GMAM 3 is a multi-asset tool uniquely capable of educating advisors on the risk and return characteristics of any investible asset. Traditional multi-asset tools rely on large samples of high-quality data, while the typical private capital fund track record is short and subjective. Metrics specific to private capital, such as IRR and PME, do not comfortably generalize to other asset classes. GMAM 3 faces neither limitation.

The model’s design and resulting efficacy is a product of four key concepts. First, GMAM 3.0 models how funds report returns. For example, given a spike in oil prices, the model predicts both the magnitude of the impact as well as the time horizon over which the movement will manifest in reported returns.

Second, the model assesses the focal fund’s exposure to a parsimonious set of economic and technical forces. By understanding how these forces drive returns, the model can identify how an asset will change in value across pertinent economic scenarios.

Third, GMAM 3.0 accounts for the inherent delay between a change in an asset’s value and the time that this change is reported to investors. For example, a change in the desirability of a particular property may take months to appear in a fund’s quarterly statement.

Finally, the information available about any fund extends beyond the fund’s track record. For instance, GMAM 3.0 can weigh the expectations of iCapital’s analysts against the realized performance of a fund. By providing a framework through which outside information can enter the analytics, the model overcomes the deleterious effects of poor quality data and limited track records.

FAQ

**How can we know if the model is effective?**

GMAM 3.0 provides the potential distribution of returns given factor movements in the form of simulated return realizations. An analyst can assess how the realized returns fit within this distribution. An analyst can use the simulated track records to construct credible bands (e.g. the 5th and 95th percentile return realization on a particular date).

More generally, any quantity of practical significance may be tested against the simulated data. For example, if the maximum observed return is 15%, and this is higher than 99% of the maximum returns among 10,000 simulated track records, than the model is most likely failing to capture the potential for a fund to generate returns as high as 15%. Similar analysis can consider statistics such as standard deviation, autocorrelation, percentile returns, cross-asset correlations, and other quantities. Note that the failure to match a particular quantity does not mean the model is useless, rather, that it is not matching a particular feature of the data.

Of course, the standard frequentist measures such as out-of-sample R-squared can also be applied to any point estimate produced by the model, albeit at the cost of ignoring the rich information on the parameter distributions that the model produces as part of its estimation procedure.

**What is a good R-squared**

A good R-squared is any value that implies that the variation captured by the model is helpful in assessing the risk and return profile of an asset. For example, an R-squared of 0.5 implies that the model is capturing 50% of the variation of a particular asset. The information provided by the model would therefore seem significantly more helpful than no model at all (R-squared of zero).

Note that while R-squared is useful an assessing a model’s practical significance in capturing the variation of an asset, it is not a measure of statistical significance or model validity. In a frequentist sense, the single factor model that predicts a beta of 1.0 for a stock might capture 80% of the variation (80% R-squared) despite standard a confidence interval of -2.0 to 4.0 for the estimate of beta.

(As an aside, there is a famous paper (Campbell and Thomson (2008)) that equates out-of-sample R-squared with expected excess profits given the market Sharpe ratio. They find that in the absence of transaction costs, a mean-variance investor could increase their returns by about a third given a 0.43% monthly R-squared. Therefore, an investor with a predictive model of the factors could realize very high excess returns in the presence of any reasonable model fit.)

**What is a Bayesian approach**

A frequentist sees a set of data and models a data generating process (DGP). The frequentist then infers bounds in which the true parameters of the data generating process are most likely located.

A Bayesian looks at the data and models a DGP. The Bayesian sets priors and, combining the priors with the data, infers the probability distribution of the parameters implied by the data. In contrast to the frequentist approach, the parameters have no true value, and are random variables whose distribution is a product of the data, modeling assumptions, and prior.