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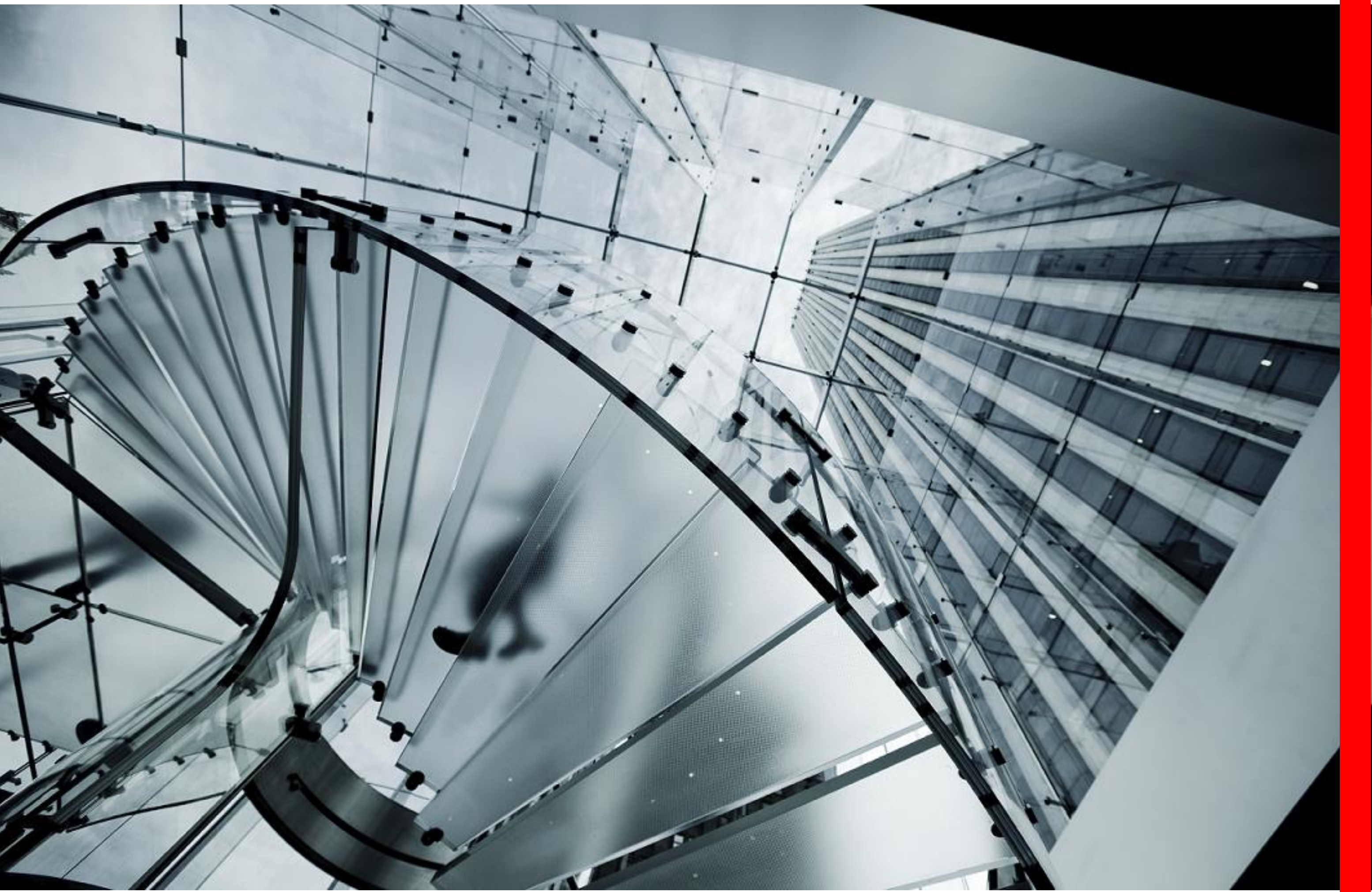

Finding a signal in noisy economic data

Nowcasting the economy to develop better investment strategy

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HSBC Global Asset Management

Nowcasting the economy to develop better investment strategy

In brief

- This White Paper presents our Nowcasting model and explains how we use it in our investment process. The Nowcasting approach compresses information from a large number of economic indicators into one single number. This number acts as a "ready reckoner" for a country's current economic growth.
- The economic environment is a key determinant of asset class risk. Having a clear understanding of where we are in the economic cycle is likely to be an important factor in investment success. The quantitative techniques discussed in the paper enable us to derive a timely and objective indicator of country activity; it helps us to separate the signal in the economic data, from the noise.

Nowcasting the economy to develop better investment strategy

"We really can't forecast all that well, and yet we pretend that we can, but really we can't"

Alan Greenspan,
former Fed Chairman

"Those who have knowledge, don't predict. Those who predict, don't have knowledge"

Lao Tzu,
6th century Chinese poet

"The only function of economic forecasting is to make astrology look respectable"

JK Galbraith,
Economist

"So what can we do about cycles? If we can't know in advance how and when the turns will occur, how can we cope? On this, I am dogmatic; we may never know where we're going, but we'd better have a good idea of where we are. That is, even if we can't predict the timing and extent of cyclical fluctuations, it's essential that we strive to ascertain where we stand in cyclical terms and act accordingly"

Howard Marks,
Investor

Introduction
Forecasting the future is a fool's game

Many economists and macro investors devote large amounts of time and resources to forecasting short-term events. Economists study a multitude of monthly indicators to build a picture of the economic cycle. Investment strategists select favoured data points or leading indicators to predict cyclical trends over the next few quarters. The objective is to beat others' best guesses of where next month's industrial production, retail sales, or labour market data might be. For many asset allocators, such cyclical macro forecasts become the foundation of their investment process.

We believe this sequence of thinking is absurd, for a number of reasons.

First, as Yogi Berra declared, "it's tough to make predictions, especially about the future". There is a huge amount of noise in economic data and, even months afterwards, time series are subject to revisions. Psychology studies have shown that economists are not well calibrated in making forecasts and frequently propose too optimistic (i.e. narrow) confidence intervals around their projections[1].

Moreover, the economy is subject to "radical uncertainty", marked by things that we simply cannot give a probability for. Economic relationships can and do shift over time. For example, we used to think trend growth would be 3-4%, but today 2% growth is as good as it gets[2]. Taken together, these limitations indicate that our Sharpe ratio on short term macro and event forecasting is likely to be poor.

Second, forecasting short run data and estimating how events are likely to turn out relative to expectations is an efficient markets interpretation of how financial markets work. If we are in equilibrium and risk is rewarded, then the only thing that can move asset prices is how the data surprises us.

In the real world, however, markets are not truly efficient. Instead, we believe there is excess volatility of asset prices versus economic and corporate fundamentals. In other words, the volatility of an asset price does not purely stem from economic risk but, more importantly, reflects shifts in the perception of risk among investors. This means that, even if we could forecast the short run data perfectly, asset markets would still "misbehave". Our economic cleverness would not necessarily result in giving us a sustainable "edge", or in delivering superior investment performance for our clients.

These ideas lead us to conclude that we should de-emphasise event forecasting in our investment process. What should we then do instead? Our answer is to take a more humble approach emphasising valuation and an understanding of what the economy is doing at present.

Valuation is crucial, because we believe that the price an investor pays for a given asset class is the key determinant of its return and riskiness. We therefore take valuation seriously and we devote a large amount of research to thinking about it (for example within our "risk premium" framework)[3].

Yet it is also critical to understand where we are in the economic cycle. The riskiness of a given asset class will change dependent on the economic environment. Bonds, for example, can be high or low risk, depending on the inflation regime. Optimising an investment strategy requires us to assess the environment in an objective, bias-free way. It also calls for an approach that deals with the "noise" inherent in economic data.

In this paper, we explore the potential of Nowcasting to meet these requirements. Nowcasting is a statistical technique that can extract a real time "signal" from all the surrounding "noise" and forms a key part of how we approach multi-asset investing.

[1] See e.g. Itzhak, Graham and Harvey (2010)
[2] See IMF (2015)
[3] See HSBC Global Asset Management (2016)

The problem with GDP

The current state of the economy is an important driver of asset returns. The cycle drives business plans, company profits, employment levels and consumer purchasing power. It directs monetary policy decisions and impacts economic policy. It is essential for investors to have a good understanding of where we are in the cycle.

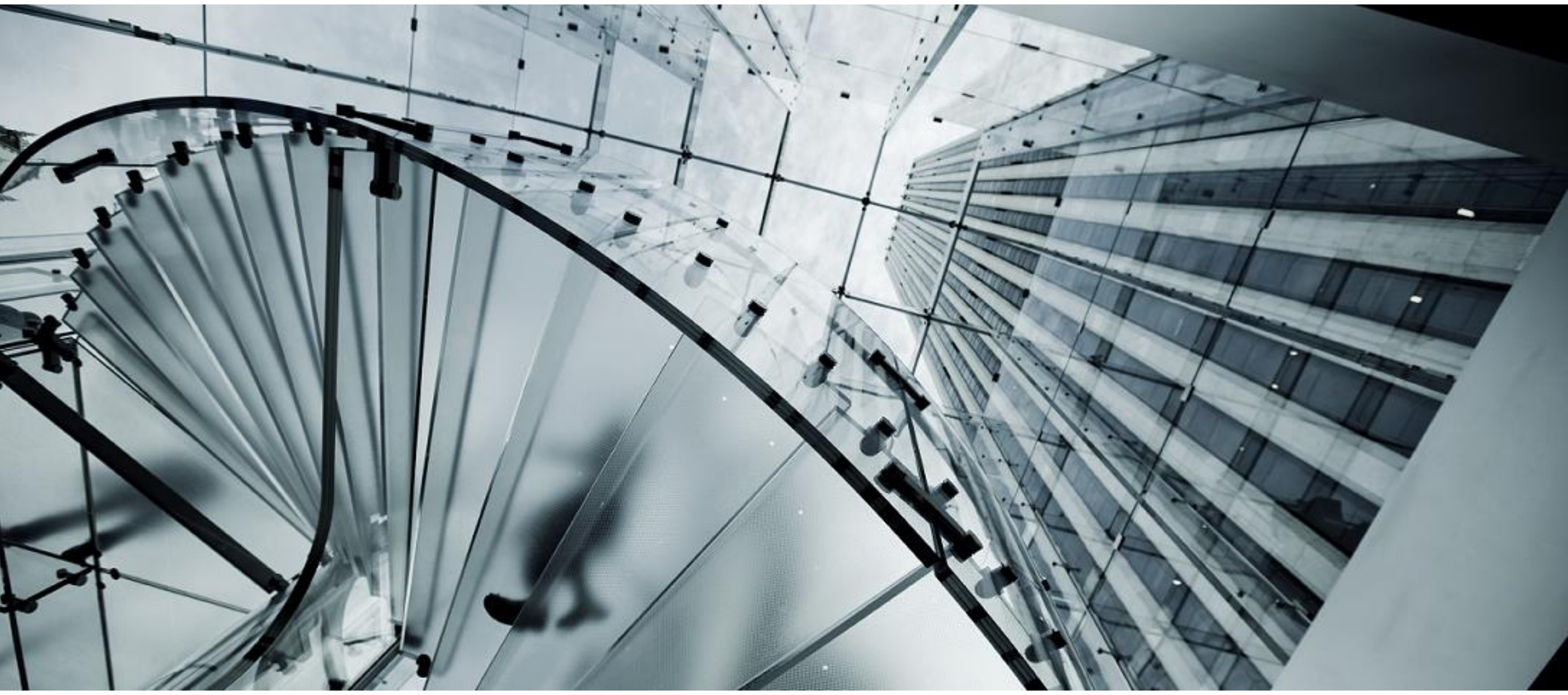
The most widely used and comprehensive summary measure of economic activity is GDP. This is an official measure covering the whole economy but, from the perspective of an investor, it is not very useful.

First, it is only available quarterly and published with a significant delay (the first estimate is usually released four weeks after the end of the reference quarter, far too late to make decisions in real time). Second, it is "noisy" and, despite being an official measure, it is heavily revised – sometimes even years after the first release[4].

In contrast, we believe that Nowcasting can fill the gap for investors and provide a complete signal about underlying economic activity and in real-time.

In the following section, we will give a brief overview of some competing techniques and summarise the scientific literature in which Nowcasting is grounded. We will then explore how the Nowcasting model is built and demonstrate how it works through a sample of data results.

[4] see Fixler et al. (2014)



The next top supermodel
Model Choices

For most economists and investors, Nowcasting remains niche and very technical but, among macro-econometric researchers, it is a live and exciting frontier of research. Recent advances have developed two separate approaches.

First, there is the bottom-up, "bean counting" approach, the best-known example of which is the Atlanta Fed's GDPNow model[5]. Mimicking the approach used by the US statistics office (the Bureau of Economic Analysis - BEA) in their calculation of GDP, this methodology involves splitting GDP into 13 separate sub-components, private and public consumption, exports, and different types of investment. Each of these sub-elements is forecast using a series of specific indicators based on statistical techniques and ad-hoc assumptions. The "bean counting" title reflects the granular and detailed focus of the approach, which is a popular one at the Fed where staff employ it to produce their Greenbook forecasts. The resulting estimates are used for monetary policy decision-making but are kept confidential[6].

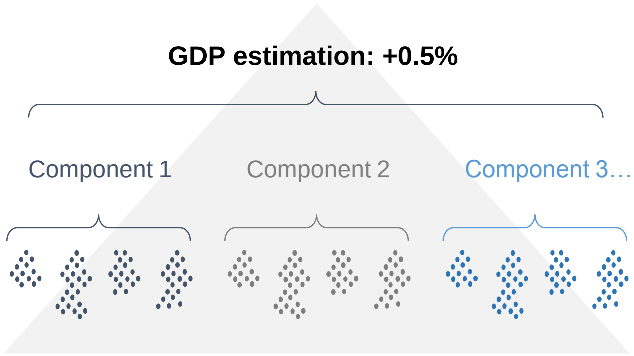
This approach's attention to detail is certainly a strength, but may be a weakness at the same time, as the very granular information is not easily available or available only with a delay – and subject to revisions. Moreover, it does not fully account for the cross-correlations between different sectors of the economy. Importantly, this method focusses squarely on building the best estimate of current quarter GDP limiting its applications for investors

The second approach – consisting of "top down" models – is more direct. The models take information from a series of economic indicators and condense it into a single measure, skipping the intermediate step of estimating sub-components. This creates a faster estimation. It also exploits the co-movements in macroeconomic data, the fact that business developments in one sector are often correlated to those in the other sectors.

Top down models also offer a choice between a "small data" and a "big data" approach.

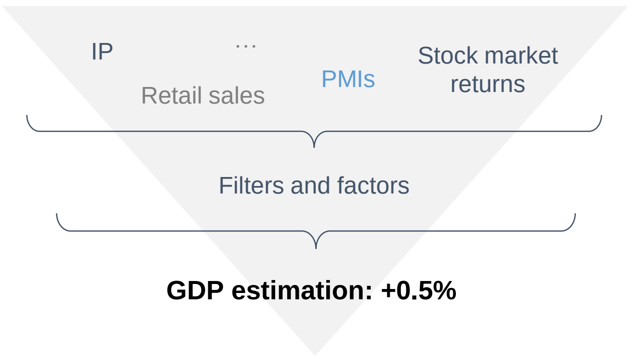
Economists have been using small data approaches for a long time. One common approach is the "bridge equation", where GDP is regressed on a handful of monthly indicators[7]. The Philadelphia Fed Business Conditions Index[8], which relies on only six time series, is a good example. It is based on the observation that a few economic indicators suffice to explain much of the variability in GDP data.

Figure 1: Bottom-up ("bean counting")



On the other hand, a "big data" approach takes a more comprehensive view of the economy. There are some technical challenges to building a regression with many predictor variables, but new statistical techniques can help deal with this[9]. This approach has been implemented by many researchers and institutions, among them the ECB and the IMF[10], and the Bank of Italy uses a similar approach for the Eurocoin index[11]. The idea of these approaches is on the one hand to use as much information, and as many time series as possible, and on the other hand to exploit the co-movements of the various data series.

Figure 2: Top-down estimation



[5] See Higgins (2014)
[6] Released with a 5 year lag
[7] See e.g. Parigi and Schlitzer, 1995
[8] Developed by Aruoba, Diebold and Scotti (2009)
[9] See Geweke (1977) and Sargent and Sims (1977). For a survey article on dynamic factor models see Stock and Watson (2010).
[10] ECB (2008) and IMF (2011)
[11] The Bank of Italy has a slightly different approach to ours – it targets the medium to long term trend of GDP growth and uses a Bandpass filter to eliminate fluctuations that have a frequency shorter than a year (Altissimo et al, 2010)

The next top supermodel
Nowcasting for investment management

What is truly relevant for investors is the underlying economic environment and the current rate of economic activity. Replicating the volatility and measurement error associated with quarterly GDP adds no value to investment decision-making. A “top down” and “big data” approach therefore makes the most sense.

Our objective is not to claim superiority over equivalent models at central banks but, more humbly, to provide a robust and structured way of thinking about global and regional economic cycles, on a live basis. However, we do believe our model has a number of attractive aspects compared with other popular approaches.

First, in traditional forecasting models, increasing the number of data series in a model increases the number of parameters that need to be estimated. Estimation error – which exists for all parameters – increases. Statisticians refer to this as the curse of dimensionality. Yet the aim is to have a Nowcast model that incorporates as much information as possible – i.e. all of the available economic indicators published!

To retain simplicity and estimation power, our model is restricted to two factors which are, in essence, sophistically-weighted averages of the individual data series regularly used by economists. Under the assumption that measurement errors are uncorrelated, the will average out as more variables are added. As such, the more variables we use in the model, the better our GDP estimate becomes. The “curse of dimensionality” itself becomes a virtue[12].

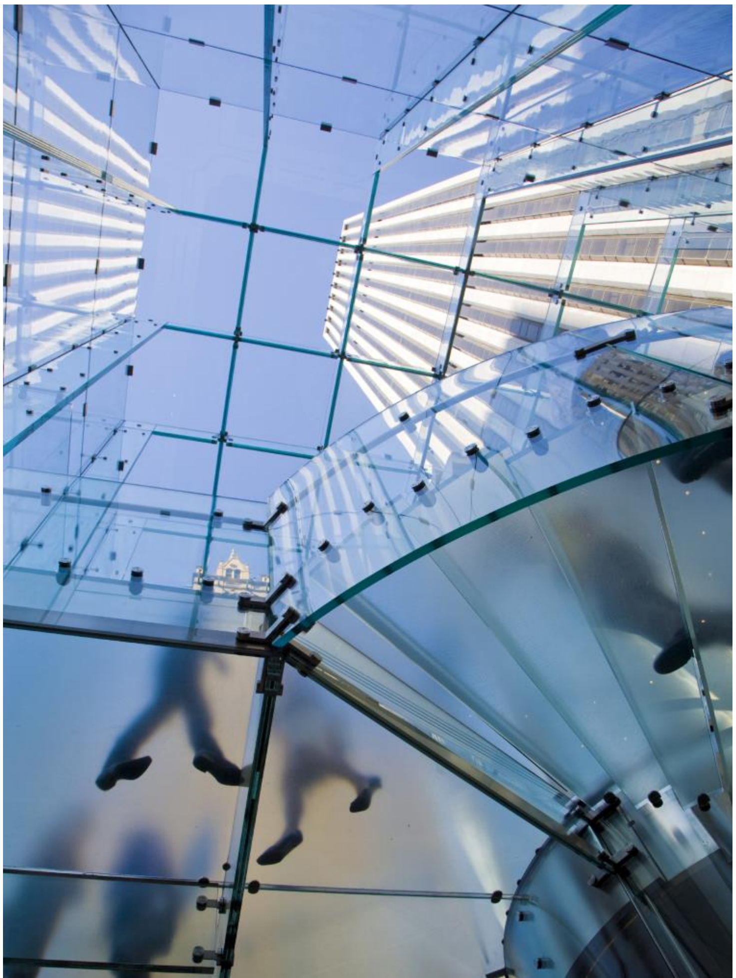
A second advantage lies in the use of the Kalman Filter for the model estimation. Economic data releases occur at different points of the month and with different frequencies. It is therefore important to have a technique to deal with the idiosyncrasies of the data calendar. When a value is missing, the Kalman Filter replaces the missing value with an estimate. This feature enables the model to easily handle missing data points and gradually improve the measure of economic activity in a particular month, as more data is released.

[12] Under the assumption that the measurement errors in the individual variables are uncorrelated, measurement errors will cancel out on average. For details on why this type of averaging works see Stock and Watson (2011)

Building a Nowcast model
Data management

Our approach covers the United States, the Euro Area, the United Kingdom, Japan and China, using a broad range of economic activity and sentiment indicators, different types of price data (e.g. commodity and consumer prices), as well as financial indicators. The models use around 60 economic and financial indicators for each economy and are re-run weekly to provide updated measures of monthly economic activity[13].

Whilst the methodology is the same for all countries, it is important to apply it with careful thought. Chinese economic data, for example, tends to have a relatively short history. This reduced time series restricts the model's power, though this can be countered by using auxiliary measures of the cycle from key regional trading partners[14]. Complementing the data with relevant information thus supports and enhances the model's ability to accurately track Chinese GDP in real-time[15].



[13] For data that is available at higher frequency, for example daily prices of oil, we use monthly averages. When a month is not yet completed we use the averages of those days that we already have, i.e. we calculate average as the average of daily end-of-day prices from the beginning of the month up to and including the previous Friday.
[14] For example, using this measure, China's quarterly GDP growth rate turns out to be strongly correlated with its neighbours': The correlation is 34% with Taiwan's GDP, 38% with Korea's, 43% with Singapore. Hong Kong stands out with a correlation of 58%. From this observation we conclude that we economic data from those neighbouring economies contain valuable information about the Chinese economic cycle.
[15] For seasonally adjusted series this will be the month-on-month (log) growth rate in most cases. Unadjusted data will be either adjusted by us or we use month-on-year growth rates. All time series are standardised by subtracting the mean and dividing by the standard deviation.

Building a Nowcast model
Signal construction

Whilst we strongly believe that the underlying level of activity in the economy is reflected in the economic data, this "signal" may be obscured by "noise", which can make it difficult for the casual observer to get clear and true picture of where we are in the cycle.

Technically, this means that each macroeconomic time series, y_{it}, can be decomposed into a common and an idiosyncratic component. The common component is the element driven by the underlying state of the economy. The idiosyncratic component captures some variable-specific volatility, noise, and measurement error. For *N* different time series, this can be translated as follows:

$$y_{it} = \xi_{it} + \varepsilon_{it} \qquad i = 1, \ldots . N$$

where ξ_{it} is the common component and ε_{it} the idiosyncratic component.

The common component itself is a weighted sum of a small number of M common factors, i.e.

$\xi_{it} = \sum_{j=1}^{M} \lambda_{ij} f_{jt}$ where λ_{ij} is the weight (loading) of factor f_{jt} on variable y_{it}.

The mechanics of the model can be expressed as a "state-space model" comprising two equations: a "measurement equation" translating the underlying stance of the economy into observable macro-economic data and a "transition equation" capturing the "law of motion" of the economy.

Formally, it can be expressed as:

- Measurement equation

  $$y_t = \mathrm{B}\, f_t + \varepsilon_t \varepsilon_t \sim N(0, Q)$$

- Transition equation

  $$f_t = A\, f_{t-1} + \eta_t \qquad \eta_t \sim N(0, R)$$

Where:

- y_t is an Nx1-vector of observable economic variables,
- f_t is an Mx1- vector of unobservable factors, summarizing the state of the economy, and
- B and A are NxM and MxM-matrices that contain the parameters of the model which have to be estimated.

In this analysis, we set the number of common factors *M* to two, which is in line with previous research[16], and we estimate the model in a two-step process[17].

Step 1 performs a "principal component analysis" to derive a first estimate of the common factors. Using these, we can derive estimates for the parameters of the two equations above.

In step 2, we re-estimate both equations using the Kalman Filter. The goal is to re-estimate the factors using the most recent time periods and letting the algorithm deal with the problem of missing observations. Step 2 thus delivers a new estimate of the common factors, taking into account information from all the latest available economic data releases.

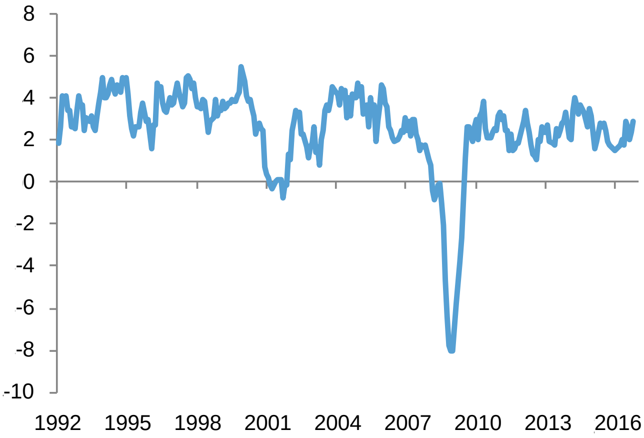
We then determine the relationship between the estimated factors and country GDP growth. Indeed, whilst the common factors provide a statistical summary of the co-movement between economic data, their interpretation is not straightforward. Mapping GDP to the common factors enables the model to embed an intuitive interpretation into the analysis. The Nowcast measure thus obtained is both more timely and less "noisy" than official country GDP measures.

[16] Most of the variability in US macroeconomic data can be explained by just two components (see Sargent and Sims, 1977 and Giannone et al., 2004).
[17] Most of the variability in US macroeconomic data can be explained by just two components (see Sargent and Sims, 1977 and Giannone et al., 2004).
As employed by Giannone et al (2005) and analysed by Doz and Reichlin (2011).

Illustrating the Nowcast model
Sample results

Figure 3 shows the model's estimate of US monthly activity as at 24 October 2016. For the most recent month (October), the model estimates a rate of activity of 2.8% annualised, up 0.4pp from the previous month. This number can be interpreted in the same way as quarterly annualised GDP figures (i.e. if the current run-rate were maintained, this would be the annual growth rate). This highlights an acceleration of activity in the months since June, after a softer growth period in the end of 2015 and the beginning of 2016, when recession fears began perturbing investors. However, our Nowcast never fell below 1.5% in that period, showing at the time, that the US economy was growing healthily and the fears were exaggerated.

Figure 3: Activity indicator, US economic activity indicator, monthly growth annualized



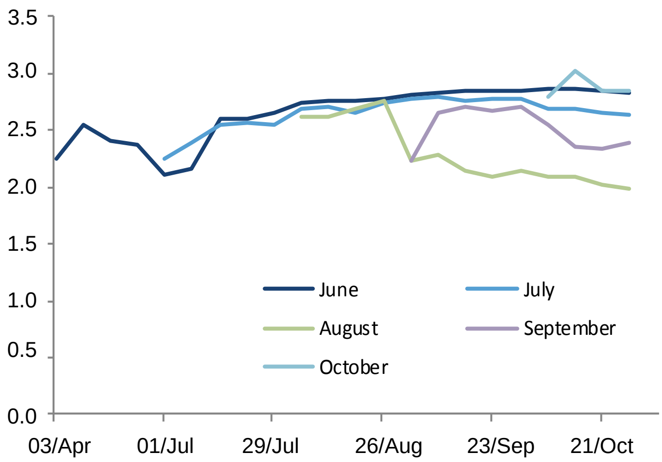
Source: HSBC Global Asset Management as at 31 October 2016

Since the estimate is updated every week and always incorporates the latest data releases, the measure of activity for a particular month changes over time. The evolution of the estimates of the most recent six months is shown in Figure 4 as an example.

There are some months when the estimates change several times before settling at a certain level., in particular in the current month, when no macroeconomic data has been published yet and we rely entirely on market prices to gauge the state of the economy. For example the estimate for June fluctuated between 2.0% and 2.5% until finally settling at 2.5% in mid-July. The estimate for July, however has barely moved over time. This is a good reminder not to rush to conclusions but, more importantly, it also shows the estimation process in action, as the algorithm gradually discards the economic noise and distils the signal

We therefore start publishing our estimates at the end of the month when we have gathered a minimum number of observations that allow us to be confident in a first estimate.

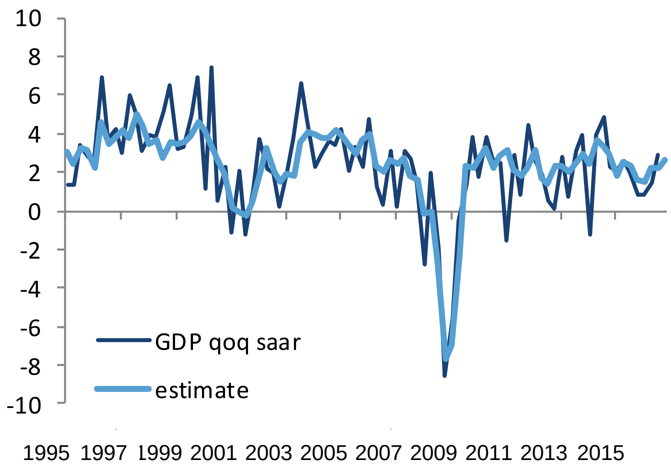
Figure 4: Evolution of activity estimate



Source: HSBC Global Asset Management as at 31 October 2016

Figure 5 compares the estimate to GDP growth. The model's measure is less volatile than headline GDP, yet captures the underlying trend, and we therefore believe it is a better gauge of underlying economic activity. GDP data is often biased by inventory or valuation adjustments, while the Nowcasting approach will look through this measurement volatility and focus on the underlying picture. As such, one might argue that GDP is a noisy proxy for the Nowcast.

Figure 5: Quarterly activity estimate versus GDP



Source: HSBC Global Asset Management as at 31 October 2016

Conclusion
A clear picture to spot investment opportunities

There is a lot of noise in economic data. Many market participants devote an enormous amount of time and effort in attempting to out-forecast each other about how short term events will unfold. We do not think this is the best way to add value for investors.

However, understanding the economic cycle remains essential. The riskiness of a given asset class will be determined by the nature of the economic environment, so investors need to understand current economic conditions to make informed decisions.

The Nowcast methodology takes a systematic approach to measuring where we are in the economic cycle. It is, not a forecast. The algorithm instead builds a real-time measure of growth, based on all the key macro-economic data. As such, it identifies the relevant economic signal amid the excitement, randomness and noise of the macroeconomic news flow.

We believe incorporating this information alongside a clear understanding of the current market-implied odds (i.e. our risk premium framework) enables us to take a rich and structured approach to finding global macro investment opportunities.

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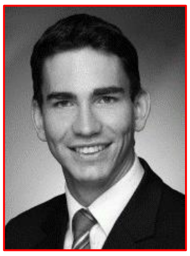
Joseph joined HSBC's Asset Management business in 2007. He is currently Chief Global Strategist, responsible for leading our work on macroeconomic and multi asset research, and for developing the house investment strategy view. He was previously Chief Strategist for Strategic Asset Allocation and a Fund Manager working on Tactical Asset Allocation strategies for an absolute return strategy. Prior to joining HSBC, he worked as a Global Economist for JP Morgan Cazenove. Joseph holds an MSc in Economics from Warwick University and is a CFA charterholder.



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