MODEL OVERVIEW

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Risk Integrated Credit Solution: Overview

Institutional investors who manage a portfolio of assets are often exposed to both market and credit risks. This is especially true given the significant increase in credit risk exposure in many of their portfolios over the last decade. Given the complexity of jointly modeling different risks, it is common practice to model market risks (interest rate, exchange rate, equity, spread, and so on.) and credit risk in separate systems, and then aggregate them with simplified top-down assumptions like copulas. However, these simple aggregation assumptions are likely to distort the overall risk analysis and lead to poor investment decisions.

This paper provides an overview of a new bottom-up Risk-Integrated Credit Solution (RICS) designed to jointly capture granular credit and market risks in projections of portfolio dynamics. RICS brings together a market-leading credit correlation model using a variant of the Moody's Analytics GCorr™ model and our award-winning Scenario Generator.

The multi-period simulation accounts for economic cycles and long-run convergence. Capturing these long-term dynamics opens the door to applications with longer horizons like Strategic Asset Allocation (SAA), cashflow matching and duration matching, in addition to portfolio management and risk measurement. While some applications may warrant adjustments to the parameters (For example, short-term vs. long-term, or rating vs. point-in-time dynamics) and portfolio granularity, RICS provides a single modeling framework that can be used across teams and applications.

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1. Introduction

Institutional investors who manage a portfolio of assets are often exposed to both market and credit risks. Understanding the interactions between these risks becomes especially important at longer horizons, for example when the assets are used to support long-term liabilities. Given the complexity of jointly modeling different risks, it is common practice to model market risks (interest rate, exchange rate, equity, spread, and so on.) and credit risk in separate systems, and then integrate them with simplified top-down assumptions like copulas. For example, combining Credit and Market Value-at-Risk (VaR) into Aggregate VaR using a copula requires a correlation parameter. Estimates of this parameter are sensitive to the portfolio composition and market conditions, making it difficult to rely on historical data and leading many investors to simply use heuristic values. As we show in Huang, R., Manning, B. and Yahalom, T. (2021), the interaction between market and credit risks can be very different across assets and sub-portfolios, making it extremely challenging to find a simple general adjustment to account for the joint impact or risks for all instruments in the portfolio. These simple adjustments will likely make some assets seem overly attractive, leading to poor investment decisions.

Some credit systems make simplifying assumptions on market risks, for example, assuming deterministic interest rates, and as a result, miss a core driver of bond values. Market risk systems can sometimes capture high-level credit effects, but without granular credit modeling, they do not capture the full concentration and diversification effects of the credit portfolio. Capturing the effects for the entire portfolio requires representation of individual credit instruments and their varying terms and conditions as well as a granular correlation model that can account for diversification effects across industries, countries, asset classes, etc.

This paper provides an overview of a new bottom-up Risk-Integrated Credit Solution (RICS) designed to jointly capture granular credit and market risks in projections of portfolio dynamics, such as pricing and risk/return measures that inform and flow into many business applications. RICS brings together a market-leading credit correlation model using a variant of the Moody's Analytics GCorr™ model[1] and our award-winning Scenario Generator[2]. Specifically, RICS accounts for three sources of interaction between market and credit risks:

1. The factors driving market risks are appropriately correlated with those driving credit migrations and defaults. The model differentiates between 61 countries, 49 industries and hundreds of commercial real estate and retail loan factors.
2. The values of credit-risky instruments are calculated based on the realization and future dynamics of spreads, exchange rates, and interest rates along each trial.
3. The reinvestment of cash payments from credit-risky instruments accounts for stochastic market risks (For example, roll up at the stochastic risk-free rate for reinvestment in cash).

RICS is a multi-period simulation tool that accounts for economic cycles and long-run convergence. Capturing these long-term dynamics opens the door to applications with longer horizons like SAA, cashflow and duration matching, in addition to portfolio management and risk measurement. While some applications may warrant adjustments to the parameters (For example, short-term vs. long-term, or rating vs. point-in-time dynamics), RICS provides a single modeling framework that can be used across teams and applications. This simplified consistency in credit modeling makes it easier for teams to communicate with each other and avoids the confusion and often conflicting results that can emerge from siloed use of different models across the organization. Having a consistent framework simplifies oversight by validation teams and senior management. To this end, we are currently working on integrating RICS with other Moody's Analytics solutions, so that the risk-integrated RICS scenarios can be directly used in other Moody's Analytics products (For Example, AXIS™ actuarial system, PFaroe™ Platform) that cover a wide range of applications across different teams: from risk and portfolio management to ALM, LDI, and SAA.

2. Credit Model Components

RICS generates capital market variable projections leveraging Moody's Analytics Scenario Generator, using the Best Views calibrations. The RICS simulation adds economically consistent multi-period credit risk projections along the same set of scenarios. These include granular projections of credit migrations and defaults at the issuer level, and price/value projections at the instrument level. Figure 1 shows the main building blocks of RICS' credit modeling components.

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[1] The GCorr model is a multi-factor correlation model, consisting of close to 1,000 geographical, sectoral, and national and regional macroeconomic factors and inter-asset class correlations for a broad range of asset classes (public and private firms, CRE, retail, sovereign, and project finance). For more information, see "Modeling Credit Correlations: An Overview of the Moody's Analytics GCorr Model" by Huang, Lanfranconi, Patel, and Pospisil (2012).

[2] MA Scenario Generator generates scenarios for economic risk factors and asset returns using Monte Carlo techniques. For more information, see "Real World Best Views Calibrations" by Hibbert, Jessop, and Aldasani-Khyami (2018).

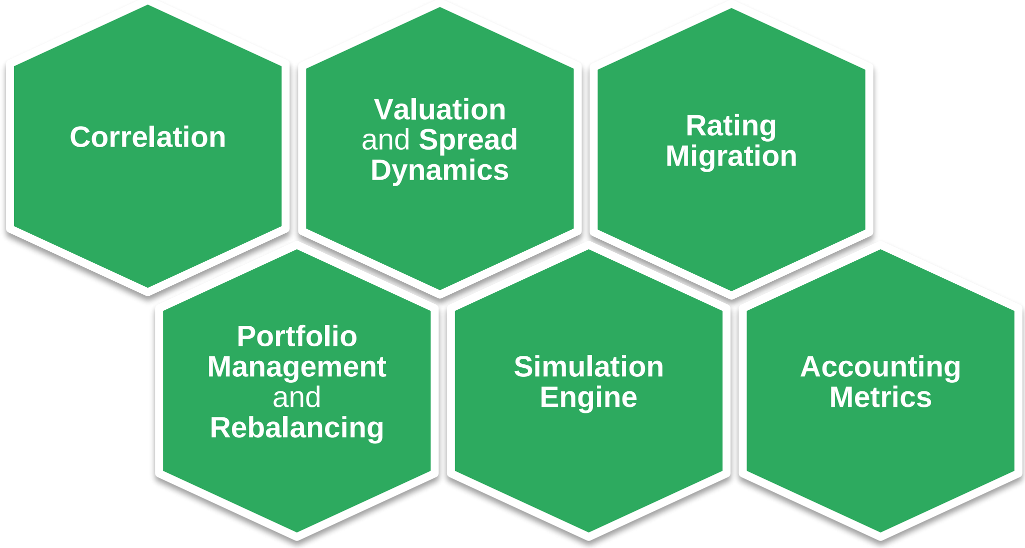

Figure 1: RICS Credit Components

These components are important to ensuring a consistent simulation:

- Correlation: The credit projections maintain appropriate correlations across issuers and with market variables.
- Rating Migration: Migration probabilities are based on historical rating migrations with adjustments to account for where we are in the credit cycle. While the migration model is based on ratings, the model can be aligned with any user-provided default probability term structure to reflect different views regarding migration and default, including Point-in-Time views like Moody's Analytics EDF™ (Expected Default Frequency).
- Valuation and Spread Dynamics: Bond valuation follows a CAPM framework, where investors are compensated for systematic risk. The credit risk premium changes with market conditions and is modeled by a dynamic Market Price of Risk variable that follows a discretized mean-reverting Constant Elasticity of Variance (OU-CEV) process with ebbs and flows representing credit-cycle dynamics.
- Portfolio Management and Rebalancing: RICS supports projections for a flexible set of bond indices. These can be important for high level applications where the precise makeup of the bond portfolio may not be known or necessary (For example, strategic asset allocation, or portfolio rebalancing and reinvestment).
- Accounting Metrics: RICS provides the necessary statistics to project accounting metrics at future horizons under different accounting regimes (For example, 1-year expected loss and lifetime loss needed for ECL under IFRS 9).
- Simulation Engine: The system is built on a proprietary framework for efficient simulation and data handling, this allows us to simulate a granular portfolio with thousands of instruments along hundreds of thousands of trials out to very long horizons.

The next few sections describe some of these components in more detail.

2.1 Credit Correlation Model

RICS uses a factor model for credit correlations with a similar structure to the GCorr™ model. That is, credit migrations for different issuers are correlated through their exposure to a common set of systematic factors. The model uses correlated factors for different credit asset classes: Corporate (49 countries, 61 industries), CRE (5 property types, 73 US MSAs), Retail (6 loan types, 51 US states/territories).

Figure 2 shows the correlation structure for a corporate bond example, where r_k denotes the migration driver for issuer k. ϕ_k and ϵ_k are the systematic and idiosyncratic shocks for that issuer, and RSQ_k measures how closely the issuer follows the systematic shock. Given this structure, the correlation between the migration drivers for two issuers is determined by the correlation between their systematic shocks, and how closely they follow these shocks. Specifically:

$$corr(r_i, r_k) = \sqrt{RSQ_i}\sqrt{RSQ_k}corr(\phi_i, \phi_k)$$

The country and industry factors comprising the systematic shocks are correlated through their exposure to a common set of 14 independent credit factors.

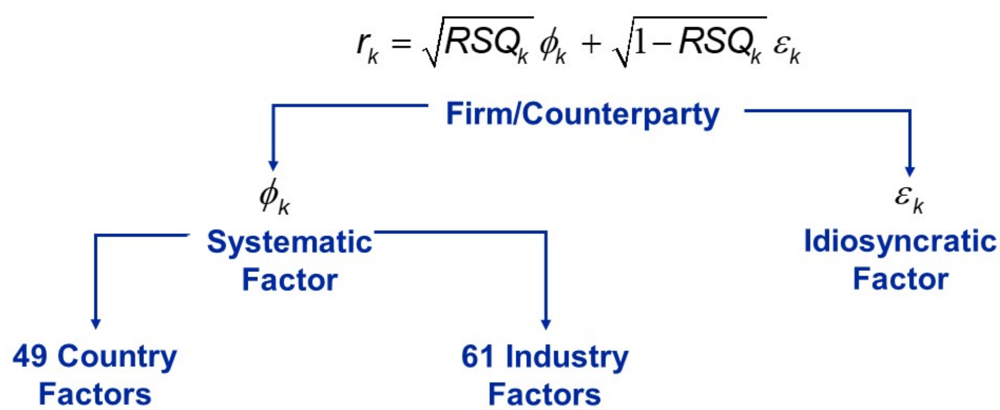

Figure 2: Corporate Factor Structure

RICS credit correlations leverage the above GCorr™ model factor structure but are calibrated to long-term rating transitions.

2.2 Migration and Default Model

The correlated issuer-specific migration drivers introduced in the previous section are used together with a migration matrix to project credit migrations for each issuer. To estimate the appropriate migration matrix for each period, we start from a base migration matrix for fine ratings (21 rating scale plus default), which represents historical migration probabilities from Moody's Investors Service DRD2 data of historical ratings dating back to 1986. We estimate a quarterly migration matrix that best fits historical transition probabilities over a range of migration horizons, and fine-tune it to ensure some basic structural properties. For example, that worse ratings maintain higher default probabilities over different horizons.

This base migration matrix is our best estimate for the unconditional quarterly rating migrations. However, RICS offers the option to adjust migrations in the first few years to account for where we are in the credit cycle at analysis date (a.k.a., conditional migrations). The magnitude of the initial adjustment is estimated based on observed migrations over the last quarter, and how they differ from the base matrix. The adjustments RICS uses in subsequent projection quarters are diminishing in size, such that quarterly migrations converge to the base matrix after a few years.

RICS can also adjust the base migration matrix to align with any user-provided PD term structures at the issuer level. This option can be used to align the projections with any views the user may have for some asset classes, regions, or individual issuers. Specifically, it can be used to align the analysis with Point-in-Time views.

2.2 Valuation and Spread Model

Bond valuation follows a CAPM framework, where investors are compensated for systematic risk. The credit risk premium changes with market conditions and is modeled by a dynamic Market Price of Risk (MPR) variable that follows an OU-CEV process with ebbs and flows representing credit-cycle dynamics. The stochastic MPR variable is the driver of spread risk.

MPR is used as the basis for a drift in migration drivers under the risk-neutral measure that makes downgrades and default more likely than under the real-world measure. This effect increases with MPR. For example, we calculate QPD_k, the risk-neutral probability of default over one quarter for issuer *k*, as

$$QPD_k = N\left(N^{-1}(PD_k) + MPR \cdot \sqrt{RSQ_k} \cdot \sqrt{\Delta t}\right),$$

where PD_k is the real-world PD for issuer *k*, $\Delta t = 0.25$, and RSQ_k is the issuer's credit R-squared, representing the proportion of variations due to credit systematic shocks.

The risk premium is higher for more systemic issuers, those with higher RSQ_k. MPR is modeled as a discretized OU-CEV process to account for ebbs and flows over multiple credit cycles. We find that the MPR required to match market prices is steeply decreasing in maturity (shown in Figure 3). RICS allows us to embed this observation in the unconditional term structure of MPR as well as ensure reasonable and arbitrage-free dynamics of the term structure throughout the simulation.

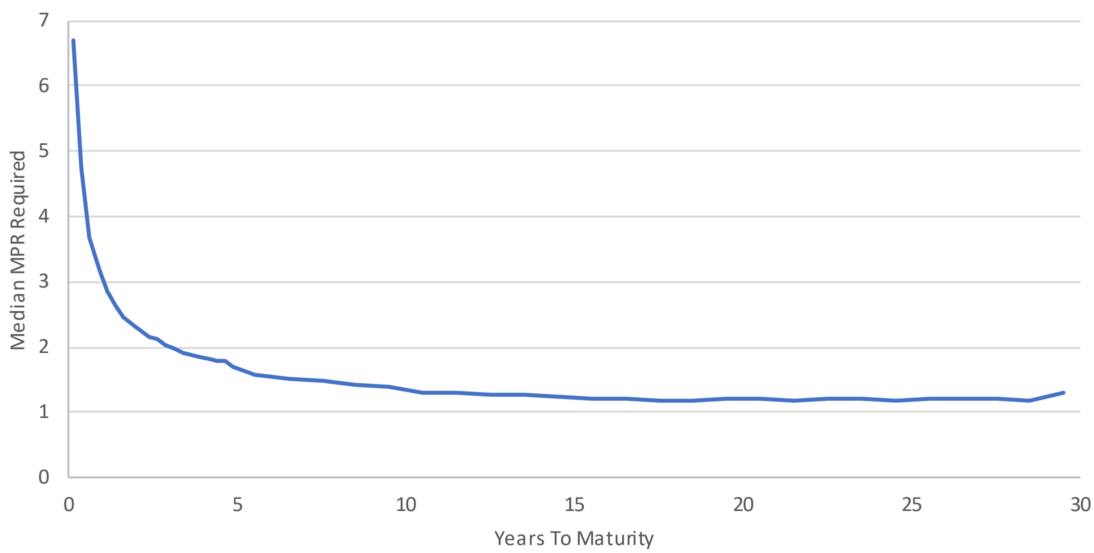

Figure 3: Median MPR required to Price Bonds of different Maturities

Using the OU-CEV process also allows us to embed several core stylized facts about MPR, and consequently spread, dynamics:

1. Long term convergence – we ensure realistic volatility and dispersion of spreads at long horizons
2. Proportional volatility – spread volatility tends to be higher when spreads are high
3. Diminishing volatility in maturity - long dated spreads are less volatile than short dated spreads

The time series of MPR for North America is shown in Figure 4, along with the average BBB spread and credit cycle migration adjustment. We see a pattern corresponding to known economic events, including the dot-com bust/9-11, 2008 financial crisis, Euro sovereign crisis, the oil price crash and COVID-19. Moreover, we see the nuanced interaction between real world credit conditions and MPR that results in spread volatility.

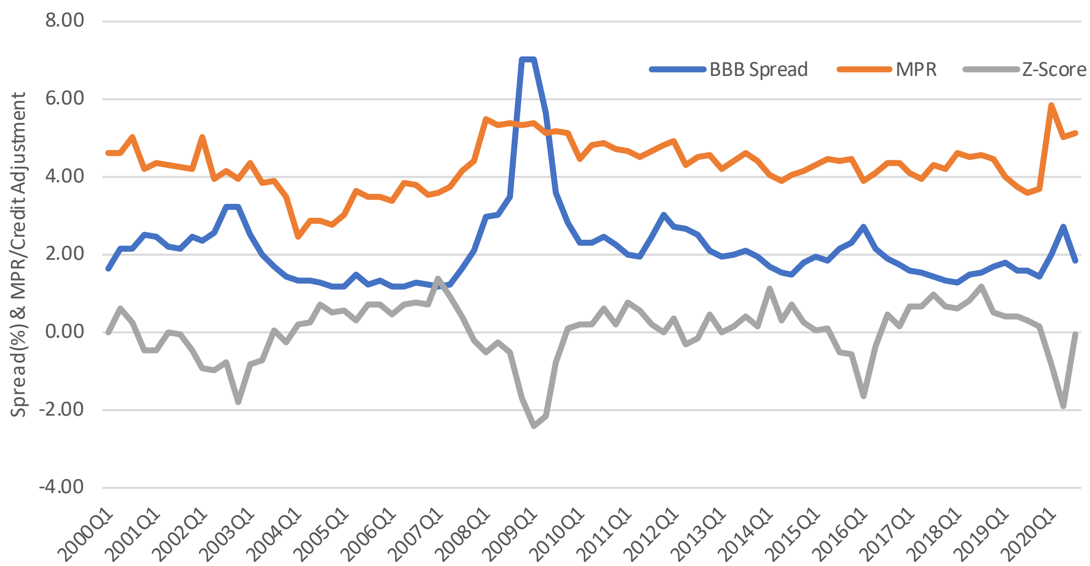

Figure 4: Time Series of MPR, Spread and Z-Score

Finally, the MPR process is correlated with other credit processes via its exposure to the same set of credit correlation factors described above. The stochastic and dynamic nature of MPR results in spread variations over time and across scenarios, making spread risk appropriately correlated with migration and default risks, as well as with other market risks.

Accounting for the dynamic nature of MPR in valuation allows us to capture pricing dynamics across bonds with different maturities, where short term bonds are more sensitive to the current MPR and long-term bonds are less sensitive to current market conditions.

RICS supports valuation and cash flow modeling for many instrument features, for example fixed and floating coupons, flexible principle amortization and call options.

3. Integration with the Market Risk Engine

RICS brings together a market-leading credit correlation model using a variant of the Moody's Analytics GCorr™ model and award-winning Scenario Generator. Specifically, RICS accounts for three sources of interaction between market and credit risks:

1. The factors driving market risks are appropriately correlated with those driving credit migrations and defaults. The model differentiates between 61 countries, 49 industries and hundreds of commercial real estate and retail loan factors.
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The last two points focus on direct effects of market risk variables on the value of credit-risky instruments. In this section we focus on the first point regarding the correlated movements in credit migration/spread/default and market risk variables.

RICS achieves this correlation by bringing together the credit factor model with the factor model for equity assets in the Scenario Generator. RICS constructs the GCorr™ model's 14 global independent factors from the same factors used by the Scenario Generator Real-World SVJD equity model. This establishes correlations between the 14 global credit factors and the equity asset factors, as well as between the systematic shocks constructed from these factors to create parent equity assets and issuer-level credit drivers.

In addition to the correlated systematic shocks, each country credit factor and the parent equity asset corresponding to the same country share the same country-specific shock.

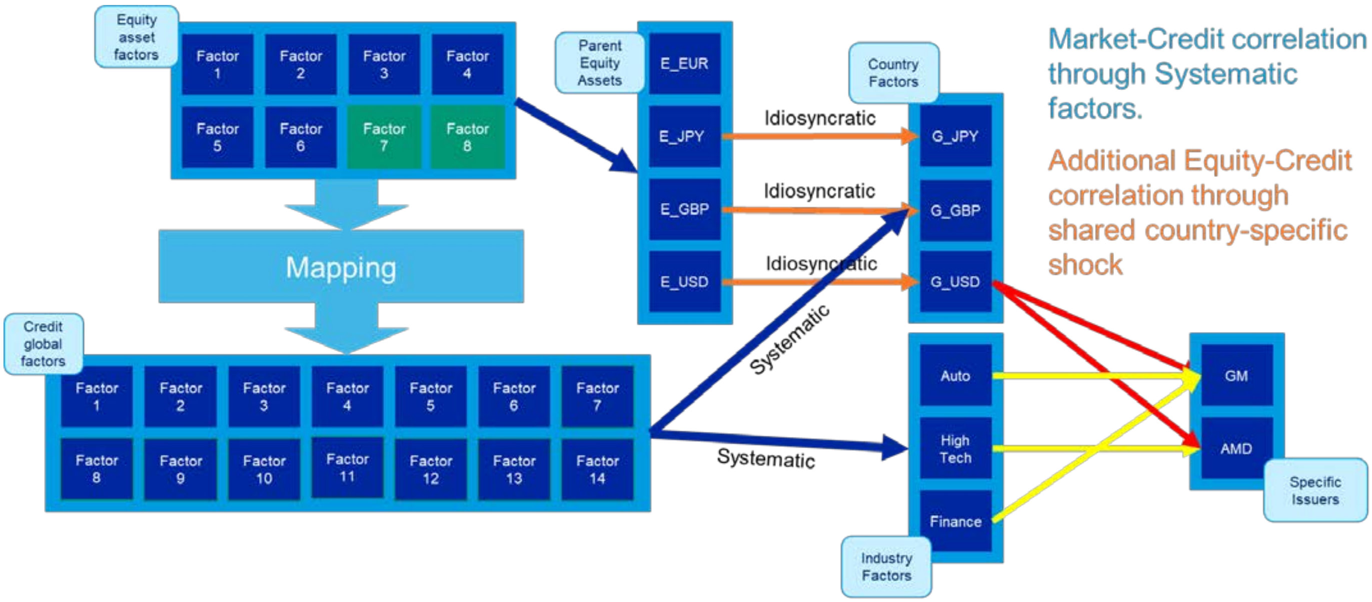

Figure 5: Bottom-up integration between Credit and Market risk factors

Figure 5 shows an example of how the credit drivers for two issuers can be traced back to the equity model systematic factors and country-specific shocks, resulting in correlations with equity assets and with other market risks variables via their Best Views correlations with equity, while maintaining the appropriate credit correlations between two issuers.

4. Additional Components

4.1 Risk Contribution

One fundamental problem institutional investors face is identifying individual instruments or groups of instruments that are the main drivers of portfolio risk. This analysis is critical for evaluating whether these instruments provide sufficient compensation for the marginal risk they impose on the portfolio. RICS uses Risk Contribution (RC) as a measure of marginal contribution of an instrument to the standard deviation of portfolio value, defined as the normalized covariance between the instrument value and the portfolio value. Given that covariances are additive and sum to the total portfolio risk (portfolio variance), RC offers a natural way to allocate portfolio risk measures (For example., VaR, EC, volatility).

Risk contribution is higher for instruments with either higher individual risk or stronger correlation with the overall portfolio. In an integrated market-credit system like RICS, RC accounts for marginal contributions due to both credit and market risk variations. For example, the risk contribution of a bond could be high because of credit considerations (For example, bad rating, high RSQ, exposure to similar credit factors as the rest of the portfolio) or because it has a long duration making it more sensitive to interest rate and spread risks.

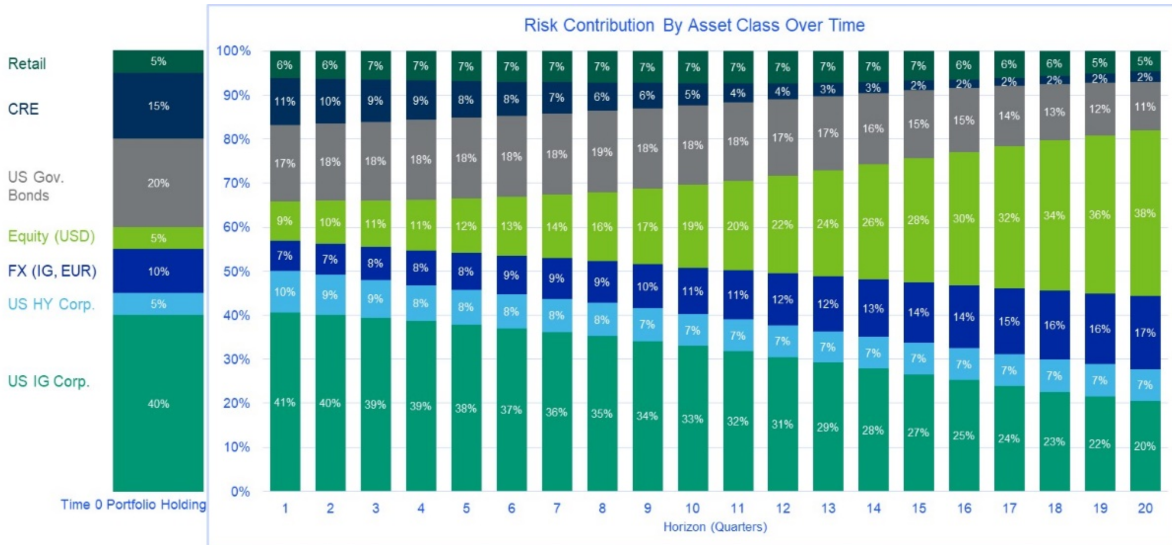

Figure 6: Risk Contribution for a Multi-Asset-Class Portfolio (buy-and-hold) vs. initial portfolio holdings

Figure 6 shows an example of RC by asset class over time in comparison to the initial portfolio holdings. We see that RC starts out similar to portfolio holding weights, with safer asset classes (e.g., Government bonds) and asset classes with lower correlation with the portfolio (For example, FX IG bonds, CRE) have lower RC than their weight in the portfolio, while riskier asset classes (Equity, HY bonds) have higher RC. Given this is a buy-and-hold portfolio, we also see equity's RC increasing over time at the expense of asset classes with a fixed maturity, like bonds and loans. See Huang, R., Manning, B. and Yahalom, T. (2021) for further analysis and discussion of portfolio dynamics.

4.2 Risk Decomposition

Jointly modeling different risks also allows us to better understand the types of risk to which we are most exposed. Figure 7 decomposes the total portfolio risk (represented as the standard deviation of portfolio value) into interest rate risk, spread risk, migration risk, and default risk for a representative insurer's portfolio. For example, the risk attributed to interest rate dynamics is calculated as the difference in standard deviation between the full portfolio distribution, and a "muted" version, where portfolio values are averaged across trials that differ only in interest rate state, but are otherwise the same (in terms of rating, spread, and so on.). This averaging effectively "mutes" the effect of interest rate variations on portfolio value. For this high-quality bond portfolio, we observe that interest rate risk accounts for roughly 20-30% of the risk throughout the 20-quarter projection. As expected, default risk becomes more pronounced over time due to increasing cumulative probability of default, while spread risk diminishes as the remaining duration of the bond portfolio decreases. See Huang, R., Manning, B. and Yahalom, T. (2021) for further analysis and discussion of portfolio dynamics.

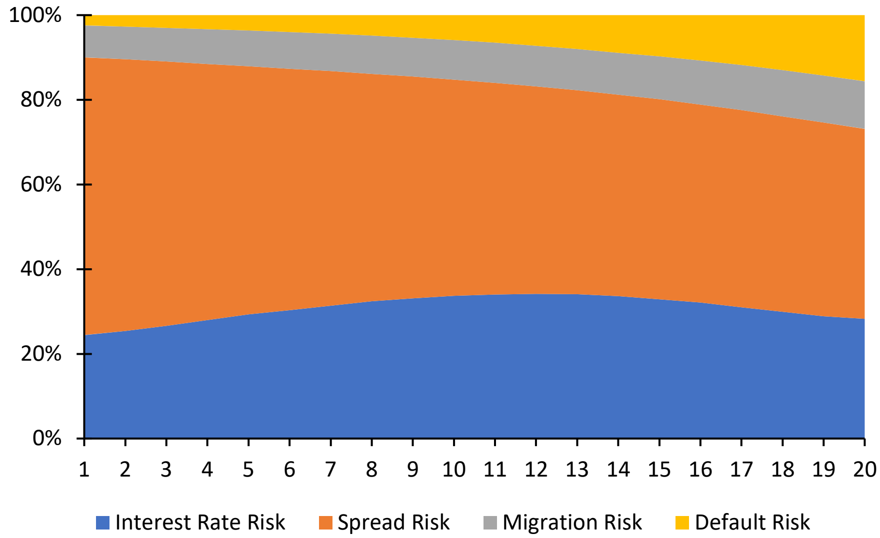

Figure 7: Risk Contribution for a Multi-Asset-Class Portfolio (buy-and-hold) vs. initial portfolio holdings

This approach to risk decomposition can be used to decompose other risk and return measures, like fair coupons or spreads and economic capital by risk type. Perhaps the most common application of risk decomposition for insurers is the separation of the portfolio Aggregate VaR into Credit VaR, Interest Rate VaR, Spread VaR, etc.

5. Summary

The increase in credit exposure by many institutional investors over the past decade has heightened the need to account for the joint effects of credit and market risks on their asset portfolios in a wide range of business applications. This paper provides an overview of a new bottom-up Risk-Integrated Credit Solution (RICS) designed to jointly capture granular credit and market risks in projections of portfolio dynamics, such as pricing and risk/return measures. RICS brings together a market-leading credit correlation model using a variant of the Moody's Analytics GCorr™ model and award-winning Scenario Generator. It is a multi-period simulation tool that accounts for economic cycles and long-run convergence. Capturing these long-term dynamics opens the door to applications with longer horizons like SAA, cashflow matching and duration matching, in addition to portfolio management and risk measurement. While some applications may warrant adjustments to the parameters (For example, short-term vs. long-term, or rating vs. point-in-time dynamics) and portfolio granularity, RICS provides a single modeling framework that can be used across teams and applications.

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