Research Insight

Constructing Quality Risk Models

Best Practices in Building Standard and Proprietary Models

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Introduction

Investment managers use multi-factor risk models to construct portfolios, to accurately measure portfolio risk, and to attribute portfolio risk and returns. While risk models are far from new, best practices in model building are being continuously improved as more data becomes available and research innovations are made. Why the effort for improvement? Because flaws in model construction can result in poor risk forecasts and may generate optimized portfolios that are not efficient.

Many investment managers use risk models from third-party providers. We refer to these models as *standard* risk models, or *base* models. Some managers hope that *proprietary* risk models may help improve the performance of their portfolios. A typical proprietary risk model is a derivative of the standard model, incorporating the manager's alpha signals as factors. It needs to fulfill the same best practices in model building as a standard model. However, there is little discussion of good practices of proprietary model construction in the public domain. In past studies, the empirical results on the performance of such models tended to be limited in scale, both in terms of the history used and in terms of the number of portfolios/signals examined.

In this paper we discuss the building blocks essential to making a good standard risk model. We then turn our attention to the use of risk models in the investment process: in constructing efficient portfolios and attributing their risk and return. Finally, we outline the best practices of proprietary model construction and provide an empirical investigation of the economic impact of using proprietary models in portfolio optimization.

In summary, our results indicate the following:

- Designing and building a good risk model requires expertise in risk model construction as well as extensive backtesting. It relies on the identification of the appropriate factor structure, a good estimation methodology, and sufficient data quality and coverage.
- Some managers prefer to attribute performance based on a set of proprietary factors. The implementation of custom factor attribution can be done by mapping the proprietary factors to the factor set of a standard risk model. A proprietary risk model is not needed for this purpose.
- Building an effective proprietary risk model is an exercise that is as demanding as building a good standard risk model. The costs of this exercise need to be balanced against the economic benefits in portfolio performance that a proprietary model is expected to provide. We outline the main challenges in the construction of a proprietary model, highlighting the possible pitfalls and potential solutions at each step.
- In our comprehensive empirical study we observed that, compared to using a standard risk model, optimizing with a proprietary model:
    - Did not necessarily improve out-of-sample portfolio performance;
    - May help improve the risk forecast accuracy if the model is well designed; however, in some cases using a proprietary risk model decreased the risk forecast accuracy.

What Makes a Good Risk Model?

Factor models decompose the return of each asset into a part that is driven by a set of common factors and a part that is specific to that asset. The asset-specific parts are assumed to be uncorrelated with the factor returns and with each other. A good fundamental factor risk model relies on solid methodology, as well as excellent data coverage and data quality. In this section we outline the contribution of each of these components.

Two Pillars of Model Methodology: Factor Structure and Calibration

Constructing a fundamental factor risk model involves two broad steps.

1. Defining factor structure – including selecting the factor set and calculating the exposure of each stock to each factor in the model.
2. Model calibration – including
    a. Estimating the factor returns and specific returns via a cross-sectional regression.
    b. Estimating the factor covariance matrix, as well as the specific risk matrix.

Factor structure is responsible for the correct characterization of systematic risk and is an important driver of risk forecasting accuracy. A risk model may be missing important risk factors, or may not accurately specify assets' exposures to the factors. This is sometimes known as *model error*. It may be the result of inadequate research or lack of comprehensive data coverage. When the set of common factors in a risk model is incomplete, systematic risk will be misrepresented, and this may result in under-forecasting portfolio risk. Inadequate factor structure, therefore, has a detrimental effect on the risk forecasts and return decomposition for all portfolios.

Factor selection therefore lies at the heart of a quality fundamental risk model. The factor set of a fundamental model should be intuitive and insightful to the investment process, reflecting the economic and behavioral drivers that determine portfolio risk and return. A model with a quality set of factors should accurately capture systematic risk, identify relevant strategy risk, and assess strategy crowding. It also enables investors to attribute performance in a way consistent with their investment process.

While all factors are selected to explain the cross sectional dispersion of returns and asset risk, some style factors represent systematic equity strategies and are frequently perceived as sources of both *alphas* (or *exotic betas*) and strategy risk. These factors capture return premia relative to the CAPM: they exhibit trending returns over the long run, often with an underlying reason for their persistence. Accurate estimation of exposures to these factors often requires access to appropriate proprietary data sources in different markets. Other factors are useful for explaining the cross-sectional dispersion of returns, but do not exhibit persistent trends in their returns through time. These factors without alphas can be used for risk control.

A good factor selection process involves a great deal of economic and statistical evaluation. During this process, the statistical significance of factors and their explanatory power is analyzed over time. Moreover, it is prudent to examine the consistency of factors in different segments of the estimation universe as well as in different time periods (in particular, periods of market crises) to help the modeler and model users fully understand the behavior of factors.

Having the right factor structure is important, but it is not enough to guarantee accurate covariance matrices. To produce reliable risk forecasts, the factor covariance matrix and asset specific risks must be estimated properly to deal with non-stationary historical data and estimation error. Lee, Ruban, Stefek and Yao (2012) discuss model calibration and estimation methodology in more detail, outlining the challenges and recent model innovations aimed at solving them.

Data coverage and data quality

Factor returns in fundamental models are estimated using a multivariate cross section regression of the returns of a universe of assets against the assets' factor exposures. As the estimation universe is finite, both factor returns and specific returns contain some noise, typically referred to as measurement error. The smaller the estimation universe the larger the measurement error becomes. It can lead to the over-forecasting factor volatility and, to some extent, the under-forecasting of specific risk. For this reason, a good standard risk model is typically estimated with a large universe of representative assets.

Besides sufficient cross-sectional coverage, adequate time series data is also needed. A risk factor is typically tested for inclusion in the model over a period of many months to identify whether it represents a meaningful source of systematic risk.

A sufficient length of factor exposure history is needed to generate the historical factor returns. These historical factor returns are used to estimate the factor covariance matrix. Newer generations of risk models typically rely on daily factor returns to estimate the factor covariance matrix. This increases the sample size[1] of available factor returns and makes the model more responsive to trends in the market. Data coverage and management become high order tasks.

Risk Model in Investment Process

As noted by Grinold and Kahn (1999), risk models have three broad uses, ranging across the present, the future, and the past. These uses are: portfolio risk analysis, performance attribution, and portfolio construction. Good factor structure, estimation methodology and data quality help ensure intuitive and accurate portfolio risk analysis. In this section we focus on the other two uses: performance attribution and portfolio construction.

Performance attribution

An important step in the investment process is to measure and explain the effect of active management decisions on the risk and return of a portfolio and allow the portfolio manager to understand sources of risk and return in meaningful way. Some managers use a specific set of alpha signals to construct their portfolios and prefer to align the attribution model along these dimensions. Therefore, they would like to attribute performance based on a set of proprietary factors, instead of the factors in the standard risk model.

Menchero and Poduri (2008) show how to align the attribution model with the investment process. A manager's active return, tracking error, and the information ratio can be attributed to a user-defined set of factors that reflect the manager's investment decision-making process.

A frequent source of confusion among quantitative portfolio managers is that a proprietary factor model is necessary to attribute risk and return to custom factors. In fact, custom factor attribution can be implemented without using a costly proprietary model. All that is needed is a standard risk model

[1] Using higher frequency data does not necessarily increase the sample size as much as one might think at first glance. Daily factor returns exhibit some autocorrelation which reduces the effective number of independent observations. Risk modelers use autocorrelation adjustments to treat these effects.

together with the set of user-defined factors. Menchero and Poduri (2008) provide a detailed exposition of the methodology for custom factor attribution; interested readers are encouraged to refer to their paper for details.

Portfolio construction

Many managers use mean-variance optimization as a tool to construct portfolios. An estimate of the covariance matrix is required in this process. Today, portfolio managers use covariance matrices based on multi-factor models of risk. These models are less sensitive to noise and produce covariance matrices that are particularly useful for optimization.

Expected returns, or alpha signals, are another input needed for mean-variance portfolio construction. A source of heated debate in the quantitative investment community is whether alpha signals should be included in the risk model. Some managers feel that having alphas in their risk model may result in the phenomenon known as "alpha-eating." An alternative view is that a subset of the alpha sources may contain systematic risk, which may be missing from the standard risk model. It is also argued that incorporating alphas into a risk model may provide better alignment between alphas and portfolios. Models that consider including alpha signals into the set of risk factors need to satisfy the same best practices in model building as the standard models. We discuss the construction of risk models with a tailored factor set, or *proprietary* models, in the next section.

Proprietary Risk Models

In general, the terms proprietary model refer to a model that is tailored to an investment process. While the process of constructing such a model can be quite involved, it aims to solve two main issues: mitigating unintended bets in optimized portfolios due to alpha-risk factor misalignment; and capturing a source of systematic risk that may be missing from the standard risk model.

The case for aligning risk and alpha factors

Some factors (for example momentum, value and residual volatility) have been proven effective as both risk and alpha factors. More often than not, however, the precise definition of a value-based alpha signal will be somewhat different from the way a risk factor measuring value is defined in a standard model. This discrepancy is at the heart of the issue known as the alpha-risk factor misalignment.

Lee and Stefek (2008) show that aligning the risk factors and alpha factors may improve performance, particularly when the discrepancy between factor definitions does not contain useful return information. Lee, Ruban, Stefek and Yao (2013) examine misalignment in detail and provide theoretical analysis. The practical extent of the improvements is also analyzed. They show that in many cases correcting misalignment is likely to lead to only minor improvements in portfolio performance out of sample.[2]

A somewhat separate concern is that the manager's (residual) alpha may also represent a source of risk that is not captured by the risk model. If the alpha represents a source of systematic risk that is not covered by the risk model, it may result in inefficient portfolios and the under-forecasting of the risk of optimized portfolios. In this case, we should assign the (residual) alpha its proper risk when building the

[2] In this paper the improvement is analyzed under penalizing residual alpha framework.

portfolio. However, not every direction outside the risk factors should always be regarded as source of systematic risk. Managers' alphas may well represent ideas that do not conflict with the risk model and are not missing risk factors. As we illustrate in our case studies, using a proprietary model without care can also hurt the accuracy of portfolio risk forecasts.

Penalizing residual alpha as a simple solution to misalignment

Estimating a proprietary model is not the only way to deal with the problems highlighted above. Bender, Lee and Stefek (2009a and 2009b) show how to modify the portfolio optimization to fix these issues by penalizing the residual alpha. While this method provides a handy solution to the problem, it requires the manager to estimate the missing volatility, and it assumes that the returns to the residual alpha and the risk model factors are uncorrelated. Proprietary models, on the other hand, account for both volatilities and correlations between the residual alpha and the model risk factors. Therefore, it seems that in theory, given that the residual alpha is a meaningful risk factor, a proprietary risk model should perform at least as well as penalizing residual alpha.

In practice, however, constructing a proprietary model can be a considerably more complex exercise than penalizing residual alpha. This extra complexity and cost needs to be balanced against the incremental benefit in portfolio performance.

Building a proprietary risk model

When constructing a proprietary model, a standard risk model is a typical starting point. It comes with a pre-defined factor set, estimation universe and calibration parameters (such as the half-life of the covariance matrix, serial correlation correction, adjustments for estimation errors in the covariance matrix, and so forth).[3] Estimating a proprietary model then involves re-running the three steps outlined above, including any factors that are not part of the standard model and potentially excluding some factors in the standard model. The calibration parameters can also be adjusted as desired.

If it is decided that a proprietary model is necessary, there are a range of practical issues that need to be addressed before it is built. Two broad questions need to be answered:

1. Is the alpha signal suitable for inclusion in the risk model?
2. Given data availability and property of the signal, how should we include the alpha signal in the risk model?

We explore these issues in detail in the sections below.

Asset coverage and data history

We have discussed the importance of cross-sectional asset coverage in the previous section. A good standard risk model is typically estimated with a large universe of representative assets. For example, the estimation universe of the Barra US Equity Model (USE4) is the MSCI USA IMI Index, which included 2,467 assets as of the end of January 2013. The Barra Global Equity Model has over 8,500 assets in its estimation universe.

Many managers, however, only have a relatively small sample of assets for which alpha forecasts are available. This can lead to difficulties in adding the alpha signal to the set of factor exposures of a

[3] For an example, see the Barra US Equity Model (USE4) Research Notes

standard model, if the estimation universe is kept unchanged. If, on the other hand, the estimation universe is restricted to the smaller universe of assets for which alpha signals are available, the resulting measurement error of the model can lead to substantial noise in the estimated factor returns and the covariance matrix.

Another concern is that the benchmark portfolio used in optimization may contain many assets not covered by a manager's alpha. Those assets will have no exposure to the alpha signal, but will still be part of the active risk computation. Consequently, it may affect the quality of the estimated active risk of an optimized portfolio.

We have also discussed the importance of sufficient data history. A risk factor is typically tested for inclusion in the model over a period of many months to identify whether it represents a meaningful source of systematic risk. Therefore, sufficient time series history of the alpha exposures is needed to perform the validation of the proprietary model. A sufficient length of alpha history is also needed to generate the historical factor returns associated with the alpha signal. These historical factor returns are used to estimate the volatility of the factor as well as correlation of the factor to the other model factors.

Are your alphas meaningful systematic risk factors?

Once sufficient cross-sectional coverage and data history are ensured, it is important to identify if the alpha signals can serve as meaningful systematic risk factors. It is a mistake to take any direction outside the space of risk model factors as a source of missing systematic risk. Forcing an unsuitable factor into the risk model may lead to over-forecasting of risk. We provide an example of this with the Alphabuilder Neglect signal in a subsequent section (Neglect signal: proprietary model overforecasts risk).

How should we test if the alpha signals are risk factors? Standard measures to evaluate this include statistical significance (t-statistics), as well as improvements in explanatory power of the model (adjusted R^2 and incremental adjusted R^2). However, these measures do not provide clear cut mechanical criteria for inclusion of exclusion of a factor. For example, some modelers would choose to include a risk factor that is significant only 20 percent of the time, while others would exclude it. Factor return volatility is also an important measure, but it too is somewhat subjective. Thus, an important element in the construction of good risk models is a thorough backtesting process performed on a wide range of real portfolios, or at least using the alpha strategies under consideration.

Incorporating alphas into a proprietary model

Expected returns may be constructed from a combination of descriptors (factors) or a single signal. For example, one manager's alpha may be the sum of value, momentum and sentiment signals; another manager's alpha may be a value based strategy that consists of book to price, forecast earnings to price, historical earnings to price and earnings growth; while the third manager may bet purely on price momentum. A crucial question in the building of a proprietary model is how to incorporate the manager's signal with the factor set of the standard model.

One approach is to use the manager's alpha scores as factor exposures directly, adding them to the exposure set of the standard model factors. However, this relies on low collinearity between the alpha score and other factor exposures. For example, if a risk model already has a momentum factor, then adding an alpha momentum factor to the model (which is likely to be strongly collinear with the risk momentum factor) will jeopardize the cross-sectional regression.[4] In this case, replacing the risk model momentum factor with the alpha momentum factor would offer a better alternative.

More complicated cases require considerable care in their treatment. For example, the alpha signal may overlap[5] significantly with the risk model, but not provide us with explicit clues of which risk model factor we should replace. Adding the residual alpha as a factor may prove an acceptable alternative in this case.

Even more intricate cases are frequently encountered. One example is the treatment of the alpha signal when it is a combination of several descriptors. A value based alpha might rely on a linear combination of forecast earnings-to-price, historical earnings-to-price, earnings growth and book-to-price. A number of questions should be investigated in this case. First, should we add the alpha descriptors as one factor or separate factors into the model? Should some existing factors in the risk model be replaced due to the addition of the alpha factors? Alternatively, should only the residual parts of the descriptors be used? If we want to bundle descriptors together as a factor, then how can we decide the weight to form a factor? To answer all of these questions, a significant amount of backtesting is prudent.

Empirical Study – Evaluating the Effectiveness of Proprietary Risk Models

In this section, we take a first step to provide an evaluation of the benefits of using proprietary models in portfolio construction. Our starting point is the Barra US Equity Model (USE4S), which we refer to as the standard model. We take a range of typical alpha signals and modify the standard model to include these signals as factors. The alpha signals chosen for the purposes of this study satisfy the data suitability criteria outlined in the previous section—i.e., they are available for the whole cross-section of assets used to estimate the standard model and have appropriate depth of history to be added as a model factor.

To build the proprietary model we apply the same modeling practices and data refining techniques[6] that we use to build the standard model. We also use the same universe as the standard model (the MSCI USA IMI index).

As we discussed in the previous section, there are many ways in which an alpha signal can potentially be incorporated into a standard risk model. In our study we adopt the following guiding rules:

- If the alpha signal is similar to a factor in the standard model,[7] we replace the risk model factor by the alpha factor.
- If the alpha factor is not similar to any specific factors in the standard model and the portion of alpha explained by the risk factor is small,[8] then we add the alpha factor to the model without modification.

[4] Moreover, having two momentum factors in the risk model would not resolve the misalignment issue.

[5] High percentage of alpha is spanned by risk model factors.

[6] This includes exposure winsorization and truncation rule, missing value treatment, regression weighting scheme, volatility and correlation half-life, Newey-West autocorrelation adjustment, cross-sectional volatility adjustment and eigenfactor adjustment.

[7] For example, the alpha is a momentum signal and there is also a momentum factor in risk model.

[8] We regress alpha against standard risk factors and look at the R-square. We use 0.5 as a benchmark in this study.

- In other cases, we compute the residual alpha by regressing the alpha factor again the risk model exposures. We then add the residual alpha to the risk model.

After the alpha signal is added to the model, we re-run the cross-sectional regressions to estimate factor returns. We then use these factor returns to estimate the factor covariance matrix.

We assess the performance of the proprietary models according to two criteria: risk forecasting accuracy (measured by the bias statistic) and out-of-sample portfolio performance (measured by the information ratio). Our results indicated that a carefully constructed proprietary risk model may improve portfolio risk forecast accuracy. However, this improvement is not a certainty: in a few cases the risk forecasting precision either declined or was not improved. With respect to out of sample portfolio performance, we did not observe a convincing improvement for portfolios constructed using proprietary models. We examine three cases in detail before presenting summary results.

Relative strength signal: proprietary model improves portfolio performance and risk forecasts

In the first case, we use a relative strength (price momentum) alpha signal.[9] Since there is also a Momentum risk factor in standard model, we replace it with the alpha factor to avoid collinearity.[10] We keep all the other factors, as well as the model calibration parameters unchanged.

Figure 1 shows the realized efficient frontiers created with the standard and the proprietary risk models. The efficient frontiers are created by setting four risk targets (2, 3, 4 and 5 percent) and running a backtest for each target. The portfolios created in the backtests are active long-only, using the MSCI USA IMI as both the investment universe and the benchmark. They have constraints on turnover (8 percent) and active holdings (4 percent). We then compute the realized return and the realized risk for each backtest. These points form the efficient frontiers. The efficient frontier of portfolios created with the proprietary model lies up and to the left of the efficient frontier of portfolios created with the standard model. This indicates an improvement in out-of-sample portfolio performance by achieved by using the proprietary model.

Figure 2 presents the ratio of realized to forecast risk (bias statistic) for the portfolios created with the standard and the proprietary models. Both portfolios are active long-only, using MSCI USA IMI as both the investment universe and the benchmark and targeting 4 percent active risk. They have the same constraints on turnover and active holdings as above. The overall bias statistic is 1.10 with the standard risk model and 1.04 with the proprietary risk model, indicating slightly better risk forecasting accuracy. This is an encouraging result, where both the risk forecasting performance of the proprietary risk model, as well as the out-of-sample performance of the optimized portfolio created with the proprietary model, show improvements relative to results obtained with the standard model. In fact, out of all signals considered, we saw the most significant improvement with the Momentum strategy.

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[9] Our relative strength model used the stock returns over the past 13 months. We adjusted these returns for the most recent month's returns due to the reversal effect. We also adjusted the returns for style characteristics of the security.

[10] We regress the relative strength signal on standard risk model factor exposures and the R-square is 0.55.

Figure 1: Efficient frontiers for optimized portfolios created with the standard and proprietary models.

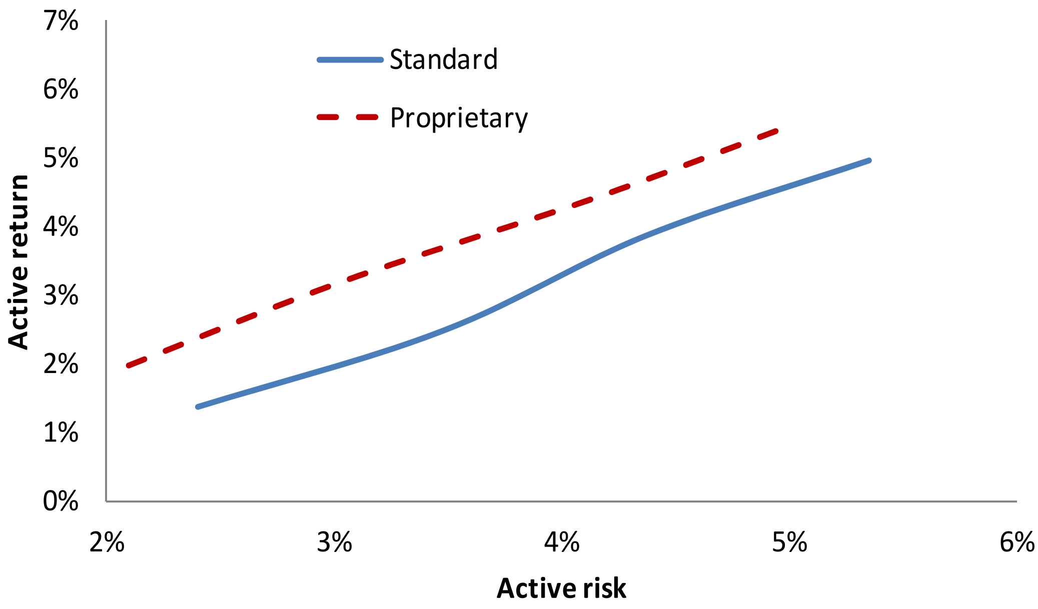
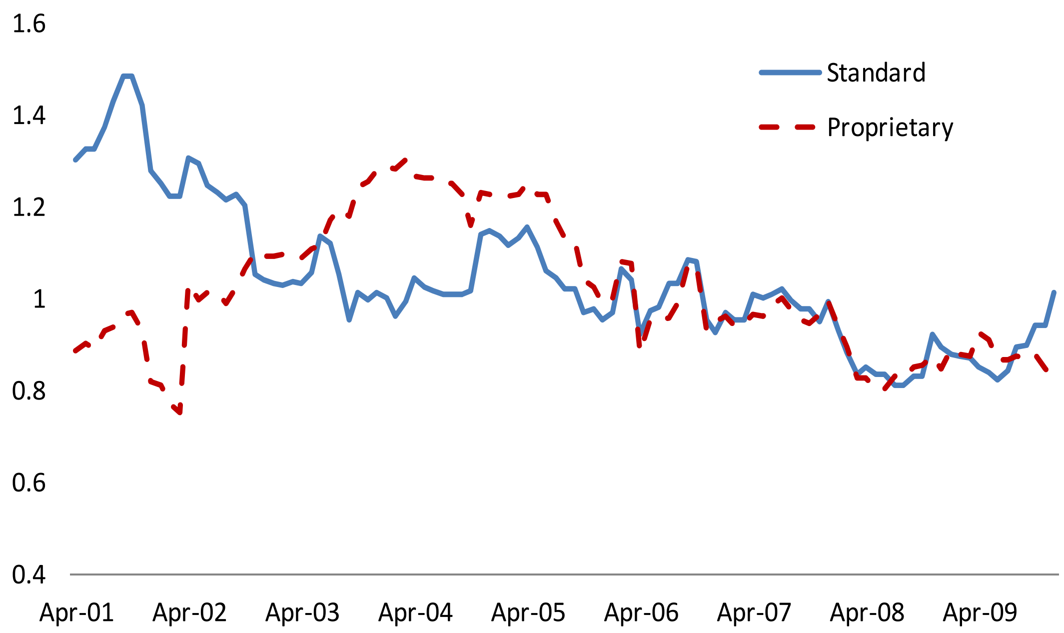


Figure 2: Ratios of realized to forecast risk (rolling 24 month) of portfolios for standard and proprietary models.

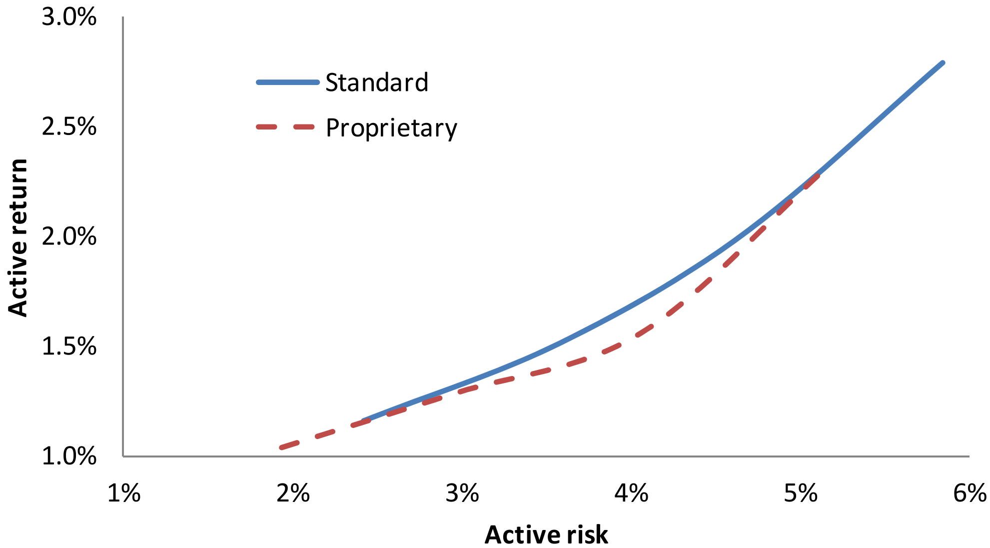


Cash plowback signal: proprietary model hinders performance

In the second case, we use the cash plowback signal as our alpha.[11] We add it to the factor set without modification, and re-estimate a new model[12].

Figure 3 shows the realized efficient frontiers created using the two models. The methodology for creating the frontiers is the same as in the relative strength example above. We see that in this case the efficient frontier of the proprietary model lies below the efficient frontier of the standard model. Constructing portfolios with the proprietary model has a detrimental effect on their out–of-sample performance in this case.

Figure 3: Efficient frontiers for optimized portfolios created with the standard and proprietary models, Cash plowback signal.



Neglect signal: proprietary model over-forecasts risk

In the third case, we use the "neglect" signal,[13] which has a high overlap with the factors in the standard model.[14] We regress this signal against the risk model factor exposures to compute the residual alpha. We add the residual alpha to the factor set of the standard model and re-estimate the risk model.

Figure 4 shows the 24-month rolling bias statistics for the portfolios created with the standard and the proprietary models. Both portfolios are active long-only, using MSCI USA IMI as both the investment

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[11] Cash plowback measures the amount of earnings a company has reinvested in its operations. The cash plowed back into the company is the earnings per share over the past year minus the dividends per share paid over the same period. We divide this number by the current stock price to put all companies on a reasonably comparable scale.

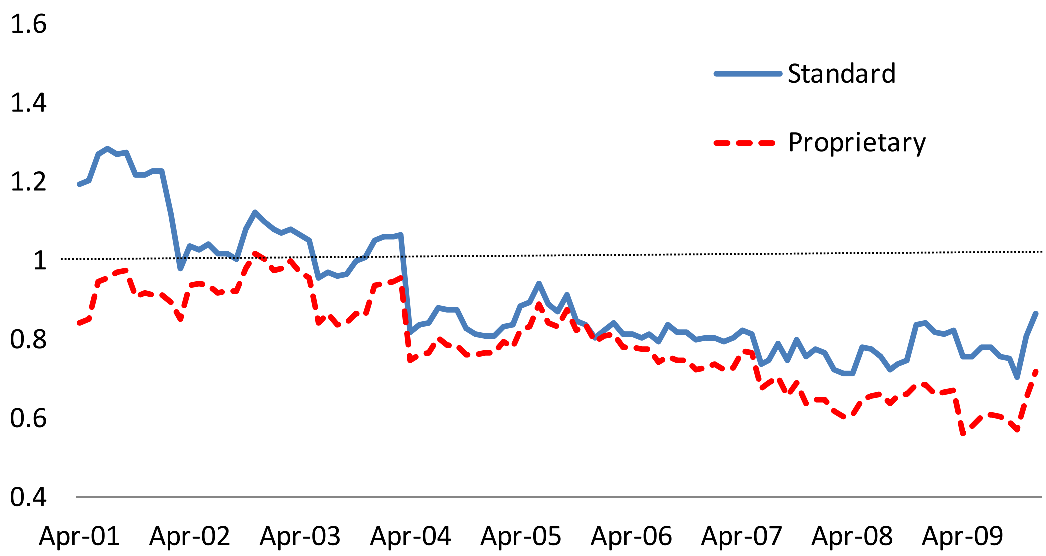
[12] We regress the cash plowback signal on standard risk model factor exposures and the R-square is 0.27.

[13] We combine two measures of neglect: institutional coverage and market capitalization. Stocks with few analyst estimates and low capitalization will tend to have high scores in this model.

[14] We regress the neglect signal on standard risk model factor exposures and the R-square is 0.65.

universe and the benchmark and targeting 4 percent active risk. The other constraint is on turnover (8 percent). The neglect signal provides an example where a proprietary risk model may hurt risk forecast accuracy. We see that while adding the extra factor increases the forecast risk (the dashed red line lies below the blue line), it does not improve the risk forecast. On average the proprietary model over-forecasts risk: the overall bias statistic is 1.03 with the standard model and 0.87 with the proprietary model.

Figure 4: Rolling bias statistics (24m) of the standard and proprietary models, neglect signal.



More general findings

We take 17 different alpha signals for US equities, spanning both technical and fundamental signals, and backtest long-only strategies with turnover and various constraints. In some cases we further use two investment universes in our test: a broad and a narrow universe of assets.[15] This provides 27 different cases. We employ the same methodology and time period as those used in our case studies above. The aggregate results are presented in Tables 1a and 1b. The first table displays bias statistics of portfolios targeting 4 percent ex-ante risk. The second table displays information ratio of portfolios with realized active risk of 4 percent.

Table 1a: Impact of using the proprietary model on the Information Ratio.

Average improvement	3.1%
Percentage of cases improved	56%

[15] This is due to inconsistent between signal coverage and benchmark. We define two investment universes: one is the set of assets in the benchmark, and the other is the set of assets with signals.

Table 1b: Impact of using the proprietary model on risk forecasting accuracy.

	Bias statistics	MRAD
Optimized with standard risk model	1.21	0.26
Optimized with proprietary risk model	1.11	0.22
Percentage of cases improved	93%	93%

Overall, we find that empirically proprietary factor models tend to improve the risk forecasts for optimized portfolios, given that the models are carefully tailor-made. The impact on information ratios, however, is mixed. We find both improvements and degradations in information ratios. Improvements were seen in just over half of the cases, and the average magnitude of improvement was modest at 3 percent.

Conclusion

In this paper we outlined the best practices in building risk models. We discussed the importance of having a long history of clean data and argued that a model methodology relies on two main pillars: factor structure and effective calibration. We also discussed the uses of risk models in the investment process.

We then examined the argument that risk models, which are customized to the investment process of an institution, can help improve portfolio performance. Our results suggested that compared to using a standard risk model, optimizing with the proprietary model:

- Does not always improve out of sample portfolio performance, and
- May help improve the risk forecast accuracy if the model is well designed;
- However, this improvement is not guaranteed. In some cases, proprietary models can lead to a deterioration of risk forecasting accuracy.

Creating a proprietary model that provides benefits over using a good standard model is possible, but the process takes effort and expertise. It is erroneous to think that simply modifying the model's factor set to include an alpha signal will result in better model performance. Our case studies provided some illustrations of good practices in building custom models, and the pitfalls to avoid.

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[1] *As of September 30, 2012, as published by eVestment, Lipper and Bloomberg on January 31, 2013* *Apr 2013*