Quantifying, Decomposing, and Managing Portfolio Concentration Risk

Abstract

Assessing and managing a credit portfolio’s concentration risk is an important component of a sound risk management process. Understanding the impacts of new concentration risks as they vary across industries and geographies, is vital, especially during crisis periods.

By taking into account stand-alone credit risk and correlation characteristics, we build a robust, streamlined, quantitative method that assesses name and segment concentration in a credit loan portfolio. This framework can be used to decompose a portfolio’s economic capital to view the effects the current level of concentration has on overall risk. The framework also measures capital relief given further diversification. The methodology maintains the portfolio’s risk profile, so that we purely isolate the effects of each type of concentration in a portfolio. The framework enables viewing concentration effects on varying levels of granularity — we can see the impact on total portfolio economic capital, or deep-dive into individual name, country, and industry effects. This methodology allows for the decomposition of capital, and we can use the results to implement strategies that improve portfolio diversification and its return/risk profile.
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1. Introduction

The pandemic-related events of 2020 and 2021 have demonstrated the inherent value of robust and streamlined methods for assessing credit portfolio concentration risks. Recognising the economic risks stemming from portfolio concentration, as well as regulatory impacts, are compelling financial institutions to develop more nuanced and insightful economic and concentration risk measures. Concentration risk is the impact of common risk factors that can result in substantial losses to a segment of a credit portfolio, and it can originate from two types of imperfect diversification. "Name concentration" relates to imperfect diversification of idiosyncratic risk in the portfolio, either because of its small size or because of large exposures to specific individual obligors. "Segment concentration" relates to imperfect diversification across systematic components of risk, namely country and industry factors. Calculating economic capital using Moody’s Analytics RiskFrontier™ accounts for various effects that can drive tail losses, including name and segment concentration.

This paper describes our methodology for assessing these concentration risks. Our approach to calculating name concentration leverages RiskFrontier’s instrument-level, trial-by-trial risk metrics from its simulation engine. We isolate the idiosyncratic component of each instrument’s return in a portfolio to obtain instrument values without the effects of name concentration; these values are then aggregated to construct a new portfolio value and loss distribution. From this new portfolio loss distribution, we can calculate various portfolio-referent risk statistics, of which our main focus is economic capital. Specifically, the method produces portfolio economic capital, without name concentration, at a given target probability, without running additional simulation analyses.

Our approach to calculating a portfolio’s segment concentration builds upon the aforementioned name concentration method, as well as one of our key findings, the fact that we must consider the cross-sectional variation in risk concentration — economic capital depends on exposure size in a non-linear fashion. After removing name-concentration effects, we can analyse either country- or industry-concentration impacts. We construct our method in a way that isolates the concentration effect of each country or industry in a portfolio, without running additional simulation analyses. We then calculate the difference between the original capital allocation for a certain segment as well as that of the portfolio with no concentration in this segment. We call this metric the “segment concentration charge.” We repeat this calculation for all segments within a portfolio, and then calculate the portfolio economic capital without country or industry concentration by taking the difference between the original portfolio economic capital and the sum of all segment concentration charges in the portfolio.

To help guard against losses, global regulators have imposed wide-ranging guidelines, recognising the importance of quantifying concentration risks. The recent European Central Bank (ECB) Guide, defines the Internal Capital Adequacy Assessment Process (or more commonly known as ICAAP) as requiring risk quantification methodologies that are “robust, risk sensitive, as well as sufficiently stable.” Organisations are required to ensure risk concentration is taken into account in their provisioning and stress test models. Similarly, the 2020 European Banking Authority (EBA) guidelines on loan origination and monitoring states that:

“The institution’s credit risk appetite should specify the scope and focus of the credit risk of the institution, the composition of the credit portfolio, including its concentration, and diversification objectives in relation to business lines, geographies, economic sectors and products ... When monitoring credit risk, institutions should have appropriate methodologies and practices, allowing the aggregation of credit risk exposures in business lines, portfolios, sub-portfolios, products, industries and geographical segments, and support the identification of credit risk concentrations.”

On the insurance front, the EU’s Solvency II Directive includes a section dedicated to the supervision of risk concentrations, calling for its member states to require insurance and reinsurance undertakings (or insurance holding companies or mixed financial holding companies) to report at least annually to the group supervisor any significant risk concentration.

In North America, guidelines published by the Office of the Superintendent of Financial Institutions (OSFI) outline expectations for institutions to monitor risk concentrations. The Federal Reserve’s guidance highlights the need for organisations to identify,

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1 For further discussion on concentration risk, see Amnon Levy, et al., “Concentration Risk Consideration During the Allowance Process and COVID-19’s Impact.” Moody’s Analytics Whitepaper, April 2020.
4 See e.g., Office of the Superintendent of Financial Institutions Canada, ICAAP for Deposit-Taking Institutions (2010): “The impact of risk concentrations should be reflected in an institution’s ICAAP. An institution should understand its firm-wide credit risk concentrations resulting from similar exposures across its
monitor, and manage concentration risk on a standalone and organisation-wide basis. In particular, according to its Correspondent Concentration Risks (CCR) guidance, financial institutions must go above and beyond the minimum requirements “to identify, monitor, and manage correspondent concentration risks in a safe and sound manner, especially when there are rapid changes in market conditions or in a correspondent’s financial condition.”\(^5\)

Some key findings from our case study include capital relief of 21% when removing the effects of name and country concentration from our most concentrated portfolio case. We find that even in our least-concentrated portfolio case — created by redistributing notional within the aforementioned portfolio, reducing the weight of the large, single name exposures, and also increasing the number of countries and industries the portfolio is exposed to — we still see economic capital relief of 6.1%. By analysing an individual name within the portfolio — the highest-weighted name in the portfolio accounting for 7.5% of total notional — we understand why name concentrations are much riskier and create larger capital values. We see that the portfolio capital value decreases as this name is split up equally into 3, 30, 300, and 3,000 names of equivalent risk profile, but it begins to converge as this name eventually reaches infinite granularity. We discuss the effects of this granularity increase on both the portfolio distribution tail and the contribution to portfolio value volatility, or, its risk contribution.

Our segment concentration case study highlights two segments that would benefit most from further diversification: Banks and S&Ls and Textiles. After removing the effects of industry concentration from the portfolio, 63.2% of the capital relief comes from these segments. We see slightly higher capital relief in the Banks and S&Ls despite having the same notional weight in the portfolio as Textiles, a difference we explore further.

We conduct a risk-limit and portfolio optimisation exercise and see further reasoning as to why we should remove weight in exposures within the Banks and S&Ls and Textiles segments. Even after removing concentration effects, we still see that these two segments are negatively mispriced. The portfolio will benefit from redistributing notional from these segments to less heavily-weighted industries within the portfolio, such as Utilities, Electric or Air Transportation, which provide potential for improved performance. The risk-limit exercise provides further proof of the benefits of this change. After removing name concentration effects, we still see that the Banks and S&Ls and Textiles segments exceed the risk limit, so the portfolio requires further diversification along with a redistribution of capital to other segments. It is clear that the notional weighting of the Utilities and Air Transportation segments may be increased, yet remain well within the risk limit of 15% total portfolio unexpected loss.

We organise the paper as follows. Section 2 introduces the methodology utilised to obtain quantification of name and segment concentration in a credit portfolio. Section 3 describes the portfolio composition, simulation outputs, and various other input data used for calculations. Section 4 discusses the results, namely the portfolio-level capital decomposition and capital decomposition by various segmentation, as well as strategic portfolio planning analysis. Section 5 concludes.

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\(\text{different business lines.}^\) Or, Office of the Superintendent of Financial Institutions Canada, \textit{Final Guideline B-2: Large Exposure Limits for D-SIBs} (2019): “While the guideline applies to D-SIBs at the consolidated entity level, OSFI expects all OSFI-regulated subsidiaries (banks, trust companies or loan companies) of the Canadian D-SIBs to have policies and processes to identify, manage and monitor single name concentration risk at the legal entity level.”

2. Methodology

This section explores the methods we employ to quantify the level of concentration risk (both name and segment) present in a credit portfolio. By applying these methods, we can view a portfolio’s decomposition of economic capital to provide an understanding of the total portfolio capital accounted for by name and segment concentration. This process allows us to view how much capital relief can be realised, if we reduce concentration levels in the portfolio by reducing weights in certain exposures. Our methodology’s flexibility enables us to assess concentration on a granular level, allowing us to identify the borrowers or segments whose concentration is of the most potential risk to portfolio performance, and also allowing us to incorporate these results into strategic decision-making exercises. Section 4 explores these ideas in more depth.

It is important to recognise that to accurately assess concentration levels, we must understand the correlations between assets in a portfolio. When a portfolio contains large exposures to a single name or segment, then instrument performance is heavily correlated, and we see a larger portion of the portfolio defaulting at any one time, creating large losses. We, therefore, review our process of modeling asset correlations in Section 2.1, before presenting our name and segment concentration methodology in Sections 2.2 and 2.3.

2.1 Modeling Asset Correlations in a Credit Portfolio

To quantify overall portfolio credit risk, it is important to determine correlations between the future value of instruments within a portfolio. Estimating correlations in large portfolios can be tricky, as it involves the computation of a correlation coefficient for each pair of instruments in the portfolio, which in itself is an extensive task, but which also can lead to noisy estimates and spurious correlations. The market value of a firm’s assets is also not directly observable.

To assess asset correlations within a portfolio, Moody’s Analytics developed a rich global factor model (GCorr™) that provides pairwise asset correlations for approximately 48,218 publicly traded firms, as well as a model for mid-market firms, retail borrowers, commercial real estate, asset-backed securities, municipal bonds, and sovereigns. In addition, RiskFrontier™ provides substantial flexibility in its correlation structure by allowing specification of an arbitrary factor model or pairwise correlation matrix for counterparties in the portfolio, where the joint distribution can be described by a Gaussian copula.

To measure credit risk in a portfolio, it is necessary to construct a portfolio value (or loss) distribution, from which risk measures can be calculated, such as economic capital. To construct such a distribution, regardless of the specified correlation structure, RiskFrontier utilises a bottom-up approach, in which correlations describe the co-movement in credit states. Specifically, for each borrower in the portfolio, correlated asset returns are simulated in a single step Monte Carlo simulation. The asset returns reflect the borrower’s credit quality at horizon, used to determine the value of each exposure.

The asset return in a single Monte Carlo simulation trial is given by:

\[ r_i = \sqrt{RSQ_i} \phi_i + \sqrt{1 - RSQ_i} \varepsilon_i \]

where

- \( r_i \) is the asset return of borrower \( i \),
- \( \phi_i \) is the systematic factor of borrower \( i \),
- \( RSQ_i \) is the R-squared of borrower \( i \), and
- \( \varepsilon_i \) is the idiosyncratic factor of borrower \( i \).

The systematic factor, \( \phi_i \), captures the risk in common with other firms. It represents the state of the economy and summarises all the relevant systematic risk factors that affect the borrower’s credit quality. \( RSQ_i \) is a name-specific component that gives the sensitivity of the name to the systematic portion of risk — in other words, the level of its exposure to market conditions.

The idiosyncratic factor, \( \varepsilon_i \), captures the individual, firm-specific risk and is modeled as a normal, random variable. The shocks of two counterparties with the same systematic factor will be the same. However, the idiosyncratic (or firm-specific) component is always unique to each counterparty.

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Simulated asset returns, \( r_i \), are mapped to instrument values, which are dependent on the valuation method selected prior to simulation.

Mathematically, the correlation between changes in credit quality measures for any two borrowers, both within and across asset classes, is equal to the following.

\[
\text{corr}(r_i, r_j) = \text{corr}\left(\sqrt{\text{RSQ}_i \phi_i} + \sqrt{1 - \text{RSQ}_i \epsilon_i}, \sqrt{\text{RSQ}_j \phi_j} + \sqrt{1 - \text{RSQ}_j \epsilon_j}\right)
\]

\[
= \frac{\text{cov}(\sqrt{\text{RSQ}_i \phi_i} + \sqrt{1 - \text{RSQ}_i \epsilon_i}, \sqrt{\text{RSQ}_j \phi_j} + \sqrt{1 - \text{RSQ}_j \epsilon_j})}{\sigma_{r_i} \sigma_{r_j}}
\]

\[
= \frac{\sqrt{\text{RSQ}_i} \sqrt{\text{RSQ}_j} \text{cov}(\phi_i, \phi_j)}{1 \ast 1} = \sqrt{\text{RSQ}_i} \sqrt{\text{RSQ}_j} \text{cov}(\phi_i, \phi_j)
\]

Note, if the underlying borrowers are part of the same market and thus share the same systematic factor, the correlation is equal to the product of the square root of the two borrower's R-squared values. Moody's Analytics GCorr framework is a multifactor correlation model with more than 800 factors. These factors are the building blocks of an individual borrower's systematic component, dependent on what systematic risk the borrower is exposed to. As an example, GCorr Corporate\(^7\) is a forward-looking, multi-factor model for asset correlations of publicly traded firms, and can be graphically represented by the scheme in Figure 1.

Figure 1  GCorr: Decomposing obligor’s risk.

The systematic component of an individual counterparty is a custom index of factors, dependent on the asset class. For instance, the custom index of a corporate asset may be calculated by the following:

\[
\phi_{m,t} = \sum_{c=1}^{49} w_{c,t} r_{m.c} + \sum_{l=1}^{61} w_{l,t} r_{m,l}
\]

where \( r_{m.c} \) and \( r_{m,l} \) represent a country and industry factor draw for an individual trial respectively, both \( w_{c,t} \) and \( w_{l,t} \) give the weight of each country/industry factor for an instrument.

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\(^7\) Moody's Analytics, "Understanding GCorr 2020 Corporate." February 2021.
2.2 Name Concentration

Name concentration arises when a portfolio contains large, single-name exposures — an imperfectly granular structure. This type of concentration reduces portfolio diversity, such that returns on individual exposures are more heavily correlated. For example, in a portfolio where 10% of total exposure can be attributed to a single name, a large shock to this name could mean at least 10% of the portfolio could default at any one time.

To quantify the level of name concentration within a portfolio, we must calculate the portfolio value distribution at a given horizon. Instrument valuation is conducted to give a distribution of each instrument’s value at horizon. The probability of realising a given value translates to the credit quality of the name, simulated as asset returns. The Monte Carlo engine simulates asset returns for each name within a portfolio, capturing correlations between each name in the portfolio via the systematic component, dependent on the specified correlation model.¹⁰

As stated in Section 2.1, asset returns are a combination of a systematic and a firm-specific component. The firm-specific risk, or idiosyncratic risk, is the key element in quantifying name concentration. A large, idiosyncratic shock to a heavily-weighted, individual counterparty inside an imperfectly granular portfolio can deteriorate the borrower’s credit quality, leading to default and, consequently, large losses. Due to the high weighting of this borrower inside the portfolio, the total portfolio loss distribution can be greatly impacted, such that economic capital increases. If this large, single counterparty is broken up into smaller and less-concentrated counterparties with the same risk profiles, such that each name contains the identical systematic risk exposure, the collection of names will have the same systematic risk posed by the state of the economy, ensuring country or industry concentration remains the same and is not included in the name concentration analysis. However, they each have unique, idiosyncratic shocks, so we do not expect this collection of names to default together at any one time, reducing the probability of large losses. As we continue to break up each name in the portfolio to the point of achieving an infinitely granular portfolio, the random, idiosyncratic component is eventually fully diversified. The asset return of a single name is then dependent only on the systematic risk, and we see a much smaller portion of defaults at any one time.

We isolate individual, firm-specific risk by utilising the results of the Monte Carlo simulation, with the number of simulation trials stated pre-simulation.

**Figure 2** Instrument return for a given custom index.

Figure 2 shows the return of an instrument in a number of individual simulation trials, given the drawn systematic component for that trial. The purpose is to illustrate how the idiosyncratic component impacts individual instrument values. An individual instrument’s return is a function of its systematic and idiosyncratic component (shown in Equation 1). For a given systematic component draw, the volatility in instrument return is largely a consequence of the individual idiosyncratic component (in a case

¹⁰ For further details on the Moody’s Analytics credit portfolio framework, see “An Overview of Modeling Credit Portfolios.” Moody’s Analytics, January 2021.
with no LGD variance). If we diversify away the risk from the idiosyncratic component, we see a smoothed line, such that the value is now purely dependent on the systematic component (for a given risk profile), and we see lower return values only in scenarios encompassing the worst possible market conditions to which the name is exposed.

Monte Carlo simulation provides trial-by-trial instrument values that are dependent on this systematic, $\phi_i$, and idiosyncratic, $\varepsilon_i$, component. We adjust the values into instrument returns, and using these with individual trial-by-trial factors draws to build the systematic component, we run a regression analysis to remove this idiosyncratic component, such that instrument returns are no longer impacted by the firm-specific risk. As the relationship between the systematic factor and returns is not linear, we regress the instrument returns on a polynomial of the systematic factor. We find the optimum order in terms of speed and performance to be of order four. The estimate from the regression after removing the residual impact is as follows:

$$\bar{r}_i = \beta_0 + \phi_i^1 \beta_1 + \phi_i^2 \beta_2 + \phi_i^3 \beta_3 + \phi_i^4 \beta_4$$

(Idiosyncratic risk is now removed from each of the individual instrument trial returns within the portfolio. After converting these returns back into values, these can be summed to obtain a distribution of portfolio values at horizon, from which we can obtain portfolio economic capital without name concentration at a given target probability. We leverage our framework for calculating economic capital. #

2.3 Country and Industry Concentration

The effects of country and industry concentration are rooted in the systematic component of the asset return. When a large portion of a portfolio is exposed to the same primary country or industry, their systematic components will be heavily correlated. If this segment performs poorly, then it is likely a number of borrowers within this large portion of the portfolio will default, and the portfolio can experience high losses. There is more complexity in distinguishing shocks that an individual factor may have encountered, as the systematic component is a combination of a number of factors. Consequently, we use a different method to quantify segment concentration. To understand the process of quantifying segment concentration in a portfolio, it is first beneficial to discuss the consequence of segment concentrations within a portfolio, the “concentration effect.”

To describe concentration effect, consider a portfolio in which each exposure can be attributed to a specific segment (for instance, either a certain country or industry). In our case, we take the segment with the highest factor weight to which the instrument is exposed (the borrower’s primary country or industry). As an example, we use the Pharmaceuticals industry. An initial capital charge is allocated to Pharmaceuticals after running a portfolio simulation. If we run a second simulation after increasing all the exposures within the Pharmaceuticals segment by the same amount (thus increasing concentration of the segment), we see an increase in the size of the capital charge. The size of the increase depends on the concentration level. We describe two cases:

- If we increase the size of each exposure in this segment by a small amount, while keeping the rest of the portfolio constant, such that the portfolio remains unconcentrated in this segment, we find this segment’s capital charge increases roughly linearly with the size of the exposure increase.
- If we increase the size of each exposure in this segment by a larger amount, while keeping the rest of the portfolio constant, such that the portfolio now has some concentration in that segment, we find that this segment’s capital charge increases more than linearly with the size of the exposure increase.

If the increase causes a concentration, the losses will be great enough that the shape of the portfolio loss distribution will be impacted. Extreme losses within this segment are more likely to be in the tail region, driving portfolio capital. Thus, the capital allocated to this segment via a tail-risk contribution is larger than beyond the initial increase in segment size. On the other hand, if we diversify the portfolio and invest the extra notional into names exposed to new segments, the shocks that caused extreme losses in the previously discussed segment do not impact the new segments included, reducing the impact on the overall portfolio loss distribution and diversifying away some of the systematic risk.

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The knowledge of these non-linear concentration effects allows us to manipulate the portfolio loss distribution, such that we can isolate each individual segment, in turn, to approximate the capital for that segment as if the portfolio has no concentration. For example, we can eliminate the concentration effects of a segment from the portfolio simply by removing that segment from the portfolio loss distribution, as we know that if a portfolio is unconcentrated in a segment, then that segment does not impact the portfolio loss distribution.\textsuperscript{10}

Using simulation trial value output after removing name concentration effects — so that there is no impact of name concentrations affecting the results — means we can aggregate segment trial values, analysing either country or industry at one time.

\(\tilde{S}_{H_1}, \tilde{S}_{H_2}, \ldots, \tilde{S}_{H_{CI}} \leq 49, I \leq 61\) \hspace{1cm} (5)

Here, \(C\) and \(I\) represent country and industry, respectively. An individual segment’s trial values can be isolated \(\tilde{S}_{H}\), while the other segments’ trial values are summed to give the portfolio value distribution \(\tilde{V}_{H}\). By doing so, we can calculate the portfolio loss distribution without the impact of the segment, or, put differently, we can remove the effects that a concentration in that segment would create. From the loss distribution, we can calculate the unconcentrated capital of the segment, leveraging our framework for capital allocation.\textsuperscript{11} From this point onwards, references to portfolio values or capital will assume the effects of the segment have been removed.

We now have two horizon value distributions:

\(S_{H}, \tilde{V}_{H}\) \hspace{1cm} (6)

For economic capital calculations, we are concerned with adverse portfolio outcomes, so these value distributions are translated into loss distributions. Here, loss is defined as the difference between the realised values in (6) and a chosen loss reference point \(V_{LP}\). The loss reference point may be chosen as the expected value (loss in excess of expected loss), or the risk-free grown value (loss in excess of total spread).

\[Loss^P = V_{LP} - \tilde{V}_{H}\] \hspace{1cm} (7)

We can now use this information to approximate the capital allocation for a segment when the portfolio is unconcentrated in that segment. For that, we use capital allocation by tail-risk contribution (TRC), and we first calculate portfolio capital, \(C^P\), which satisfies the following:

\[P[Loss^P \geq C^P (1 + r^\text{zero-PD}H)] = \alpha\] \hspace{1cm} (8)

where \(\alpha\) is a given target probability, and \(r^\text{zero-PD}\) is the risk-free rate to horizon, \(H\).

Once the portfolio capital has been calculated, we evaluate the expected present value of losses of the unconcentrated segment within an interval surrounding portfolio capital — a lower bound \(C^P_{LB}\) and an upper bound \(C^P_{UB}\) is specified:

\[TRC_S = E\left(\frac{V_{LP,S} - \tilde{S}_H}{\text{Norm}_S} \cdot DF \right) \left( C^P_{LB} < \text{Portfolio Loss} \cdot DF < C^P_{UB} \right)\] \hspace{1cm} (9)

where \(DF\) denotes the discount factor.

\textsuperscript{10} For proof of the non-linear concentration effects, see “Calculating Capital Charges for Sector Concentration Risk,” Journal of Credit Risk, July 2018.

This gives us the tail-risk contribution of the segment, $T_{RC_s}$, when the portfolio has no concentration in that segment. This process can be repeated for each segment within the portfolio to obtain the tail-risk contribution for each unconcentrated segment, so segment capital can be estimated by multiplying the unconcentrated portfolio capital by the ratio of weighted $T_{RC_s}$ to the weighted sum of all $T_{RC_s}$ in the portfolio.

$$C^S = \frac{w_S \cdot T_{RC_s}}{\sum w_S \cdot T_{RC_s}} C^P$$ (10)

These unconcentrated segment capitals, $C^S$, can be simply summed to reach the total portfolio capital value estimation in the case of the portfolio having no concentrations in any given segment.

When removing a segment’s influence from the portfolio, removing its concentration, the loss distribution of the portfolio is driven by the other segments. What we expect to see depends on how concentrated the portfolio originally was in the segment prior to its removal.

- Originally **unconcentrated** in a given segment: When removing the impact of the segment, the portfolio loss distribution remains largely unaffected. The interval used in tail-risk allocation remains mostly the same, and, therefore, any changes in capital allocation are marginal.
- Originally **concentrated** in a given segment: When removing the impact of the segment, the shape of the portfolio loss distribution changes, such that, the interval surrounding the unconcentrated portfolio capital is now a different set of simulation trials. The tail risk-allocation reduces, as we are no longer using the trials containing the large losses (the given segment’s losses previously drove the tail of the loss distribution). We also see the unconcentrated portfolio capital reduce in-line with the removal of that segment’s large losses.

These are the two basic scenarios we expect to see when removing the concentration of a certain segment. There may be times where we see an increase in capital allocation of a segment when removing concentration effects. This can happen if a particular segment’s loss values have a positive impact on portfolio loss distribution (negative loss values), such that, by removing this segment from the portfolio, we actually see an increase in losses within the tail region of the distribution. On a portfolio-level, we expect to see an overall reduction in economic capital. However, on a segment-level, the allocation of capital can experience an increase or decrease.

The advantage to this approach of removing the segment from the portfolio loss distribution to understand the concentration impact is that, we maintain the portfolio’s overall risk profile, such that we can isolate the concentration effect inside the portfolio without making changes to portfolio construction. This way, we can decompose economic capital into its constituent, concentration counterparts robustly, without running additional portfolio simulations.
3. Data

This section outlines the composition of the portfolios used in the analyses. It provides a snapshot of the risk profiles and highlights the most heavily-weighted counterparties or segments by notional, from which we can gain intuition into the levels of capital relief we may see when removing concentration effects. For segment concentration, we provide a larger focus on the portfolio composition by industry, as we further examine these industries later in the paper.

3.1 Portfolio Statistics

Table 1 details differences among the three example portfolios we use to decompose the concentration risk. For the purpose of this study, the risk profile of all exposures within each portfolio is homogeneous, with each name in the portfolio having the same value for probability of default, PD, loss given default, LGD (assuming no LGD variance), and RSQ. By maintaining such homogeneity within the portfolios, we can explore concentration effects without any influence of underlying risk characteristics, as they impact the level of capital attributed to name or segment concentration.

Table 1  Summary Statistics for Example Portfolios

<table>
<thead>
<tr>
<th>RISK STATISTICS</th>
<th>PORTFOLIO A</th>
<th>PORTFOLIO B</th>
<th>PORTFOLIO C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Notional</td>
<td>USD 6bn</td>
<td>USD 6bn</td>
<td>USD 6bn</td>
</tr>
<tr>
<td>No. of Exposures</td>
<td>6,000</td>
<td>6,000</td>
<td>6,000</td>
</tr>
<tr>
<td>No. of Counterparties</td>
<td>2,000</td>
<td>2,000</td>
<td>2,000</td>
</tr>
<tr>
<td>No. of Industries</td>
<td>10</td>
<td>10</td>
<td>30</td>
</tr>
<tr>
<td>No. of Countries</td>
<td>10</td>
<td>10</td>
<td>25</td>
</tr>
<tr>
<td>PD</td>
<td>1.4%</td>
<td>1.4%</td>
<td>1.4%</td>
</tr>
<tr>
<td>LGD</td>
<td>40.5%</td>
<td>40.5%</td>
<td>40.5%</td>
</tr>
<tr>
<td>RSQ</td>
<td>40.0%</td>
<td>40.0%</td>
<td>40.0%</td>
</tr>
<tr>
<td>The 10 largest exposures account for:</td>
<td>20.2% of Total Notional</td>
<td>6.2% of Total Notional</td>
<td>6.2% of Total Notional</td>
</tr>
</tbody>
</table>

All three portfolios contain the same number of exposures and counterparties. Portfolio A represents the most concentrated portfolio case; it differs from Portfolio B purely by exposure weights.

Table 2 shows further portfolio risk characteristics, namely the weights of the five largest counterparties (by notional). It is immediately evident that Portfolio A contains much larger single name exposures than Portfolios B or C. We expect to see the largest overall economic capital for Portfolio A, with the highest contributors shown in Table 2. Also, this portfolio should provide the largest capital relief when removing the effects of name concentration. Portfolio C differs from Portfolio B only by the number of industries and countries to which the portfolio is exposed, allowing us to better understand the segment concentration effects.

Table 2  Five Largest Counterparties by Notional

<table>
<thead>
<tr>
<th>COUNTERPARTY</th>
<th>PORTFOLIO A</th>
<th>PORTFOLIO B</th>
<th>PORTFOLIO C</th>
</tr>
</thead>
<tbody>
<tr>
<td>RF_002535</td>
<td>7.5%</td>
<td>1.2%</td>
<td>1.2%</td>
</tr>
<tr>
<td>RF_002824</td>
<td>5%</td>
<td>1.1%</td>
<td>1.1%</td>
</tr>
<tr>
<td>RF_011311</td>
<td>2.5%</td>
<td>0.9%</td>
<td>0.9%</td>
</tr>
<tr>
<td>RF_011659</td>
<td>2.5%</td>
<td>0.5%</td>
<td>0.5%</td>
</tr>
<tr>
<td>RF_015389</td>
<td>2.5%</td>
<td>0.5%</td>
<td>0.5%</td>
</tr>
</tbody>
</table>

Table 3 shows the weights of the five largest industries (by notional). Again, Portfolio A exhibits larger concentrations, with 58% of total notional exposed to just five industries. This value reduces to 51.7% in Portfolio B and 22.7% in Portfolio C. It follows that we hypothesise the level of capital relief due to segment concentration will also decrease from Portfolio A to C.
Table 3  Five Largest Industries by Notional

<table>
<thead>
<tr>
<th>Industry</th>
<th>Portfolio A</th>
<th>Industry</th>
<th>Portfolio B</th>
<th>Industry</th>
<th>Portfolio C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WEIGHT AS % OF TOTAL NOTIONAL</td>
<td></td>
<td>WEIGHT AS % OF TOTAL NOTIONAL</td>
<td></td>
<td>WEIGHT AS % OF TOTAL NOTIONAL</td>
</tr>
<tr>
<td>BANKS AND S&amp;Ls</td>
<td>15%</td>
<td>TEXTILES</td>
<td>11.5%</td>
<td>APPAREL &amp; SHOES</td>
<td>5.2%</td>
</tr>
<tr>
<td>TEXTILES</td>
<td>15%</td>
<td>BANKS AND S&amp;Ls</td>
<td>10.4%</td>
<td>AIR TRANSPORTATION</td>
<td>4.7%</td>
</tr>
<tr>
<td>BUSINESS SERVICES</td>
<td>10%</td>
<td>AIR TRANSPORTATION</td>
<td>10.0%</td>
<td>MEDICAL EQUIPMENT</td>
<td>4.4%</td>
</tr>
<tr>
<td>CONSUMER PRODUCTS</td>
<td>10%</td>
<td>APPAREL &amp; SHOES</td>
<td>10.0%</td>
<td>AEROSPACE &amp; DEFENSE</td>
<td>4.2%</td>
</tr>
<tr>
<td>RETL/WHSL</td>
<td>10%</td>
<td>BUSINESS SERVICES</td>
<td>9.8%</td>
<td>CHEMICALS</td>
<td>4.2%</td>
</tr>
</tbody>
</table>

Figure 3  Industry composition.

Figure 3 displays the industry compositions of the three portfolios by notional; both Portfolio A and B contain ten unique industries. However, note that, although we maintain the same number of industries and countries in the two portfolios, as we spread notional more evenly among counterparties, we also alter the weights of exposure to each segment, giving a more even exposure between the different factors. This is why, in Portfolio A, both segments Banks and S&Ls and Textiles have a noticeably larger weight than other segments. Portfolio C is exposed to 25 equally-weighted industries, and, with a larger segment exposure, the number of custom indexes (the combination of country-industry segment an individual name is exposed to) increases further.
4. Results

The effects of both name and segment concentration can be viewed at a portfolio level as well as a more granular level, allowing for a better strategic understanding of the sources of concentration within a portfolio. This section contains a decomposition of portfolio economic capital for the three example portfolios presented in Section 3. We illustrate how concentrations can make a portfolio riskier. To further understand the effects of concentration within a portfolio, we provide a more detailed analysis on single name and segment concentration.

While it is important to quantify and decompose concentration risk within a portfolio, it is also beneficial to understand how to manage these risks and design strategies to enhance portfolio performance. The final part of this section provides such analysis. We discuss mispricing in a portfolio context and show how to arrive at optimal or improved portfolio allocations when removing concentration. We also conduct a risk-based limit exercise that may be used to adhere to a financial institution’s risk appetite statement. These exercises enable an organisation to make informed decisions about which borrowers or segments may be the most beneficial to reduce exposure and where to redistribute notional.

4.1 Decomposing Portfolio Economic Capital

In assessing the performance of the above-described portfolios without name and segment concentration, we look at one of the key portfolio-level RiskFrontier outputs: economic capital calculated at 10 bps target probability.

Table 4  Portfolio-level Results

<table>
<thead>
<tr>
<th>Economic Capital</th>
<th>PORTFOLIO A</th>
<th>PORTFOLIO B</th>
<th>PORTFOLIO C</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Notional</td>
<td>$6 bn</td>
<td>$6 bn</td>
<td>$6 bn</td>
<td></td>
</tr>
<tr>
<td>RISK OUTPUTS</td>
<td>TOTAL</td>
<td>RELIEF</td>
<td>TOTAL</td>
<td>RELIEF</td>
</tr>
<tr>
<td>Original</td>
<td>$471 mil</td>
<td>-</td>
<td>$405 mil</td>
<td>-</td>
</tr>
<tr>
<td>No Name Concentration</td>
<td>$423 mil</td>
<td>-10%</td>
<td>$400 mil</td>
<td>-1%</td>
</tr>
<tr>
<td>No Name and No Industry Concentration</td>
<td>$375 mil</td>
<td>-20%</td>
<td>$362 mil</td>
<td>-11%</td>
</tr>
<tr>
<td>No Name and No Country Concentration</td>
<td>$370 mil</td>
<td>-21%</td>
<td>$360 mil</td>
<td>-11%</td>
</tr>
</tbody>
</table>

Table 4 first shows the original economic capital of each of the three portfolios. The rows below give the economic capital that remains after removing name concentration effects, and after removing either name and industry or name and country concentration effects. The relief column shows the decrease in capital from the original value. As expected, all three portfolios show lower economic capital when removing either type of concentration risk, but the magnitude of the decrease varies.

Figure 4  Portfolio economic capital decomposition.
Figure 4 provides a visual representation of the overall decomposition of economic capital at the portfolio level. Each bar’s total represents the economic capital of the respective portfolio. The green and light blue portions of each bar give the capital relief we see if we remove the effects of industry concentration or name concentration, respectively, whilst the dark blue portion of each bar is the remaining economic capital. We see the highest level of capital relief for Portfolio A, as it is the most concentrated portfolio in both name and segment terms, with 20% of total notional residing in just 10 counterparties and exposure to only 10 different countries and industries; here, total capital relief equates to $96 million (20% of total portfolio capital). The capital is lower for Portfolio B, as the notional is more evenly weighted across counterparties (6% of total notional resides in 10 counterparties). We observe lower capital relief after removing name concentration effects than we do for Portfolio A. There is still room for further name diversification benefits, however, as we still see a capital relief of $5 million when removing name concentration. With 6% of notional in just 10 counterparties, one could expect to see a larger benefit of removing name concentration. However, as the average weight of counterparties inside the portfolio is just 0.05%, the portfolio is heavily skewed in terms of notional to a small number of counterparties; in a portfolio where each of the constituent counterparties accounts for a very small portion of total notional, we expect to see very little, if any, name concentration diversification benefits.

Portfolio C is the least-concentrated portfolio, and we observe the smallest capital relief when removing concentration. Name and industry concentration effects account for $3 million and $16 million, respectively, or 1% and 5% of total capital. We see a different name concentration capital relief for Portfolio C than for Portfolio B despite the number of counterparties and their weights across the portfolios are the same. In Portfolio C, the counterparties have more country and industry pairings, which reduces the correlation between borrowers in the portfolio; the portfolio also has lower undiversified capital. This difference in undiversified capital arises from increased exposure to a wider set of country and industry factors — a large number of combinations of factors leads to more diversification in the portfolio. There are 486 unique combinations of country and industry factors that a Portfolio C counterparty may be exposed to, in comparison to only 100 different such combinations in Portfolios A and B.

To further understand the change in total capital between portfolios of varying concentration levels, Figure 5 shows the distribution of loss values, with a focus on the tail regions, with the dashed lines representing the capital value for each portfolio (red for Portfolio A, green for Portfolio B, and blue for Portfolio C). The most concentrated portfolio displays the fattest tail, a fact that indicates a relatively higher probability of large losses. However, if we break up the concentrated areas it is less likely that a large group of counterparties will all default at the same time; this is why we observe the lowest probability of extreme losses in Portfolio C.
4.2 Single Name Analysis

To explore the consequences of name concentration at the most granular level, we investigate an individual name that accounts for 8.5% of the total notional of Portfolio A, which makes it the most concentrated name in that portfolio. The portfolio is simulated in this initial state — Case Number 1. We then split the name into 3, 15, 30, 300, and 3,000 separate names. By doing so, we can understand why having name concentrations can be detrimental to portfolio performance.

Table 5 Portfolio-level Results

<table>
<thead>
<tr>
<th>CASE NO.</th>
<th>TOTAL NO. OF NAMES IN THE PORTFOLIO</th>
<th>UNEXPECTED LOSS</th>
<th>RELIEF W.R.T CASE NO. 6</th>
<th>ECONOMIC CAPITAL (TRC)</th>
<th>RELIEF W.R.T CASE NO. 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>$57.958 mil</td>
<td>-7.7%</td>
<td>$471 mil</td>
<td>-8.5%</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>$55.059 mil</td>
<td>-2.4%</td>
<td>$443 mil</td>
<td>-2.1%</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>$54.014 mil</td>
<td>-0.4%</td>
<td>$439 mil</td>
<td>-1.2%</td>
</tr>
<tr>
<td>4</td>
<td>30</td>
<td>$53.829 mil</td>
<td>-0.07%</td>
<td>$437 mil</td>
<td>-0.7%</td>
</tr>
<tr>
<td>5</td>
<td>300</td>
<td>$53.792 mil</td>
<td>-0.004%</td>
<td>$436 mil</td>
<td>-0.5%</td>
</tr>
<tr>
<td>6</td>
<td>3,000</td>
<td>$53.790 mil</td>
<td>-</td>
<td>$434 mil</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 5 shows the unexpected loss (UL) and economic capital on a portfolio level, after the reduction of concentration in the single name. The relief column shows the percentage decrease from Cases 1–5 to the most unconcentrated case (when the name has been split into 3,000 identical names i.e., Case Number 6). For instance, the capital relief for Case Number 3 is calculated by ($434-$439)/$434. We see that concentration in a single name can have a great impact on overall portfolio capital and the standard deviation of losses. As we reduce this concentration and the name becomes almost perfectly granular, the impact weakens, and the idiosyncratic effects fade away.

Figure 6 Economic capital (tail-risk contribution-based capital allocation).

Figure 6 shows how both total portfolio capital and tail-risk allocated capital decrease when splitting a single name into 3,000 different names of equivalent risk profile. Each bar's total represents the value of portfolio economic capital (also given in Table 5). The light blue portion represents the capital allocation either to the single name or to the 3,000 names.

This name originally makes up 21% of total portfolio capital; this percentage decreases to 8.4% when the name is split into 3,000 identically-profiled names. Originally, the default of this name would lead to large losses and drive the tail region of the portfolio loss distribution, due to its large weight within the portfolio. After this split, the systematic component remains the same throughout these counterparties for each individual trial of the simulation, but the idiosyncratic component is unique to each

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12 Risk Contribution-based capital allocation displays a very similar relationship to tail-risk contribution-based capital allocation when removing the name concentration effects.
counterparty. Therefore, where we may have previously experienced a default due to a large shock, we now only expect to see a portion of these counterparties defaulting at any one time as the shocks vary between counterparties. As we split each issuer inside a portfolio into a larger number of names, we eventually approach an infinitely granular portfolio — one in which we have removed all name concentration effects — and the risk posed by the idiosyncratic component is diversified away. The tail-risk contribution also decreases significantly, as now other names within the portfolio are driving losses in the tail.

Not only does the process of removing name concentration in a portfolio impact the tail region of the loss distribution by accruing much smaller losses at any one time, the variance in portfolio values also decreases, leading to a reduction in portfolio UL. To better illustrate this reduced variance effect at a name level, Figure 7 shows the range of simulated instrument values for a range of systematic factor values. The black line gives the instrument value for a given custom index value when we fully diversify away the idiosyncratic risk in the portfolio. The purple shaded area shows the range of instrument values attained in simulation trials. The chart on the left shows a split into 300 while the one on the right into 3,000 identical names.

We see a much larger range in simulated instrument values for the case with 300 names, where the difference between maximum and minimum values is $23 million. After increasing the number of counterparties to 3,000 names, the range in values becomes more closely centered around the mean, and the randomness in simulated values decreases. Here, the range between maximum and minimum instrument value is just $10.7 million.

**Figure 7** Instrument value range for a given custom index.

![Figure 7](image)

As the variance in simulated values is reduced, the counterparties’ contribution to the volatility of overall portfolio value decreases. Not only does portfolio UL drop due to the reduced randomness of values, the randomness in portfolio values is now being driven predominantly by other counterparties within the portfolio. The correlation between counterparty and portfolio values is greatly reduced, and the capital allocated via the risk-contribution method decreases. If we remove the name concentration from every name within the portfolio, the randomness in the simulation will be driven purely by the systematic component.

### 4.3 Capital Decomposition by Different Segments

This section explores the decomposition of economic capital at a segment level, developing an understanding of why some segments may see larger capital relief when removing concentration.

Figures 8 and 9 show the capital relief of each segment for Portfolios A and C, where capital is allocated by tail-risk contribution. Each bar represents total capital allocation; the dark portion gives the capital remaining after removing the effects of industry concentration and the light blue portion gives the amount of capital relief achieved. Overall, we observe lower capital relief for portfolio C after removing industry concentration. From Table 4, we see that we reduce the capital required for Portfolio A by
roughly 10% in comparison to just 4% for Portfolio C. Looking back at Figure 3, we see that not only is Portfolio C exposed to a larger spread of industries compared to Portfolio A (30 unique industries, in contrast to 10 unique industries in Portfolio A), but also the notional weights are more evenly distributed among industries. The two most heavily-weighted industries in Portfolio A — Banks and S&Ls and Textiles — account for 30% of the portfolio notional.

Figure 8 reveals that the size of individual industry capital relief follows that of each industry weight, shown in Table 3. The Banks and S&Ls and Textiles segments experience the largest reductions in capital when removing concentration effects, followed by Business Services and Consumer Products Retail/Whsl. The total portfolio capital relief is $48 million — combined, the Banks and S&Ls and Textiles segments make up 63.2% of this amount.

The trend occurs due to the large disparities in notional in these segments. Figure 9 shows that, when the notional weights between segments are equal, Banks and S&Ls, Textiles, and other previously mentioned segments no longer stand out as having larger capital allocations or relief. It is purely the concentration effects that cause the large capital allocations in Portfolio A.
that, per Figure 8, the capital allocation after removing name concentration for both Banks and S&Ls and Textiles is almost equivalent. However, we observe a much larger reduction in capital for the former segment after removing industry concentration effects. To understand why this occurs, we further investigate these two segments; Figure 10 shows the total capital decomposition for both.

**Figure 10  Capital decomposition by segment.**

The total of each bar gives the initial tail-risk capital allocation for each segment — $127 million for Banks and S&Ls and $93 million for Textiles. Note, this large difference in allocation, given that both segments make up 15% of the portfolio notional. If we look deeper into the portfolio set-up, we can see that, within the Banks and S&Ls segment, there is a single counterparty making up 48.4% of notional, whereas, within the Textiles segment, this portion is shared by two counterparties that make up 32% and 16% of the notional. The single name analysis section of this paper describes how splitting up a single, large-weighted name can have a great impact on economic capital allocation. A simultaneous default of the two largest counterparties is less likely than a single default within the Banks and S&Ls segment, and we see a lower probability of high losses inside the Textiles segment. After removing these effects of name concentration, we can see a very similar capital allocation.

Figure 11 shows the distribution of each segment’s losses within the tail-risk interval, before and after removing the effects of industry concentration. The dark blue box plots show the distribution within the interval of Portfolio A. The light blue box plots show the distribution within the interval after removing the effects of industry concentration, i.e. the losses within the interval that would occur if the portfolio loss distribution was unaffected by that segment. The dots inside the plots show the mean value of each distribution. The Banks and S&Ls segment has a larger range of values within the original “concentrated” interval, showing more extreme losses while the losses in the Textiles segment are centered more closely around the mean. Despite this difference in value range, the average values within the concentrated intervals have a percentage difference of just 0.25%, and the capital allocation is similar.

We observe a noticeable difference in the range of values before and after removing concentration from the Banks and S&Ls segment. The interval of the original portfolio loss distribution contains several trials of losses exceeding $200mil within this segment. However, after we remove the impact of this segment on the portfolio loss distribution, the interval moves to a region in which other segments’ losses are driving the tail, and we no longer see this amount of extreme values from this segment. This observation suggests that the extreme losses of exposures within this segment drive the portfolio loss distribution tail — after removing this segment, the interval changes to a position in which the losses of the segment are no longer as significant.
Figure 11  Losses in capital interval — before and after removing industry concentration.

Figure 12  Losses exceeding $100mil in the Banks and S&Ls and Textiles segments.

Figure 12 shows the distribution of losses exceeding $100mil within the Banks and S&Ls and Textiles segments. It illustrates the reason the Banks and S&Ls segment is the key driver in the tail of the portfolio loss distribution, despite having the same notional weight as the Textiles segment — the Banks and S&Ls segment has a higher probability of extreme losses. When the impact of the Banks and S&Ls segment is removed from the portfolio, large losses of other segments now drive the tail and the shape of the portfolio loss distribution changes; large losses of this segment within the new TRC interval are much less common. While there are occurrences of losses exceeding $175mil within the Textiles segment, when we remove the impact of the Textiles segment, there is only a small movement in the shape of the portfolio loss distribution, as the tail is being predominantly driven by the Banks and S&Ls segment.

To summarise, although the portfolio is exposed to the same notional weight of these two industries, concentration within the Banks and S&Ls is a greater risk to the portfolio performance due to the potential for large losses. This is why we see a greater capital relief within this segment when removing concentration effects.
4.4 Strategic Portfolio Planning

Utilising these exercises, portfolio managers can understand and quantify the concentration risks in their portfolios robustly, and, based on the risk-return profile of their portfolios and segments, they can design portfolio strategies to set risk based-limits and determine optimal asset allocation. This approach can help institutions adhere to their risk appetite framework, while optimising their portfolio investment strategy. By reviewing these exercises after concentration effects have been removed, an organisation can make informed, strategic decisions as to which exposures it could be most beneficial to reduce concentrations in.

Figure 13 shows the Vasicek-mispricing (or TRC-based mispricing) of industries within Portfolio A, and how mispricing changes after removing name or industry concentration. The triangular icons represent the Vasicek-mispricing of each industry, and the slope of the line is the portfolio’s Vasicek ratio. Points to the left side of the line indicate positive mispricing, while points to the right indicate negative mispricing. In a portfolio optimised to yield a maximum Vasicek ratio, exposure weight would be adjusted so that all points line up along and close to the Vasicek ratio line. In reality, however, we optimise a portfolio by shifting weights of exposures whose points fall in the negatively mispriced group to those in the positively mispriced group. The reason we see an equal expected spread between industries is due to the equal risk profile (having the same PD, LGD, and RSQ values) of each exposure in the portfolio.

We can see from the plot of the original portfolio that industries are much more spread out in terms of differing capitalisation rates and, thus, some industries display positive mispricing, while two industries in particular are quite negatively mispriced: the Banks and S&Ls and Textiles segments. To optimise the risk-return profile of the portfolio, we should reduce concentration within these two segments and redistribute this notional into the other, all positively-mispriced segments. By reducing concentration within these two segments, we reduce the portfolio economic capital and improve the risk-return ratio. This point is further supported by the fact that, in the mispricing chart where the portfolio has no impacts of concentration, these two industries still display negative mispricing. The industries displaying the most positive mispricing are the Utilities, Electric and Air Transportation segments. Portfolio performance can be improved if notional is redistributed to exposures within these industries.

After removing name and, subsequently, industry concentration, we see an improvement in the Vasicek ratio of the portfolio as the slope of the line gets steeper, due to the reduction in economic capital. The mispricing of all industries moves closer to the portfolio Vasicek ratio. Although, technically, we have not adjusted the exposure weights within the portfolio, by removing the effects of concentration we theoretically break up the weights of each counterparty/industry/country into smaller pieces (removing the concentration within those segments), which, in turn, reduces each individual component’s capital, improving the portfolio’s risk-return profile. Table 6 shows the improvement in Vasicek ratio for each of the three portfolios. When removing the effects of name and segment concentration, it is clear we experience a lower risk for a given expected return in all cases.

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A financial institution may want to define risk-based limits, adhering to firm strategy and stakeholders’ risk appetite. There are a number of ways to translate an institution’s risk appetite framework into risk-based, sub-portfolio limits. Here, we explore portfolio-referent sub-portfolio risk limits that consider the risk of a segment in the context of a portfolio. These limits incorporate the idea that riskier segments are likely to incur substantial losses when the portfolio performs poorly, so that segments that contribute more to large portfolio losses face a tighter limit.

Capital may be allocated via either a tail-risk contribution-based or a risk contribution (RC)-based measure, specific to an institution’s risk preference. Here, we focus on an RC-based risk allocation. Figure 14 shows the proportion of portfolio notional and UL owing to each industry in the portfolio. The light blue bar refers to the segment RC (% of portfolio UL) prior to removing name concentration. The dark blue bar refers to the segment RC after removing name concentration. Focusing on the original portfolio results, the pattern in the relative proportion of notional and RC follows the distribution of notional weights shown in Figure 3; the more heavily-weighted segments have a larger RC allocation than the percent of holdings. Then, as the weights decrease, we see segment RC become smaller in comparison to the holding amount. The Banks and S&Ls and Textiles segments both have larger RC than notional percentage in the portfolio. This is due to the concentration effects, which is why, after removing the name concentration of each name within the portfolio, segment RC declines significantly. The proportion of these segments’ contribution to portfolio UL remains higher than the portion of notional, and much greater than other segments within the portfolio, as there are still concentration effects occurring due to the high portion of notional in these segments. It is worth noting that the Utilities, Electric segment shows the most striking disparity between notional proportion and the RC allocation, with RC being roughly a third less than the notional allocation. Air Transportation also shows a similar relationship. The red dashed line in the graph gives the limit of risk we have set for this exercise; no segment should contribute more than 15% of portfolio UL. In reality, we choose this limit in order to align with the organisation’s risk appetite.

<table>
<thead>
<tr>
<th>Notional</th>
<th>$6 bn</th>
<th>PORTFOLIO A</th>
<th>TOTAL</th>
<th>INCREASE</th>
<th>PORTFOLIO B</th>
<th>TOTAL</th>
<th>INCREASE</th>
<th>PORTFOLIO C</th>
<th>TOTAL</th>
<th>INCREASE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vasicek Ratio</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Original</td>
<td>0.133</td>
<td>-</td>
<td>0.155</td>
<td>-</td>
<td>0.186</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Name Concentration</td>
<td>0.148</td>
<td>11%</td>
<td>0.157</td>
<td>1%</td>
<td>0.187</td>
<td>1%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Name and No Industry Concentration</td>
<td>0.167</td>
<td>26%</td>
<td>0.173</td>
<td>12%</td>
<td>0.196</td>
<td>5%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Name and No Country Concentration</td>
<td>0.169</td>
<td>27%</td>
<td>0.174</td>
<td>12%</td>
<td>0.198</td>
<td>6%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 13  Vasicek-mispricing of industries within Portfolio A.
To define risk-based limits, it is important to understand the tradeoff between each individual segment’s risk and invested notional. Figure 15 presents the relationship between the RC allocation for the 10 industries and their notional weight, before and after removing name concentration effects, illustrating how each industry’s RC is impacted by increasing notional. Take Banks and S&Ls as an example. The weight of this sector in the portfolio is 15% and comprises 25% of the original portfolio UL (also shown in Figure 14). If this segment made up 100% of portfolio notional, the RC would represent portfolio UL. On the other hand, if there is no weight of that segment in the portfolio, the RC portion will equal 0. Again, we highlight the 15% of the portfolio risk limit with a red dashed line.

Notice how the relationship between RC and notional weight of the segments changes after removing name concentration. The notional limits of the original portfolio vary between 10.6% (for Banks and S&Ls) and 19.7% (for Utilities, Electric). After removing name concentration, we see the limits ranging between 13.8% (for Textiles) and 16.7% (for Utilities, Electric). RC-based limits are impacted by the characteristics of each segment. The portfolio we simulate is homogeneous in risk profile, so the notional-based limits are being driven by the concentration risk. We see lower notional weight limits in the original portfolio, as we have larger concentrations of names within these higher-weighted segments, which increases risk for a given total segment weight. After we remove the effects of name concentration from each segment, we find that weight limits for these segments have now increased, and we can allocate a larger portion of notional to these segments and still adhere to the risk limit.
The notional limits of each industry become much more evenly spread after removing name concentration effects. Figure 16 shows the current notional weight of each industry in the portfolio, as well as the risk-based notional limits before and after removing name concentration. Note that the notional weight limit increases for just two industries, Banks and S&Ls and Textiles, whereas we see a decrease in the limit for all other industries. This is because, after removing name concentration, these two heavily concentrated industries are largely reducing their risk contribution to the portfolio — the industries that previously had little name concentration now have more impact on the portfolio loss distribution. The previously unconcentrated industries contribute more risk to the overall portfolio UL, so, for a given risk limit, we require less notional weight in the portfolio.

Figure 16 shows that, after removing name concentration, to maintain a risk contribution allocation to each industry below 15% of portfolio UL, we must reduce the notional weight of both Banks and S&Ls and Textiles segments by 1.2% and 1.7%, respectively. Similar to the mispricing exercise, we see a benefit in reducing concentrations within the Banks and S&Ls and Textiles segments, as a reduction of 4.9% and 2.6% in notional weight is required for these segments in the original portfolio composition. By redistributing the notional to segments such as Utilities, Electric and Air Transportation, we see a more even spread of risk.
contribution in the portfolio and remain within the risk limits. Figure 16 shows it is possible to increase the exposures within Utilities, Electric and Air Transportation without violating the 15% limit on risk contribution.

Figure 16  Notional weight limits.
5. Summary

This paper illustrates a concentration risk quantification framework that can be used to decompose a portfolio’s economic capital, to view the effects the existing level of concentration has on the overall risk. In addition, the method quantifies the effect of diversification on economic capital relief, while maintaining a portfolio’s risk profile, to isolate the impact of each source of concentration in the portfolio. Offering analysis of concentration effects at varying levels of granularity, the approach enables the user to investigate the impact on total portfolio economic capital or focus on individual names, country, or industry effects. This unique capability of our solution can be used by financial institutions to implement more diversified portfolio strategies that minimise potential losses, improve liquidity management and capital allocation, and yield better return-to-risk ratios.
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EVALUATION OF EACH SECURITY THAT IS UNDER CONSIDERATION FOR PURCHASE, HOLDING, OR SALE.

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