Building Smarter Risk Factor Modeling with Jacobi

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1. Introduction

Risk factor modeling is attractive to managers of multi-asset class portfolios for its ability to cut through the sometimes-arbitrary layers of diversification embedded in portfolios and provide insight into the underlying drivers of risk and return. Portfolios that are highly diversified by manager or asset class labels can oftentimes be wholly exposed to the exact same risks, and this is where understanding the risk factors inherent in portfolios is an advantage.

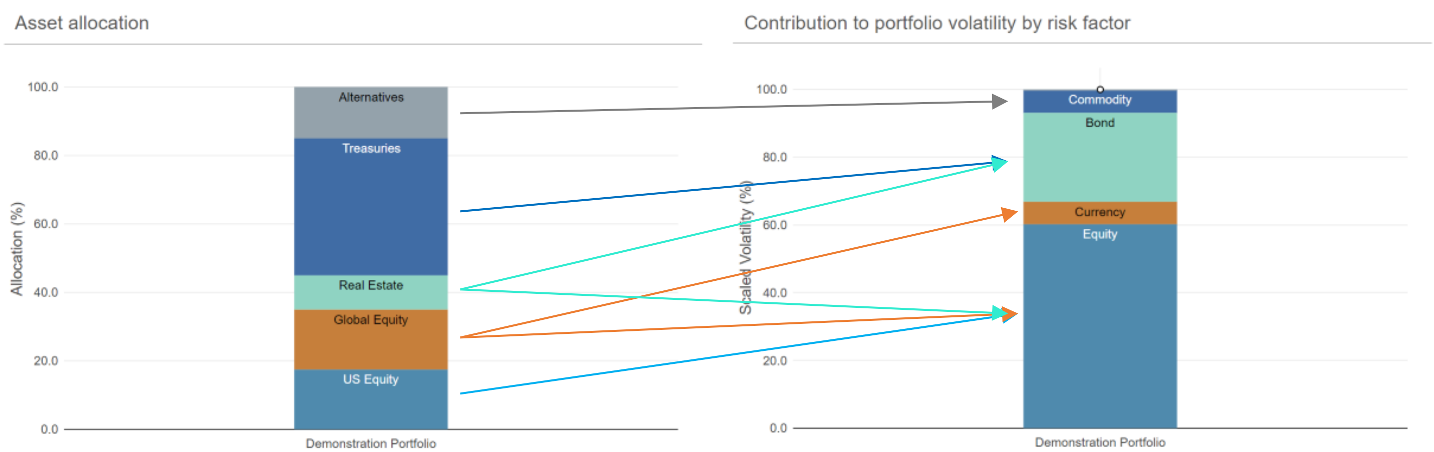
Jacobi has many tools to help investors gain insight into the risk factor exposures embedded in their portfolios such as risk factor risk decompositions and risk factor stress tests. However, for ex-ante analysis, investors are required to formulate assumptions that drive the risk factor returns, and how the asset classes relate to those risk factors. For those investors coming at the problem of risk factor modeling for the first time this can be a daunting task. Jacobi has developed an in-system application to help with this calibration problem. In this paper, we briefly discuss some of the advantages of using a risk factor modeling approach and the assumptions required to perform ex-ante risk factor-based modeling in Jacobi. We then highlight how Jacobi's risk factor calibration app can be used to get started in setting up and parameterizing a risk factor-based Monte Carlo simulation.

2. What are risk factors and why adopt a risk factor modeling approach?

Risk factors are a set of common elements that explain returns across asset classes. Risk factors can help explain why listed equity, credit securities, private equity investments and some real estate assets all tend to do well or poorly at the same time. Each of these asset classes has a significant exposure to a common risk factor that we call the "equity factor". The exact definition of this factor is less important than the ability to model its common impact across asset classes.

Within a risk factor modeling framework, investors first and foremost model how the risk factors are expected to behave, and then how asset classes, managers or other portfolio exposures are exposed to those risk factors. While asset class return, volatility and correlation are typically *inputs* in an asset class-driven modeling framework, these parameters will often be *outputs* of a risk factor-driven framework. When asset class returns are broken down into the common building blocks of risk and return, it allows the investor to focus on sourcing those common exposures as efficiently as possible, while also identifying where there are unique and valuable sources of alpha.

Figure 1: Comparison of asset allocation and contribution to volatility by risk factor



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Another key advantage of the risk factor approach is that it allows you to have intelligent correlations across asset classes where there are multiple return drivers and relationships. For instance, real estate assets and corporate bonds typically display sensitivities to both equity and bond risk factors. Modeling each as a combination of these factors means their simulated returns will consistently reflect underlying influences on the common factors (e.g. "flight to quality" vs "reach for yield"). The factor weights for these asset classes can also be varied over time to reflect changes such as credit quality in corporate bonds, or leverage in real estate, allowing the correlations between asset classes to shift.

A risk factor-based approach also creates the ability to stress a given factor and see the impact as the stress event flows through each asset class exposed to that factor. For historical stress testing this means that informed portfolio stress estimates can be derived even where specific asset classes in the portfolio don't have a long history of actual data. It also means that future, or scenario-based stress tests can quickly and easily be constructed. Rather than having to forecast how each asset class might perform relative to each other in a 1 in 100-year event, under a risk factor-based approach the user can focus on a smaller, more easily defined set of factors.

Creating asset class forecasts across multiple economic or market regimes (e.g. low volatility vs high volatility regimes) is easily accomplished via changing the common risk factor linkages. With the correct portfolio design tools, the investor can then easily and seamlessly compare expected portfolio outcomes across a range of economic and market scenarios, even combining them under a regime-switching approach.

Risk factors also allow the investor to develop new and tailored asset classes that match investments in the portfolio, or that are being considered for the portfolio. By way of example, private infrastructure is a common asset class amongst institutional investors, but individual infrastructure programs can look very different. One investor's program might include only regulated assets with secure cash flows (high sensitivity to term and inflation factors), another's might focus on assets exposed to market demand and greenfield development opportunities (high sensitivity to the equity factor), and of course the amount of leverage used in the program can shift the resulting factor exposures as well.

3. Different requirements for risk factor-based modeling

Many investors are starting from a place of modeling the asset classes in their portfolios using a normal distribution framework where the required inputs are asset class mean return, standard deviation, and correlations. Within Jacobi, investors can then extend this framework to include higher moments of the distribution like skew and kurtosis, as well as introducing time-varying effects like mean reversion or time-varying return means.

Under a risk factor approach, the inputs described above are provided for the risk factors rather than the asset classes. As there will typically be far less factors compared to assets, there are far fewer correlation inputs required. A key limitation of the asset class approach is that anytime a new asset class is added to the schema, the user is required to supply an assumption for how it is correlated with every other asset class in the schema.

In addition to supplying the risk factor inputs, under the risk factor modeling approach the user supplies betas of the asset classes to the factors that help construct the asset class returns in a linear fashion. Asset classes can then also have an idiosyncratic component unique to that asset class which can be supplied directly (like tracking error assumptions) or derived from the combination of the asset class's expected risk and return and risk factor exposures. It is these sets of inputs that many investors find challenging to specify, and where Jacobi has developed our app to help. The next section of this paper showcases that app and the functionality it offers users.

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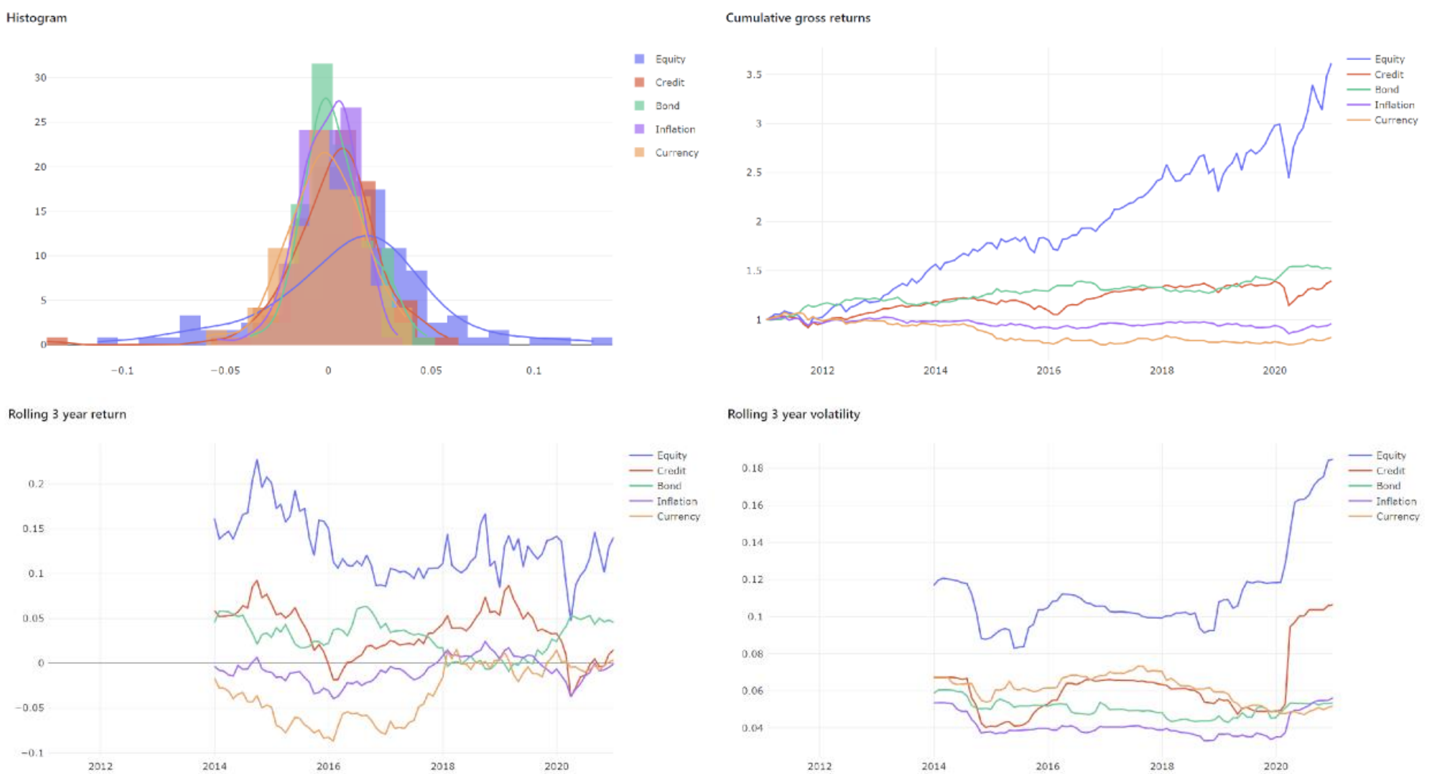
4. Jacobi risk factor calibration app

As a starting point for setting up the inputs for a risk factor-based Monte Carlo simulation the Jacobi risk factor calibration app allows the user to parameterize the key inputs from historical data. The user can then vary these inputs and visualize how the revisions would have performed versus the actual historical data. The app's iterative nature means that it is simple to calibrate assumptions over different historical periods, so if a user was interested to see how certain asset classes and factors behaved in particular market environments, like stressed environments for instance, users could run and re-run the analysis over stressed periods in history. There are two steps to calibrating a new risk factor-based simulation – calibrating the risk factors and calibrating the asset classes.

Risk factor assumptions

Calibrating the risk factor assumptions in the app firstly involves deriving the required inputs from representative time series returns of each factor. For the equity risk factor, this could be the excess returns of a large, liquid equity market index. The required inputs are return mean, standard deviation, skew, kurtosis and correlation to other factors. Users later have the ability to override the historical values if their assumptions for the future are different from what has been the experience of the past. To assist with this, various visualizations are included in the app that can display the distribution of returns as well as key variables over rolling horizons to highlight the range and stability of those variables.

Figure 2: Example visualizations of risk factor series



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Asset class assumptions

The required inputs for the asset classes in the risk factor-based simulation are the betas of the asset classes to the risk factors, as well as the return mean and volatility of the asset class idiosyncratic component. To estimate the risk factor betas, the app can perform different types of regressions.

Figure 3: Example regression output

Full date-range regression results

Export

Forward asset class	Regression type	Alpha	Equity	Credit	Bond	Inflation	Currency	R-squared
filter data...								
US High Yield	OLS	0.011	−0.0035	0.96	0.46	0.042	0.039	0.98
US High Yield	Lasso	0.028	0.047	0.66	0.047	0	0	0.86
US High Yield	Ridge	0.018	0.069	0.72	0.28	0.049	0.06	0.94

Export returns data

Various visualizations are again provided to enable the user to assess the stability of these results over time or in particular windows of history. These visualizations could show all the betas for a particular regression type over a rolling window, compare the betas produced by different regression types on a rolling basis, or compare the results of different asset classes on a rolling basis.

Figure 4: Visualization of rolling betas over time for a given regression type, by asset class

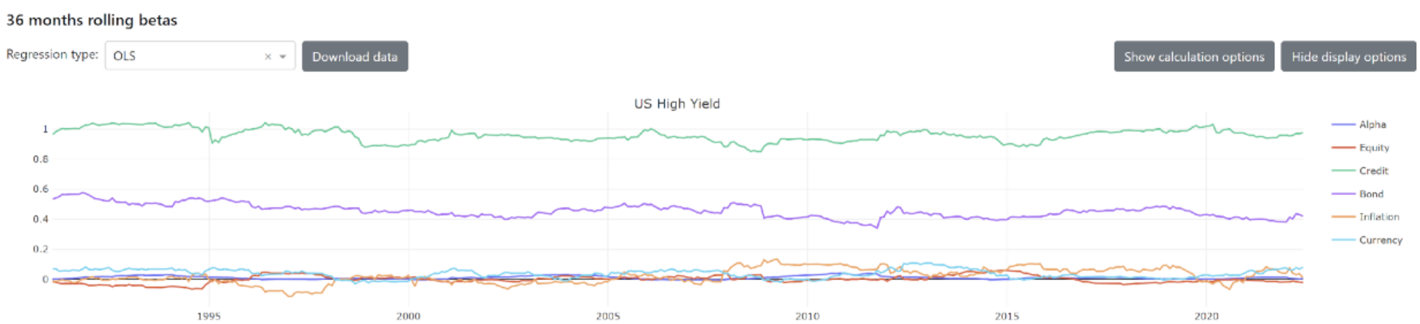

Figure 5: Visualization of rolling betas over time for a given factor, by regression type

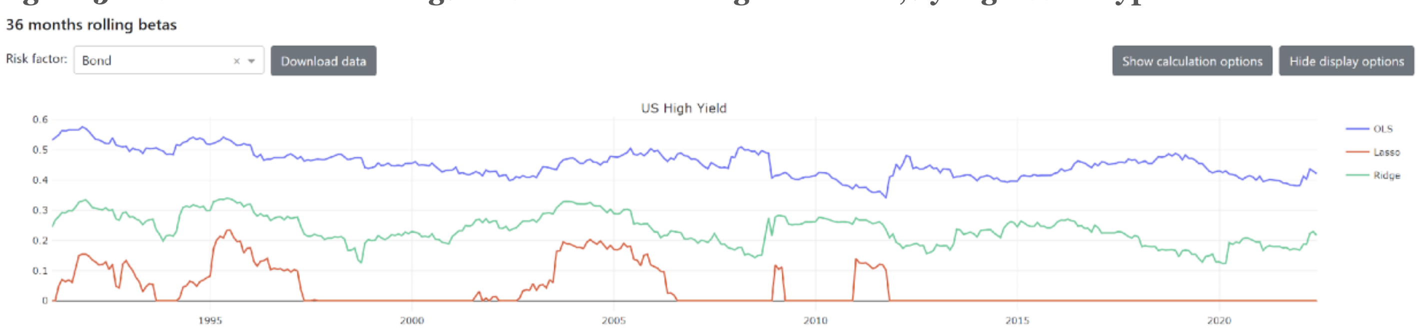

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Figure 6: Visualization of rolling betas over time for a given regression type, by factor and asset class

The final step of the app allows the user to test various input assumptions for the asset class parameters and see how that model specification would have performed given the performance of the risk factors over the historical window. This step can be especially useful for calibrating models with limited historical data, to get a sense of what various input assumptions would have implied for historical performance.

Figure 7: Backtest statistics for various model specifications

Forward asset class historical backtest statistics

Export

Regression type	Forward asset class	Return	Volatility	EWMA volatility	Skewness	Excess kurtosis	Cornish-Fisher VaR	Historical CVaR	Sharpe ratio	Maximum drawdown
filter data...										
Actual	US High Yield	7.97%	8.23%	9.31%	−0.38	0.88	−3.54%	−5.53%	0.61	−33.23%
Current	US High Yield	5.84%	9.17%	10.53%	−0.37	0.8	−4.22%	−6.71%	0.32	−40.82%
Incoming	US High Yield	4.92%	8.21%	9.20%	−0.44	1	−3.80%	−5.80%	0.24	−36.98%
Lasso	US High Yield	7.99%	6.38%	7.50%	−0.45	0.87	−2.70%	−4.44%	0.79	−26.99%
OLS	US High Yield	7.98%	8.17%	9.23%	−0.48	1.1	−3.58%	−5.53%	0.62	−34.73%
Ridge	US High Yield	8.07%	7.04%	8.26%	−0.5	1	−3.05%	−4.81%	0.73	−29.99%

Once the user has settled on the input assumptions (which could simply be the results from a particular regression approach over a given lookback period), the assumptions can be saved down in Jacobi and a Monte Carlo simulation is run that generates 10,000 paths based on those inputs. The results of this process can then be used to forecast asset class or portfolio performance, calculate risk measures, and risk factor-specific calculations like marginal contribution to risk on custom storyboards in Jacobi.

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5. Conclusion

Risk factor-based modeling allows investors to model the underlying risks inherent in multi-asset class portfolios and can provide a deeper insight into what drives multi-asset class risk and return. Getting started with risk factor modeling can be a challenge, because it requires investors to determine additional input assumptions compared to direct asset class modeling. The Jacobi risk factor calibration app has been built to help our clients get started with risk factor-based modeling by calculating those input assumptions from historical data, while providing the tools and flexibility for them to assess those results and qualitatively override them for use in ex-ante modeling.

About Jacobi

Jacobi's multi-asset investment platform has its roots in institutional management and brings together investment expertise and market-leading cloud-based technology. Headquartered in San Francisco, the company is led by a team of experienced investment professionals and engineers

For more information on Jacobi's highly customizable technology to support the scaling of investment processes and client engagement, please contact us or visit www.jacobistrategies.com

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