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Views, Factor Models and Optimal Asset Allocation

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Abstract

Making investment decisions in general is a decision-making problem under uncertainty. How well an actual investment portfolio performs depends on the future evolution of economic and financial variables such as interest rates, asset returns and inflation rates. The future evolution of these risk drivers is traditionally modelled using time series models, and it is assumed that historical data are relevant for assessing future risk and return. However, opinions vary about the extent to which all forward-looking information can be derived from historical data. Consequently, a framework for combining views and model-based (density) forecasts is indispensable. We present a concrete example of how views can consistently be combined with model-based (density) forecasts and how this affects investment decisions.

Keywords: Imposing Views; Portfolio optimisation; Factor models.

1. Combining views and models

Making investment decisions is a decision-making problem under uncertainty and is, especially for institutional investors, part of the risk management process. In general, the risk management process is characterised by three phases. In the first phase, there is an assessment of the risk and return trade-off, taking account of the stakeholders' objectives, constraints and the assumptions on various asset classes and risk drivers; this phase then leads to a strategic asset allocation. In the second phase, called portfolio construction, the strategic asset allocation is translated

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into an actual investment portfolio. In the third phase, monitoring takes place to ensure that the assumptions contributing to the strategic asset allocation remain valid and that the implementation indeed conforms to the strategic asset allocation.

How well an actual investment portfolio will perform in terms of the objectives and constraints of the stakeholders will depend on the future evolution of economic and financial risk drivers such as interest rates, asset returns and inflation rates. The uncertainty about the future evolution of these risk drivers is traditionally modelled using time series models; see Campbell and Viceira (2002) for an example. A fundamental assumption underlying these time series modelling approaches is that there is relevance in historical data for assessing future risk and return. Although there are many arguments to support this claim, it is debatable whether all relevant forward-looking information can actually be derived from historical data. An obvious topical example in today's world is the impact of unprecedented central bank interventions on interest rate levels, and the expected speed of normalisation. Consequently, in practical applications, a framework for combining views and model-based (density) forecasts is indispensable.

Consistently combining expert views with model-based (density) forecasts is not at all straightforward. The difficulty is threefold: first, views are typically not formulated for financial variables, but rather in terms of macroeconomic variables such as economic growth and inflation; second, views are usually not formulated for the full investment horizon; and third, even when views are formulated in terms of certain financial variables – say, equity returns – on the full investment horizon, it is unclear how these views should impact other financial variables, e.g., bond returns. Especially when the number of views and number of assets in the investment portfolio is large, it is all the more important to apply a modelling approach to resolve these difficulties.

In this paper, we show how to consistently combine expert views with model-based (density) forecasts and outline how this can impact investment decisions. First, we present a model that is both realistic and simple enough to serve as an example and work out the methodology for this model. Then, we estimate the model on data and give a concrete example of how the views influence the forecast. Finally, we discuss the impact of the views on investment decisions using portfolio optimization.

2. Dynamic factor models

A realistic modelling application supporting the investment decision process typically involves forecasting the joint behaviour of a large number of financial and economic variables. Not all models are suited for this task, as estimating high dimensional models is usually difficult. The widely used Dynamic Factor Model (DFM) does not have this drawback and is very efficient in forecasting the joint behaviour of a large number of time series. The underlying assumption that validates the use of a DFM is that the simultaneous behaviour can be described by only a small number of (usually unobservable) factors. See Sargent and Sims (1977), Geweke (1977) and Stock and Watson (2002) for more details on DFMs.

A well-known example is the factor model presented in Stock and Watson (2002, 2011). In this type of DFM, the historical time series of the factors are estimated from a dataset containing 108 economic and financial time series for the United States by a principal component analysis (PCA). A common choice is to use the first four to 10 principal components. These principal components, and consequently the factors, explain a large part of the variance and correlation structure of the whole dataset.

The specific DFM used in this paper is based on the factor model presented in Stock and Watson (2012b) and has the following form:

$$F_t = C_F + AF_{t-1} + \varepsilon_t^F, \quad (1a)$$
$$R_t = C_R + BF_t + \varepsilon_t^R \quad , \quad (1b)$$