Volatility	Volatility	Europe	EUR
RPJPLBEU	QTJPLBEL	Low Beta	Volatility	Europe	EUR
RPJPLSEU	QTJPLSEL	Small Size	Volatility	Europe	EUR

J.P. Morgan Asia ERP Investable Indices				
Long/Short Tickers	**Factor Name**	**Factor Style**	**Region**	**Currency**
QTJPXEYS	Forward Earnings Yield	Value	Asia ex JP	USD
QTJPJBPS	Book to Price	Value	Japan	USD
QTJPXPMS	Price Momentum	Momentum	Asia ex JP	USD
QTJPXRES	Return On Equity	Quality	Asia ex JP	USD
QTJPJRES	Return On Equity	Quality	Japan	USD
QTJPXLVS	Low Volatility	Volatility	Asia ex JP	USD
QTJPJLVS	Low Volatility	Volatility	Japan	USD

[61] Bloomberg subscribers can use the tickers above to access tracking information on baskets created by the J.P. Morgan Structuring desk to leverage the theme indicated. Over time, the performance of the above indices could diverge from returns quoted in our research, because of differences in methodology. J.P. Morgan Research does not provide research coverage of these baskets and investors should not expect continuous analysis or additional reports relating to them. For more information, please contact your J.P. Morgan salesperson or the Structuring Desk.

Global Style Benchmarks

In order to further analyze the properties of Risk Factor Styles, we created **Global Style Benchmarks** by combining regional Risk Factors introduced in the previous sections. In the second and third chapter we used these benchmarks to analyze style correlation and design multi-factor portfolios. We have narrowed down the selection of Factors in each region, in order to more closely capture the properties of Risk Factor Styles. For instance, we have omitted the PEG factor from the Growth style as it behaves as a Value Style in a number of regions. The specific selection of underlying regional Risk Factors is as follows:

Global Value: 12-month forward P/E Factors for Asia, the US and Europe, P/B Factor for Japan

Global Quality: ROE Factors for Asia, the US, and Europe

Global Growth: FCF/IC Growth Factor for the US and Earnings Growth Factor for Europe

Global Momentum: Extended Price MOM for the US, 12M Price MOM Factors for Asia and Europe

Global Low-Volatility: 90-Day Low Volatility Factor for Asia, Japan, the US and Europe

Each Style benchmark is designed as an Equal Marginal Volatility (EMV) portfolio. Portfolio weights are rebalanced each month-end based on a trailing 63-day volatility of the underlying Risk Factor (weights are inversely proportional to the marginal volatilities). EMV ensures equal risk weighting of factors within a Style benchmark (more details on different portfolio methodologies can be found in Chapter 3 of our primer on Cross-Asset Risk Factors).

Table 58 below shows the performance/risk statistics for global style benchmarks (Value, Quality, Growth, Momentum, Low Volatility) as well as Global Equities and Global Government Bonds. Figure 95 plots the historical performance for the five Styles, and Global Equities (MSCI All-Country World Index).

Table 58: Performance-Risk Metrics for Global Styles and Traditional Assets

	Equity	Bond	Value	Quality	Growth	MOM	LowVol
Ann. Ex Ret (%)	5.0	2.7	9.0	2.7	7.9	7.6	-0.1
CAGR (%)	3.8	2.6	8.8	2.4	7.8	6.6	-1.4
STDev (%)	16.0	3.0	9.9	8.1	8.8	14.9	16.5
MaxDD (%)	-57.0	-5.8	-30.9	-20.1	-25.4	-43.3	-53.8
MaxDDur (in yrs)	7.3	3.4	2.7	5.7	2.9	5.2	10.8
***t*-Statistic**	**1.4**	**3.8**	**4.0**	**1.5**	**3.9**	**2.2**	**0.0**
Sharpe Ratio	**0.32**	**0.88**	**0.91**	**0.33**	**0.90**	**0.51**	**0.00**
Hit Rate (%)	58.8	62.7	61.4	54.4	68.9	65.4	47.8
Skewness	-0.80	-0.08	-0.03	-0.11	-0.77	-1.19	-0.41
Kurtosis	1.87	0.07	2.08	1.09	6.49	3.49	1.75
Correl w/Equity*	1.00	-0.22	0.05	-0.34	-0.20	-0.28	-0.68
Correl w/Bond*	-0.22	1.00	0.00	0.16	0.12	0.14	0.29

Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.
* We used MSCI AC World Index (in excess returns) for "Equity" and J.P. Morgan Global Government Bond USD Index (hedged, in excess returns) for "Bond".
** Performance is calculated during the backtesting period from February 1995 to January 2014.

During this 19-year backtest period from February 1995 to January 2014, Global Equities and Global Government Bonds delivered compounded annual excess returns of +3.8% and +2.6%, respectively. Moreover, Global Equities suffered a notable drawdown of -57% during the recent Global Financial Crisis. During the same period, our Global Value, Quality, Growth and Momentum Risk Factor indices delivered higher Sharpe ratios and lower drawdowns than the Global Equity Market.

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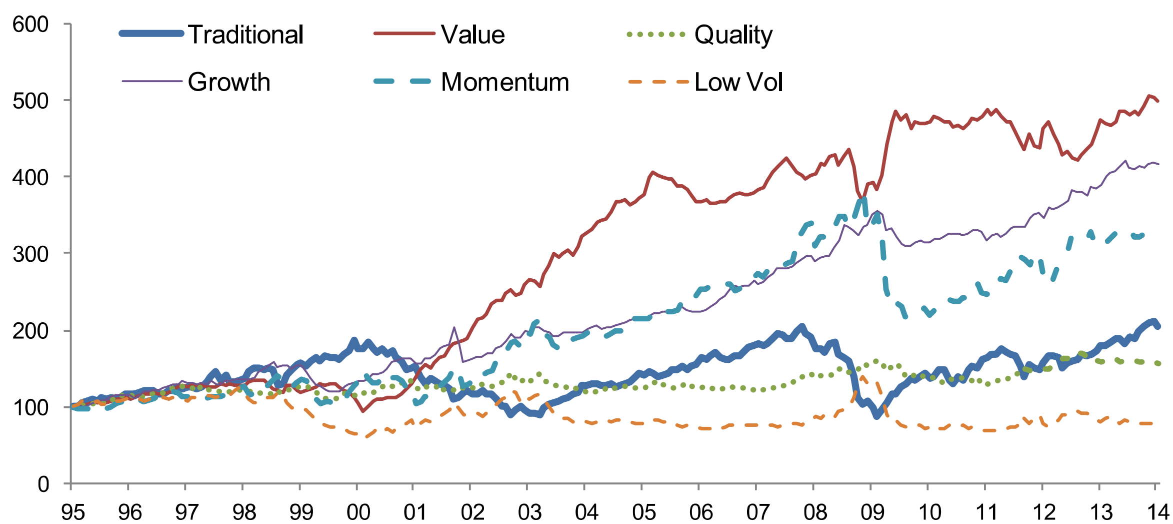
Among the five Global Equity Risk Factor indices, we find that Value, Growth and Momentum styles historically delivered high returns (compounded annual excess returns of +8.8%, +7.8% and +6.6%, respectively) as well as good Sharpe ratios (0.91, 0.90 and 0.51, respectively), while Quality and Low Volatility Risk Factors displayed more significant return cyclicality and less significant Sharpe ratios. As a result**, a portfolio of Global Value, Growth and Momentum Risk Factors could suit the investment need to harvest long-term risk premia, whereas Global Quality and Low Volatility Risk Factors could be employed as trading tools to take tactical style views**.

In addition, during the full 19-year backtest period, **our Global Value Risk Factor indices had close-to-zero correlations with Global Equities and Global Government Bonds, while other Global Risk Factor indices (Quality, Growth, Momentum and Low Volatility) had negative correlations with Global Equities and positive correlations with Global Government Bonds**. These findings validate the use of our suite of Global Equity Risk Factors effectively as diversifiers in a Traditional Equity/Bond long-only portfolio.

Figure 95: Performance of Traditional (Global Equities) and Risk Factor Style Composites



Source: J.P. Morgan Quantitative and Derivatives Strategy. Past performance is not indicative of future returns.

To better understand the performance of Global Equity Risk Factors under different macro/market regimes, we analyze below each Risk Factor's exposure to economic Growth, Inflation, Market Volatility and Funding Liquidity indicators.[62] In Table 59 below we summarize annualized average returns (and related *t*-statistics, in parentheses) for our Global Value, Quality, Growth, Momentum and Low Volatility Risk Factors under "Low", "Mid" and "High" regimes of Growth, Inflation, Volatility and Liquidity, respectively.

Table 60 summarizes the exposure of our Global Value, Quality, Growth, Momentum and Low Volatility Equity Risk Factors to macro/market regime indicators over the full backtest period from February 1995 to January 2014. We report both regression coefficients (Beta to the corresponding regime indicator) and related *t*-statistics.

[62] Consistent with our primer to Cross-Asset Risk Factors, the macro/market regime indicators are defined as follows. Growth is defined as YoY change of OECD leading indicator; Inflation is defined as OECD global consumer price inflation indicator; Volatility is defined as the VIX indicator; Liquidity is defined as the difference between 3-month Treasury Bill rate and 3-month US$ Libor rate.

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Table 59: Performance (t-statistics*) of Global Equity Risk Factors Under Different Macro/Market Regimes

	Growth			Inflation			Volatility			Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Value	13.45	8.89	4.58	14.08	6.54	7.23	7.22	11.05	8.65	4.08	7.09	15.75
	(1.40)	(-0.03)	(-1.37)	(1.47)	(-0.94)	(-0.46)	(-0.55)	(0.65)	(-0.10)	(-1.53)	(-0.59)	(2.13)
Quality	3.64	3.69	0.74	-0.99	3.86	4.89	3.56	-1.83	6.34	5.25	3.28	-0.46
	(0.36)	(0.38)	(-0.74)	(-1.30)	(0.55)	(0.72)	(0.33)	(-1.73)	(1.40)	(0.98)	(0.23)	(-1.21)
Growth	6.08	9.52	8.12	2.34	9.02	12.31	12.52	7.98	3.22	8.74	5.68	9.30
	(-0.64)	(0.57)	(0.07)	(-1.81)	(0.48)	(1.33)	(1.63)	(0.03)	(-1.66)	(0.29)	(-0.78)	(0.49)
Momentum	0.79	9.14	12.80	-1.63	16.56	3.27	13.58	5.05	4.11	3.90	0.91	17.93
	(-1.41)	(0.32)	(1.08)	(-1.77)	(2.33)	(-0.76)	(1.24)	(-0.52)	(-0.72)	(-0.76)	(-1.38)	(2.16)
Low Volatility	1.96	-0.46	-1.68	-15.18	0.24	16.31	-1.22	-9.46	10.50	1.27	-3.36	1.91
	(0.38)	(-0.07)	(-0.30)	(-2.64)	(0.07)	(2.65)	(-0.22)	(-1.76)	(1.99)	(0.25)	(-0.62)	(0.37)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The *t*-statistic shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 60: Global Equity Risk Factors' Exposures (t-stats*) to Macro/Market Regime Factors over the Full Sample Period

	Growth	Inflation	Volatility	Liquidity
Value	-0.41	-0.34	-0.17	0.61
	(-2.19)	(-1.82)	(-0.88)	(3.38)
Quality	-0.11	0.35	0.31	-0.33
	(-0.69)	(2.36)	(2.01)	(-2.18)
Growth	0.12	0.48	-0.22	-0.03
	(0.74)	(2.95)	(-1.30)	(-0.18)
Momentum	0.79	0.63	-0.24	0.05
	(2.81)	(2.27)	(-0.85)	(0.19)
Low Volatility	0.14	1.53	0.76	-0.85
	(0.43)	(5.23)	(2.44)	(-2.80)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
*The *t*-statistic shown in parentheses is from regression of factor return versus respective macro/market regime indicator.

From Table 59 and Table 60, we can highlight a few observations below:

- The performance of the Value Risk Factor is negatively correlated with Growth/Inflation, while positively correlated with Liquidity. Hence, **a Low Growth, Low Inflation and High Liquidity regime fares well for Value**, while a High Growth, Mid/High Inflation, and Low Liquidity regime does not bode well for Value.
- The performance of the Quality Risk Factor is negatively correlated with Liquidity, while positively correlated with Inflation and Volatility. Hence, **a High Inflation, High Volatility and Low Liquidity regime supports Quality**, while a Low Inflation, Low Volatility and High Liquidity regime doesn't seem to favor Quality.
- The performance of the Growth Risk Factor is negatively correlated with Volatility, while positively correlated with Inflation. Hence, **a Mid/High Inflation and Low Volatility regime is ideal for Growth Risk Factor investing**.
- **The Momentum Risk Factor performed best in a High Growth, Mid Inflation, Low Volatility and High Liquidity regime**, and performed worst in a Low Growth, Low Inflation, Mid/High Volatility and Mid Liquidity regime.
- The performance of the Volatility Risk Factor is positively correlated with Inflation and Volatility. Hence, **a High Inflation and High Volatility regime supports Volatility Risk Factor performance**, while a Low/Mid Inflation and Low/Mid Volatility regime often related to poor performance of our Volatility Risk Factor. The negative correlation between our Volatility Risk Factor and market volatility also stems from its negative 'risk tilt' by (non-neutralized) factor construction.

Select J.P. Morgan Quantitative Equity Strategy Publications

Our Global Quantitative and Derivatives Research team have written extensively on different aspects of Equity Risk Premia (ERP) Strategies. The table below lists a selected collection of research papers that we think is of long shelf value to investors in this field.

"China in Style: Quantitative Factors in the China A-Share Market" (2014)

"Framework for Regional Equity Allocation Country Selection based on Fundamental, Macro and Technical Signals" (2014)

"Game of Accruals, What Approach Maximizes Alpha?" (2014)

"Sectors Unchained II: Industry Selection Model – Capturing Alpha" (2014)

"Systematic Strategies Across Asset Classes: Risk Factor Approach to Investing and Portfolio Management" (2013)

"Accruals Unchained, Revisiting the Comeback Factor" (2013)

"The Trend Is Your Friend, A robust return predictor using a blend of price trends" (2013)

"Beta Aware Alpha, Shifting Beta 'gears' in an Alpha model" (2013)

"Minimum-Variance Strategies: Frequently Asked Questions and Methods to Improve Min-Var strategies" (2013)

"Dynamic Factor Selection, A novel approach based on using Factors to select Factors" (2013)

"Harnessing Geographic Revenue Exposure, Implications for Stock Selection" (2013)

"Sectors Unchained, Building a Case for Sector and Industry Selection" (2013)

"Introducing the J.P. Morgan Risk Studio" (2013)

"Asia-ex Japan Factor Reference Asian Quant Retrospective: Factor performance in Countries, Sectors & Regimes" (2012)

"Short Interest Signal Ideas: Chasing Short Sellers and Adjusting Stock Valuations Using Short Interest Sentiment" (2012)

"Stock Selection via CDS Market: Analyzing the Impact of Single-Name CDS on Stock Returns" (2012)

"Enhanced Price Momentum: Viewing Price Momentum through the Lens of Market Breadth and Depth" (2012)

"Factor Reference Book – Europe: Summarising 20 Years of Backtests" (2012)

"Risk & Portfolio Analytics – Part 1: The Black-Litterman Model: A Practical Approach to a Complex and Advanced Framework" (2012)

"Do Dynamic Peer Groups Make Sense?: Improving Risk Adjusted Returns by making "Smarter" Comparisons between stocks in Asia Pacific Ex Japan" (2012)

"Quant Concepts: Credit Rating Signal Ideas – Part II: Analyzing the Impact of Credit Ratings on Stock Performance" (2011)

"The Importance of Financial Strength for Value Investing: Filtering Using Piotroski's F-Score" (2011)

"News Analytics – can they add value to your Quant process? Using a Language Recognition Algorithm to Analyse News Flow" (2011)

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"Australian Factor Reference Book: Return-Driver's Fast Lap Around Oz" (2008)

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"Value/Growth – Introducing our Style Switching Model" (2008)

"Dynamic Factor Rotation – Using Momentum and Price Overreaction" (2007)

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Performance-Risk Metrics

Similar to our primer on Cross-Asset Risk Factors, we define the performance and risk metrics we reported in our analysis of Equity Risk Factor styles.

For a time series observation of total returns $\boldsymbol{R} = (r_1, \ldots, r_T)'$ with N observations per annum and the corresponding time series of risk-free rates $\boldsymbol{R}_f$, $\boldsymbol{R}_e = \boldsymbol{R} - \boldsymbol{R}_f = (r_1^e, \ldots, r_T^e)'$ is the excess return. In addition, $\boldsymbol{S_R} = (S_1, \ldots, S_T)^T$ with $S_t = \prod_{i=1}^{t}(1 + r_i)$ is the net asset value (NAV) for the return series $\boldsymbol{R}$. We define the following performance-risk metrics:

- **Annualized Average Return (Average):**

$$\boldsymbol{\mu_R} = \frac{N}{T}\sum_{i=1}^{T} r_i$$

- **Annualized Compounded Return (CAGR):**

$$\boldsymbol{g_R} = \left[\prod_{i=1}^{T}(1 + r_i)\right]^{\frac{N}{T}} - 1 = (S_T)^{\frac{N}{T}} - 1$$

- **Annualized Standard Deviation (StDev):**

$$\boldsymbol{\sigma_R} = \sqrt{N\frac{\sum_{i=1}^{T}(r_i - \bar{r})^2}{T - 1}}$$

  where $\bar{r} = \frac{1}{T}\sum_{i=1}^{T} r_i = \boldsymbol{\mu_R}/N$ is the arithmetic average of the returns.

- **Annualized Downside Deviation (DownDev):**

$$\boldsymbol{D\sigma_R}\left(R_{\text{Target}}\right) = \sqrt{N\frac{\sum_{i=1}^{T}\left[\min\left(r_i - R_{\text{Target}}, 0\right)\right]^2}{T}}$$

  where $R_{\textbf{Target}}$ is so-called target return (or Minimum Acceptable Return to evaluate the relative performance). The downside deviation is also called the “loss standard deviation”.

- **Annualized Upside Deviation (UpDev)** or “Gain standard deviation”:

$$\boldsymbol{U\sigma_R}\left(R_{\text{Target}}\right) = \sqrt{N\frac{\sum_{i=1}^{T}\left[\max\left(r_i - R_{\text{Target}}, 0\right)\right]^2}{T}}$$

- **Annualized Covariance (CoVar)** between $\boldsymbol{R}$ and another return series $\boldsymbol{X}$:

$$\textbf{CoVar}_{\boldsymbol{R,X}} = \frac{N}{T - 1}\sum_{i=1}^{T}(r_i - \bar{r})(x_i - \bar{x})$$

- **Correlation (Correl)** between $\boldsymbol{R}$ and another return series $\boldsymbol{X}$:

$$\textbf{Correl}_{\boldsymbol{R,X}} = \frac{\textbf{CoVar}_{\boldsymbol{R,X}}}{\boldsymbol{\sigma_R\sigma_X}}$$

  Covariance and correlation could be calculated either in total returns or excess returns.

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- **Skewness (Skew)** measures the symmetry of a distribution:

$$\mathbf{Skew}_{\boldsymbol{R}} = \frac{T}{(T-1)(T-2)} \sum_{i=1}^{T} \left(\frac{r_i - \bar{r}}{\boldsymbol{s_R}}\right)^3$$

  where $\boldsymbol{s_R} = \boldsymbol{\sigma_R}/\sqrt{\boldsymbol{N}}$ is the (un-annualized) standard deviation of the returns.

- **Kurtosis (Kurt)** characterizes the relative richness of the tail of a distribution compared with a normal distribution:

$$\mathbf{Kurt}_{\boldsymbol{R}} = \frac{T(T+1)}{(T-1)(T-2)(T-3)} \sum_{i=1}^{T} \left(\frac{r_i - \bar{r}}{\boldsymbol{s_R}}\right)^4 - \frac{3(T-1)^2}{(T-2)(T-3)}$$

- **Drawdown (DD)** measures the current percentage loss of NAV from the previous high-water mark (HWM) within a specific time window:

$$\mathbf{DD}_{\boldsymbol{R}}(t_1, t_2) = \frac{S_{t_2}}{\mathrm{HWM}(t_1, t_2)} - 1, \text{where } \mathrm{HWM}(t_1, t_2) = \max_{t_1 \le t \le t_2} S_t$$

- **Maximum Drawdown (MaxDD)** measures the maximum peak-to-trough percentage change of the NAV during a specific period:

$$\mathbf{MaxDD}_{\boldsymbol{R}}(t_1, t_2) = -\max_{t_1 \le t \le t_2} |\mathbf{DD}_{\boldsymbol{R}}(t_1, t)|$$

  As the absolute value of maximum drawdown is higher for longer periods, a reasonable window (e.g. past three years) is usually applied to the calculation so as not to disadvantage managers with longer track records.

- **Drawdown Duration (DDur)** measures the time in years from the last HWM:

$$\mathbf{DDur}_{\boldsymbol{R}}(t_1, t_2) = \frac{t_2 - \tau}{N}, \text{for } t_1 \le \tau \le t_2 \text{ such that } S_\tau = \mathrm{HWM}(t_1, t_2)$$

- **Maximum Drawdown Duration (MaxDDur)** measures the maximum amount of time in years to reach previous HWM:

$$\mathbf{MaxDDur}_{\boldsymbol{R}}(t_1, t_2) = \max_{t_1 \le t \le t_2} \mathbf{DDur}_{\boldsymbol{R}}(t_1, t)$$

- **Information Coefficient (IC):** Measures the predictive power of an 'alpha signal' by the cross-sectional correlation or ranked correlation between an 'alpha signal' and the subsequent return. 'The fundamental law of active management' by Grinold (1989) stated that the information ratio of an active portfolio is equal to the product of its information coefficient and the square root of the number of independent trials.

- **Sharpe Ratio (SR):**

$$\mathrm{SR}_{\boldsymbol{R_e}} = \frac{\boldsymbol{\mu_{R_e}}}{\boldsymbol{\sigma_{R_e}}}$$

  When the benchmark used for the calculation of excess return is not a risk-free asset, this is often called **Information Ratio**.

- **Adjusted Sharpe Ratio (ASR):**

$$\mathrm{ASR}_{\boldsymbol{R_e}} = \mathrm{SR}_{\boldsymbol{R_e}} \times \left[1 + \frac{\mathbf{Skew}_{\boldsymbol{R_e}}}{6} \mathrm{SR}_{\boldsymbol{R_e}} - \frac{\mathbf{Kurt}_{\boldsymbol{R_e}}}{24} \left(\mathrm{SR}_{\boldsymbol{R_e}}\right)^2\right]$$

  The adjusted Sharpe Ratio was proposed as an alternative to the standard Sharpe ratio when related performance is not normally distributed. The measure is derived from a Taylor series expansion of an exponential utility function.

- **Sortino Ratio (Sortino):**

$$\text{Sortino}_{\boldsymbol{R_e}} = \frac{\boldsymbol{\mu_{R_e}}}{\boldsymbol{D\sigma_{R_e}}\left(R_{\text{Target}}\right)}$$

where the target return R_{Target} is usually set to be 0 for an excess return series.

- **Calmar Ratio (Calmar):**

$$\text{Calmar}_{\boldsymbol{R_e}} = -\frac{\boldsymbol{\mu_{R_e}}}{\mathbf{MaxDD}_{\boldsymbol{R_e}}(\text{Past 3 years})}$$

- **Pain Ratio (PainRatio):**

$$\text{PainRatio}_{\boldsymbol{R_e}} = \frac{\boldsymbol{\mu_{R_e}}}{\mathbf{PainIdx}_{\boldsymbol{R_e}}}$$

- **Reward to VaR Ratio (VaRatio):**

$$\text{VaRatio}_{\boldsymbol{R_e}} = -\frac{\boldsymbol{\mu_{R_e}}}{N \times \mathbf{VaR}_{\boldsymbol{R_e}}(\delta)}$$

- **Reward to CVaR Ratio (CVaRatio):**

$$\text{CVaRatio}_{\boldsymbol{R_e}} = -\frac{\boldsymbol{\mu_{R_e}}}{N \times \mathbf{CVaR}_{\boldsymbol{R_e}}(\delta)}$$

- **Hit Rate** measures the percentage of non-negative returns relative to a certain benchmark:

$$\text{Hit}_{\boldsymbol{R_e}} = \frac{\sum_{i=1}^{T} 1\{r_i^e \geq 0\}}{T}$$

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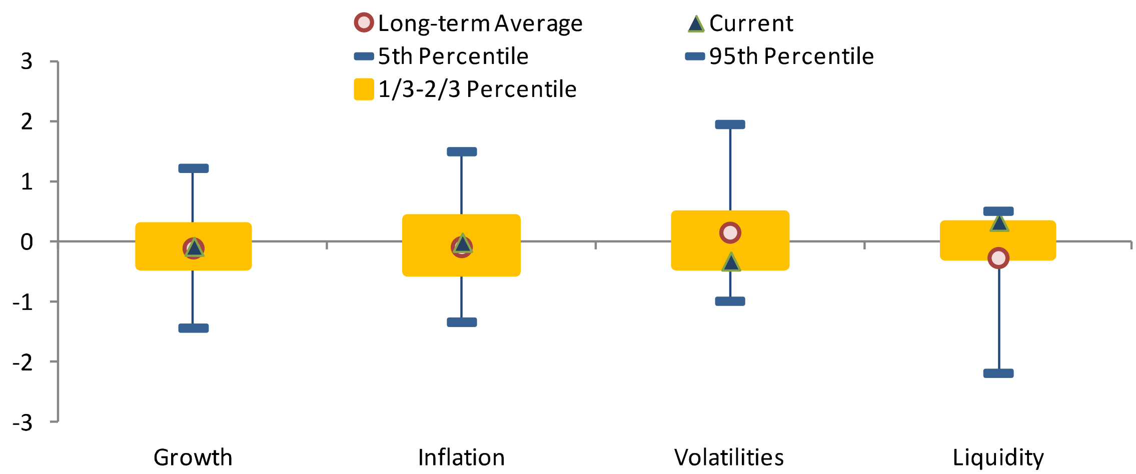
Macro and Market Regimes

To develop a better understanding of Equity Risk Factors, we studied properties of each factor under different macroeconomic and market-technical regimes. In particular, we examined factor performance in different regimes of **Growth** (YoY change of OECD CLI, a leading indicator of global economic growth), **Inflation (**OECD global consumer price inflation indicator), **Volatility** (VIX Index), **Funding Liquidity** (TED Spread, defined as the difference between 3-month Treasury Bill rate and 3-month US$ Libor rate, measures broad US$ funding risk).

Figure 96 below shows the historical distribution of the five regime indicators[63] – Growth, Inflation, Volatility, Funding Liquidity during the period from January 1994 to June 2014, using monthly data.

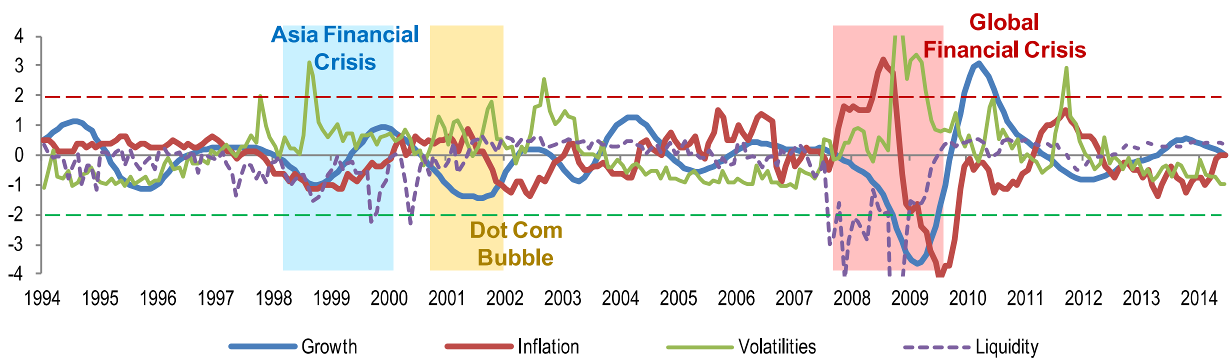
Figure 96: Historical Profile of Macroeconomic and Market Regime Factors During 1994-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg, OECD.
` Regime factors are standardized to unit variance and zero median.
`` Current values (green triangles) for Growth, Inflation, Volatilities and Funding Liquidity factors are based July 2014 readings.

We note that Volatility has a tendency to spike (positive skewness), and the Liquidity measure has a tendency to drop (negative skewness). On the other hand, during the past two decades (1994-2014), Growth and Inflation displayed relatively even distribution on both tails. Figure 97 below shows the history of these measures over the past 20 years. Notable features include the Growth/Inflation cycles during the 2007-08 Global Financial Crisis, High Volatility during market crises of 1997-1998 and 2008-2009, etc. Figure 97 shows that we are currently in a Mid Growth, Mid Inflation, Low Volatility, and High Liqudity regime.

Figure 97: Growth, Inflation, Volatility and Liquidity During the Past Four Decades`



Source: J.P. Morgan Quantitative and Derivatives Strategy. ` Regime factors are standardized to unit variance and zeros median.

[63] These indicators were standardized "in-sample" to have unit variance and zeros median.

The four macro and market-technical regime indicators discussed are not independent of one another. Table 61 below shows the correlation of these regime indicators over the past 20 years, as well as during three crisis periods. For instance, Volatility was negatively correlated with all the other factors, and the negative correlation was most pronounced during crisis periods. Liquidity was significantly negatively correlated with Inflation, partly reflecting the secular decline in inflation and improvements in systemic banking credibility and so on.

Table 61: Correlation Matrix of Growth, Inflation, Volatility and Liquidity Indicators (lower triangular statistics are the all-sample pair-wise correlation, upper triangular are the correlation statistics during crisis periods`)

	Growth	Inflation	Volatilities	Liquidity
Growth		**38**	**-83**	**28**
Inflation	4		**-39**	**-22**
Volatilities	**-39**	**-21**		**-54**
Liquidity	**38**	**-28**	**-47**	

Full Sample Ave	1	**-15**	**-36**	-12
Crisis Average	-9	**-17**	**-46**	**-18**
During GFC	-5	-8	**-59**	**-16**

Source: J.P. Morgan Quantitative and Derivatives Strategy.
` Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods.
`` Crisis periods we include for the correlation calculations are July 1997 to August 1998 (Asian Financial Crisis, Russian Default and LTCM), January 2000 to September 2001 (Tech Bubble), and June 2007 to February 2009 (Global Financial Crisis or GFC).

What Is 'Smart Beta'?

'Smart Beta' is a loosely defined term used to label any systematic strategy that invests in risk factors (other than the broad market). Given the lack of a precise definition, we prefer using the terminology around 'Risk Factors' over labeling a group of strategies as 'Smart Beta' (Risk Factor terminology was developed in our primer on Systematic Strategies). The 'Smart Beta' label also contains the word 'Smart' which implies that the strategy is always superior to investing in a broad market. However, this is not necessarily the case. For instance, the S&P 500 outperformed most Risk Factor strategies in 2013, on a risk-adjusted basis.

For a Risk Factor strategy to be labeled 'smart', perhaps there should be some additional requirements – a strong economic rationale behind the factor design and selection, and sound portfolio risk management to take advantage of offsetting correlation and to minimize factor tail risk. The strategy should also be free of any implicit or explicit look-back biases. Even if all of these criteria are met, there is no assurance that the strategy will outperform in relative or absolute terms. While it is legitimate to label a specific, well-defined strategy as 'smart', we think that applying the term to a broad group of Risk Factor-based strategies could be potentially misleading.

Recently there has been a lively debate about Smart Beta and the merits of Risk Factor investing. On one side of debate one can often find some firms offering Smart Beta products (e.g. ETF providers, sell-side desks, asset managers), and on the other some of the active managers that are skeptical of 'Smart Beta' as a passive investment concept. There is yet a third party to the discussion – tactical asset allocation funds and quantitative managers that are often successfully employing Risk Factor strategies, and are less interested in debate and publicizing their research.

Some proponents claim that 'Smart Beta' can deliver hedge fund returns at significantly lower fees. We do not agree with this claim, as Smart Beta strategies deliver Risk Premia rather than pure alpha. In other words, risk premia are the compensation for specific risks, and cannot effectively replace the timing and selection ability of a skilled active manager. On the other hand, opponents of Smart Beta often point to problems with in-sample biases, hidden transaction costs, or claim that one specific style (e.g. Value) is responsible for the positive performance of many 'Smart Beta' strategies. In our previous work, we have discussed potential pitfalls related to the factor lifecycle and flawed designs, and how to avoid them. We have also shown that there are a number of distinct Risk Factor styles with rich correlation structures, and 'Smart Beta' returns can not be explained with one particular style or risk management methodology.

The aim of our research on Systematic Strategies is to formulate and study a rigorous framework for Risk Factor investing across asset classes. In our reports, we provided historical studies of individual factors, styles, correlations and factor portfolios. We believe that investors on both sides of the 'Smart Beta' debate should be able find our work helpful to their investment process.

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Glossary

Absolute Return
Absolute return strategies aim to produce a positive return regardless of the performance of the general market. This is usually achieved by taking positions in a portfolio of diversified risk premium factors with prudent risk management.

Accruals
Accruals are the difference between the reported earnings based on Accruals accounting and cash flow. The difference is usually normalized (made comparable across stocks) by dividing the Accruals by average assets and calculated as

$$\mathrm{Accruals(t)} = \frac{\Delta\mathrm{NonCashAssets(t)} - \Delta\mathrm{LiabilitiesXDebt(t)}}{\mathrm{Average\ Total\ Assets(t)}}$$

where:

ΔNonCashAssets(t) = ΔTotal Assets(t,t-12) – ΔCash & Cash Equivalent(t,t-12)

ΔLiabilitiesXDebt(t) = ΔTotal Liabilities(t,t-12) – ΔShort-Term Debt(t,t-12) - ΔLongTerm Debt(t,t-12)

Average Total Assets(t) = Average(Total Assets(t to t-11))

Algorithm
An algorithm is a set of formulaic steps that uses a series of inputs to arrive at an output. An algorithm could be implemented as an automatic process that takes input data into some calculation engine and produces the outputs.

Alpha
Alpha (positive or negative) is attributable to the manager's selection and timing skills on stocks, sectors, country/regions and investment themes.

Alternative Beta
Alternative Beta is the systematic risk premium attained which is beyond pure market exposures and that can be attributed purely to Risk Factors. Equity Risk Factors are exposure to specific risks (e.g. high-low momentum, low-high valuation, etc.) that are independent of traditional beta.

ALTMAN Z-score
ALTMAN Z-score is a combination of four factors (Sales/Total Assets, EBITDA/Total Assets, Retained Earnings/Total Assets and Net Liquid Assets/Total Assets). It is used to determine the probability of a firm's bankruptcy. Risk factors based on this signal allocate stocks with greater ALTMAN Z-score in the long leg while the ones with poor Z-score are put in the short leg.

Analyst Coverage
The total number of analysts that follow/give recommendations/release estimates for the stock. The bigger/more renowned the company is, the more analysts typically cover it.

Annualized Return
An annualized rate of return is the return on an underlying converted into an annual equivalent. For example, a 1-month return of 1% could be stated as an annualized rate of return of 12%. Or a five-year return of 10% could be stated as an annualized rate of return of 2%.

Asset Allocation
The mechanism of allocating investment capital across different underlying asset classes, such as equities, bonds and commodities. The assets could also be Equity Risk Factors introduced in this primer.

Asset Class
An asset class is a set of financial instruments that show similar characteristics or follow a common theme. Examples of asset classes are equities, commodities, government bonds, corporate bonds, real estate, etc. Volatility is recently recognized as a separate asset class.

Backtesting
The analysis of an algorithm or model using historical data. Many of the Equity Risk Factor indices contain backtested data, which shows how the model would have performed under historical market conditions.

Benchmark
A reference index or underlying, against which performance of another index is compared.

Beta
The beta of an asset measures how much it moves compared with a benchmark. In other words, it measures sensitivity of returns with respect to the benchmark. For example, stocks with a high beta tend to have larger positive returns when the broader market rises, and conversely, have a larger negative return when the broader market declines.

Beta Neutralization
A pure long-short strategy alone does not completely eliminate market risk. Beta neutralization is a hedging method to remove market exposure. Beta neutralization can be implemented in different ways. For instance, one can use trailing (historical) beta of the long and the short side to obtain long-short factor with (ex-post) zero beta. Another way is to work with forecasted betas for individual stocks.

Black-Litterman (BL)
The BL methodology employs a Bayesian framework to tackle portfolio allocation after incorporating investor views on expected returns.

Carry Strategy
A systematic strategy that stays overweight in higher-yielding instruments and/or underweight in lower-yielding instruments.

Cash Flow
Total amount of net cash flow generated by the firm over a time period. Cash flow arises from three sources – Operations, Capital Expenditures and Financing. For instance, operating cash flows are cash flows generated from a firm’s operating activities.

Cash Neutral
Cash Neutral is a method of making a strategy cashless (i.e. requires no net cash in order to perform the transaction).

Confirmation Bias
Confirmation bias is a cognitive bias whereby one tends to notice and look for information that confirms one’s existing beliefs, whilst ignoring anything that contradicts those beliefs. It is a type of selective-thinking behavior rooted in investor psychology that contributes to the momentum effect.

Consensus Recommendation
Rating of the stock is formed by aggregating all analyst recommendations. The aggregation method can be to average ratings or to get the median. Risk factors based on this signal allocate stocks with better recommendations, e.g. OW, in the long leg of the portfolio while the ones with poor recommendations, e.g. UW, are put in the short leg of the portfolio.

Correlation
Correlation is a measure of the degree to which changes in two underlyings are related. It is a number that takes a value between plus one (meaning that they both move in tandem) and minus one (which means they move in opposite directions).

Constant Mix
Constant Mix is a portfolio risk management technique that invests a constant proportion of capital in the underlying asset/factor and the rest to risk-free asset.

Constant Proportional Portfolio Insurance (CPPI)
Constant Proportional Portfolio Insurance (CPPI) is a dynamic portfolio risk management technique that invests a constant proportion of the cushion above a guaranteed floor to the risky asset/factor and the rest to risk-free asset.

Directional
A directional strategy is one that has outright long or short positions in some underlying financial instruments. For example, a strategy with a long position would be described as a bullish (or long) strategy and will deliver positive returns if the underlying financial instrument displays positive returns.

Disposition Effect
The behavioral bias by which people tend to be more conservative with gains and reckless with losses. For example, investors tend to sell winning investments too early and hold on to losing investments too long.

Dividend Yield
Calculated as the annual dividend per share (can be trailing or consensus forward) divided by the current market price per share of the company. Dividend Yield is one of the factors in Value investing to identify cheaply valued stocks. Risk factors based on this signal rank stocks with the highest Dividend Yield being allocated to long bucket and those with the poorest Dividend Yield being allocated to short bucket.

Downside Risk
The risk of losses that an investor may experience if there is a decline in the price of an underlying investment.

Drawdown
Drawdown is calculated as the percentage return from the peak level of the index to some reference position. **Maximum Drawdown** measures the largest Drawdown of the index over some history.

Earnings Growth or Earnings Momentum
Earning Growth or Earnings Momentum is a Risk Factor signal used to rank stocks based on the increase in their reported or consensus forward Earnings per Share, usually on a YoY basis. For stock analysts' consensus EPS, investors typically consider FY1 or FY2 estimates and 1-month or 3-month spans of time to calculate respective Earnings Growth factors.

Earnings Yield
Inverse of P/E ratio. Earnings Yield (trailing or forward) can be used to compare stocks with bond yields, to check relative valuation between stocks and bonds. Risk factors based on this signal rank stocks, with the highest earning yields allocated to the long bucket and those with the poorest Earnings Yield allocated to the short bucket.

Equal Marginal Volatility (EMV)
Equal Marginal Volatility (or Volatility Parity) is a portfolio allocation technique that weights each asset according the inverse of its volatility.

Equity Risk Factor
Equity Risk Factors provide exposure to specific risks (e.g. high-low momentum, low-high valuation, etc.) that are independent of traditional beta and alpha, and are expected to deliver long-term positive premia.

Enhanced Price Momentum

Enhanced Price Momentum is defined as 12-Month Price Momentum, taking a reversal view on the last month, adjusted for 3-month daily return volatility. Mathematically it can be expressed as:

$$Pmom_i(t) = \left(\frac{Price_i(t-1) - Price_i(t-12)}{Price_i(t-12)} - \frac{Price_i(t) - Price_i(t-1)}{Price_i(t-1)}\right) \Big/ \sigma(t, t-3)_i$$

Excess Return

The difference between a fully collateralized total return and the risk-free rate. More generally, it is the fully financed return of an investment (e.g. the P/L of being long a portfolio of stocks financed by shorting another portfolio of stocks).

Fama-French Model

An asset pricing model designed by Eugene Fama and Kenneth French to describe expected future portfolio returns. In addition to market risk, the Fama-French model uses two additional Risk Factors – size and value.

Fundamental Analysis

Refers to a type of analysis, typically used in the context of stocks, that involves analyzing company assets and liabilities, cash flows, management structure and competitive advantages, along with competitors and markets. It is performed on historical and current data with the aim of making forecasts about the securities. The term is used to distinguish such analysis from other types of investment analysis, such as quantitative or technical analysis.

Factors

Factors can refer to certain macroeconomic or market indicators. They can also refer to some systematic strategies capturing different risk premia. See also "Risk Factors" and "Risk Premia".

Free Cash Flow

Defined as operating cash flow minus capital expenditures. Positive free cash flow indicates a company is able to generate more cash than is required for daily operating activities and capital expenditures.

Free Cash Flow (FCF) Yield

The ratio is calculated by taking the free cash flow (FCF) per share divided by the share price, where FCF is defined as: EBIT (1-Tax Rate) + Depreciation & Amortization – Change in Net Working Capital – Capital Expenditure. See also 'Cash Flow' and 'Free Cash Flow'.

Free Cash Flow Return on Invested Capital (FCF/IC)

Free cash flow return on invested capital is designed to measure the free cash flow profitability of a company, which looks at how well the company generates cash flow relative to the capital it has invested into its business. The ratio is calculated by taking the free cash flow divided by invested capital from Compustat (Compustat defines Invested Capital as Common Equity + Long Term Debt + Minority Interest + Preferred Stock).

$$\text{FCF to IC}(t) = \frac{\text{FCF}(t)}{\text{IC}(t)}$$

Future

A future is a contract between two parties to buy or sell a standard quantity of a given instrument, at a price agreed today, on a specific date in the future. Futures are traded on a range of underlying instruments including commodities, bonds, currencies and stock indexes.

Gearing
Gearing describes a firm's financial leverage and is typically defined as the Debt/Equity ratio.

Global Minimum Variance (GMV)
Global Minimum Variance is a risk-based portfolio allocation technique that minimizes the portfolio variance under various weight constraints.

Growth Stocks
Refers to stocks that have higher Earnings Growth potential than the market average. These stocks typically have a high share price compared with their earnings (i.e. high P/E ratio). The opposite of growth stocks are **value stocks**.

Herding Bias
The phenomenon by which the pack decides and the individual follows, and investors forsake judgment to follow the actions of others, e.g. the 17th century tulip bubble, the dot-com bubble.

Historical Volatility
Historical volatility refers to the volatility of an index or financial instrument over some period in the past. This compares with implied volatility, which is an expectation of the future level of volatility priced into a derivative contract.

Hit Rate
The hit rate is a measure of the frequency and consistency of success of a given strategy. It is defined as the number of months in which the strategy produced positive (active) returns.

Idiosyncratic Risk
Idiosyncratic risk is the risk specific to a particular asset and can be diversified away by portfolio diversification.

Implied Volatility
Implied volatility refers an expectation of the future level of volatility of an underlying instrument priced into a derivative contract. It is typically derived from the prices of options on the instrument by backing out the volatility parameter from a pricing formula like the Black-Scholes equation.

Independent Component Analysis (PCA)
Independent component analysis is a mathematical procedure that separates a multivariate variable into set of independent component variables which are statistically independent from each other.

Information Coefficient
Measures the predictive power of an 'alpha signal' by the cross-sectional correlation or ranked correlation between an 'alpha signal' and the subsequent return. The 'fundamental law of active management' by Grinold (1989) stated that the information ratio of an active portfolio is equal to the product of its information coefficient and the square root of the number of independent trials.

Information Ratio
A measure that aims to capture the potential return of an underlying per unit of risk. It is calculated as the return of an underlying above the returns of a benchmark divided by its volatility.

Interest Coverage
Interest coverage is a measure of a company's ability to meet its interest-payment obligations. It is calculated as EBIT/ Interest Expense.

Leverage

Refers to the exposure of an index (or position) to another underlying index. A position is said to be leveraged if the exposure is greater than 100%, meaning that a 1% change in the underlying index will generate a greater than 1% change in the value of the position. Another definition of Leverage relates to a firm's financial leverage. See 'Gearing'.

Leverage Invariant

Portfolio weights on the unleveraged assets are not affected by leveraging up or down on a certain subset of assets.

Libor

The London inter-bank offered rate (LIBOR) is a daily reference rate based on the interest rates at which banks borrow unsecured funds from other banks in the London wholesale interbank market. This rate is typically set every business day.

Liquidity

Liquidity is a measure of the ease of trading in and out of financial instruments. An instrument is said to be liquid if the costs to enter and exit that position are low.

Mental Accounting

The behavioral bias by which gains and losses are considered independently and undue emphasis is placed on current gains/losses when making investment decisions.

Mean-Variance Optimization (MVO)

MVO solves one-period portfolio optimization by using only the first two moments of the underlying return series. It achieves minimum variance given a certain expected return target.

Mean Reversion

The tendency of a certain metric (price, yield, portfolio, etc.) to revert to its short-term or long-term fair value determined by technical or fundamental variables. It can work in either absolute or relative terms. Mean reversion belongs to the Value style in systematic strategy terms.

Momentum

The tendency of a trend to continue or the best- (worst-) performing assets to continue to outperform (underperform). See also 'Price Momentum'.

Most-Diversified Portfolio (MDP)

Most-Diversified Portfolio is a portfolio allocation technique that maximizes the diversification ratio defined by the ratio of weighted-average marginal volatility to portfolio volatility. It is equivalent to Mean-Variance Optimization (MVO) when the Sharpe ratios for all the assets are equal to a certain positive constant.

Multi-Factor Model

A Multi-Factor Model selects stocks based on how they rank according to several factor metrics at the same time. An example would be a Value and Momentum model that selects stocks that rank highly on a combined score of Value and Momentum. A well-designed multi-factor model usually gives better risk-adjusted performance due to generally lower correlation between different factor styles.

Net Profit Margin

Net Profit Margin is defined as Net Profit (after tax) divided by Revenue. Companies with higher margins (i.e. generating a larger amount of profits per unit of sales) should be much more attractive to investors than companies with low margins.

Option

An option is a contract that gives the holder the right, but not the obligation, to buy or sell an underlying at a certain price in the future. In exchange for this right, the purchaser of the option has to pay the seller a premium. Options that are exercisable at only at a specific point in the future (the options expiry date) are called European options, while those that are exercisable at any point in time before expiry (from the date of purchase) are termed American options.

Option-Based Portfolio Insurance Strategies (OBPI)

Option-Based Portfolio Insurance (OBPI) is a portfolio risk management technique that synthetically replicates a "protective put" on the underlying risky asset/portfolio.

Overlay

A strategy designed to tweak the return profile of a portfolio using derivatives or other financial instruments, but generally leaving the securities in the underlying portfolio unchanged. For example, a fund manager may wish to implement a covered call overlay which generates extra income from the sale of options, but reduces the maximum portfolio upside potential.

Payout Ratio

Payout Ratio indicates how much of a company's earnings is paid out to common shareholders in the form of cash dividends. Calculated as Dividend per Share/Earnings per Share.

PIOTROSKI Fundamental Score

A fundamental scorecard that measures a company's financial strength. Factors include Market Cap, P/B, ROA, Leverage, Net Margin, Net Operating Income, Operating Cash Flow/Liabilities, Cash/Liabilities and Sales/Total Assets. It scores a company between 0 and 9. Risk factors based on this signal allocate stocks with greater PIOTROSKI Score in the long basket while the ones with poor scores are put in the short basket.

Portfolio Turnover

A measure of the percentage change of a portfolio on a rebalance. Lower portfolio turnover is preferred in a strategy due to lower transaction costs.

Price/Book Ratio

It is calculated as the current market price of the share divided by the latest reported (or consensus forward) book value per share. P/B Ratio is used mostly to identify under- or overvalued companies. A company with low P/B ratio is generally considered a cheap stock.

Price/Earnings Ratio

It is calculated as the current market price of the share divided by the trailing (or consensus forward) 12-month Earnings per Share. A higher P/E is generally indicative that investors are willing to pay more per dollar of earnings, thus indicating that higher growth is anticipated.

PEG Ratio

The ratio of (trailing or forward) price/earnings ratio to the consensus estimate of a company's long-term EPS growth rate.

Price/Cash Ratio

It is calculated as the current market price of the share divided by its trailing (or consensus forward) cash flow per share. A stock with lower price to cash flow ratio is generally preferred as it generally indicates that the firm is generating ample cash flow that is not priced into the stock price yet.

Price/Sales Ratio

It is calculated as the current market price of the share divided by trailing (or consensus forward) 12-month sales per share. It can also be calculated by dividing the market cap by the trailing 12-month sales. A low price to sales ratio coupled with other factors such as high profit margins, low debt, etc. can be indicative of a high value stock and is typically preferred by investors.

Price Acceleration

Price acceleration can be defined as the rate of change of Price Momentum over a period of time. To calculate N-month price acceleration, we perform a regression on 1 year of daily prices to calculate the gradient of the trend and repeat the same process as of N months back. We then look at the change in trend to provide a measure of price acceleration. Stocks are ranked such that the stocks that have accelerated most are awarded the highest scores.

Price Momentum

Price Momentum can be defined as the rate at which prices increase or decrease over a period of time. It is generally calculated by their total return over the previous months. Price Momentum is generally used to determine price movement and trend lines, and can be used in combination with other technical indicators as a buy/sell indicator.

Price Return

The price return is the return on an underlying over some period, in which the return measure takes into account only the appreciation in price of underlying and not any income or distributions generated over the period. Often, indices like the S&P 500 are described as price return, as they only measure the price changes of the component securities (and not any dividends paid by these components).

Principal Component Analysis (PCA)

Principal component analysis is a mathematical procedure that orthogonally transforms the set of correlated variables into smaller number of uncorrelated variables (principal components).

Quality Strategies

Refers to systematic strategies that go long assets/factors that have High Quality characteristics and short assets/factors with Low Quality characteristics. Quality Risk Factors rely on balance sheet items that indicate a company's ability to sustain earnings over time such as ROE, profit margin, earnings volatility, etc.

Quantitative Strategies

Quantitative (or "Quant") strategies are investment strategies that use large amounts of financial and market data with the aim of looking for exploitable price behavior based on fundamental or technical signals to make investment decisions. They are typically employed by more sophisticated fund managers or hedge funds.

Q-Score

Q-Score is a multi-factor quantitative model designed by J.P. Morgan's Quantitative and Derivatives Strategy team. The approach incorporates Value, Growth, Momentum and Quality factors in a composite score to rank and select stocks.

Rebalance Period

The rebalance period or investment horizon is the interval between portfolio rebalancing. It defines in the backtest the points in time when historical investment decisions were made and the composition of the portfolio was updated. For most backtests, 1 month is the commonly accepted rebalance period as a good compromise between reactivity of the portfolio and turnover of the portfolio.

Replication

Replication of an index refers to the purchase of securities whose returns match the returns of the index. For example, to replicate the performance of the S&P 500 Index, one would need to purchase all 500 securities within the S&P 500, in their respective weightings. One could also exercise partial replication or statistical replication to match the risk/return profile of an index.

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Redundancy Invariant

Portfolio weights on the unleveraged assets are not affected by introducing one or more linear combinations of the original assets.

Return on Equity

Return on equity is a measure of how effective a company is at generating income compared to the funding shareholders have contributed. Calculated as Net Income/Shareholder Equity.

Risk Budgeting (RB)

Risk Budgeting (RB) is a generalized version of Risk Parity, which allows for a pre-specified total contribution to risk of the marginal assets. See also "Risk Parity".

Risk Factors

Also called alternative betas, or exotic betas, Risk Factors are systematic drivers of portfolio returns. Risk factors are defined by a set of trading rules that often involve multiple assets/trading instruments, and a rebalancing strategy. See also 'Equity Risk Factors'.

Risk Parity (RP)

Risk Parity (RP) or equal contribution to total risk (equal-CTR) is a portfolio allocation technique that achieves equal total contribution to risk of all the marginal assets.

Risk Premium

Risk premium is generally defined as excess compensation for taking a certain risk, such as macro risks, liquidity risks or tail risks. They are usually implemented as different investable Risk Factors. See also "Excess Return".

Relative Strength Indicator (RSI)

The Relative Strength Indicator is used to highlight stocks as overbought or oversold. Generally an RSI of 80 or higher indicates an overbought stock and an RSI of sub-20 indicates an oversold stock. Calculated as $100 - 100 / (1 + RS)$ where RS = Average Up Days/Average Down Days.

Seasonality

We calculate this by using total return versus local country MSCI index, and the hit rate represents the percentage of times the stock has outperformed in the specified month. Stocks that outperformed/ underperformed in a particular period of the year tend to continue doing so in future years.

Sharpe Ratio

A measure that aims to capture the potential return of an underlying per unit of risk. It is calculated as the Excess Return of an underlying divided by its Volatility.

Smart Beta

'Smart Beta' is a form of 'enhanced beta' strategy by dynamically applying an active factor tilt to a portfolio of securities such as stocks or corporate bonds. The 'active tilt' is usually relative to a (free-float) market cap weighted index and the degree of the tilt is determined by factor construction methodology.

Size

'Size' usually refers to the market capitalization of a company, defined as current market price times shares outstanding. Companies that are smaller in size could be more attractive to investors than companies that are larger as they may provide more growth opportunities than their larger counterparts. That said, generally speaking smaller caps have higher information uncertainty and are associated with higher risk.

Sortino Ratio

Similar to a Sharpe Ratio, the Sortino Ratio measures the excess return of an underlying divided by Downside Volatility. Downside Volatility refers to the volatility of the underlying measured by considering only returns below a certain target. It is a metric that focuses on the downside risk of a portfolio.

Stock Index Future

Refers to a futures contract on a stock index (see "Futures" definition above). For example, the S&P 500 has listed futures which allow professional investors to replicate the returns of the index in a cost-efficient manner.

Style

Most Equity Risk Factors can be classified into five broad styles: Value, Growth, Quality, Momentum and Volatility. The Value style goes long stocks that appear cheap. Growth Risk Factors provide exposure to companies that are expected to achieve a high Earnings Growth rate. Momentum Factors rely on a stock's price trends and patterns (as opposed to fundamental data). Quality Risk Factors rely on balance sheet items that indicate a company's ability to sustain earnings over time. Volatility style includes factors such as (low-high) stock Volatility and (low-high) stock Beta with respect to a broad equity benchmark.

Short Interest Trend

The basic idea behind this strategy is to use a stock's intermediate (split-adjusted) short interest trend for differentiating between future winners and losers. The strategy goes long stocks with falling short interest levels and goes short those with rising short interest levels relative to historical levels.

Stop Loss

A stop-loss strategy is a portfolio risk management technique that is fully invested in a risky portfolio but unwinds this investment and switches to 100% allocation to the risk-free asset when the portfolio value touches a designated floor level.

Survivorship Bias

A type of 'logical error' while doing a historical backtesting analysis in which one includes only surviving stocks while failing to account for failed/bankrupt stocks. This can lead to false conclusions.

Systematic Risk

Systematic risk is the risk inherent to entire market and cannot be diversified away by portfolio diversification.

Systematic Strategy

An investment strategy that runs using an algorithm, typically with little or no investor discretion. Systemic Strategies can run on virtually any set of assets.

Time-Invariant Portfolio Protection (TIPP)

Time-Invariant Portfolio Protection (TIPP) is a class of generic portfolio risk management techniques that aims to maintain a minimum value of the portfolio. See also "CPPI" and "OBPI".

Total Return

The total return of an investment is the return of the investment including price appreciation and income generated. A total-return stock index reflects the price return of the stocks in addition to the reinvested dividends paid by the stocks within the index.

Traditional Beta

Traditional Beta is the risk premia that is purely attributed to market movements. Also see 'Beta'.

Transaction Cost

Cost incurred during buying or selling of securities. It includes commissions, stamp duty, bid-ask spreads and market impact cost.

Value-at-Risk

Refers to a measurement that aims to calculate the worst-case loss of a portfolio over a particular holding period, with a particular degree of confidence. For example, a "99%, 1-day Value at Risk (VaR) of US$1 million" for a given portfolio means that the there is a 99% probability that the return of that portfolio over a given day will be at least greater than negative US$1 million.

Value Investing

Refers to an investment strategy that involves buying stocks that appear underpriced on the basis of some form of fundamental analysis.

Value Strategies

Refers to systematic strategies that go long assets/factors that are cheaply valued and short assets/factors with expensive valuation. See also "Mean Reversion".

Variance

Variance is a statistical measure that refers to how "spread out" a distribution is. For example, the returns of a factor can be described as having high variance if the returns are fairly wide ranging and dispersed.

Volatility

Volatility usually refers to the standard deviation of the returns of a financial instrument within a specific time horizon. It is a widely used measure to express the risk of the financial instrument over the specified time period. Volatility is normally expressed in annualized terms as a percentage. For example, emerging market equities historically exhibit high volatility. On the other hand, short-term treasury bills would be classified as an asset with Low Volatility.

Volatility Premium

Refers to the long-term positive average spread between implied and realized volatility (variance).

Volatility Targeting

Volatility Targeting is a dynamic portfolio risk management technique that targets a constant portfolio/factor volatility via periodic rebalancing.

Winsorization

Winsorization is a technique to control for outliers and possible data errors. A typical strategy is to set all outliers to a specified percentile/standard deviation of the data; for example, a +/- 3 standard deviations Winsorization would set all data outside of +/- 3 standard deviation to 3 standard deviation levels.

Z-Score Normalization

Z-Score Normalization is a technique by which raw factor values are transformed into Z-Scores. A Z-Score is a stock's standardized exposure to a fundamental factor. To compute the factor Z-scores for a given universe of stocks, the average factor value of the universe is subtracted from each stock's individual factor value and that difference is then scaled by the standard deviation of factor values for that universe. The universe of stocks is selected to strip the raw score of its sector or country bias. For example, Z-Score methodology for section neutrality applies the following standardization to each stock X in the sector Y:

$$\frac{\text{E/P Stock } X - \text{average E/P of all stocks in sector } Y}{\text{Standard deviation of E/P for all stocks in sector } Y}$$

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Developed vs. Emerging Markets

In the report we discussed both developed and emerging market Risk Factor performances. These have been shown excluding the impact of transaction costs, shorting restrictions, or borrow availability. It is important to note that the implementation of these factors in emerging markets is more expensive than in developed markets, but this can be balanced against EM's generally stronger factor performance.

Transaction costs vary greatly in emerging markets and in the table below we illustrate a cross-section of those in Asia. For instance, countries with lower transaction costs include Australia, Japan, and Malaysia, while it is generally more expensive to trade in China and Thailand stocks.

Table 62: Transaction costs in EM are typically higher – see below for some representative costs out of Asia Pacific for comparison

Countries	Avg Spread (bps)	MI (bps)	All-in cost* (bps)
Australia	15.6	13.8	19.0
China	13.3	30.7	35.1
Hong Kong	22.7	17.5	24.9
India	5.7	31.2	33.1
Indonesia	31.3	21.9	32.3
Japan	13.7	17.3	21.8
Korea	19.6	27.0	33.4
Malaysia	31.9	12.2	22.7
Philippines	16.5	11.3	16.7
Singapore	31.5	7.9	18.3
Taiwan	25.9	25.1	33.7
Thailand	59.5	25.9	45.6

Source: J.P. Morgan Asia Pacific Linear Quantitative Research.
* All-in cost assumes Market Impact + 0.33 average spread.
** Average execution cost by country assuming a 10% ADV order traded with 10% POV.

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Factor Reference Books

The J.P. Morgan Quantitative & Derivatives Strategy team has produced a number of equity factor reference books that tested various Equity Risk Factors by region and by country:

- US: We look at quantitative Risk Factor performance when tested across the Russell 3000 universe and its subsets, focusing on size, style, sectors, as well as different factor investment horizons.
- Europe: Examines Risk Factor performance historically across MSCI Europe and drills down into European Sectors, with a summary of the performance of specific European sub-regions (Scandinavia, Continental Europe and UK).
- Asia (ex Japan): We look at Risk Factors in Asia (by country and by sector) and when they worked best (by market regime). Four companion chartbooks that cover regional Asia ex-Japan, country, sector, and GEM are also available.
- Japan: In this report we test commonly used Risk Factors against a large-cap MSCI Japan universe.
- Australia: In this report we review the performance of Risk Factors in the Australian equity market since 1992.

In addition to the factor reference books, the JPM QDS team monitors and updates factor and style performance on a regular basis, in the following regular publications:

- Global Factor Performance Summary
- Style Investing

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Additional Basket Methodology

In order to keep the basket relevant to the investment theme, J.P. Morgan reserves the right to review the following at any time:

- **Basket methodology.** This is to ensure the rules of the basket remain relevant following any strucural changes to the theme. This may include ensuring that the sector exposure of the basket remains broadly consistent with the investment theme.

- **Basket change implementation.** J.P. Morgan will consider extending the implementation of changes to the basket composition from one trading session to any period up to five trading sessions in the event that a material increase in the liquidity or capacity of the basket is required to minimize market impact.

Corporate actions may affect the basket created by J.P. Morgan. The composition of a custom basket is typically adjusted in the following manner:

- **Cash merger.** The divisor is adjusted, and we remove the merging company from the basket on the day of merger and redistribute gains into remaining companies according to recalculated market-cap weights of surviving constituents in the basket.

- **Stock merger.** If the acquirer is a member of the basket, then the weight allocated to the acquired company will transfer to the surviving entity on the close of the last day it trades. If the acquirer is not a part of the basket, then proceeds (losses) from the acquired company will be redistributed to the surviving basket constituents based on the recalculated weighting on the close of its last trading day.

- **Spinoffs.** The spinoff company and parent will be included in the basket, and both the spinoff and parent company weights will be readjusted according to new market capitalizations after the spinoff date.

- **Tender offers and share buybacks.** The company remains in the basket and its weight is adjusted according to the impact the tender/buyback has on the stock's market value.

- **Delisting/insolvency/bankruptcy.** The company is removed from the basket as of the close of the last trading day, and the proceeds (losses) will be redistributed into remaining companies according to recalculated weights of remaining companies in the basket. If a stock trades on "pink sheets" it will not be included in the basket.

Risks of Common Option Strategies

Risks to Strategies: Not all option strategies are suitable for investors; certain strategies may expose investors to significant potential losses. We have summarized the risks of selected derivative strategies. For additional risk information, please call your sales representative for a copy of "Characteristics and Risks of Standardized Options." We advise investors to consult their tax advisors and legal counsel about the tax implications of these strategies. Please also refer to option risk disclosure documents.

Put Sale: Investors who sell put options will own the underlying asset if the asset's price falls below the strike price of the put option. Investors, therefore, will be exposed to any decline in the underlying asset's price below the strike potentially to zero, and they will not participate in any price appreciation in the underlying asset if the option expires unexercised.

Call Sale: Investors who sell uncovered call options have exposure on the upside that is theoretically unlimited.

Call Overwrite or Buywrite: Investors who sell call options against a long position in the underlying asset give up any appreciation in the underlying asset's price above the strike price of the call option, and they remain exposed to the downside of the underlying asset in the return for the receipt of the option premium.

Booster : In a sell-off, the maximum realized downside potential of a double-up booster is the net premium paid. In a rally, option losses are potentially unlimited as the investor is net short a call. When overlaid onto a long position in the underlying asset, upside losses are capped (as for a covered call), but downside losses are not.

Collar: Locks in the amount that can be realized at maturity to a range defined by the put and call strike. If the collar is not costless, investors risk losing 100% of the premium paid. Since investors are selling a call option, they give up any price appreciation in the underlying asset above the strike price of the call option.

Call Purchase: Options are a decaying asset, and investors risk losing 100% of the premium paid if the underlying asset's price is below the strike price of the call option.

Put Purchase: Options are a decaying asset, and investors risk losing 100% of the premium paid if the underlying asset's price is above the strike price of the put option.

Straddle or Strangle: The seller of a straddle or strangle is exposed to increases in the underlying asset's price above the call strike and declines in the underlying asset's price below the put strike. Since exposure on the upside is theoretically unlimited, investors who also own the underlying asset would have limited losses should the underlying asset rally. Covered writers are exposed to declines in the underlying asset position as well as any additional exposure should the underlying asset decline below the strike price of the put option. Having sold a covered call option, the investor gives up all appreciation in the underlying asset above the strike price of the call option.

Put Spread: The buyer of a put spread risks losing 100% of the premium paid. The buyer of higher-ratio put spread has unlimited downside below the lower strike (down to zero), dependent on the number of lower-struck puts sold. The maximum gain is limited to the spread between the two put strikes, when the underlying is at the lower strike. Investors who own the underlying asset will have downside protection between the higher-strike put and the lower-strike put. However, should the underlying asset's price fall below the strike price of the lower-strike put, investors regain exposure to the underlying asset, and this exposure is multiplied by the number of puts sold.

Call Spread: The buyer risks losing 100% of the premium paid. The gain is limited to the spread between the two strike prices. The seller of a call spread risks losing an amount equal to the spread between the two call strikes less the net premium received. By selling a covered call spread, the investor remains exposed to the downside of the underlying asset and gives up the spread between the two call strikes should the underlying asset rally.

Butterfly Spread: A butterfly spread consists of two spreads established simultaneously – one a bull spread and the other a bear spread. The resulting position is neutral, that is, the investor will profit if the underlying is stable. Butterfly spreads are established at a net debit. The maximum profit will occur at the middle strike price; the maximum loss is the net debit.

Pricing Is Illustrative Only: Prices quoted in the above trade ideas are our estimate of current market levels, and are not indicative trading levels.

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J.P. Morgan Equity Research Ratings Distribution, as of June 30, 2014

	Overweight (buy)	Neutral (hold)	Underweight (sell)
J.P. Morgan Global Equity Research Coverage	45%	43%	11%
IB clients*	55%	49%	34%
JPMS Equity Research Coverage	46%	47%	7%
IB clients*	75%	66%	54%

*Percentage of investment banking clients in each rating category.
For purposes only of FINRA/NYSE ratings distribution rules, our Overweight rating falls into a buy rating category; our Neutral rating falls into a hold rating category; and our Underweight rating falls into a sell rating category. Please note that stocks with an NR designation are not included in the table above.

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