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Analyzing Credit Concentrations

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This article focuses on one key idea from a paper submitted to the ERM Symposium: risk attribution analysis.

CONCENTRATION RISK IN GENERAL AND CREDIT CONCENTRATIONS IN PARTICULAR, CAN CREATE CONSIDERABLE SYSTEMIC RISK. For this reason, particular emphasis is currently being placed on assessing, monitoring and managing credit concentration risks. From the business perspective, models that fail to consider existing portfolio concentrations corrupt signals used to make business decisions.

To illustrate, consider a case where two investments are possible. Both investments have exactly the same profit profile: product type, default probability, maturity horizon and loss given default. However, one investment lies in the sector in which the firm is highly concentrated, while the other is in an emerging business area for the firm. The second investment clearly adds more diversification, creating an overall more optimal portfolio.

The usefulness of portfolio models lies in their ability to incorporate many facets of credit risk into a single measure. Typically, such models acknowledge and capitalize various types of risk and the interactions between key risk types. For example, market-driven derivative exposures might combine with macroeconomic impacts on probabilities of default and recovery values over the varying life-cycles of each transaction.

The result is a single benchmark metric useful in controlling risks, managing limits and creating consistency with the overall risk appetite of the firm.

However, a single number is not sufficient for risk management and mitigation. Manipulating the risk profile to best serve the needs and preferences of an organization is a multi-dimensional task, making it important to understand the sources and interactions of risk in the portfolio at a more granular level. This can be done through the process of capital attribution.

Estimated losses at the portfolio level can be attributed to different risk types (or sources) by recalculating the risk measures using different combinations of assumptions to isolate particular risks. Usually, the most influential risks are: default risk, migration risk, name risk and sector risk. It is possible to isolate each of these risks in turn by varying the model assumptions.

To illustrate the information gleaned from such analysis, and the details of its implementation, we make extensive use of a case study based on an international portfolio of 500 publicly traded and rated exposures. The overall exposure of the portfolio is approximately $44.5 billion USD, with individual exposures ranging from just over $1 million to almost $3.5 billion. The average exposure is approximately $88 million, but the median exposure is only $10 million.

Exposure breaks down into six major ratings grades (Fitch Ratings) and 10 major industries (Dow Jones) across 10 countries. By design, clear concentrations are apparent in the financial and energy sectors, in single-A-rated firms and in the United Kingdom, United States and Canada.

In the base case of the case study, all credit risk factors are modeled using a mark-to-market approach that includes both default and migration risks. Specifically, a multi-factor model is used in which drivers of systematic credit risk are used to represent all default correlations. These credit drivers are associated to names based on their country and industry. Idiosyncratic risks are modeled using Monte Carlo simulations. The overall loss (99.9 percent) is estimated to be $2.58 billion USD.

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To assess the impact of these factors on total capital is not entirely straightforward. The immediate tendency would be to modify the settings for each factor, one by one. In fact, this is insufficient because of the interaction between components. So, we consider eight cases, including the base case just discussed. The other cases involve turning on and off the key assumptions in various combinations. The cases are divided into three

CONTINUED ON PAGE 20

Analyzing Credit Concentrations | from Page 19

Table 1: Risks Measured in Each Case

	Migration Risk	Name Concentrations	Sector Concentrations
Core Models			
Base Case	Yes	Yes	Yes
Simple Model	No	No	No
First-Order Effects			
Default-No Default (DND)	No	Yes	Yes
Full Diversification (FD)	Yes	No	Yes
Single-Factor (SF)	Yes	Yes	No
Second-Order Effects			
DND / FD	No	No	Yes
DND / SF	No	Yes	No
FD / SF	Yes	No	No

Table 2: First-Order Effects

Model	Loss (99.9%)	Interpretation	Attribution (Base - Model)
Base Case	2,581,738,825		
Default / No Default (DND)	1,944,680,630	Migration Risk	637,058,195
Full Diversification	2,125,727,123	Name Concentration	456,011,702
Single Factor	3,533,178,245	Sector Diversification	951,439,420
		Total First-Order Effects	141,630,477

categories: core models, first-order effects and second-order effects, as summarized in Table 1.

To attribute a portion of this risk to migration risk, we "turn off" migration risk and recalculate under the assumption of a two-state model: default and no-default. The resulting loss (99.9 percent) level is $1.94 billion USD. Thus, we can attribute the difference, i.e., $637 million USD, to migration risk.

Recall that the base case is a multi-factor model. By changing to a single-factor model, we see a loss (99.9 percent) level of $3.53 billion USD. Thus, the multi-factor environment (expressed partially through sector diversification within the portfolio) is providing $951 million USD of diversification benefit.

If the increase in loss (99.9 percent) seems unintuitive initially, it is easily explained by examining the correlation assumptions. Overall, higher correlations imply higher losses. Because the multiple factors are correlated, but not perfectly correlated, having only a single credit driver for all counterparties increases the average pair wise asset correlations significantly, from 18.7 percent in the multi-factor case to more than 31 percent in the single-factor case. Higher asset correlations lead to higher default correlations as well (2.1 percent vs. 0.9 percent).

To isolate the name risk, we change from Monte Carlo models for idiosyncratic risk to the assumption of full diversification. As a result, loss (99.9 percent) drops to $2.13 billion USD. Clearly, the portfolio is not large enough to completely diversify away the idiosyncratic risk. Attributing the $456 million USD difference to name concentration risk in the portfolio provides significant insight: no matter what diversification strategy we assume, we are unlikely to reduce capital requirements, as measured by loss (99.9 percent), beyond the $2.13 billion USD level.

For each of the three sources of risk, we have measured its isolated impact on the portfolio-level risk measure, loss (99.9 percent). Such first-order attributions allow ranking of the risks in order of importance: sector diversification, migration risk and name diversification. These are referred to as first-order effects because, in each case, only one assumption was changed. Table 2 shows a summary of the results of the first-order attributions.

"It is not only important to assess the impact of each risk but also to look at the interactions between them in creating a complete picture of concentrations."

Can the first-order effects be used to explain changes in the capital support for the portfolio? Consider an experiment where all three changes identified above are made simultaneously. The result is a default-only model assuming full diversification and based on a single factor. (It is worth noting that this model is well-aligned with the assumptions underpinning the formulae for Basel II calculation.)

Under this very basic model, the loss (99.9 percent) result when all three assumptions are changed simultaneously is $1.95 billion USD. The total change is thus $626 million USD. So, in fact, the total first-order effect of $141 million USD comprises less than 23 percent of the total change.

The reason for the discrepancy is that the model is neither straightforward nor linear. It includes interdependencies, correlations and interactions between these sources of credit risk. Clearly, with higher-order effects contributing $485 million USD or almost 88 percent of the total change, interactions are critical. These calculations are summarized in Table 3.

Table 3: Higher-Order Effects

Model	Loss (99.9%)
Base Case	2,581,738,825
Single Factor, No Name Concentration, DND	1,954,955,399
Difference	626,783,426
Total First-Order Effects	141,630,477
Total to be Explained by Higher-Order Effects	485,152,949

Further assessment of second-order effects provides additional information, and renders an accounting of almost all differences observed between the base case and the most basic model. From the results in Table 4, we see that the second-order effects account for almost all of the initial discrepancy. The largest of the second-order effects arises from the interaction between the multi-factor models and migration risk. This might arise if migration risk has a regional or sector-specific component, indicating the need for further investigation before attempting to hedge either type of risk.

Table 4: Second-Order Effects

Model	Loss 99.9%	Deviation	Total First-Order Effects	Second-Order Effect
Base Case	2,581,738,825			
DND / FD	1,340,623,229	1,241,115,596	1,093,069,897	148,045,699
DND / SF	2,404,043,868	177,694,957	-314,381,225	492,076,182
FD / SF	3,241,306,962	-659,568,137	-495,427,718	-164,140,419
Total Second-Order Effects				475,921,462

In contrast, the largest combined effect is from the removal of name concentration risk and migration risk. This second result is expected, since the single-factor model is based on an overall higher level of correlation. When we remove the idiosyncratic risk from the portfolio and no longer allow migration between credit states, the capital requirements decrease substantially. However, the decrease is only slightly more than the sum of the decreases from applying each of these assumptions individually. This implies that there is little relationship between name concentrations and migration risk, indicating independent hedging strategies are likely to be as effective as a coordinated effort.

In actual portfolios we've assessed, the breakdown between first- and second- order effects has varied substantially. We have seen, as illustrated in this case study, that it is not only important to assess the impact of migration risk, name risk and sector risk, but also to look at the interactions between these types of risk in creating a complete picture of concentrations.

Concentration risk is likely to remain an issue that requires a significant amount of time and effort to manage. However, regulators and other stakeholders are demanding more accurate and precise answers which can only be obtained by using comprehensive models to support more detailed, multi-dimensional analyses. ✦