






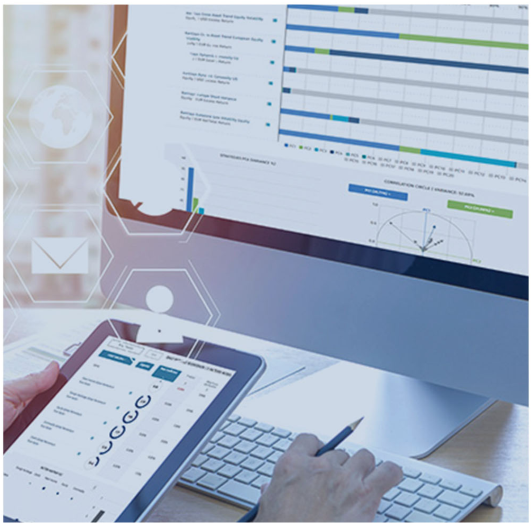

PremiaLab

Advanced Factor Analytics

May 2019

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Abstract

This paper outlines an advanced statistical and analytical methodology to benchmark, classify and assess the universe of quantitative investment strategies deployed in the market.

Using a rigorous top-down analysis of our extensive strategy database of leading providers, we will introduce the Pure Factor framework to model seven universally accepted style premia - Value, Size, Quality, Carry, Momentum, Volatility, and Low Volatility - within five different asset classes.

We shall then analyze how PremiaLab Pure Factors are providing a unique referential to benchmark the universe, measure factor exposures and their performance attribution across asset classes and investment styles.

A comprehensive correlation study demonstrates the lack of intra correlation of PremiaLab Pure Factors and showcases the dynamics of each factor versus its relevant market beta.

Furthermore, the factor model is tested on a wide range of investment products - Equities, Mutual Funds, Hedge Funds (CTAs, Global Macro, L/S Equity, Risk Premia Funds) Fund of Hedge Funds, demonstrating a unique explanatory power whilst quantitatively decomposing their risk and performance drivers.

1. Introduction to Alternative Risk Premia

1.1 Introduction

The development of systematic trading strategies has created a new dimension in the asset management industry. These strategies, capturing a specific risk premium, have proven to be an efficient performance engine and allowing a higher level of diversification within an investment portfolio. Systematic strategies are widely used in quantitative portfolio management and are accessible via numerous investment vehicles.

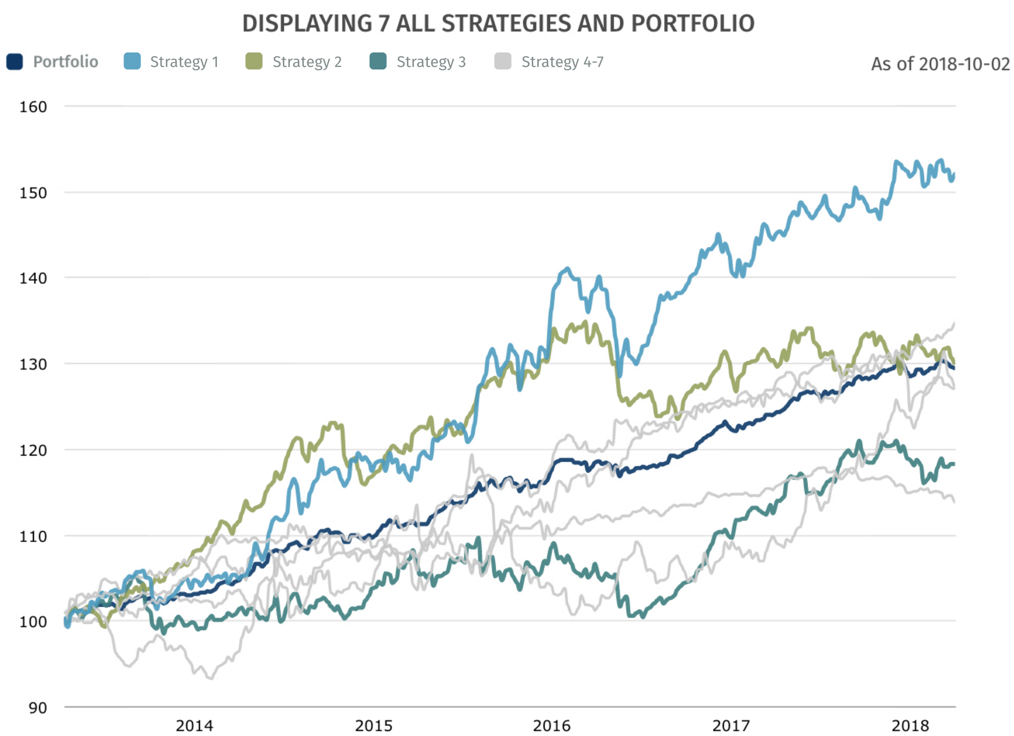
The objectives of this paper are to analyze, cluster and position the universe of strategies deployed in the market. We will introduce a unique top-down methodology to measure factor intensity across strategies. This factor referential is then applied to conduct independent market risk factor decomposition and regress quantitative fund returns to differentiate between genuine alpha from alternative risk premia (ARP) factors.

1.2 Alternative Risk Premia

With the rapid pace of globalization and growth of strong macro-policy drivers, assets from different asset classes are exhibiting strong co-movement behaviors. This shift in financial market characteristics has increased asset volatility, increased cross-asset correlations and drastically diminished investment portfolio diversification exposing investors to higher downside risk.

In recent years, there has been a quest for cost-efficient diversification alternatives, specifically a new set of uncorrelated risk premia, commonly known as “Alternative Risk Premia” (ARP). ARP strategies are rule-based systematic trading strategies that implement various algorithms to harvest market inefficiencies or investment flows in liquid financial underlying (such as behavioral effects, market inelasticity, and risk aversion).

Figure 1: Portfolio Construction with ARP



Source: Generated from PremiaLab platform

Risk premia strategies exhibit low inter-correlation levels, persistent performance, and low access fees. Investors are therefore able to construct cost-efficient and diversified portfolios that generate high risk-adjusted returns with a low correlation with traditional asset classes.

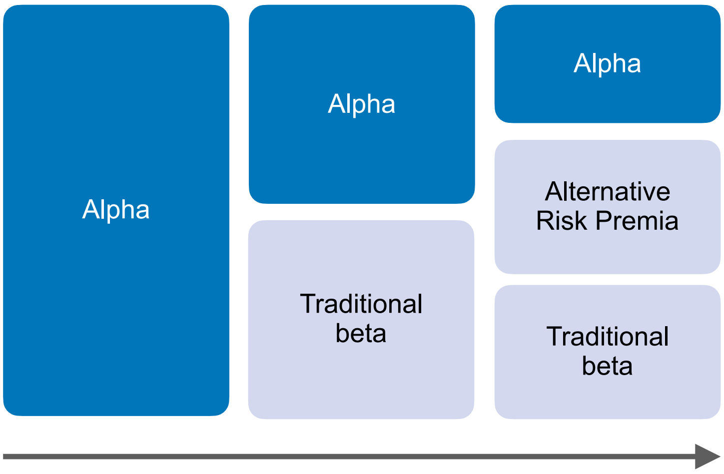
1.3 Distinction between Alpha, Traditional Beta, Smart Beta, and ARP

“Smart Beta” and “Alternative Risk Premia” are sometimes used interchangeably; however, conspicuous differences are evident in their structure and behavior.

Table 1.1: Comparison table between Beta, Smart Beta, ARP, and Alpha

	Traditional beta	Smart Beta	ARP	Alpha
Positive Expected Return	+	+	+	+
Correlation with beta	+	+		
Fees	Low	Low	Low	High
Long/Short			+	+

Figure 2: Refinement of the definition of Alpha



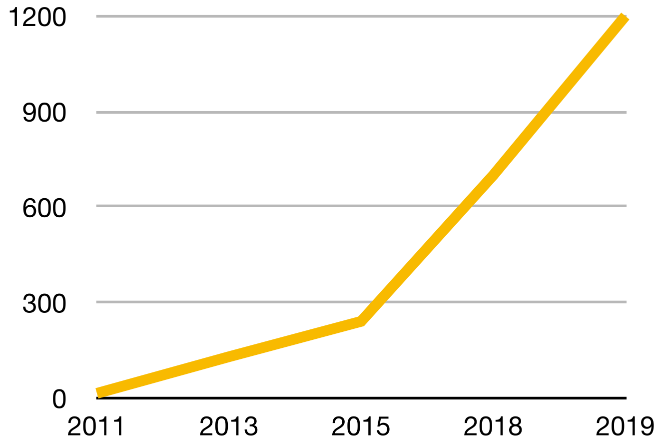
Source: PremiaLab

Smart Beta strategies are factor-based strategies using a long-only implementation while ARP strategies have a Long/Short implementation to control market beta exposure.

In comparison with the matured Hedge Fund industry, the development of the ARP market is more recent. According to Citigroup, ARP asset under management (AUM) increased from $15 billion (2011) to $241 billion (2015) and are projected to rise to $1.2 trillion by the end of 2019[1].

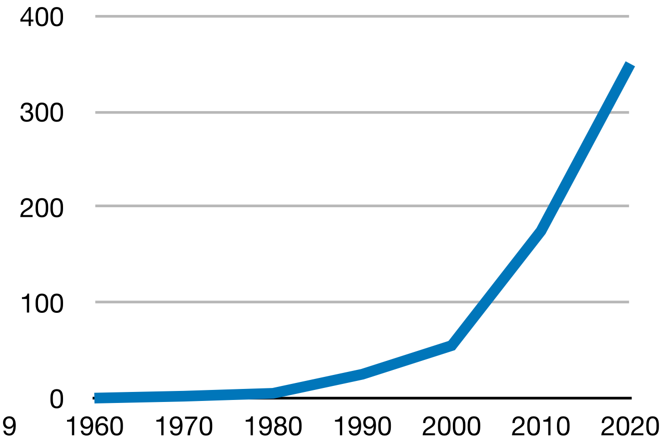
[1] Citi Prime Finance survey projected the AUM in risk premia related strategies to rise to $1.2 trillion USD by the end of 2019

Figure 3: ARP AUM (Billion)



Source: CitiGroup

Figure 4: Cumulative number of factors



Source: LYXOR Research

1.4 The Academic Foundation

Despite its recent popularity, the concept of risk premia has been extensively discussed in academic research papers for the past 50 years, with its first introduction in the form of Capital Asset Pricing Model (CAPM) by Sharpe (1964). In his paper, Sharpe introduced a single market risk premium (market beta) that aimed to explain the excess return which compensated investors for being exposed to non-diversifiable risk. This one-factor model assumed all financial assets were exposed to the same underlying market risk, which was later proven to be overly simplistic. However, CAPM is still widely employed within the industry, and Sharpe's work became the fundamental framework for modern finance.

Following Sharpe's effort to relate asset pricing with systematic risk, Fama and French (1993) expanded the CAPM model to build a three-factor model. In addition to the market factor, Fama and French found that market capitalization (Size) and the book-to-market ratio (Value) were also effective in explaining excess return in relation to market risk.

The Fama-French factor model developments led to the discovery of other risk premia factors. Among the newly discovered factors, the Momentum factor presented by Jedadeesh and Titman (1993) proved to be a valuable addition to the three-factor model. Following the said discovery, a four-factor model was soon developed by Carhart (1997), which included the Momentum factor. This four-factor model was shown to significantly improve the ability to describe asset return.

Since then, financial researchers have repeatedly taken advantage of data mining and machine learning to provide empirical evidence in an attempt to prove the existence of more factors. According to LYXOR Research[2], there are as many as 250 factors[3] discovered in published academic papers representing a factor "zoo."[4]

[2] LYXOR Research – "A Primer on Alternative Risk Premia" P.15

[3] Working paper are not included. Factor discovery are expected to grow exponentially with the improvement of data mining techniques.

[4] LYXOR Research quoted the term from John Cochrane, president of the American Finance Association

1.5 The rise of Risk Premia Indices

Investment banks have capitalized on the research in this area and utilized their extensive structuring and execution capabilities to design a large panel of proprietary indices based on these factors in response to the growing market demand. These indices are designed to be investible, available in multiple liquid asset classes and across risk factors. Strategies can then be selected and combined by portfolio managers through different investment products, including Funds, notes, ETFs, derivatives or direct replication.

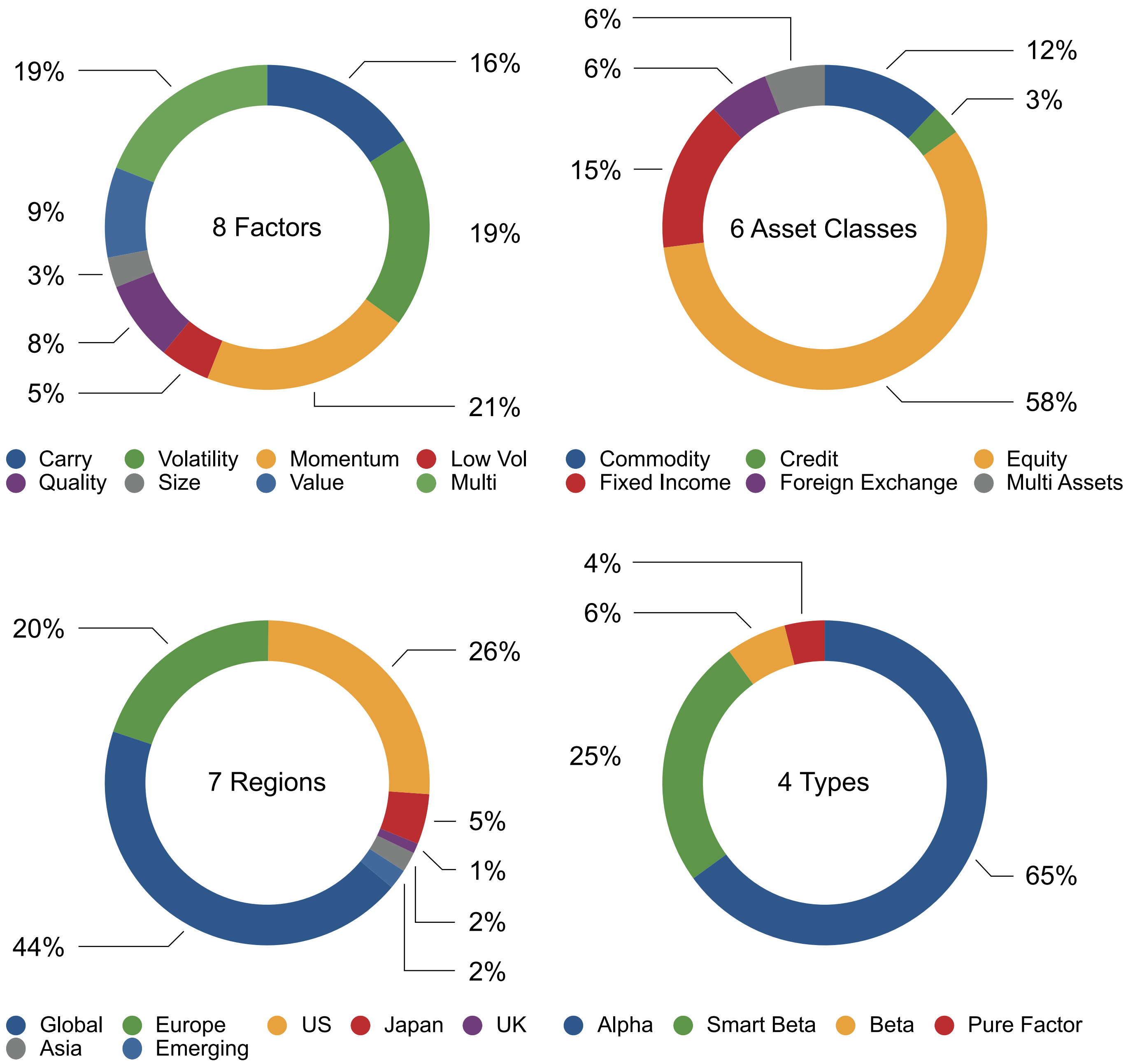
These indices are composed of liquid underlying assets that are listed securities or derivative contracts; rebalanced on a daily, weekly, monthly or quarterly basis. The index level is independently computed on a daily basis by the Index Calculation Agent based on observable market prices.

PremiaLab offers a comprehensive platform on systematic strategies from fifteen leading investment banks active in this growing market segment.

With consolidated data on over 1,500 strategies, the PremiaLab platform provides a unique source of data and analytics on the universe of strategies deployed in the market.

In the next section of the paper, we shall analyze, cluster, and position the universe of strategies from these leading index providers. Through this analysis, we demonstrate how to capture the risk profiles associated with the key market risk factors by incorporating market consensus and eliminating model interferences with a top-down PCA methodology.

Figure 5: PremiaLab's Strategies Overview



Source: PremiaLab

2. PremiaLab Pure Factor Construction

2.1 Pure Factor Construction

The classification within the PremiaLab database follows a seven-factor model which is built upon the four-factor model developed by Carhart (1997). From **Size** (Fama & French, 1993), **Value** (Fama & French, 1993) and **Momentum** (Jedageesh & Titman, 1997); PremiaLab Research have expanded the model to include **Quality** (Ashess, Frazzing, Pedersen, 2013), **Volatility** (Brière et al. 2010), **Low Volatility** (Fama & French, 1992, Ang, Hodrick, Xing, Zhang 2006, 2009), and **Carry** (Koijen et al. 2015).

PremiaLab's methodology to construct an unbiased factor model consists of integrating the maximum amount of market information while eliminating model-specific interference. After an explicit categorization, a diligent top-down approach is applied for the clustering of the strategies and then modeling of Pure Risk Factors, as opposed to the more prevalent bottom-up methodology.

The top-down methodology is more transparent and robust in order to provide an "aerial view" of the systematic factors driving market returns. Bottom-up approaches, focusing on individual constituents, are model dependent and based on specific assumptions. The differences in the broad modelization of underlyings can generate factor distortion. The bottom-up system falls short with regard to robustness when compared to the top-down approach which addresses these caveats.

2.2 From a Consensus Factor…to a Pure Factor

PremiaLab Factors are constructed by harvesting data from leading index providers to capture the general market consensus which, in this context, implies the market acceptance of certain factors. Within our extensive database, an implicit selection methodology based on the risk profile of strategies is used to define the cluster of strategies from the same risk factor.

We then remove noise and model discrepancies from our sample and eventually extract Pure Factors. One of the fundamental assumptions is that strategies from the same factor should have a similar risk profile as they capitalize on the same set of market inefficiencies (risk premium). In theory, Pure Factors can be portrayed as the independent component with the maximum amount of variance within strategies of the same factor.

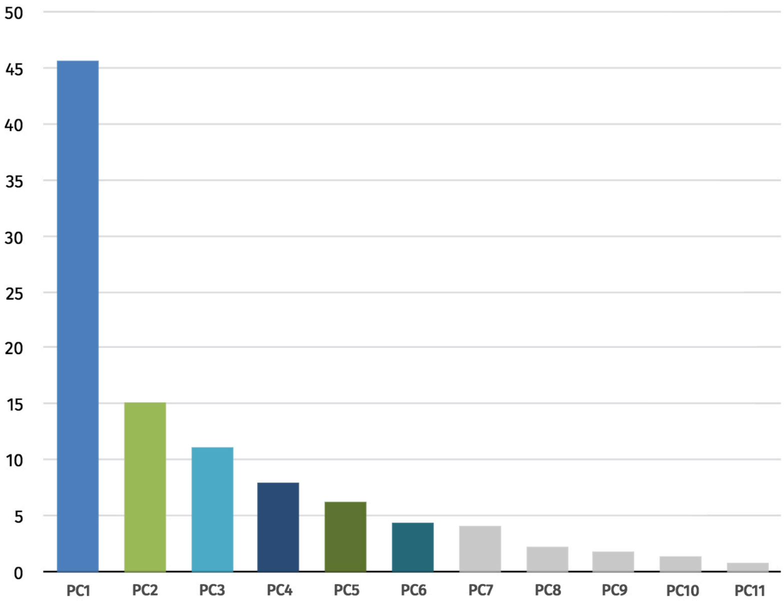
The subsequent section of the paper shall describe in further detail how the clustering and Pure Factor extraction can be achieved via the Principal Component Analysis methodology.

2.3 Principal Component Analysis (PCA)

An effective technique to visualize the distribution of variance within a given set of strategies is achieved through Principal Component Analysis (PCA). PCA reduces complex data into a set of independent variables and represents their variance proportion as per principal components (PCs). PCs are linearly uncorrelated variables that explain the variance of a selection of strategies, with PC1 as the largest explanatory variable. Such information can be used to identify risk clustering within our universe of strategies. For a more detailed explanation of our construction of PCA, please refer to the technical section in Appendix A.1 (P.40).

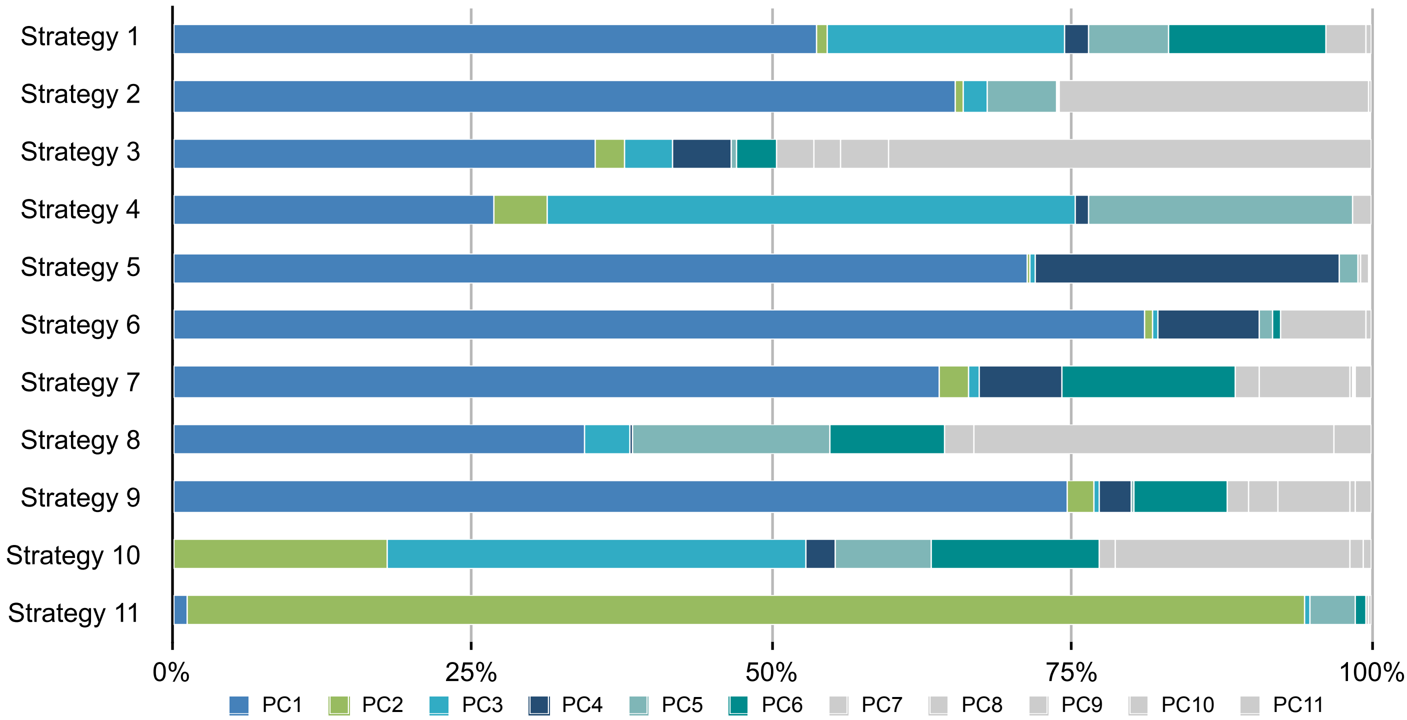
2.3.1 Clustering with PCA (Example 1)

Figure 6: PCA on US Equity Value
% of variance explained by PC



The standard PCA output in *Figure 6* displays the variance contribution of each principal component for a set of US Value strategies. High concentration of variance in the first Principal Component confirms that most of these strategies share a common risk driver which is de facto the US Value factor.

Figure 7: Variance Distribution by PCs

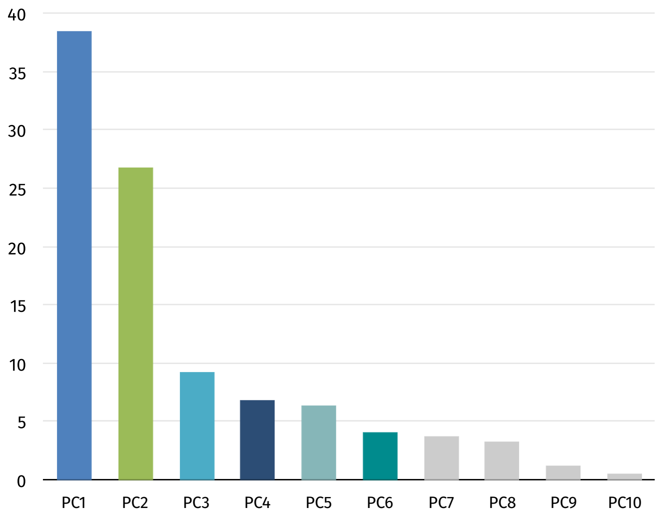


Source: Generated from PremiaLab Platform

Looking closely at the variance distribution within each strategy (*Figure 7*), one can immediately identify that the first 9 strategies are indeed driven by PC1; and further assess that strategy 10 and 11 are different as their variance is dominated other PCs. We have therefore successfully identified PC1 as the main driver for US Value strategy and that strategies 9, 10 are strategies with idiosyncratic behavior to be excluded from the cluster.

2.3.2 Clustering with PCA (Example 2)

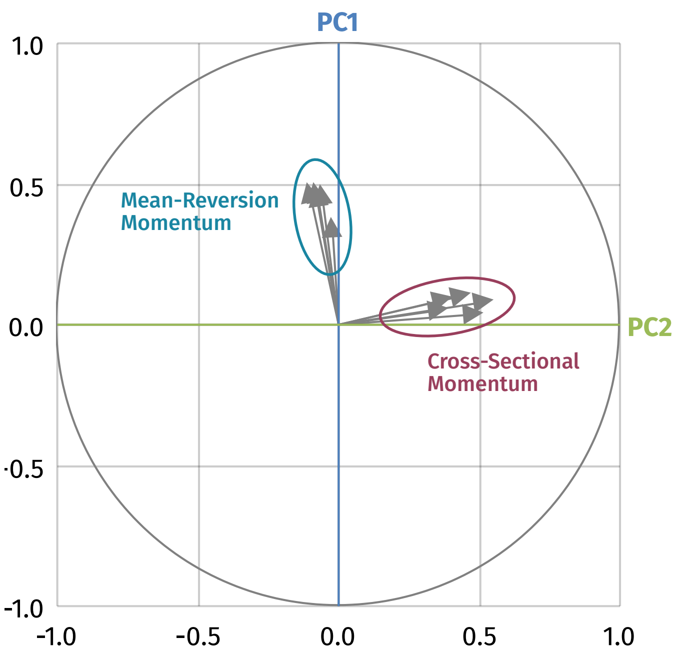
Figure 8: PCA on US Equity Momentum
% of variance explained by each PC



Example 2 illustrates how the PCA methodology identifies clustering beyond the explicit classification. PCA is applied to a set of similar strategies labeled as "US Equity Momentum"; the variance distribution output generated by the PremiaLab platform (*Figure 8)* shows that the high concentration of variance in strategies is explained by PC1 and PC2. Even though a larger PC1 proportion is revealed through this example, PC2 is significant as well. This provides a signal that a secondary risk driver is present within the strategy set.

Source: Generated from PremiaLab Platform

Figure 9: Clustering within US Equity Momentum



A deeper insight can be obtained with the correlation circle in *Figure 9*. The circular graph (which sets the strategies' correlation against PC1 and PC2 as the cartesian coordinates), visually displays two distinguishable clusters around the axes, suggesting that US Equity Momentum can be further divided into two sub-groups. Upon further investigation into the strategies' construction methodology, PC1 represents Mean-Reversion Momentum factor, and PC2 represents Cross-Sectional Momentum factor.

Note: 11-Year PCA on US Equity Momentum
Source: Generated from PremiaLab Platform

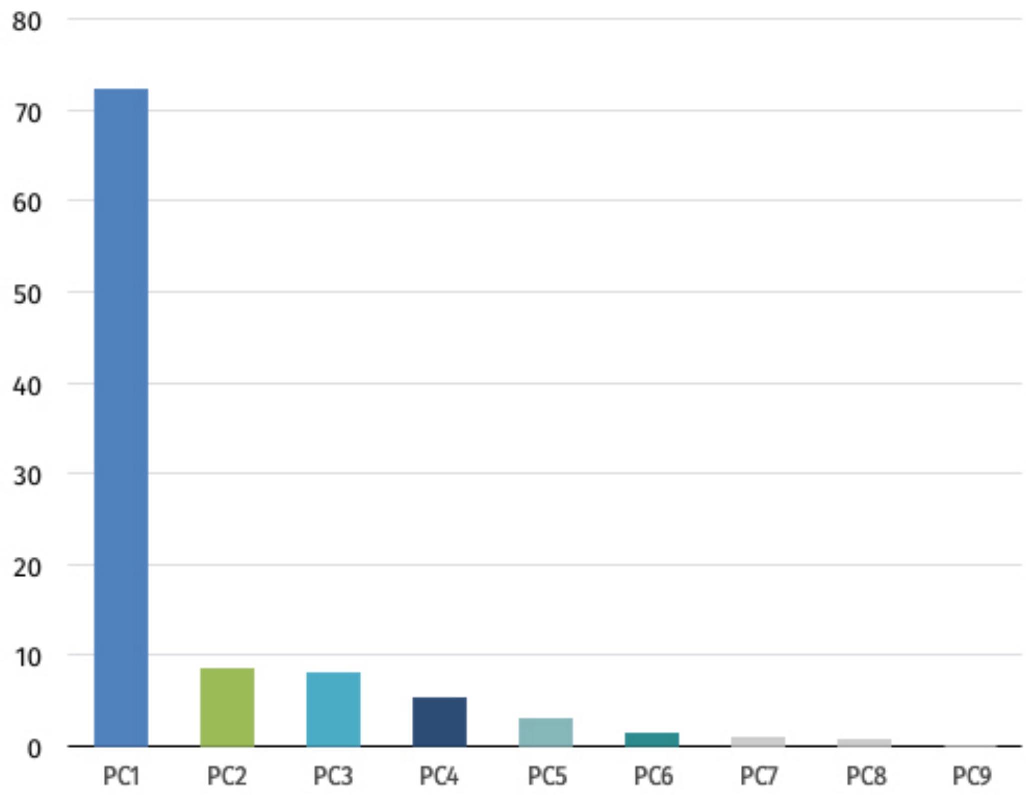
Example 2 demonstrates that PCA allows refining classification beyond the providers' general categorization. This provides additional insights for portfolio risk factor analysis.

2.4 Pure Factor Generation

Following the thorough filtering and clustering process through PCA to identify the main driver of the selected risk factor, the chosen PC (mostly PC1) is extracted in the form of daily returns to recreate the track of what shall become the PremiaLab Pure Factor. This process allows capturing the PC explaining the largest proportion of the variance disregarding any interference that arises through implementation discrepancy (disparity of constituent selection process, rebalancing models, weighting options etc.). We, therefore, introduce the concept of purity and create an independent factor referential.

Taking the previous example of US Value, after the PCA filtering, we observe a relatively homogeneous cluster with PC1 explaining 72% of the variance of the strategies. The weightings implied for the construction of PC1 are extracted for the construction of the US Value Pure Factor and remaining PCs representing disruptive noise and implementation interferences are excluded.

Figure 10: Pure Factor Extraction US Value
% of variance explained by PC



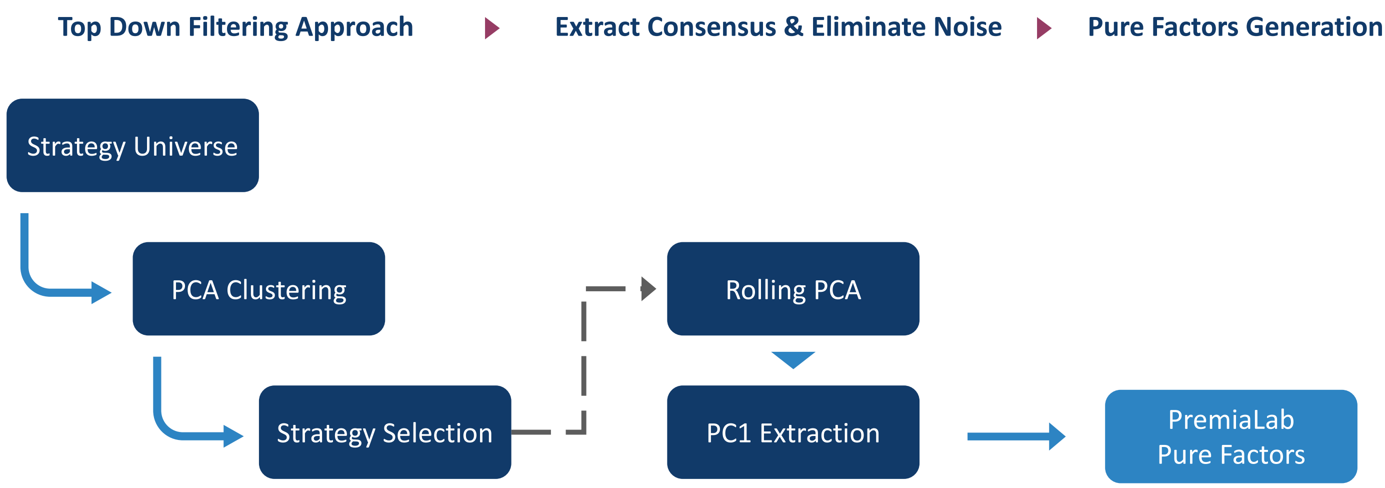
Source: Generated from PremiaLab Platform

2.5 Technical Implementation

The previous section introduces the diligent process for strategy categorization, PCA bucket construction and clustering and finally Pure Factor extraction. Using this top-down approach, 44 Pure Factors have been constructed across 7 risk factors (Carry, Volatility, Momentum, Low Volatility, Quality, Size, Value), 5 asset classes (Commodity, Credit, Equity, Fixed Income, Foreign Exchange) and 3 regions (Global, US, EU).

PremiaLab recognizes the dynamic interpretations of ARP strategies associated with the different implementations. According to J.P Morgan, “new factors will emerge, or risk factors may also weaken or completely disappear”[5], inferring that ARP strategy definition may be slightly different from one investor to another, but also that the number of factors in the market can vary over time as well. We will therefore conduct regular reviews of our universe of Pure Factors.

Figure 11: Pure Factor Construction Overview



Source: PremiaLab

PremiaLab research observed that the market consensus can shift over time. In addition, a static PC weighting scheme may not be appropriate in certain scenarios. Thus, PremiaLab applies a quarterly rolling PCA to update the weighting coefficients. This periodic rebalancing allows to capture the maximum market information at any point in time and to homogenize the PC track extracted.

To generate a representative Pure Factor for the market consensus, correlation PCA is used to standardize strategies’ variance. Contrary to covariance PCA, the correlation PCA does not overweight strategies with higher variance, which casts a fair representation of each strategy as it reduces biases that may arise.

Other advanced models can also be used to extract commonality among variables such as Robust Principal Component Analysis (ROBPCA), Principal Skewness Analysis (PSA), Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA), and Moment Component Analysis (MCA). Although these models might have specific advantages, a standard PCA applied to a relevant dataset has demonstrated its ability for an effective application in our case. Further statistical validation of our methodology is provided in Appendix B.1-2 (P.42-43)

[5] JP Morgan “Systematic Strategies Across Asset Class – Risk Factor Approach to Investing and Portfolio Management” P.8

3. Interpretation and Analysis

3.1 Correlation Analysis

Factor investing has gained enormous interest among institutional investors in order to achieve cost-efficient portfolio diversification. The objective of this section is to address the key questions from investors on factors diversification properties and their implication for portfolio construction.

- Factor independency: How can we assess cross-sectional behaviors across factors?
- Correlation with market beta: How Long/Short implementations achieve (or not) uncorrelated performance versus their respective benchmark?
- Factor regionalization: Are factors global or shall we take into account regional differences?
- Factor dynamics: Could the shift in factor correlation demonstrate the shift in market dynamics?

With PremiaLab Pure Factors, investors can access an extensive market-factor dataset to gauge and compare diversification with a high level of granularity. Furthermore, the data represents actual, deployable strategies taking into account liquidity and transactional constraints making the analysis very relevant for portfolio construction and allocation.

3.1.1 Factors Independency

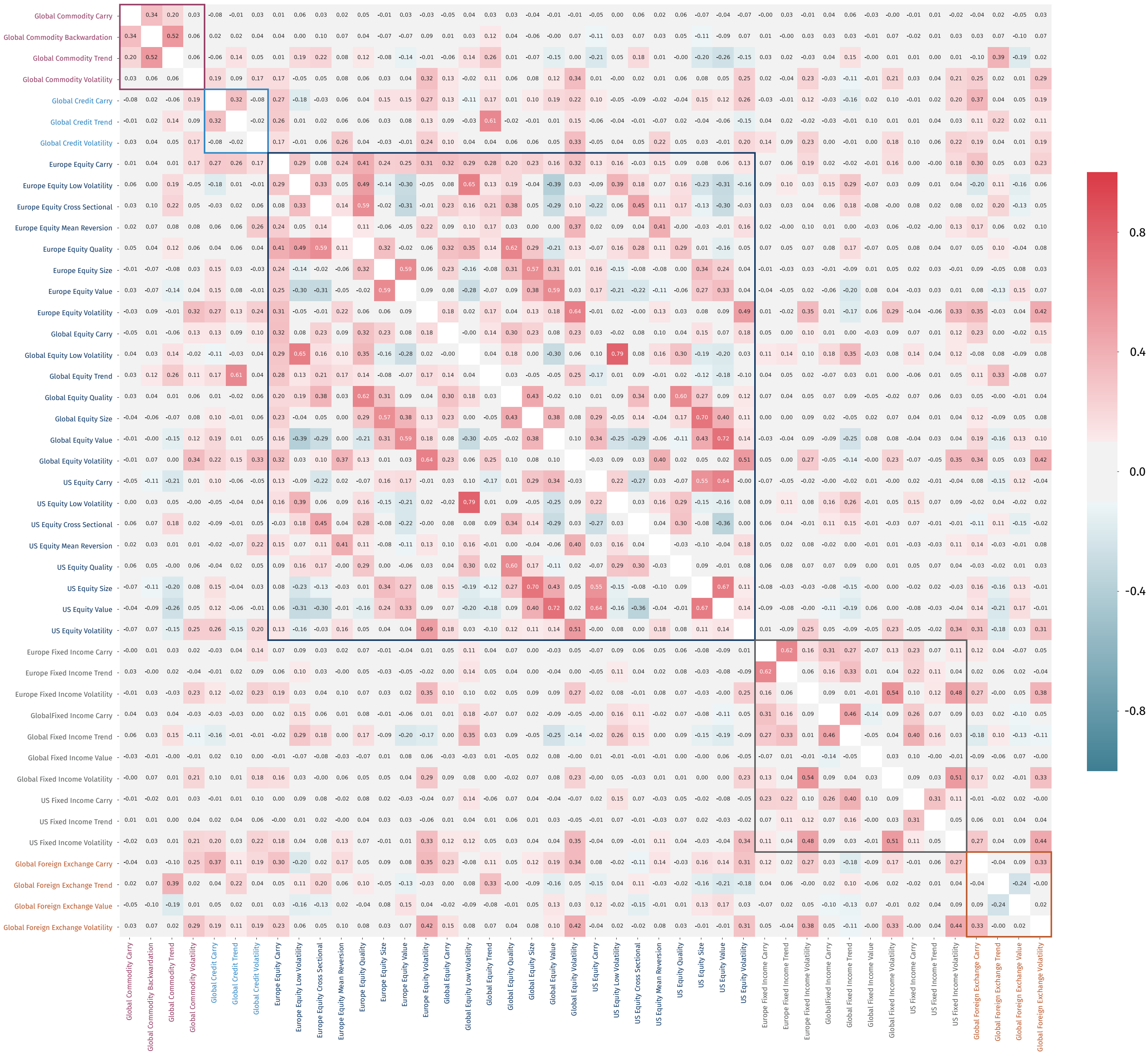
First, an emphasis is placed on factor independency through cross-sectional consideration on the Pure Factor Dataset. Evidence, *Figure 13* (next page), shows uncorrelated behavior of PremiaLab Pure Factors with interesting exceptions.

Overall, most cross-factors correlation values indicate a low level of correlation within each asset class. For Foreign Exchange (*Figure 12*), most of the correlation pairs demonstrate uncorrelated behavior, with the exception between Carry and Volatility at 0.33.

Figure 12: Global Foreign Exchange 3-Day Correlation Matrix

Note: 3-Day Correlation is calculated from April 2008 to May 2019
Source: PremiaLab

Figure 13: 3-Day Correlation Matrix of All Pure Factors
44 Pure Factors, 5 Asset Classes, 3 Regions

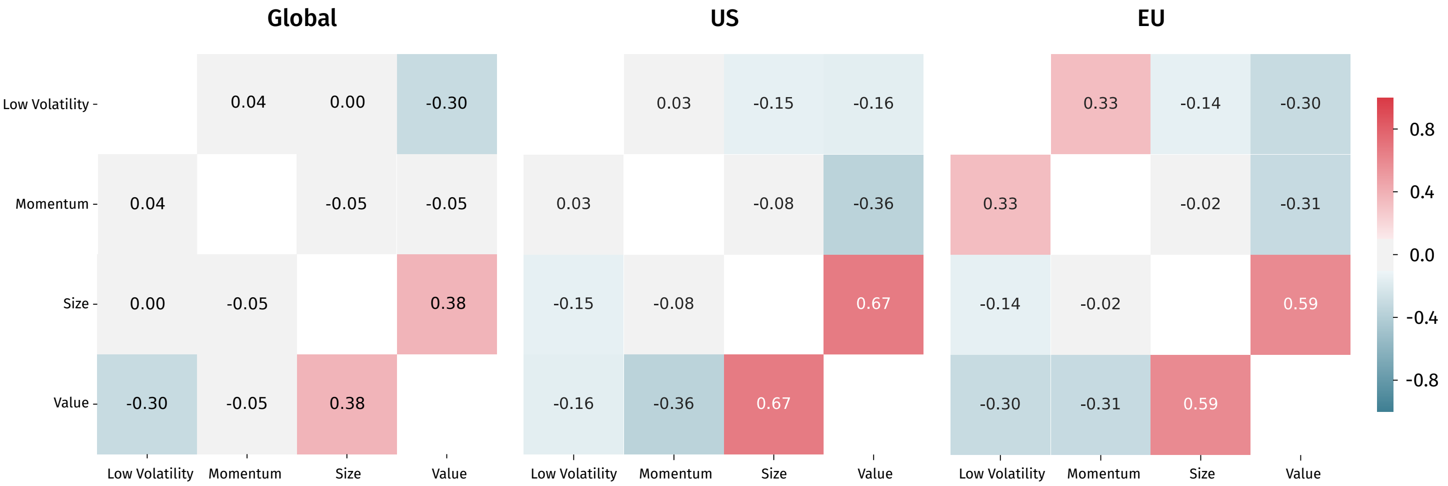


Note: 3-Day Correlation is calculated from April 2008 to May 2019

Source: PremiaLab

However, some outliers possess a highly consistent of patterns. For example, we can notice a hidden structure within the Equity matrix factor correlation matrix as demonstrated below:

Figure 14: 3-Day Correlation Matrix between Value, Low Vol, Size, Momentum



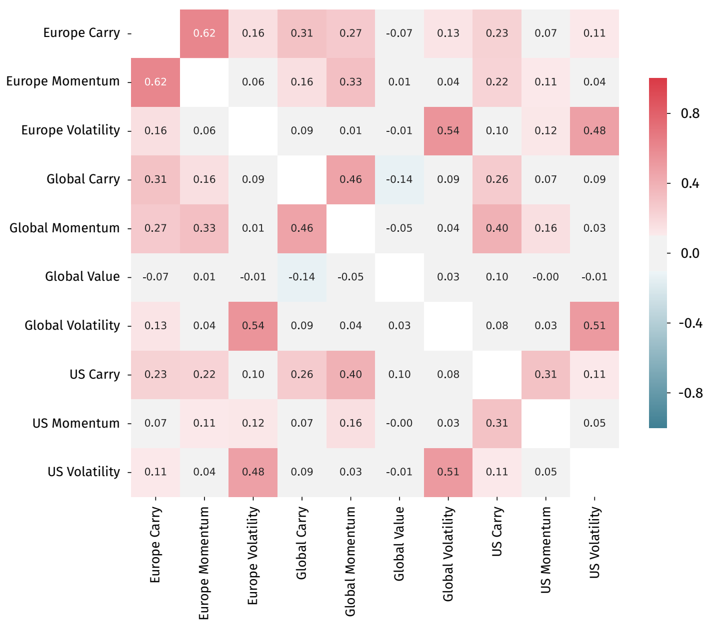
Note: 3-Day Correlation is calculated from April 2008 to May 2019 *Source: PremiaLab*

The correlations between above-mentioned pairs are consistent in magnitude, scale and even across regions. Evidence gathered from robust Pure Factors suggests that the relationship between these factors appears as more fundamental in nature.

3.2 Regional Difference between Factors

While the theory could induce the existence of universal or global factors across markets, strong evidence derived from the correlation matrix suggests the need to separate factors by region to obtain more accurate Equity and Fixed Income Pure Factors.

Figure 15: Fixed Income 3-Day Correlation Matrix



For Fixed Income correlation, the highest inter-region correlation is between Global Volatility and Europe Volatility at +0.54, implying that the Volatility risk premium across regions have similar behavior.

We observe that Carry and Momentum factors have a relatively higher intra-region correlation (Global: 0.46, US: 0.31, EU: 0.62), suggesting certain factors are fundamentally related as shown in all three regions.

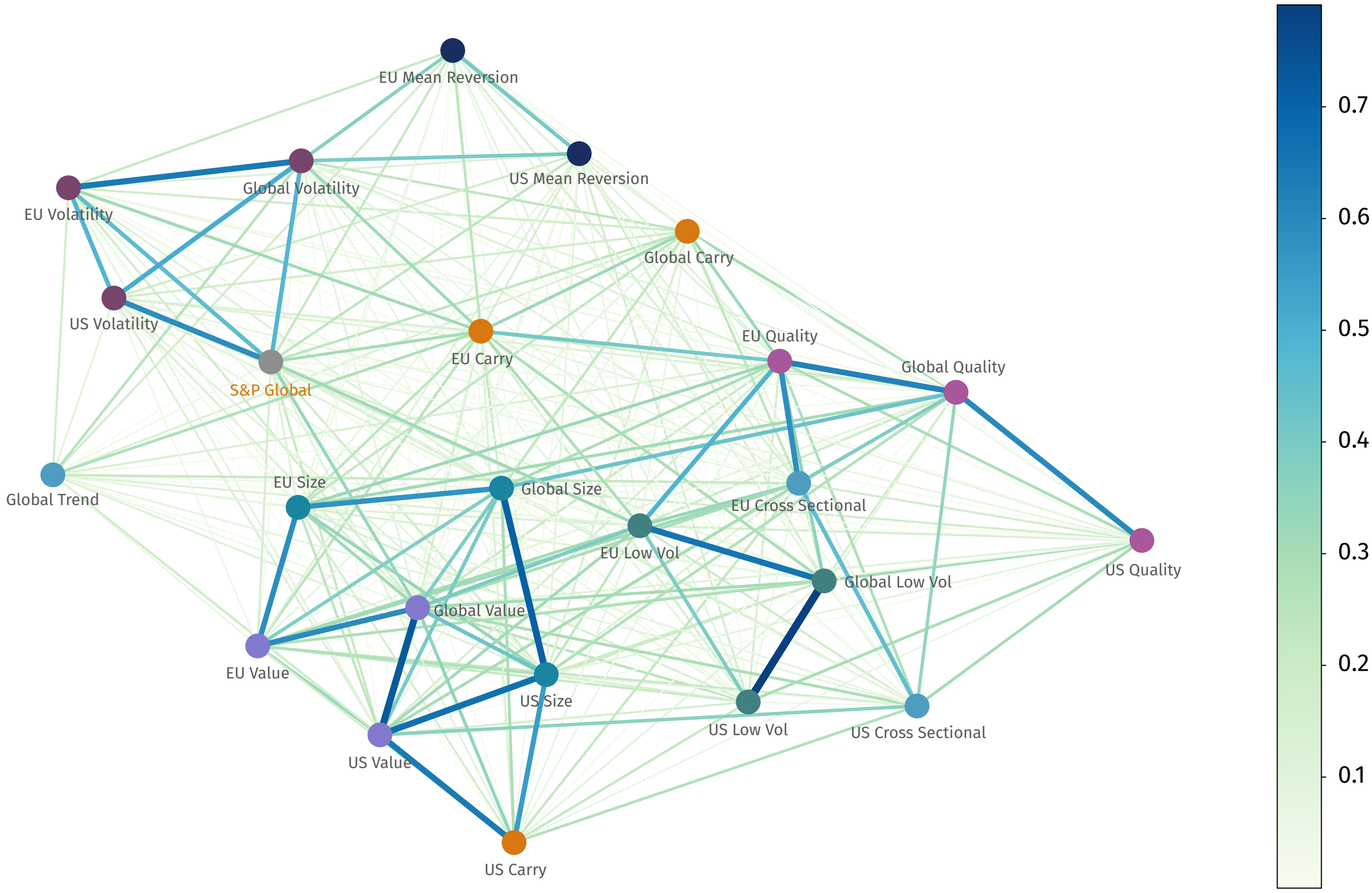
Note: Correlation is calculated from April 2008 to May 2019
Source: PremiaLab

However, correlation values are not significant enough to discredit the separation of different regions among Pure Factors.

The most relevant effect is for Equity Low Vol with an inter-region correlation coefficient equal to +0.79 between Global and US and +0.65 between Global and Europe.

It is, however, worth outlining that Equity Carry and Equity Momentum strategies are uncorrelated across regions. A more in-depth explanation can be found in the next sections.

Figure 16: Correlation Network for all Equity Pure Factors



Note: Correlation is calculated from April 2008 to May 2019; Factor nodes connected by darker edges are more correlated
Source: PremiaLab

3.2.1 Regional Difference in Equity Carry Factor

Carry is often defined as a long/short portfolio between high dividend stocks and their relevant benchmark. The economic rationale behind the Carry factor is that high dividend stocks provide better downside protection during crises therefore generating better returns in the long term.

The correlation matrix reveals that the Carry factor is not correlated regionally, suggesting that Carry strategies across regions are independent from one to another.

A further analysis of high dividend stocks in each region reveals fundamental differences in high yielding sectors across US and Europe. (NYU Stern Dividend Data in *Table 3.1*[6]). Furthermore, the divergence can be explained by considering dividend culture and taxing policy between the two regions.

Table 3.1: High Yield Sector in US & EU

TOP 15 High Yield Sector (US)	
Telecom. Services	4.64%
R.E.I.T.	3.91%
Tobacco	3.75%
Oil/Gas (Integrated)	3.59%
Utility (General)	3.23%
Power	3.15%
Insurance (Life)	3.02%
Advertising	2.83%
Auto & Truck	2.77%
Oil/Gas Distribution	2.67%
Recreation	2.62%
Beverage (Soft)	2.58%
Drugs (Pharmaceutical)	2.55%
Coal & Related Energy	2.54%
Household Products	2.47%

TOP 15 High Yield Sector (EU)	
Shipbuilding & Marine	7.23%
Oil/Gas Distribution	6.52%
Utility (General)	5.20%
Telecom (Wireless)	4.95%
Reinsurance	4.59%
Utility (Water)	4.37%
Brokerage & Investment Banking	3.83%
Computers/Peripherals	3.77%
Telecom. Services	3.71%
Retail (Automotive)	3.69%
Paper/Forest Products	3.63%
Chemical (Basic)	3.61%
R.E.I.T.	3.37%
Bank (Money Center)	3.31%
Broadcasting	3.30%

Source: NYU Stern, Prof. Anwath Damodaran

[6] Dividend Payout ratios and dividend yields, with key drivers, Prof. Aswath Damodaran

3.2.2 Regional Difference in Equity Momentum Factor

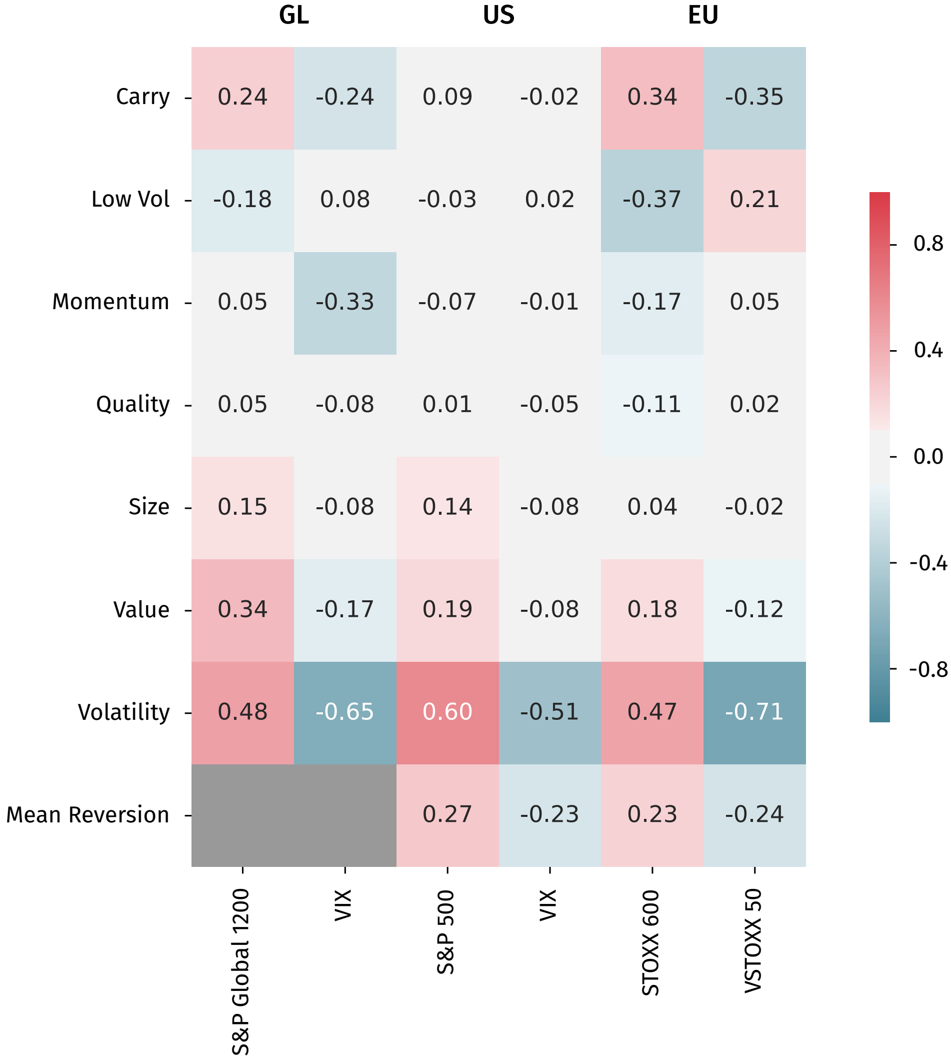
Momentum factor also exhibits region independence as seen in the matrix. The Momentum factor does not capitalize on any economic traits, it can rather be seen exploiting asset mispricing and psychological biases (such as herding behavior). As a result, it is reasonable to conclude that Momentum is independent across regions.

3.3 Low Correlation with Benchmarks

The long/short implementation of factor-based strategies should imply low sensitivity to market benchmarks (i.e. market beta). However, factor performance is impacted by market movements and investors need to control their exposure to market beta to avoid risk concentration in their portfolio.

In this section, equity factors are regressed against S&P 500 (SPX), STOXX 600 (SXXP), and S&P Global 1200 (SPGLOB) over the 11-year sample period. Results demonstrate that most of the factors are indeed not correlated with the relevant benchmarks on a consistent basis over the period. The exceptions are Carry, Volatility and Low Volatility with significant correlation against the relative benchmarks.

Figure 17: 3-Day Correlation of Equity Factors vs Benchmarks



Note: Correlation is calculated from April 2008 to May 2019
Source: PremiaLab

3.3.1 Equity Low Vol (GL & EU) vs Benchmark

One of the interesting characteristics of Low Volatility factors is their noticeable correlation with benchmarks. While Low Volatility or Low-Beta factor is constructed with a long/short portfolio, it carries a negative beta overall. Such a phenomenon can be explained by the fact that low beta stocks are not able to totally offset the elasticity of high beta stocks within a long/short portfolio. This defensive characteristic of Low Volatility was amplified during the financial crisis in 2008. Beta dispersion among stocks is higher during volatile periods and Low Volatility premium is able to outperform their high beta peers.

3.3.2 Equity Carry vs Benchmark

“The Carry factor is the expected return assuming that market conditions, including its price stays the same”, (Koijen 2015). Since the Carry factor is trading on the expectation of future dividend yield, it can be further generalized as a “forward looking measure related to dividend yields in equity”. One can expect Carry strategies to experience drawdown and expansion coinciding with varying global business cycles.

3.3.3 Equity Volatility vs Benchmark

The correlation between Volatility factor and the market comes as no surprise. Numerous publications have observed and detailed this relationship. Volatility strategies, that capture Volatility premium between implied and realized volatility, will also suffer in market downturns.

3.3.4 Fixed Income Carry vs Benchmark

Fixed Income Carry strategies are usually implemented to capitalize on the slope of the interest rate curve with a long position which will outperform the short position in a decreasing interest rates environment from the duration convexity effect.

3.3.5 Commodity Carry vs Benchmark

Interestingly, we observe an opposite effect for Commodity Carry strategies with a negative correlation with the market benchmark. We do observe a shift in slope for commodity future prices from contango to backwardation according to the market performance.

3.4 Factor Rolling Correlation

After analyzing PremiaLab Pure Factors’ average correlations, we have validated the anticipated behavior of factors and discovered interesting patterns across factors and geographies. The appropriate next step is to look at how the correlation trends behave over time.

As the economic climate is constantly evolving and market dynamics are an important characteristic of risk premium, the rolling correlation plots shall demonstrate potential interactions between factors and market beta.

In the 252-day rolling correlation graph (*Figure 18*, next page), Low Volatility, Carry, Quality, Size, and Value are relatively stable around the -0.25 and +0.25 interval.

Figure 18: Rolling Correlation against SPGLOB

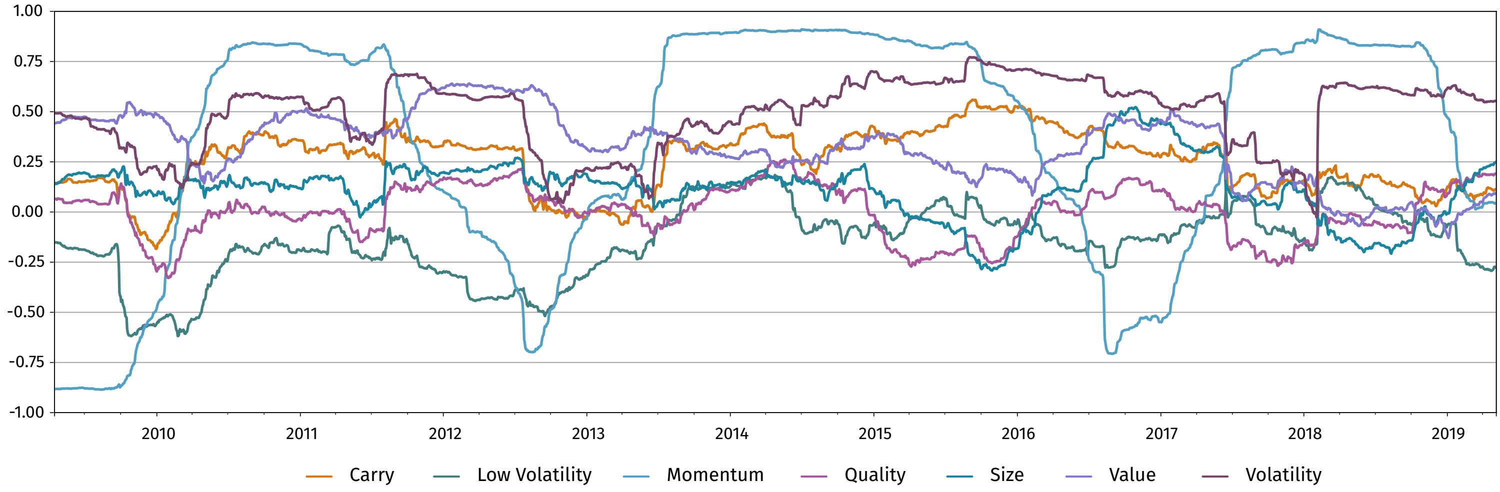
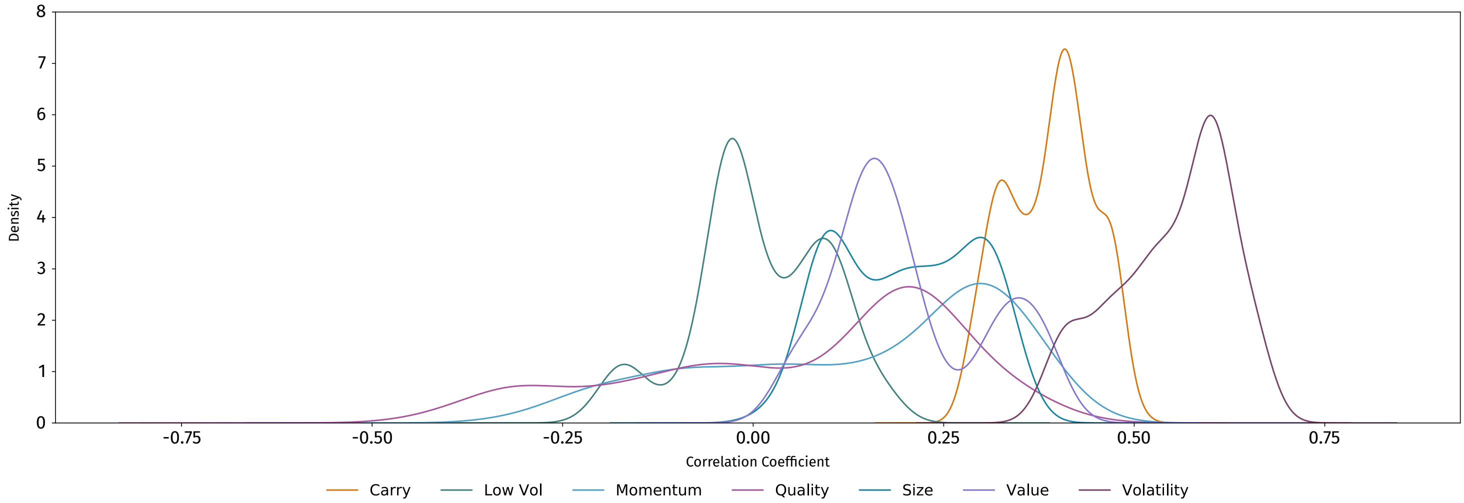


Figure 19: KDE of Rolling Correlation against SPGLOB



Note: Rolling Correlation is measured from April 2008 to May 2019 *Source: PremiaLab*

Meanwhile, Volatility and Carry exhibit high positive correlation against SPGLOB throughout the entire period. Conversely, Quality is negatively correlated with SPGLOB after mid-2010.

The second test for stability of the Pure Factors can be done with the Kernel Density Estimation (KDE) plot. KDE estimates the probability density function (PDF) of the correlation during the 11-year period based on the 252-day rolling correlation result. As shown in *Figure 19*, the density plot confirms that Volatility and Carry fundamentally correlated with the market risk (SPGLOB) as the average correlations deviate away from zero. In addition, the plot can also provide insights into factor stability through the analysis of the distribution. (Please refer to Appendix A.2 (P. 41) for the summary statistics of the rolling correlation result.)

3.5 Market Dynamics of Factors

Under perfect circumstances, factors are uncorrelated to each other i.e. all factors are fundamentally exposed to different sets of risks. In reality, factors capitalize on macroeconomic risks and different market regimes. Hence, it is essential to extract factor dynamics within the PremiaLab factor model to measure the degree of interdependence including the impact or response to shifts in market dynamics.

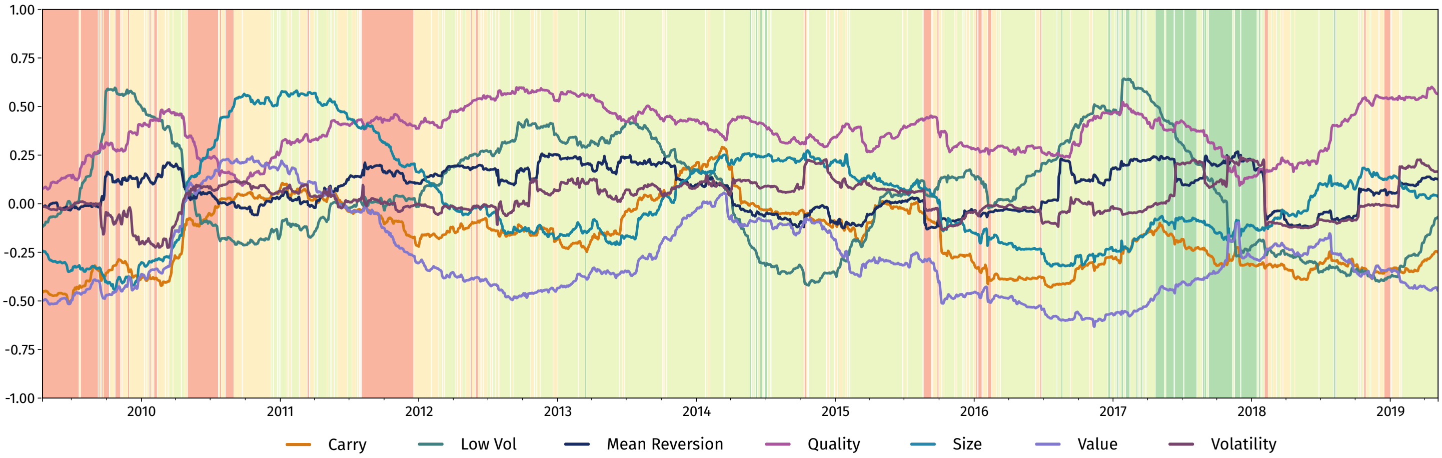
To illustrate this phenomenon, this section shows the inter-factor correlation evolution of factors over a 11-year period with a Volatility Index (VIX) underlay to model risk on and off market regimes.

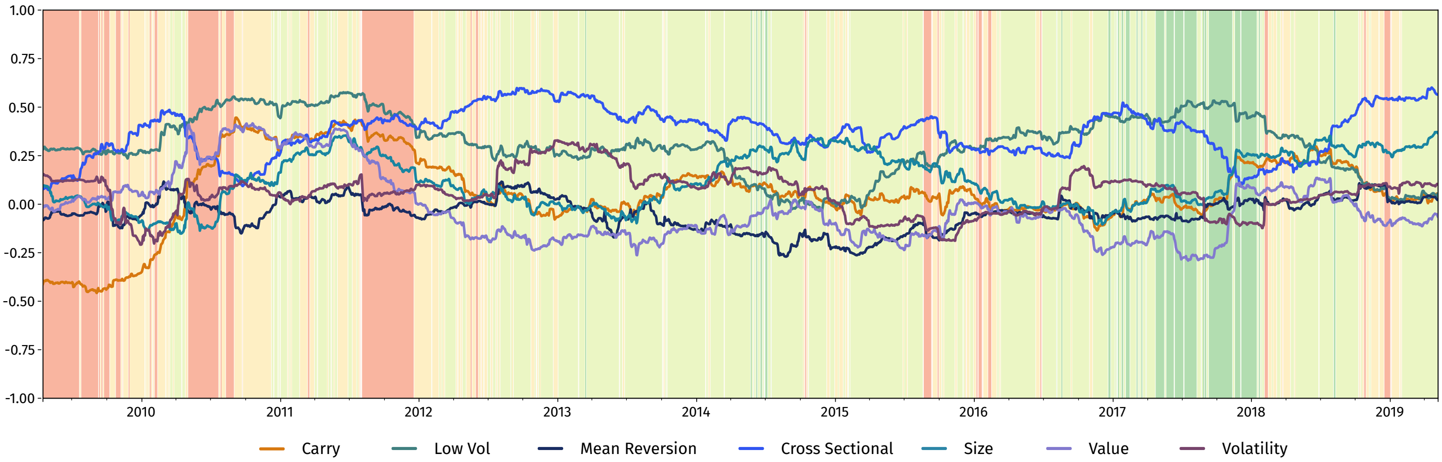
The VIX overlay coloring is based on the daily VIX level; with Orange as highly volatile (greater than +1 S.D.), Dark Green as stable (less than -1 S.D.), yellow and light green as slightly volatile and natural.

The graph below models the rolling correlation of US Equity Momentum against other US equity factors (US Equity Carry, Low Volatility, Mean Reversion, Quality, Size, Value, and Volatility). It is clear that Momentum correlation against certain other factors within the same region and asset class is constantly fluctuating.

On the contrary, the correlation measures of US Equity Quality against other US equity factors (US Equity Carry, Low Volatility, Mean Reversion, Momentum, Size, Value, and Volatility) are relatively consistent throughout the 11-year period.

Figure 20: Rolling Correlation of US Equity Cross Sectional (top), US Equity Quality (bottom) against other US Equity Factors
VIX Overlay in background to indicate risk level





Note: Rolling Correlation is calculated from April 2008 to May 2019 *Source: PremiaLab*

4. Application of Pure Factors

4.1 Factor Regression

Combining Pure Factors with regression creates a very insightful way to quantify factor risk. This section focuses on the application of the Pure Factors, with the emphasis on automated regression on large datasets. The objective is to demonstrate the versatile applications of Pure Factors by examining how factor investing is impacting financial markets and how strategies are combined in investment products.

Pure Factors provide a unique pivot to independently assess the universe of strategies they are generated from. The guiding motivation is to quantify the relevancy of each factor towards a given strategy by measuring its factor intensity or obtaining an independent assessment of its classification. Such analysis can both single-out specific strategies with idiosyncratic behavior or obtain a fine measure of the degree of purity of a strategy for factor and market beta exposure.

In this first section, after validating the Pure Factors classification capability, regression on smart beta and multi-factor strategies is conducted to quantify Pure Factors' explanatory power. As a follow up analysis, a case study of a multi-factor strategy further demonstrates how a Pure Factor regression can reveal and identify factor rotation within multi-factor strategy.

Ultimately, Pure Factors are tested to regress beyond systematic strategies:

1. Mutual Funds and Hedge Funds, to understand how factor strategies are combined by asset managers and to measure alpha generation.
2. Individual stocks to quantify how factors are driving the performance of the cash equity market.

Insightful results and many interesting observations are produced through the use of Pure Factors. The following section will discuss these results more in-depth analysis.

4.2 First… the Regression Model

A typical regression model is often represented as follow:

$$Y = \alpha + \beta_1 x_1 + \ldots + \beta_i x_i + \varepsilon$$

With variable either being PremiaLab Pure Factors or Market Benchmarks (S&P 500, STOXX 600, S&P GSCI, Citi World Government Bonds) or both.

The calibration of Betas (β_i) is generated through an objective algorithm to minimize squared error either on a fixed period or with a rolling window period. The rolling window methodology measures the stability of the regression or the dynamic of factor allocation.

Since we are facing a potential large number of Pure Factors for certain asset classes, we are also applying a LASSO shrinkage algorithm to select the relevant factors for our analysis. For a technical explanation of the LASSO algorithm, please refer to the Appendix A.3 (P.41).

The output of the regression can then be expressed as:

R^2: the regression accuracy indicator:

$$\frac{var(y) - var(\varepsilon)}{var(y)}$$

The variance proportion of the k-th factor:

$$\frac{Var(\beta_k x_k) + \sum Cov(\beta_k x_k, \beta_i x_i)}{Var(y)}$$

The performance proportion of the k-th factor:

$$\frac{performance(\beta_k x_k)}{performance(y)}$$

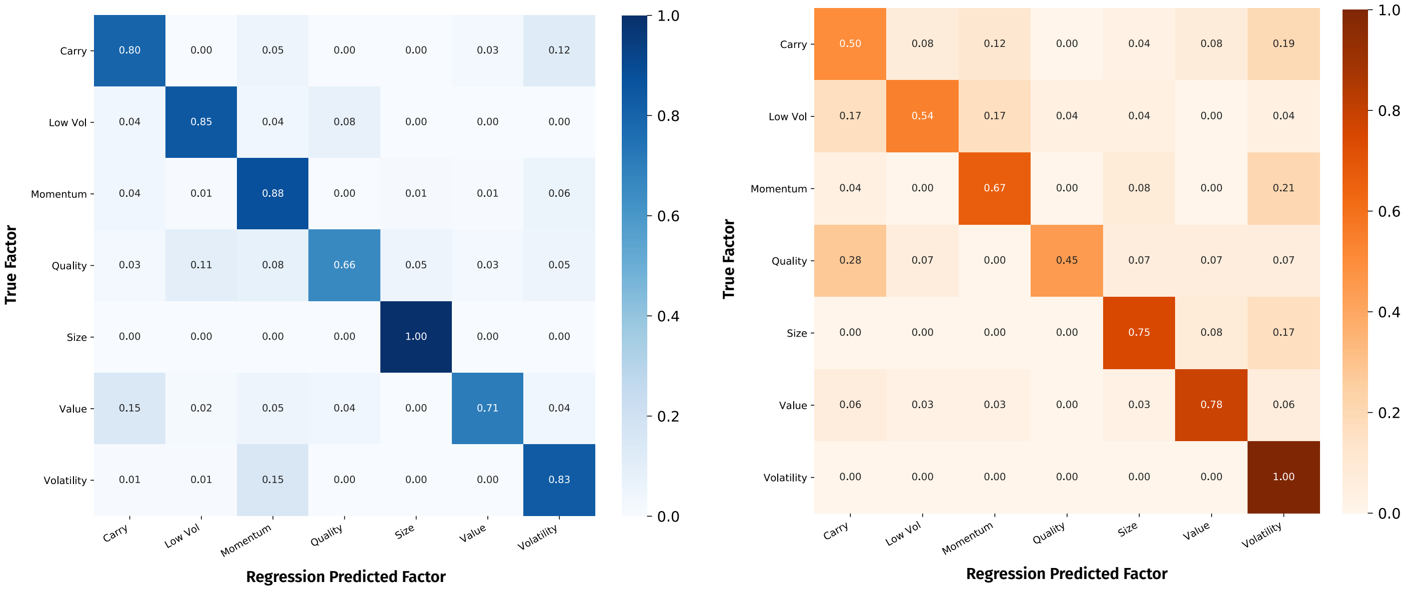
4.3 Classification and Factor Intensity

The following analysis implements a mass regression of PremiaLab universe of strategies including Alpha, Smart Beta, and Multi-factor strategies. It is important to note that Smart Beta strategies and Multi-factor strategies are not included from the universe of strategies used for the calibration of PremiaLab Pure Factors (out of sample).

The first analysis focuses on the maximum factor variance explanation test to validate the explicit classification of the strategy. The result is then summarized as a confusion matrix that represents the categorization of strategies by factors. The Y-axis is the provider's categorization, while the X-axis is the predicted factors based on the regression result. The predicted factor is based on the factor with maximum variance proportion within the regression. The graph is then normalized to represent the percentages of strategies (true label) classified as the predicted factors.

The diagonal cells, as seen in *Figure 21* (next page), represent the correct classification and have a high percentage of success rate, verifying the Pure Factor accuracy. The overall in sample accuracy rate is 72.7% for Alpha strategies and the out of sample accuracy rate is 60% for Smart Beta strategies.

Figure 21: Confusion Matrix
In sample (left) & Out of sample (right)



Note: Regression is calculated from April 2008 to May 2019 *Source: PremiaLab*

This analysis provides an independent assessment of the classification and also highlights the diversity of implementations across providers. Some of the misclassifications can also be explained by the blurred definition of some of the strategies.

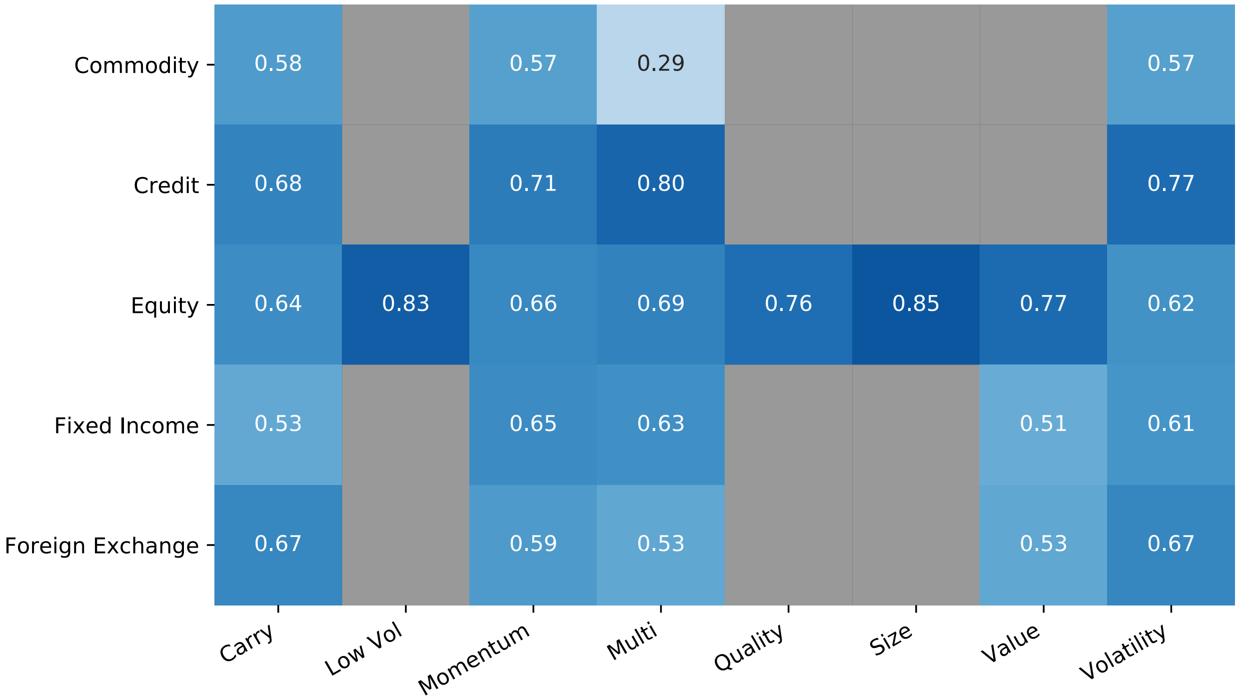
4.4 Explanatory Power

In this analysis, the R^2 of the regression is measured. All the strategies with more than a 5 Year track in the database, excluding benchmark indices, are included in the heatmap. The average R^2 measures are generated by regressing the weekly returns of all the strategies against all the applicable Pure Factors of the same asset class (factor model) and the relevant market beta. The regression result can then be further transposed to produce an average R^2 Heatmap measuring the explanatory power of the target Pure Factor.

In *Figure 22*, each blue square represents the average R^2 associated with strategies from the same asset class and factor. Overall the weighted average R^2 is at 66% for single factor strategies. For multi-factor strategies, the explanatory power of PremiaLab Factor Model is fairly high with a weighted average R^2 at 62%.

Commodity strategies demonstrate the highest level of heterogeneity which can be explained by the large variety of products/produces each strategies .

Figure 22: Average R^2 Heatmap

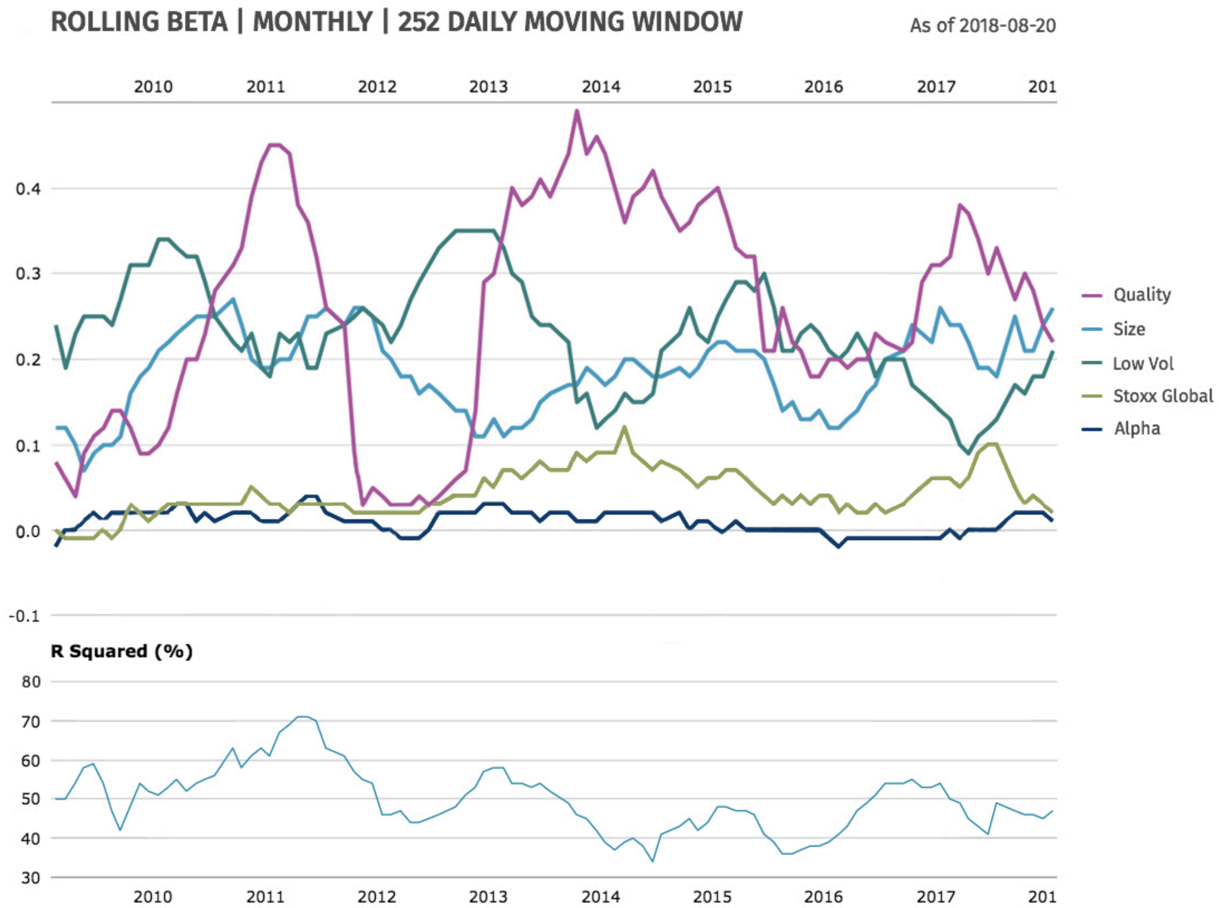


Note: Regression is calculated from April 2008 to May 2019
Source: PremiaLab

4.5 Case Study: Multi-factor strategy Regression

Multi-factors strategies allocate across certain factors depending on various market conditions or signals. To capture the factor rotation, a rolling regression is applied to measure factor intensity across different periods of time.

Figure 23: Multi-Factor Rolling Regression



Source: Generated from PremiaLab Platform

In this example, a 10 Year rolling regression (daily return, 1 year moving window) is selected to regress against a global multi-factor equity strategy. A market beta of STOXX Global 3000 and the full PremiaLab Equity Factor Model (Carry, Volatility, Momentum, Low Vol, Quality, Size, and Value) are used to explain most of the variance. Next, a LASSO shrinkage technique is applied to extract the most relevant factors.

The rolling beta graphic (*Figure 23*) reveals that Quality, Size, and Low Vol are the key factors driving the strategy while the market beta (STOXX Global 3000) exposure remains benign during the period. Throughout the ten-year period, these three factors clearly have uneven allocations, with Quality factor fluctuating the most. The opposite movement of Quality and Low Vol betas provide evidence that the multi-factor strategy primarily rotates between Quality factor and Low Vol factor.

The rolling R^2 further illustrates the factor rotation. The rolling R^2 varies from 40% to 60%. Looking closely at the rolling R^2 plot, the R^2 reduces during the factor rotation period. This can be explained by the lagging period for the regression to calibrate on the new factor allocation. Once the transitional period is over, the R^2 is back up again capturing the new factors dominating the strategy.

4.6 Factors’ explanatory power: Application to quant funds

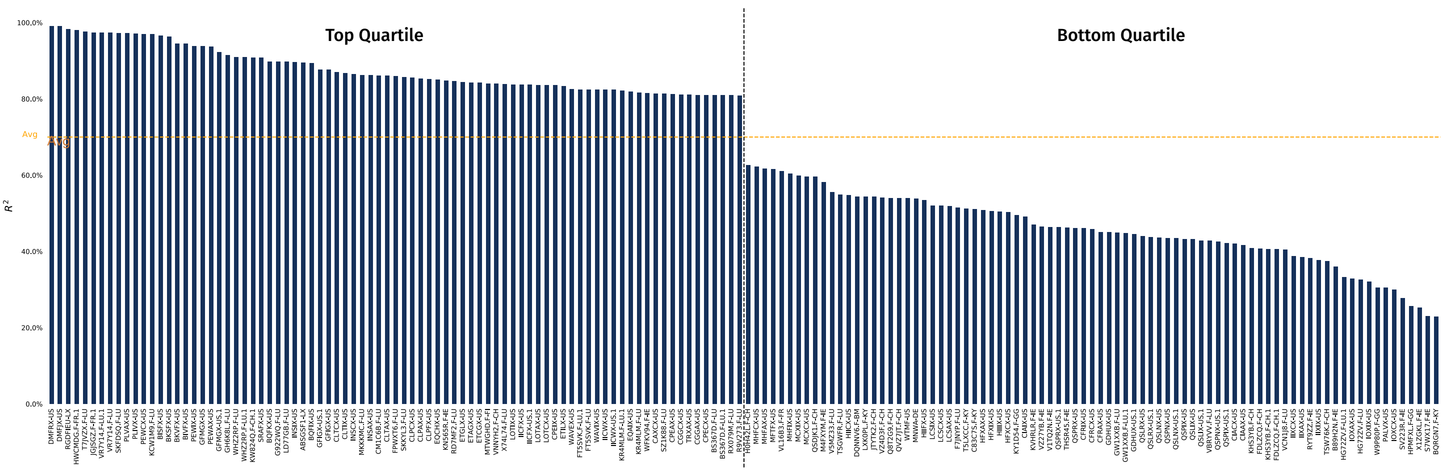
The popularity of factor investing, as well as the rationalization of trading techniques, have fundamentally transformed active asset management. Risk premia strategies are widely used by absolute return managers, especially quant funds; risk factor tilts are often applied by long only managers to outperform their respective benchmark.

When using factor regression beyond systematic strategies, PremiaLab found a high degree of factor risks within actively managed mutual funds and hedge funds. The goal of this section is to demystify Alpha and investigate the extent of factor-based strategies within actively managed funds and especially quant funds.

In this study, factor analysis has been conducted on 344 funds, with a daily liquidity, categorized as either factor or risk premia mutual funds or CTA funds. Our sample data includes flagship funds from 13 leading fund houses active in quantitative investing.

All funds have been regressed with the complete Factor Model (including beta) on weekly returns on a 52 weeks window on a yearly basis and a LASSO shrinkage technique has been applied to extract the 10 most relevant factors. The rolling R^2 is aggregated and averaged to produce an average of 70% R^2. *Figure 24* shows the majority of funds have a R^2 above 60% with only a small group of quant funds (~10-15%) not driven by factor-risk.

Figure 24: Average R^2 Measures



Note: Regression is calculated from April 2008 to May 2019 *Source: PremiaLab*

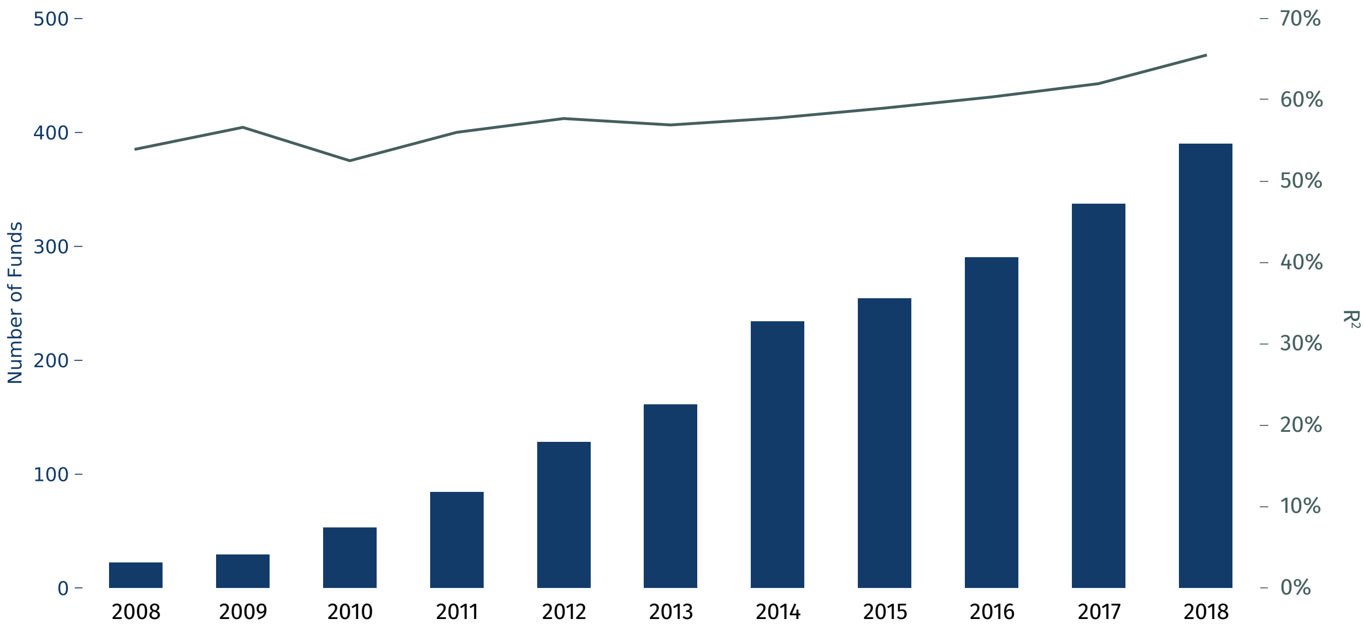
When the variance explained (R^2) is separated back into the corresponding factor, specific type of risk exposure common between these funds can be observed. *Figure 25* is a factor heatmap illustrating the distribution and proportion of the common risk exposures. As expected, equity risk dominates quant funds risk exposure, with equity beta being the biggest risk drivers. From the factor perspective, Cross Asset Momentum appear to be more common within quant funds.

Figure 25: Factor Heatmap

Note: Regression is calculated from April 2008 to May 2019 *Source: PremiaLab*

Motivated by the high R^2 recorded through the regression, we created *Figure 26* to investigate if the changing market condition would influence the fluctuation of the rolling R^2. The left axis represents the number of active funds within the sample and the right axis plots the average R^2 of all the active funds in that given year. As shown in *Figure 26*, the rolling R^2 remains rather stable despite the growing number of active quant funds within the sample; this suggests that these funds did not change their factor risk exposure and the Factor Model is robust and consistent over time.

Figure 26: Rolling Yearly R^2



Note: Regression is calculated from April 2008 to May 2019 *Source: PremiaLab*

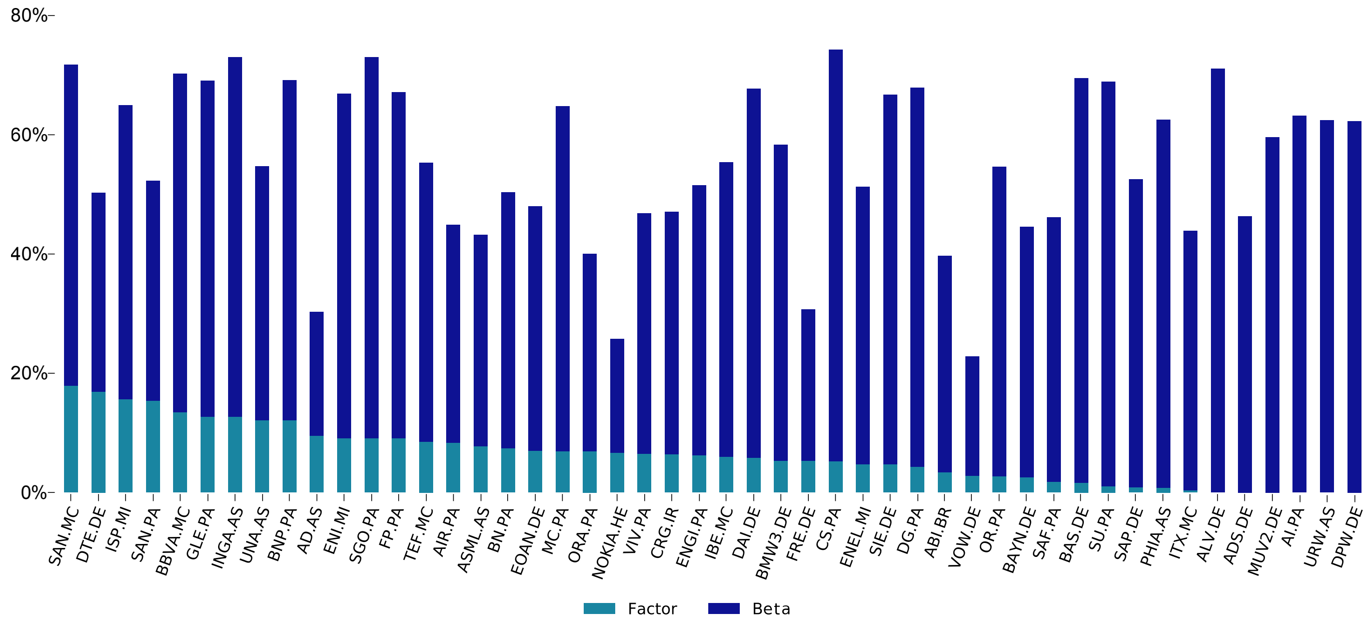
4.7 Impact to the Cash Equity Market

Factor investing has demonstrated a sizable R^2 contribution in quant funds and thus proved its influential role and relevancy in quantitative investing. The next logical step is to quantify the extent of factor risks driving stocks performance. In doing so, we can complete the circle of causality and validate that factor behavior are linked to individual stock characteristics. This analysis can identify stock selected within quant strategies and provide an independent measure of the factor performance impact from the market beta.

To achieve quantifiable conclusions, a quarterly rolling regression is applied to all the constituents of STOXX 50 across the 11-year period. The results are then aggregated and analyzed, to measure the impact of risk factors in driving stock returns.

The constituents are regressed against the complete Europe Equity Factor Model (7 factors) and STOXX 600 as the market beta variable. An average of 56% R^2 is recorded along with an average of 15% variance explained by the equity Factor Model. Within the entire list of constituent stocks of STOXX 50, the Pharma and Banking Sectors are found to be reacting to factor risks the most, with an average of 15.41% and 14.11% factor risk and 36.9% and 55.6% beta risk respectively.

Figure 27: Variance Explained Decomposition



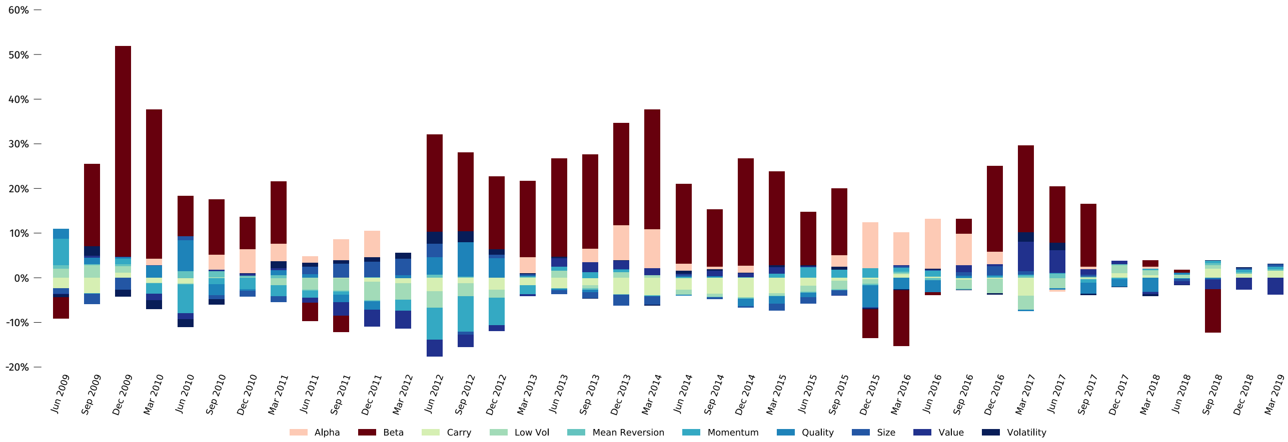
Note: Regression is calculated from April 2008 to May 2019 *Source: PremiaLab*

To put the variance explained (R^2) into context, a transformation is applied to generate the return p.a. attribution graph (*Figure 28*). The graph dissects the aggregated stock performance into Alpha, Beta, and factor-based performance attribution. The transformation is done by multiplying the betas with their respective return p.a. For each period, the return p.a. for Y is:

$$r_Y = r_\alpha + \beta_1 r_1 + \ldots + \beta_i r_i$$

Where r_Y is the return p.a. for variable, and r_α is the return p.a. difference between the actual and model predicted return p.a. $(\beta_1 r_1 + \ldots + \beta_i r_i)$.

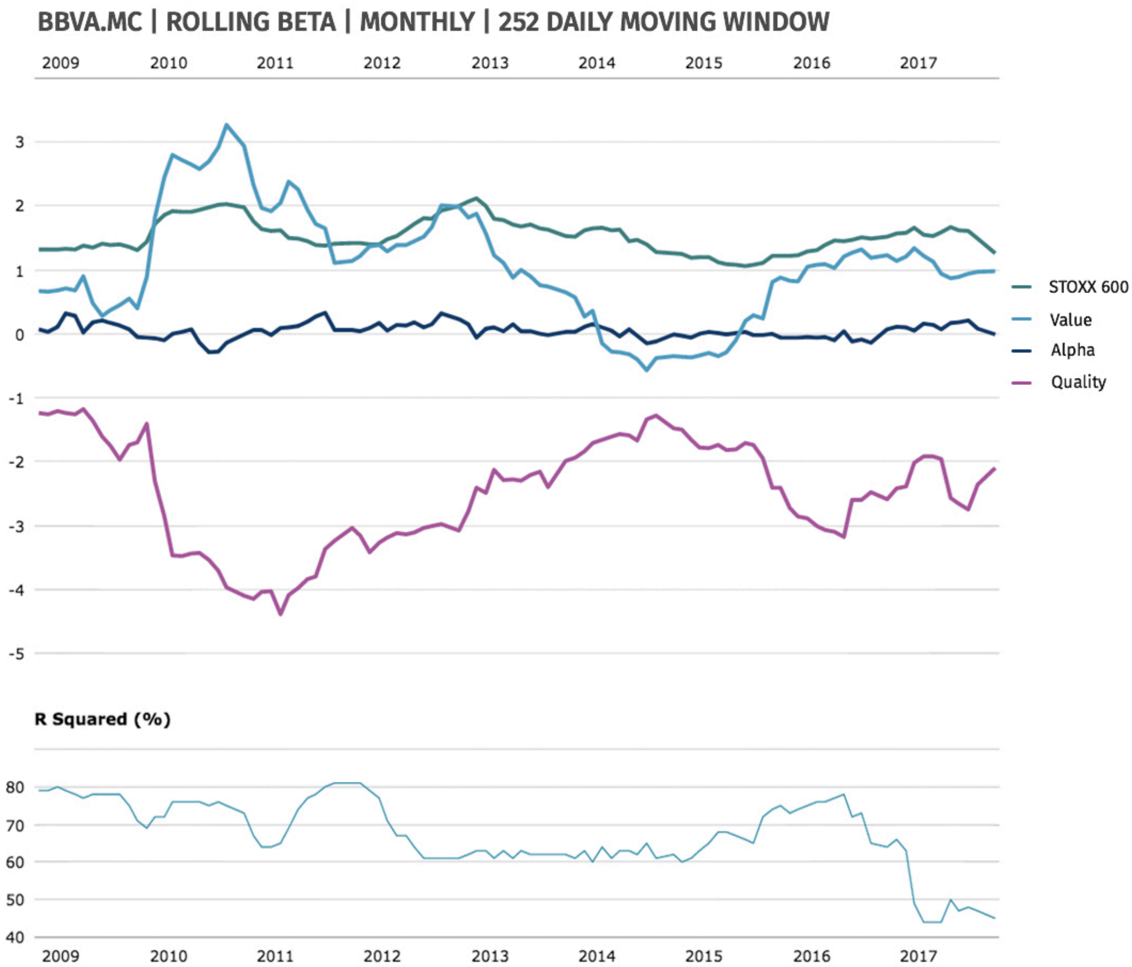
Figure 28: Average quarterly return p.a. attribution



Note: Regression is calculated from April 2008 to May 2019 *Source: PremiaLab*

With this performance decomposition, we can better comprehend the drivers of individual stock performance and measure the impact of factor investing on the cash equity market. *Figure 29* illustrates the regression of BBVA stock against market beta and the two main driving factors Value and Quality.

Figure 29: Regression on BBVA stock



Source: Generated from PremiaLab Platform

Conclusion

Conclusion

As demonstrated in this paper, PremiaLab developed a factor analytic solution through a process of factor classification and statistical clustering based on the universe of strategies deployed in the market. Investors can take advantage of such a solution to better assess the dynamics of risk premia factors across asset classes. Applied for benchmarking, quantitative research and risk analysis, the model can also be used to understand the behavior of the underlying market better.

PremiaLab Pure Factors independently measures factor exposure towards a referential representation of actual assets under management and provides a unique dataset to apprehend better the dynamics of factors which have profound effects in today's markets. While not exhaustive, the Factor Model has been tested on a wide range of investment products and has demonstrated a unique granularity and explanatory power.

We would like to thank all the industry experts who have guided us in designing the platform's analysis tools, which have led to the construction of the PremiaLab Pure Factors. Finally, we would like to thank the Foundation Paris Dauphine and their professors for their academic guidance for this research paper.

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Appendix

A.1 Principal Component Analysis (PCA)

Let $x_{i,t}$ be the daily return of the i-th strategy at time t, $\bar{x}_i$ be the average return of the i-th strategy, and Σ be the covariance matrix of the returns.
PCA applies eigendecomposition on Σ:

$$\Sigma = Q\Lambda Q^{-1}$$

Q is a square matrix and its columns are eigenvectors of Σ. The columns can also be interpreted as principal axes, denoting the directions of the principal components. Λ is a diagonal matrix, where the diagonal entries are eigenvalues of Σ.

Let $u_{i,t}$ be the return of the i-th principal component at time t. It satisfies the following equation.

$$u_{i,t} = Q_{1i}(x_{1,t} - \bar{x}_1) + \ldots + Q_{pi}(x_{p,t} - \bar{x}_p)$$

$u_{i,t}$ by design has mean zero and variance Λ_{ii}. The principal components are linearly independent among themselves, so their correlations are zeros. We can also recreate returns of the strategies with $u_{i,t}, \ldots, u_{p,t}$

$$x_{i,t} - \bar{x}_i = Q_{i1}u_{1,t} + \ldots + Q_{ip}u_{p,t}$$

From this, we can calculate the proportion of variance of the i-th strategy explained by the j-th principal component:

$$\frac{Q_{ij}^2 \Lambda_{jj}}{Var(x_i)}$$

Proposed Adjustments

The first principal component is the factor index returns. The mean and variance of $u_{1,t}$ are not meaningful so we need adjustments. Instead of $u_{1,t}$, we use

$$u'_{1,t} = \frac{Q_{11}x_{1,t} + \ldots + Q_{p1}x_{p,t}}{Q_{11} + \ldots + Q_{p1}}$$

as the returns of the factor index. The means of strategies returns are not subtracted so $u'_{1,t}$ preserves the long-term trend of the strategies. $u'_{1,t}$ is rescaled from $u_{i,t}$ so that the weights of the strategies sum to one. $u'_{1,t}$ should have a variance similar to the underlying strategies. It should also have a stable variance when more strategies are added to the bucket.

A.2 KDE Summary Statistics

Table 1: Summary Statistics of Global Equity Factors vs SPGLOB 252-day Rolling Correlations

	Carry	Low Vol	Momentum	Quality	Size	Value	Volatility
Mean	0.347	-0.009	0.012	0.085	0.209	0.210	0.564
Std. Dev	0.064	0.103	0.058	0.083	0.098	0.112	0.065
Min	0.192	-0.224	-0.135	-0.213	0.035	0.009	0.428
Max	0.475	0.214	0.136	0.236	0.480	0.502	0.702

A.3 Least Absolute Shrinkage And Selection Operator (LASSO)

Lasso (least absolute shrinkage and selection operator), like ordinary least square (OLS), is a regression analysis method that seeks to fit a linear model by minimizing the error. However, it introduces a cost on large coefficients. The result of Lasso therefore achieves factor selection and regularization.

Lasso solves the following minimization problem. For a non-negative constant t, we choose β_0 and $\beta = (\beta_1, \beta_2, \ldots, \beta_p)$ to satisfy the objective below.

$$min\left\{\sum_{i=0}^{n}(y_i - \beta_0 - x_i^T\beta)^2\right\} \quad subject \quad to \quad \sum_{j=0}^{p}|\beta_j| \leq t$$

The constraint imposed on $\sum_{j=0}^{p}|\beta_j|$ is core to the Lasso regression. When t is chosen to be ∞, the constraint has no effect and the regression problem becomes OLS. As t decreases from a large number to zero, the entries in β will gradually shrink to zero. Eventually, more and more entries will become and stay exactly zero. When t is chosen to be zero, then the constraint dominates the minimization problem and β becomes a zero factor.

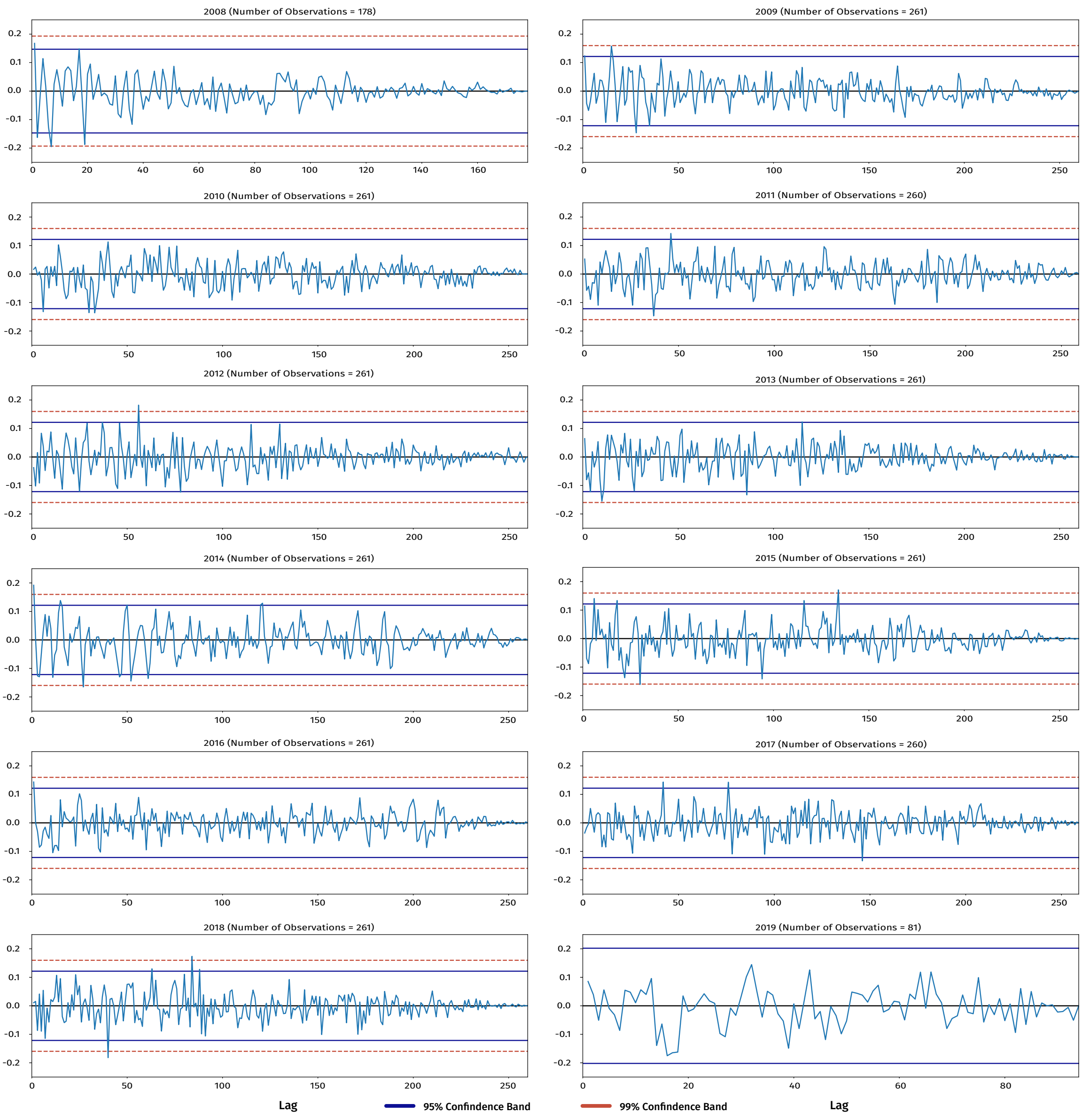
The shrinkage set some entries of β to be zero, so their corresponding factors have no effect in the fitted model. The factors remaining, i.e. those with non-zero coefficients, are selected by Lasso. Adjusting t varies the number of chosen factors so we can determine the number of important factors in the final model. Lasso even accepts the case when there are more factors than observations, as long as the number of factors selected is smaller than that of the observations.

In practice, x and y are standardized so that the dependent variable and the independent variables have means of zero and standard deviations of one. This prevents the standard deviations of the independent variables from biasing the variable selection. The result will also be consistent under factors rescaling. After fitting the model with Lasso, the coefficients are transformed back for the original scale.

B.1 Technical Implementation - Autocorrelation Analysis

Principle Components, at its core, are linear combinations of cross-correlated variables that are assumed to be independent with a function of time. In the case that PCA is used as a descriptive statistical tool, the independent structure of the data (or lack thereof) will not significantly affect the results (Jolliffe & Cadima, 2016). However, in cases where PCA is used as an inferential tool instead, the independent assumption of the dataset will need to be tested for serial dependence, or autocorrelation. Since PremiaLab's objective is to infer information and generalizations regarding sets of strategies that its Pure Factors represent, it is important to observe a minimal autocorrelation within the Pure Factors themselves. Results from our analysis demonstrate that PremiaLab Pure Factors, do not have serial dependence and therefore, can be utilized to model the universe of factor-based strategies.

Figure 30: US Equity Momentum Autocorrelation



Note: Autocorrelation is calculated from April 2008 to May 2019 *Source: PremiaLab*

The graph above displays the yearly autocorrelation coefficients of US Equity Momentum to a lag period of 252 days. The plots clearly demonstrate that the Pure Factors do not exhibit autocorrelation in the last eleven years suggesting consistently invariant and independent behavior.

B.2 Technical Implementation - Skewness Analysis

A key concern surrounding Pure Factor construction is that PCA assumes Gaussian properties, which may not be true for the strategies' return distribution. As PC1 is purely optimized for the total variance it can capture based on the correlation metrics, it may not be necessary to retain the higher-ordered statistical features such as skewness and kurtosis.

As strategies' return distribution may not satisfy the normality assumption and PCA is not designed to process skewed data, PremiaLab's implementation fosters a due-diligence and clustering process ensuring that only qualified strategies with similar risk properties can be placed in the Pure Factor bucket. These additional constraints drastically increase the risk profile retention effect.

As per *Table B.1*, it can be seen that PC1 does not overweigh any particular strategy and retains all the necessary risk profiles. The process of extracting PC1 can be understood as a noise removal procedure to strip off any non-essential variance associated.

Table B.1: US Equity Volatility Risk Metrics

	Pure Factor	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6
Sharpe	**1.30**	0.38	1.60	1.39	1.27	0.92	0.25
Return p.a	**7.59%**	3.68%	6.68%	10.17%	14.77%	7.64%	1.80%
Volatility	**5.82%**	8.96%	3.99%	7.08%	11.42%	7.96%	5.92%
Skewness	**-6.24**	-9.42	-5.86	-2.75	-2.20	-3.83	-0.45
Kurtosis	**132.75**	204.76	138.43	32.10	64.29	41.28	45.66
Max DD	**-10.26%**	-28.30%	-6.53%	-13.08%	-14.38%	-15.95%	-26.32%

Source: PremiaLab

About PremiaLab

PremiaLab is an independent platform providing data, analytics and risk solutions on systematic & factor-based strategies in collaboration with leading investment banks and institutional investors globally. Combining intelligent technology with a unique source of information we empower asset allocators to make better investment decisions whilst achieving utmost time and cost efficiency.

With offices in Paris, New York, Hong Kong and Stockholm, our international team is dedicated to supporting our global client base with the most up-to-date risk premia dataset, advanced portfolio construction, performance & risk analytics. The firm has established strong partnerships with the top 15 investments banks, global asset managers, pensions funds & insurance companies.

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