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Introduction to Qi Macro Factors

Increasing equity portfolio Sharpe through systematic macro risk reduction

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Summary

Factor investing has become widely popular across a broad swathe of the investment universe in the last three decades. The large majority of solutions focus on fundamental factor models which work well for linear instruments such as equities. Until now, macroeconomic factor models and macro effects were largely ignored. In this paper, we introduce Quant Insight's (Qi) cutting-edge macro factors as vital and unique tools in the efforts to identify, understand and control the macroeconomic risks whipsawing portfolios in the post COVID world.

A factor can be thought of as any characteristic relating a group of stocks that is important in explaining their return and risk. Extensive academic research has shown the validity of the style factor approach, viz that certain factors, effectively intrinsic stock characteristics, have historically earned a long-term risk premium and represent exposure to systematic sources of risk. Common "equity risk premia" factors include **Value, Low Size, Low Volatility, High Yield, Quality and Momentum.**

Style Factors work over the long term but shorter term, the market is more and more driven by macroeconomic indicators that change at much shorter frequencies and drive prices. Qi gathers a broad range of macro factors and builds models that demonstrate their strong explanatory power over securities prices. These factors include **GDP growth, interest rates, FX, commodity prices, inflation rates and risk indicators.**

Critically, Qi's macro factors are not intrinsic to stocks. They are dynamic and can change in magnitude and sign. A stock may begin the year being positively related to GDP growth but by the end of the year that relationship could have reversed to a negative sensitivity. The dynamic nature of these macro factor relationships, the inter-relatedness of macro factors themselves and the infrequent nature of data releases has stymied the development of solutions despite the dominance of macro in day-to-day market moves. Qi solves the problem and presents a solution to control macro risk and improve the risk adjusted returns of portfolios.

In this paper we will introduce Qi macro factors and discuss Qi's modelling method and practical applications.

We round off with some indicative results showing the power of our methods in improving risk adjusted returns. **Specifically, we see a significant increase in Sharpe through systematic monthly reduction of macro exposures. We use the S&P500 index as the test portfolio.**

Fundamental Style Factors and Macro Factors

In general, a factor can be thought of as any characteristic relating a group of securities that is important in explaining their returns and risk. As noted in the early CAPM-related literature, the market ("beta") can be viewed as the first and most important equity factor. Beyond the market factor, researchers generally look for factors that are persistent over time and have strong explanatory power over a broad range of stocks. There are three main categories of factors: macroeconomic, statistical, and fundamental.

The mostly widely used factors today are fundamental factors. Fundamental factors capture stock characteristics such as Value, Growth, Size, Momentum and have been studied for decades as part of academic asset pricing literature and practitioner risk factor modelling research. Fama and French (1992, 1993) put forward a model explaining US equity market returns with three factors: the "market", the size factor (large vs. small capitalization stocks) and the value factor (low vs. high book to market). The momentum factor was added later and further development continues (you can now have "Google Hits" as a factor).

However, stocks have other characteristics – in particular, related to their price performance. Included in this are the impacts of macro changes on whole sectors or individual stocks. These are outside the focus of providers of fundamental factor models. Qi has developed macro factors describing the relationship of stock prices and other assets to macro changes.

We find that with a complete set of macroeconomic factors, encompassing the broad macroeconomic universe, we can typically explain over 60% of the shorter term (1 to 2 month) price movement of stocks, depending on the sector in question. This far exceeds what a fundamental factor approach can explain in such a short time.

The models use daily prices to derive linear price models for stocks based on a broad set of macroeconomic factors. Principal component analysis is used to develop the models. Over the long term a stock's fundamentals may well win out (e.g. superior earnings driven by innovation – an "alpha" factor). Now the shorter term volatility (weeks and months) is heavily influenced by macro events. Like fundamental factor models, Qi macro models can be used at the portfolio level or asset level to decompose risk sensitivities – i.e. to identify, understand and control, in particular, the macroeconomic exposure of portfolios.

Motivations

It has long been successfully argued that stocks, in the long run, are driven by fundamentals which represent an intrinsic quality of the stock. This intrinsic quality is often associated with the microeconomic characteristics of the company – its relative competitiveness as a company in the business world. The quantification and modelling of microeconomics is constrained by the quarterly (at best) frequency of stock earnings updates, while stock prices move tick-to-tick through the day. Alternative data sources have tried to fill this gap with higher frequency data but thus far a compelling widely applicable model has not been forthcoming. Thus, we are presented with a significant challenge and opportunity -- understanding the shorter term moves in stocks.

It is broadly acknowledged throughout the history of markets that macro is often a significant source of short-term risk and return. However, macro is the among the least understood of equity drivers owing to its diversity, the interconnectedness of the various macro factors and general complexity. Furthermore, in the post-GFC world of low rates, outside of a company's microeconomic characteristics, macro effects were subdued while fundamental factors dominated risk.

An added layer of complexity, macro is also a dynamic driver that changes over time, it is not an intrinsic characteristic of a stock. Macro impacts tend to change over time => e.g. S&P500 index is sometimes positively sensitive to economic growth, but sometimes it is the reverse. This type of behavior is outside the purview of traditional fundamental factor model construction.

Asset managers need to identify the macro drivers of financial markets and securities. These drivers encompass a range of factors, such as economic growth, monetary policy, impact of quantitative easing, risk aversion, credit spreads, commodity prices, and many more. Qi's macro factor framework drives insights in a quick, straightforward and automated manner. It enables asset managers to visualise financial data, identify patterns and determine fair valuations. Resulting in a reduction of trade selection errors and maximising the value of the managers view by identifying the most appropriate trades. Moreover, such an understanding also reveals the residual, unintended or implicit macro exposures within a portfolio, and identifies how best to mitigate them.

Method *(See "Envision by Qi: Financial data visualisation, pattern identification and fair valuation" Hobson et al, 2015)*

Qi's innovative answer to this challenge is a dynamic solution picking up macro regime changes quickly. It also deals with the essential collinearity that exists in the macro universe and with non-stationarity – the trending nature of many macro factors and indeed the stock market. Driving the next evolution of factor development, Qi's method yields provable independent associations between macro factors and stocks – i.e. macro risk sensitivities for individual stocks and portfolios.

At its heart, Qi employs a novel version of a mathematical technique called principal component analysis (PCA) to accommodate the large number of macro factors that are potentially relevant in driving a given security, many of which may share a high degree of collinearity. PCA performs an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The PCA transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components.

In general, there are as many principal components as there are original variables, and together they retain all the information present in the data. Typically, however, one need keep only a handful of the first few principal components, since they are able to account for the vast majority of the variability in the data. Thus, as well as producing uncorrelated linear combinations of the original variables, PCA provides a natural means of vastly compressing the data with almost no loss of information. This idea is illustrated in three dimensions in Figure 1. In its standard form, the PCA technique is widely used in the scientific community, most notably in image processing and bioinformatics, and has also already been applied in different parts of the financial industry, such as the interest rate market and risk management. It has not, however, been applied to the fair valuation process. Moreover, Qi employs a novel version of PCA, which is ideally suited to this application for easier interpretation of the large number of potentially relevant macro factors driving a given security.

Once the final set of principal components has been determined, Qi then performs a linear regression of the observed behaviour of the security under consideration against the first few components. This yields estimates of the unknown coefficients in the model defined by the linear combination of this subset of principal components. This principal component regression (PCR) technique overcomes the multicollinearity problem that would arise in a standard linear regression analysis, where one attempts to regress a security directly against a large number of macro factors that might potentially drive its value.

In the standard approach, with a large number of variables the danger is always overfitting the model. Since PCR uses only a subset of all the principal components for regression, it achieves dimensionality reduction by substantially lowering the effective number of parameters characterizing the underlying model. This concentration of most of the signal into a few principal components increases the signal-to-noise ratio in the fit and stabilises the solution. Moreover, the use of our novel PCA approach to select the principal components to be used for the regression leads to a very efficient, accurate and easily interpreted representation of the behaviour of the security under consideration.

To provide a measure of how well the observed outcomes are recovered by the model, Qi calculates the R2-statistic, which is based on the proportion of the total variation of outcomes explained by the model. The value of R2 provides a measure of the global fit of the model.

Specifically, $R2$ lies in the range [0; 1] and represents the proportion of variability in the outcome that may be attributed to some linear combination of the explanatory variables. In such models, $R2$ is often interpreted as the proportion of response variation "explained" by the regressors in the model. Thus, $R2 = 1$ indicates that the fitted model explains all variability in the outcome, while $R2 = 0$ indicates no `linear' relationship between the response variable and regressors. Thus, an interior value such as $R2 = 0.7$ may be interpreted as follows: seventy percent of the variance in the response variable can be explained by the explanatory variables; the remaining thirty percent can be attributed to unknown, lurking variables or inherent variability.

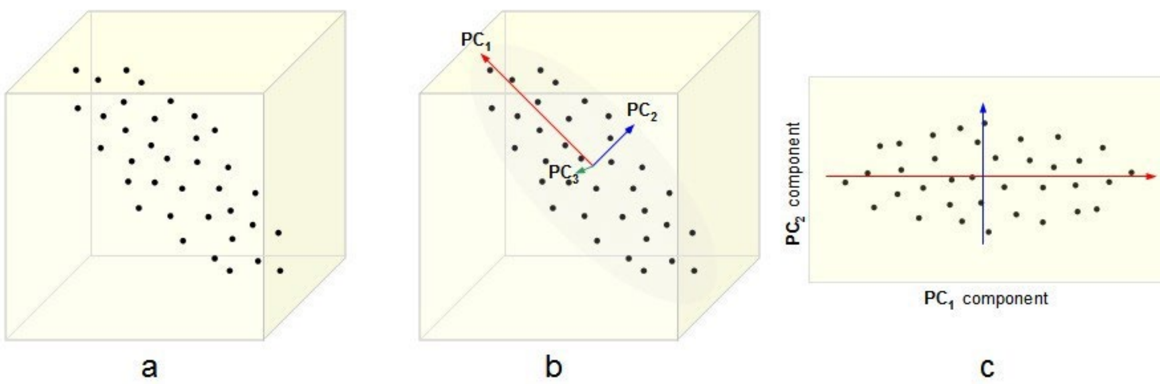

FIG. 1: Illustration of PCA in three dimensions: (a) the original data; (b) the principal components; (c) compression into the plane of the first two components.

Applications

As stated, the principal application of the Qi method is to **identify macro risk sensitivities** whether of an **individual stock** or of an **entire portfolio**. It is a much needed addition in the modern risk management toolkit. With Qi an independent relationship between a stock and each macro factor can finally be established. This quantifies the expected response in the stock price for a move in a particular macro factor. This can be aggregated either across a portfolio to understand portfolio moves or across macro factor moves in a particular scenario to understand the exposure of the stock or portfolio to a fully delineated macro outcome.

The PCR set out above gives a formula for a stock as a linear function of the macro factors along with an error term (this is simply the addition of the different PC formulas). Hence, the stock may be modelled based on the macro factors and a **macro warranted fair value for the stock** determined. Once such a fair value has been established, we systematically compare it to the actual price of the stock and create a "fair value gap" between the two. Further analysis of this gap and its characteristic of reverting to zero (i.e. the fair value and actual stock price tend to converge) can help provide shorter-term trading signals.

Clustering macro sensitivities in a portfolio can also reveal the key macro themes that the portfolio is exposed to. Typically, markets and portfolios are driven by a few key themes that are front and centre in the minds of most investors in a given period. The **clustering of macro sensitivities into themes** allows the investor to determine these themes within markets and within their own portfolios. Once this is quantified the investor can test whether she is comfortable with the thematic exposures of the portfolio, whether they are in line with her historic levels of exposure and whether there is a significant variance between her portfolio and the market.

Ultimately, all of these applications can lead **to systematic macro risk reduction** and allow the investor to generate a more pure "fundamental alpha" portfolio. The risk reduction can be achieved by hedging the portfolio using macro securities such as futures. This directly reduces the exposure of the portfolio to those macro factors. Alternatively, changing the weights (and ultimately, in extremis, the membership itself) of the portfolio can also yield significantly lower exposure to certain macro factors or reduce macro risk in general. In the next section we present a systematic method for general macro risk reduction and therefore **superior risk adjusted returns.**

Measuring Qi Macro Factors' Efficacy: Using MacroVAR to improve S&P500 Sharpe

Our experience is that if you can isolate which stocks are most sensitive to movements in macro factors (inflation, interest rates, economic growth etc.), you can adjust your holdings to reduce your exposure to these macro factors and therefore reduce the volatility of your portfolio (or here the S&P500 index) and increase Sharpe.

Method

Qi employs Principal Component Analysis (PCA) to explain a large macro data set with a few uncorrelated timeseries. The MacroVAR is the beta of the asset in question to the first of these timeseries (1st principal component). The 1st PC usually accounts for 40 – 60% of the variance in the total macro data set. In short, we are using one timeseries to explain the macro world and analysing the impact of that timeseries on each asset.

Steps for creating Qi's S&P500 Index with reduced macro exposure (SPQ):

• Calculate PC1 beta (MacroVAR) for all constituents of the S&P500

• Calculate the S&P500 aggregate exposure to PC1 using the individual stocks PC1 betas and weights

• Every month look to rebalance the index to reduce this aggregate exposure (S&P500's MacroVAR) (*End of day prices were used to calculate returns, rebalances were done every 22 trading days using at open prices. Trading costs were not considered as this is rebalancing of an index and not an investible product)*

• If the S&P500 MacroVAR > 0.05 standard deviations (σ):

- Take the 200 stocks from the index with the largest MacroVAR and reduce their weights by 25%
- Use the available % weights from the reduction to proportionately increase the 200 stock weights which have the smallest MacroVAR

• If the S&P500 MacroVAR < -0.05 σ:

- Take the 200 stocks from the index with the smallest MacroVAR (most negative) and reduce their weights by 25%
- Use the available % weights from the reduction to proportionately increase the 200 stock weights which have the largest MacroVAR
- If the S&P500 macro exposure is between -0.05 and 0.05, leave the index as is and do not adjust the weights

The aim of this is to try and create an SPQ Index with a beta to PC1 of close to 0 at each rebalance and therefore reduce the exposure it has to the macro world.

An "SPQ-" Index was also created. This did the opposite of the method above and looked to increase the macro exposure of the index at each rebalance.

The results clearly demonstrate the efficacy of the Qi in improving risk adjusted returns (i.e. Sharpe):

Results

	SPQ	SPQ-	SPX
Average Monthly Return	1.1%	1.0%	1.0%
Max Monthly Return	11.4%	13.9%	12.8%
Worst Monthly Return	-11.2%	-11.4%	-12.4%
Monthly Return Std.	4.1%	4.5%	4.2%
Annualised Return	12.9%	11.9%	11.7%
Annualised Std.	14.1%	15.7%	14.6%
Sharpe Ratio (rf = 0%)	0.92	0.76	0.80
Sharpe Ratio (rf = 1.0%)	0.85	0.70	0.74
Sharpe Ratio (rf = 2.5%)	0.74	0.60	0.63
Avg. monthly Gain	3.3%	3.6%	3.2%
Avg. monthly Loss	-3.1%	-3.4%	-3.5%
Max drawdown	-30.3%	-31.9%	-33.8%

Yearly Sharpes

	SPQ	SPX	Outperformance
2010	0.54	0.85	-0.31
2011	0.16	0.09	0.07
2012	1.56	1.28	0.28
2013	3.40	2.98	0.43
2014	1.44	1.22	0.22
2015	0.37	0.09	0.28
2016	0.75	0.93	-0.18
2017	3.13	3.33	-0.20
2018	-0.23	-0.26	0.03
2019	2.67	2.57	0.10
2020	0.90	0.54	0.36
2021	2.45	2.23	0.22
2022	-1.08	-1.00	-0.08