Macroeconomic Uncertainty & Stock Selection

By Emin Baghramyan and Tianyu Tan

Nearly a decade after the end of the 2008-2009 U.S. housing crisis, which swiftly morphed into the largest global economic contraction and the worst market downturn since the Great Depression, investors are currently exhibiting heightened sensitivity to the prevailing macroeconomic environment; and its impact on financial markets. The increase in investor angst over the past few years can be partially attributed to unprecedented monetary policy measures, such as quantitative easing, negative interest rates and Operation Twist[1]. Varying political crises and standoffs such as Brexit, the European debt debacle, OPEC-initiated crude oil production limits and trade wars have also been contributing factors for investor anxiety.

[1]Operation Twist is the name given to a Federal Reserve monetary policy initiative where the Fed buys and sells short-term and long-term bonds, depending on their objective.

The increasing regularity of these events has created a new normal set of expectations for investors; and macroeconomic data itself has been equally puzzling. The inconclusiveness of data has given birth to heated debates over the impact of the enormous monetary stimulus on consumer prices, the size of the fiscal multiplier, the shape of the Phillips curve, lack of wage growth, reconciliation of stagnating productivity versus high corporate profit margins, impact of border taxes on inflation and topics of a similar nature. The jury is still out on some of these issues, yet one thing has become clear — macro uncertainty has been on the rise. Given the aforementioned concerns, the notion has been raised as to what would be the best way to quantify macroeconomic uncertainty and where it can be applied. This paper seeks to examine this idea and the possibility of developing a profitable systematic trading strategy to select stocks.

How to measure uncertainty

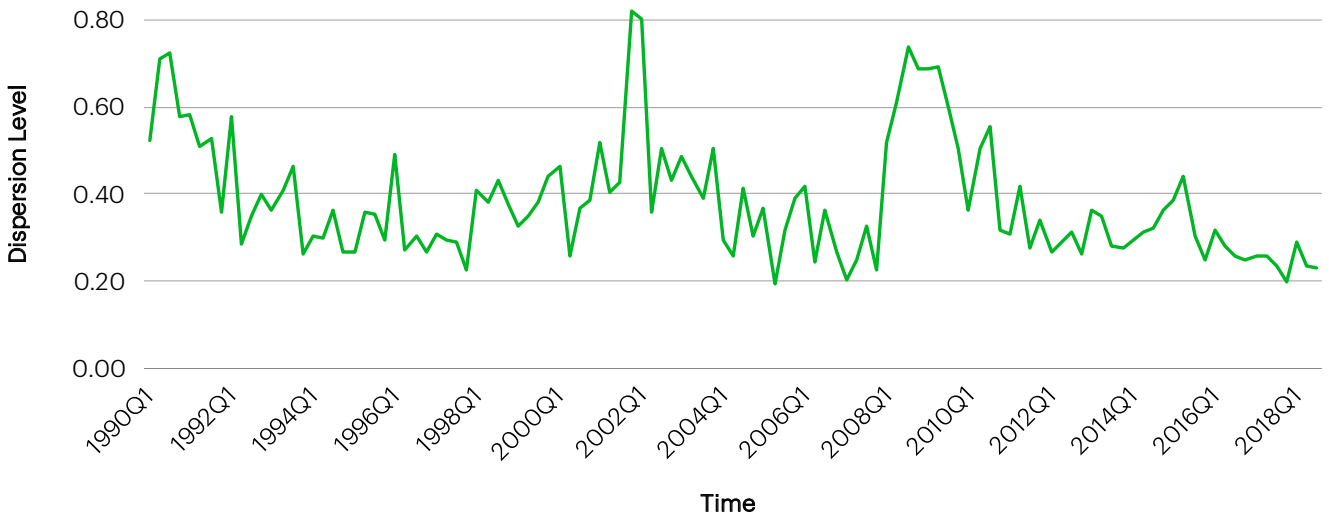
The first steps taken in quantifying macroeconomic uncertainty was the creation of economic and financial uncertainty indices, using proxy indicators. The economic uncertainty index is designed to capture the ambiguity regarding future macroeconomic conditions, whereas the financial uncertainty index reflects liquidity, credit and leverage conditions in the economy to capture future financial instability and market distress. In assessing economic uncertainty, we utilized the forecasts done by leading blue chip forecasters included in the Survey of Professional Forecasters database. The survey, dating back to 1986, is conducted by the Federal Reserve Bank of Philadelphia and is one of the most widely-used databases to gauge general macroeconomic expectations of market participants.

To create an index that would measure uncertainty from this survey, we evaluated the level of disagreements between forecasters on possible future outcomes for the seven major economic variables in the U.S. (real and nominal GDP levels and growth rates, GDP price index level and its growth rates; as well as the level of the U.S. unemployment rate). The idea behind this being, when disagreements among professional economy watchers increase, then uncertainty is likely on the rise, and vice versa.

The upcoming chart (Chart 1) illustrates the computed dispersion among economic forecasters regarding U.S. real GDP. Increases in the dispersion measures would indicate that there are larger disagreements among the participants, thus economic uncertainty is larger.

Furthermore, for each dispersion measure at the beginning of the quarter, we estimated the standardized residuals from rolling auto-regressions and created an equally-weighted average of

Chart 1: Measures of Cross-Sectional Dispersion for Quarterly Forecasts of Real GDP (RGDP)
Q1 1990 to Q3 2018



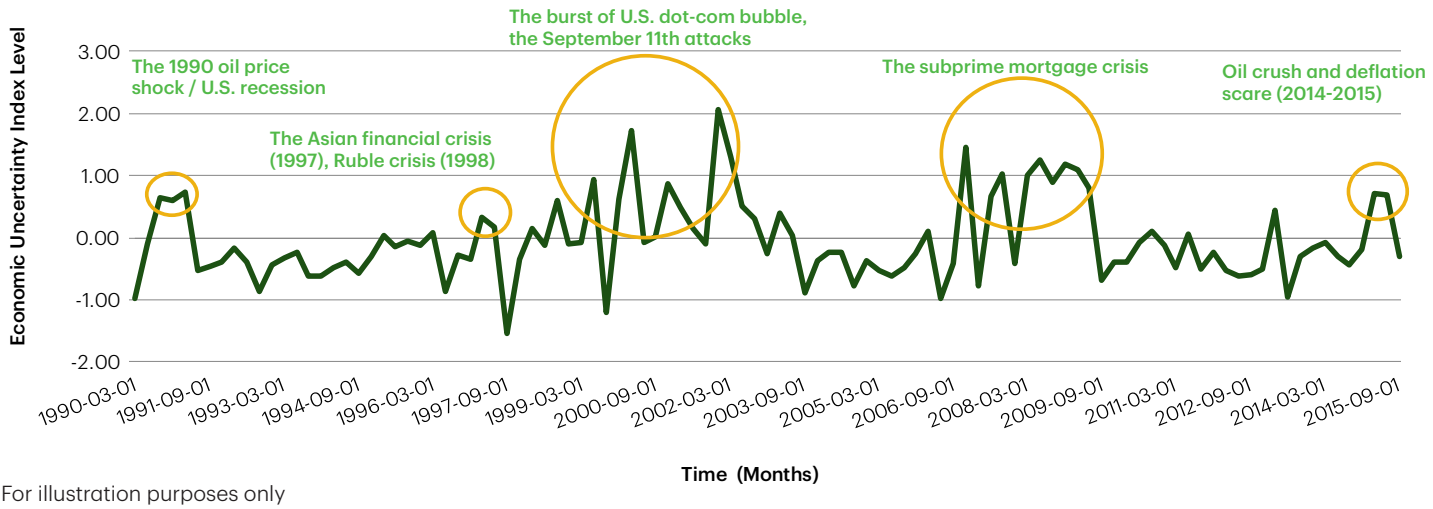
For illustration purposes only
Source: Federal Reserve Bank of Philadelphia, TDAM

changes in forecast for all seven macroeconomic variables mentioned earlier.

In estimating financial uncertainty, the Federal Reserve Bank of Chicago's National Financial Conditions index was utilized. This index was constructed to measure risk, liquidity and leverage of the broad financial market, extending back to 1973. The positive values of the index indicate that financial conditions are tighter than average and would imply a larger likelihood of financial distress and instability down the road. Conversely, negative values mean that financial conditions are looser than average, indicative of a supportive environment for financial assets. The index is constructed from a state-space model and includes 100 variables in three broad categories, namely money market, debt/fixed income and equity; as well as variables representative of the shadow-banking system. Similar to the earlier referenced economic uncertainty index, we used changes in financial conditions from auto regressions.

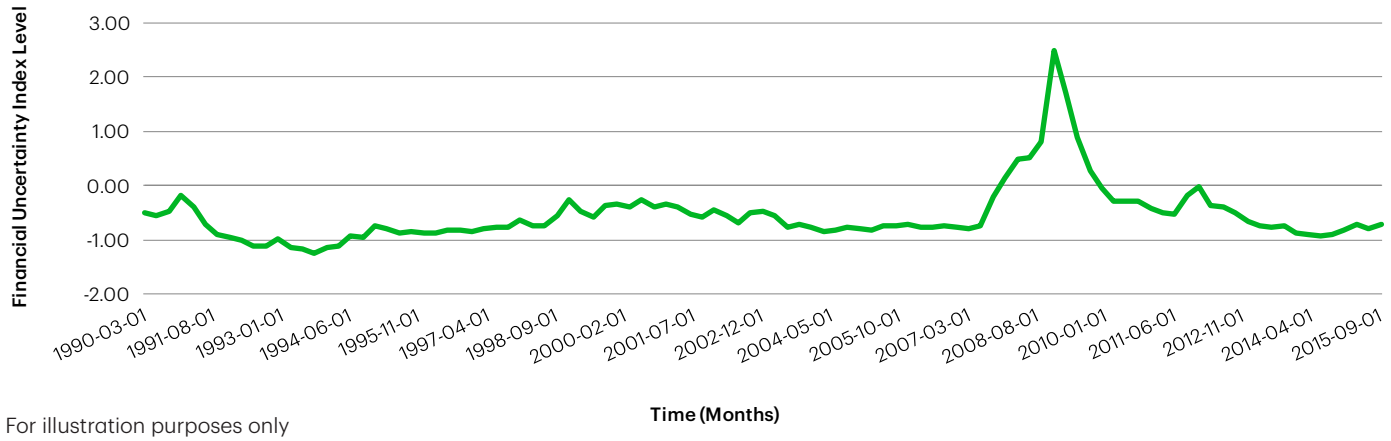
The following charts (Charts 2 & Chart 3), respectively illustrate our economic uncertainty indicator and financial uncertainty indicator. Peaks in the economic uncertainty tend to precede or coincide with periods of high unemployment, weak industrial activity and overall poor economic conditions. The circles on the chart highlight well-known periods of macroeconomic shocks. The profile for the financial uncertainty indicator is broadly the same.

Chart 2: Economic Uncertainty Index
March 1990 to September 2015



For illustration purposes only
Source: Federal Reserve Bank of Philadelphia, TDAM

Chart 3: Financial Uncertainty Index
March 1990 to September 2015



For illustration purposes only
Source: Federal Reserve Bank of Chicago, TDAM

Uncertainty beta is a unique source of alpha

The question now becomes whether it is possible to use these metrics in practice to profitably select stocks. To start, we modeled stock price covariance with our measures of economic and financial uncertainties using the following two regression models:

$$Ret_{it} = \alpha_i + \text{Econ Uncertainty Index} * \beta_i^{EUnc} + \varepsilon_{it}$$

$$Ret_{it} = \alpha_i + \text{Fin Uncertainty Index} * \beta_i^{FUnc} + e_{it}$$

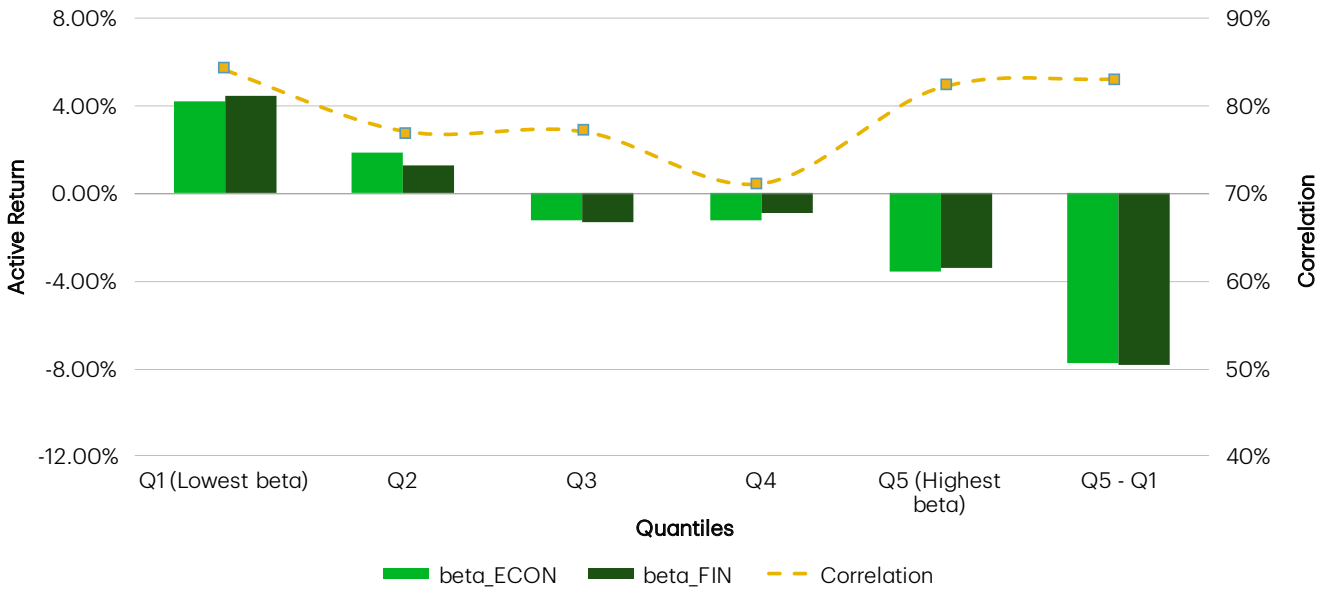
Here, β_i^{EUnc} and β_i^{FUnc} respectively captures the sensitivity of each stock to economic and financial uncertainties. By design, stocks with larger ßs outperform stocks with smaller ßs during periods of rising uncertainty.

At the end of each month, between 2007 and 2017, we sorted all S&P 1500 member stocks into five equally-weighted quantiles based on their uncertainty factor loadings (see Chart 4) and examined their subsequent performance. The first five bars represent annualized active returns estimated for the whole period, for each quantile relative to the market portfolio. The first quantile (Q1) includes stocks that have the lowest beta loadings to macro uncertainty, that is, they have the worst performance when uncertainty increases. Conversely, the fifth quantile (Q5) consists of the stocks that have the highest betas to macro uncertainty, that is, they tend to perform best when economic uncertainty increase. The final bar, to the far right, shows the differential between the highest and lowest quantiles.

The results shown in Chart 4 indicate that stocks in Q1 have the highest annualized returns, while companies included in Q5 have the lowest. Quantile returns of uncertainty betas follow a monotonic pattern with the lowest uncertainty beta group outperforming the highest beta group by about eight percent (8%) per annum.

Simply put, the companies that do well when uncertainty increases (i.e. Q5), tend to have a worse performance than companies that are hindered, when uncertainty increases (i.e. Q1). This can imply the existence of an uncertainty premium, possibly stemming from some type of behavioral bias, such as ambiguity aversion that can force investors to overpay for companies that do well during economic duress; in order to avoid economic ambiguity. Another explanation could simply be the tendency of individuals to overestimate their ability to time the ever-changing macroeconomic backdrop surrounding their financial assets.

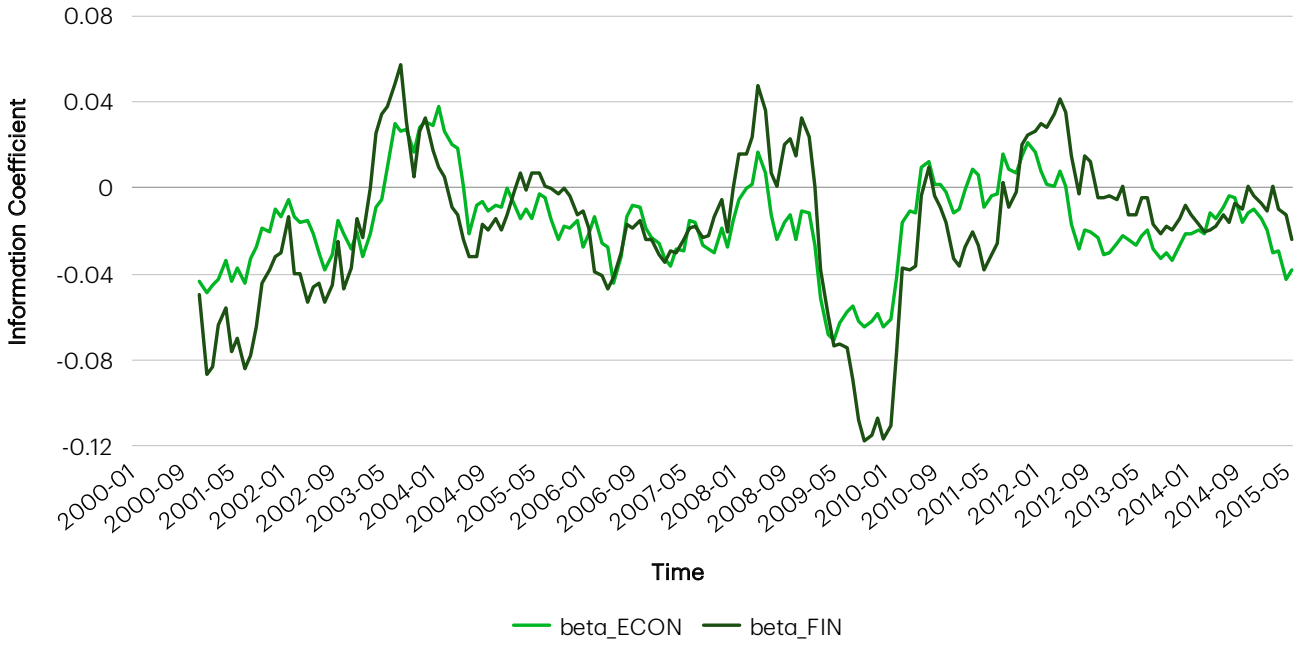
Chart 4: Active Return of Uncertainty Beta Quantile
Data as of August 2018



For illustration purposes only
Source: Compustat, S&P, TDAM

The image below (Chart 5) plots the 12-month trailing information coefficients for uncertainty betas. Here, information coefficients are used to depict cross-sectional correlations between ex-ante beta and returns during the subsequent period. Both 12-month trailing information coefficients are below zero for most of the time period in focus. The results confirm previous findings.

Chart 5: Trailing 12-month Information Coefficient
January 2000 to July 2016



For illustration purposes only
Source: Compustat, S&P, TDAM

In observing both time series, it can be seen that similar long term dynamics exist. This implies that despite different construction methods, both measures of uncertainty could be acceptable proxies for the same type of risk premium.

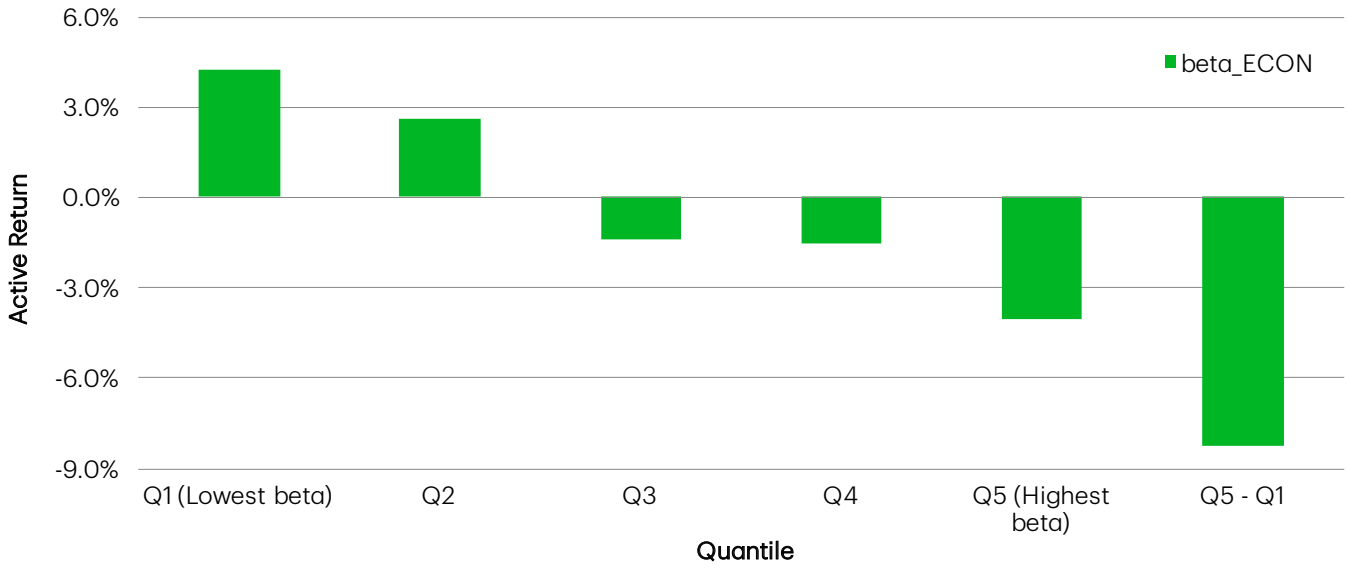
We also estimated correlations between β_i^{EUnc} and β_i^{FUnc} for each time period, per quintile. Referring back to Chart 4, the results of this assessment is depicted as bullet points and measured on the right-axis of the chart. The correlations per quintile rages from 70% to 85%, indicating that both macro and financial uncertainty betas could be used to build similar types of investment strategies.

The observed similarity prompted us to form a composite signal that would equally weight β_i^{EUnc} and β_i^{FUnc}:

$$\beta_i^{Unc} = 0.5 * \beta_i^{EUnc} + 0.5 * \beta_i^{FUnc}$$

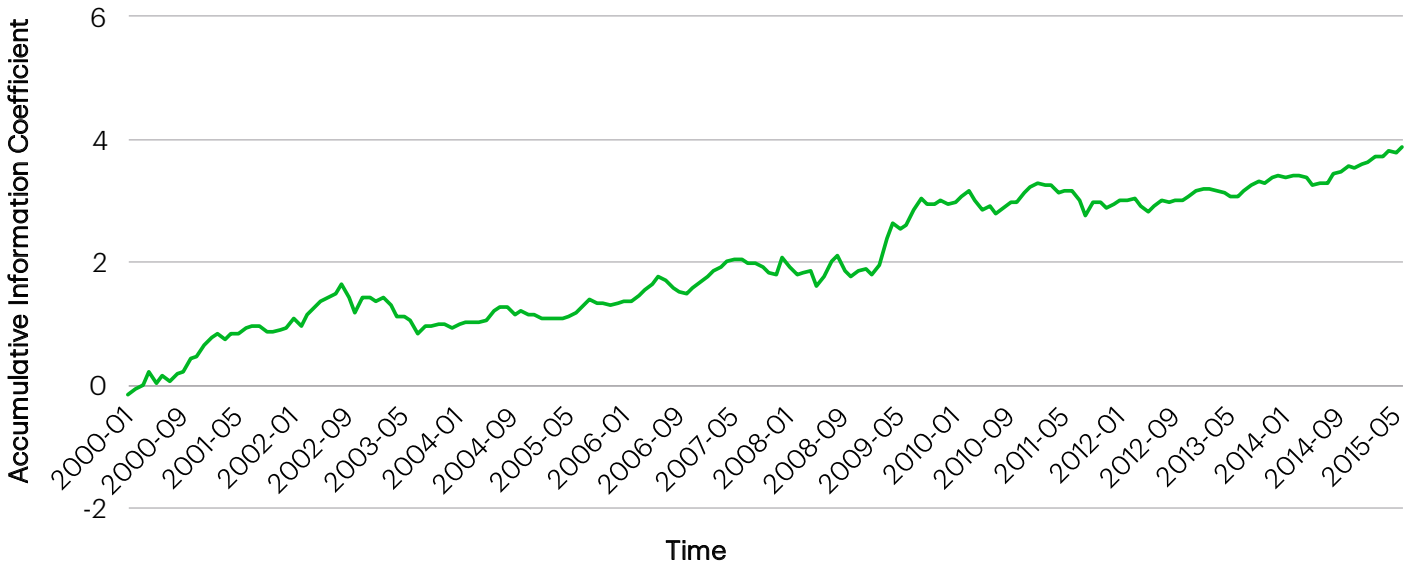
The following two images (Chart 6 and Chart 7) report quintile returns and information coefficients for the composite β_i^{Unc}. Similar to individual uncertainty beta returns and information coefficients calculated previously, the average annualized returns for stocks assigned to quintiles using the composite measure are larger for the quintile consisting of stocks with the smallest betas (Chart 6). The information coefficient measure (inverted) for the composite is also consistently trending upward (Chart 7), which supports the position that stocks that are poor hedges against rising uncertainty, more often outperform stocks that are better hedges against rising uncertainty.

Chart 6: Active Return of Uncertainty Beta Composite Quantile
Data as of August 2018



For illustration purposes only
Source: Compustat, S&P, TDAM

Chart 7: Accumulative Information Coefficient (inversed) for Uncertainty Beta Composite
January 2000 to July 2015



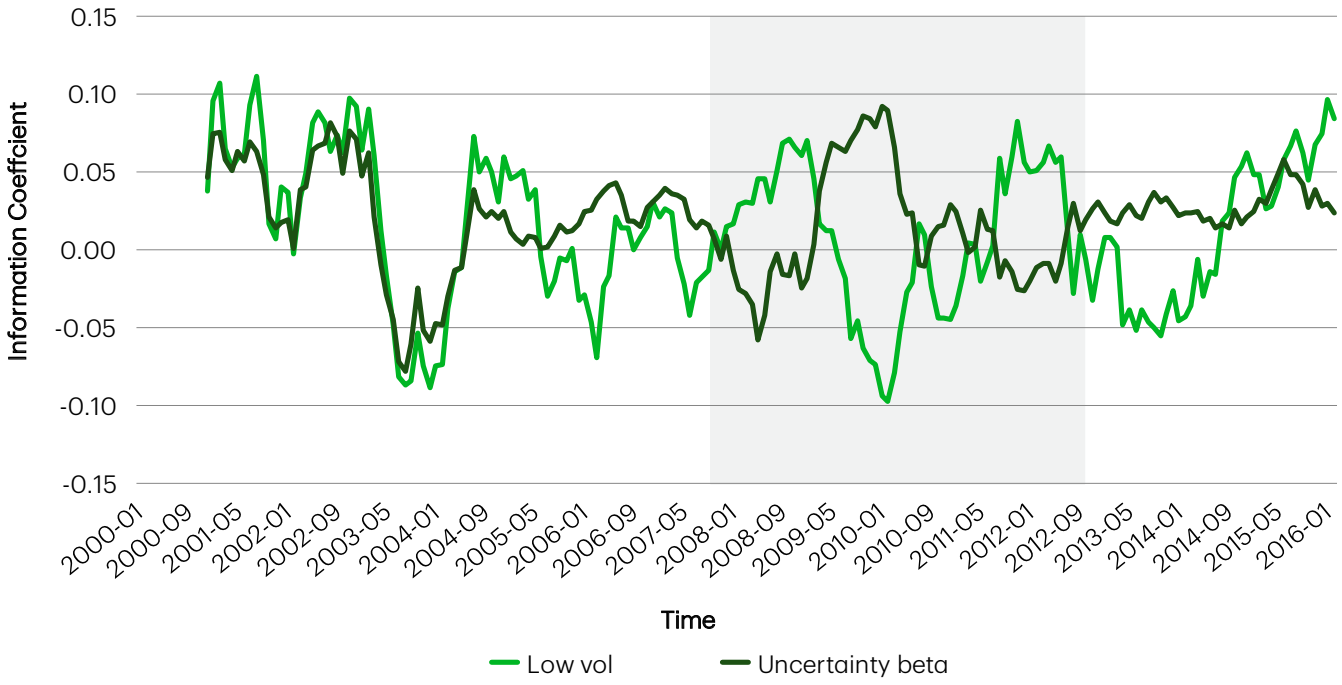
For illustration purposes only
Source: Compustat, S&P, TDAM

However, some words of caution are required. Despite being an effective long-term return predictor, the performance of the β_i^{Unc} is dampened from regular and sometimes prolonged drawdowns occurring during bouts of economic and financial distress. Even though most of the time investors tend to overreact to adverse economic news or increased uncertainty which could be seen as unwarranted panic, on the occasions where rising uncertainty does indeed materialize into actual economic shock, investors who have a long/short portfolio that favors more economically sensitive names could suffer heavy losses.

It could be more optimal for investors to jointly consider the uncertainty beta with a low volatility factor. On one hand, during periods of distress, the uncertainty beta tends to lag the cap-weighted benchmark while the low volatility factor would be able to provide the necessary protection.

On the other hand, when uncertainty starts to unwind which is usually accompanied with a stock market rally and the recovery of risk taking appetite, the low volatility factor tends to struggle; whereas the uncertainty beta can perform strongly (Chart 8).

Chart 8: Trailing 12-month Information Coeffcient Uncertainty Beta versus Low Volatility Factor
January 2000 to July 2015



For illustration purposes only
Source: Compustat, S&P, TDAM

Conclusion

Given the increased uncertainty by market participants, about the macroeconomic and financial environment over the past several year, we have attempted to quantify uncertainty. Initially, we used two separate methods (survey based and one that incorporates large amount of financial market variables). However, after examining their qualitative qualities, we ended up merging them into one; which could provide strong results when used in a systematic stock selection strategy. Finally, we demonstrated that the uncertainty factor is best used in combination with a low volatility factor, to help smooth out returns during beginning and ending periods of market shocks.