Credit Benchmark

Credit Consensus Ratings and Risk Sharing Portfolios

July 2022

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Executive Summary

- Investors can use Credit Consensus Ratings to price risk in otherwise unrated names; but they can also use Credit Consensus aggregates to proxy risk for undisclosed Capital Relief Trades (CRT) portfolios.
- CRT portfolio credit risk can be proxied in a number of ways using Credit Consensus data – average default probabilities, proportions of names in very high yield categories (**b** and **c**).
- These metrics can be combined with market credit spreads to plot efficient frontiers and identify anomalies or scope for portfolio optimization; US Corporate bond spreads are closely correlated with aggregate average PDs and tail risk (% in **b** and **c** credit categories).
- Diversification benefits can be quantified by adjusting for correlations between aggregates. These correlations are more stable and potentially more meaningful than market-derived equivalents. Correlations between aggregates reduce measured portfolio risk in some cases by more than 20%.
- US Non-Life, Latin American Corporates and Belgian Corporates are the most diversifying aggregates. Regional and large country corporates are the least diversifying, followed by major US sectors. See Appendix for a return and risk chart for all (800+) aggregates.
- Risk estimates can also be adjusted by Point-in-Time stress scenarios. PIT adjustments approximately double the TTC default risk; the adjustment is larger for some higher risk portfolios.
- Risk estimates can also be adjusted by medium term credit transition rates. Long term transition effects increase risk by up to 5x, less for lower risk portfolios.

Risk sharing transactions (also known as Capital Relief Trades, Credit Risk Transfers, Significant Risk Transfers, Synthetic Risk Transfers, amongst other variations) are a rapidly growing asset class.

The sector has provided attractive risk-adjusted returns in the low-yield / low-default environment of the past decade; but global supply shocks and rising interest rates are expected to push corporate default rates higher

For risk-sharing investors, emerging risks – and opportunities – highlight the need for timely and comprehensive credit data for accurate transaction pricing. This paper details how Credit Consensus Ratings and Aggregates provide a detailed map of the credit market risk-reward landscape, including possible anomalies.

About Credit Benchmark

Credit Benchmark produces a comprehensive view of credit risk by creating Credit Consensus Ratings ("CCRs") and analytics on the credit quality of companies, financial institutions, sovereigns, and funds.

The data is sourced from more than 40 global financial institutions, representing the work of over 20,000 analysts and is also used by regulators to monitor Basel rules on capital adequacy.

Credit Benchmark collects a specific measure of credit risk: a one-year, forward-looking Probability of Default (PD) and forward-looking senior unsecured Loss Given Default (LGD).

The underlying inputs are subject to a rigorous data quality approval process and derived from models that are approved by regulatory authorities. The resultant accuracy of each PD and LGD leads to a credible market view of credit risk for each given entity.

After being anonymized and aggregated, the contributed risk estimates are mapped to the appropriate credit category on the Credit Benchmark Consensus scale, which is calibrated periodically and can be used as a comparison to the scales published by the rating agencies.

Credit Benchmark produces regular data updates with history going back to 2015.

Foreword

The importance of solid risk management is rising in prominence after two years of relative and unexpected calm in the world of credit risk. This change is being propelled by a combination of macro geopolitical and economic events. After the initial shock, the coordinated accommodative economic policy driven by central bankers in response to the global pandemic, created conditions for a relatively "benign" credit environment. The scale of this unprecedented action protected much of the global economy and the majority of companies from default. However, as liquidity and fiscal support are now inevitably being withdrawn, the global economy finds itself adjusting to a "new normal"; positioned at the epicentre of a dramatic storm. Supply chain dysfunction had already been dramatically impacted by the pandemic and is now being exacerbated by the war in Ukraine. The ongoing battle between the monetary and fiscal responses to extreme inflationary pressures rages globally. Rising inflation, interest rates, and ongoing supply chain challenges are having a major impact upon all aspects of the economy, from Governments to Corporates, and are inevitably concerning to Investors. As the transition from a benign to a malign credit environment takes place, the need for Investors to maintain rigorous, empirical and analytical composure is critical. Now is a time for calm heads to prevail.

Prudent regulation over the past decade has ensured that the global banking sector is now in a much stronger capital position than it was before the global financial crisis and the intervention of the central banks during the pandemic has helped maintain that strength. In recent years, Risk Sharing transactions have grown in popularity for a number of different reasons as Banks look to release and redeploy regulatory capital, with Investors happy to take on the higher returns of Bank-owned high-yield assets. We believe that it is essential that this market can always operate at scale and efficiently, especially amidst times of extreme economic turbulence. Banking business models increasingly factor in the ability to originate and distribute risk to investors via strategic Risk Sharing programs and these programs need to be able to function in an orderly manner.

Listening to some impressive presentations at recent conferences, it is clear that investors are seeking a higher level of informational transparency than that currently available as standard. The provision of this additional complementary information will benefit Banks and Investors alike and is a prerequisite to building and maintaining confidence in the asset class both for existing practitioners and the newer, less-experienced entrants. One way to ensure that Risk Sharing continues to function smoothly at this challenging time is to recognise the need to consider additional data provision that maintains appropriate levels of confidentiality and to simultaneously ensure that is not too onerous for the banks to provide.

The purpose of this paper is to introduce the reader to a growing dataset that has been built up over the past seven years which can serve to enhance transparency across risk sharing transactions. Listening to our Investor and Banking clients over recent months, it has become apparent to us that the Credit Benchmark dataset can potentially deliver insights that are deeper and more macro in nature and go beyond those associated with any singular entity. We believe that this information can provide tangible value to risk and portfolio managers on either side of the market when considering portfolio risk transfer – and might be just what the market needs at this challenging time.

As we've listened and learned more about the Risk Sharing market, we've looked deeper into our dataset. This paper demonstrates our current thinking about a number of ways in which the informational value of the data might be unlocked and applied: through an aggregated approach in addition to entity level; using correlation matrices (favourably described by one asset manager client as "probably the best proxy in the market"); by the application of transition matrices; and perhaps most interestingly, given the pace of change in the world, the overlaying of point-in-time (PIT) data upon the through-the-cycle (TTC) data.

We highly value the feedback and learnings gleaned from our clients on both the Bank and Investor side of the market who use Credit Consensus data to facilitate their Risk Sharing activities. Our objective is to build upon this feedback and to use it to inform our research and development efforts, so that we may continue to build tools and data sets that can help our clients.

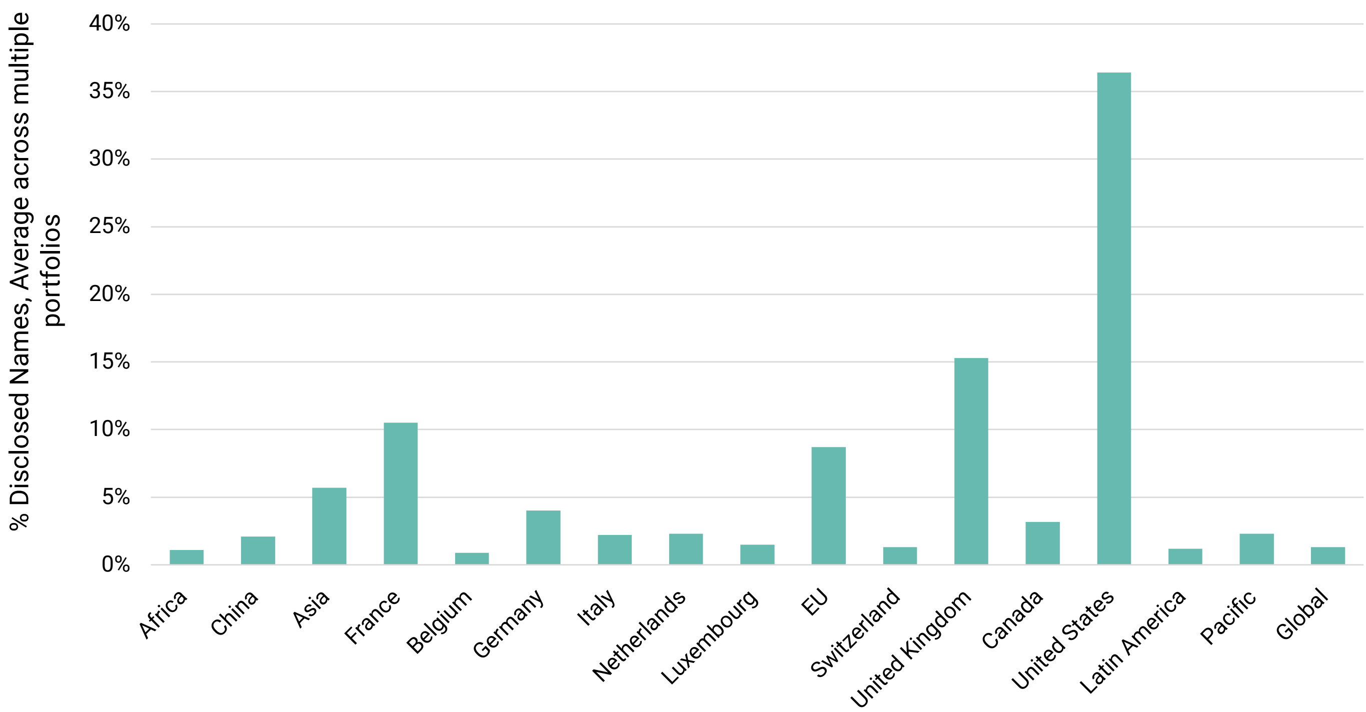
We welcome the opportunity to discuss any of the themes of this paper in greater detail with interested parties and encourage you to get in touch. Please enjoy the paper and share it as you see fit.

Mark C. Faulkner
Co-Founder, Credit Benchmark

1. Introduction

Europe has traditionally been the main source of risk sharing trades, but the US and Canada are increasingly important. Figure 1 shows the average geographic distribution of names from a small survey of (disclosed) CRT portfolios.

Figure 1.1 Average Geographic Distribution, Recent Disclosed Risk Sharing Portfolios



The geographic and sector diversity of CRT portfolios is a challenge for portfolio risk managers – a significant portion of the issuers involved are unrated, and in many cases the issuer names are not disclosed to investors. Credit Consensus data coverage includes many of the otherwise unrated corporates and financials that feature in risk-sharing transactions; it also shows detailed geographic and sector risk trends in the absence of detailed issuer information.

Risk sharing investors are a diverse group, with variable credit risk appetites and differing tolerances for transparency between disclosed and undisclosed lists of borrowers. Issuance of tranched investments (Senior, Mezzanine, First Loss) highlights the need for estimates of correlations between different credit categories and geography / industry combinations. Credit Consensus aggregates cover more than 1,200 such combinations and can be used to calculate correlations and PD volatilities at a granular country / sector level using recent or full cycle time series.

A subset of these aggregates are used in this note to compare several typical risk-sharing portfolios across a range of credit risk metrics. The outputs suggest that the Credit Consensus dataset may have significant value in the risk sharing segment.

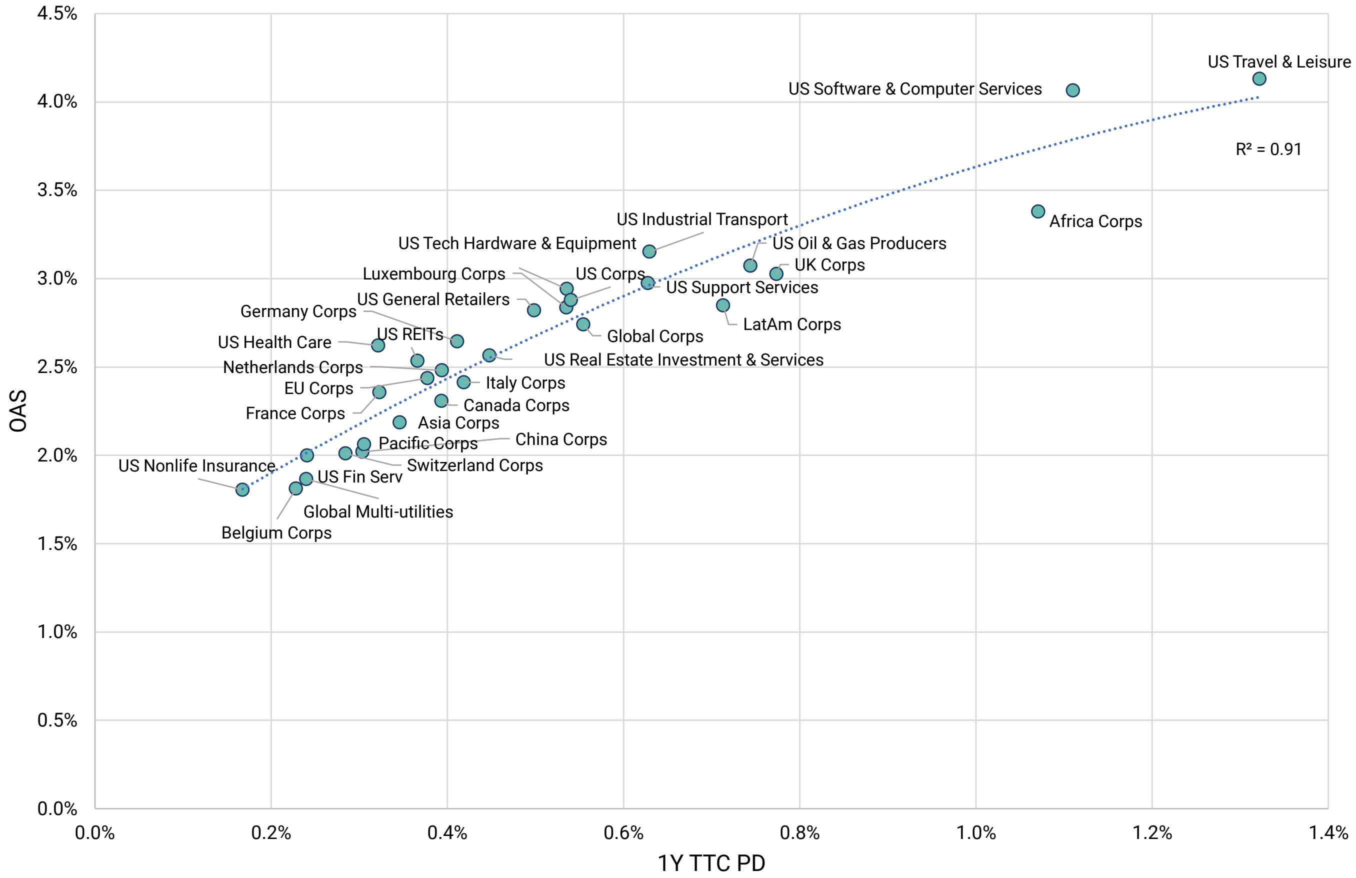
For investors in Risk Sharing products, transparency is key. Credit Consensus Ratings speed up decision making, particularly where no public ratings exist and even when analysing undisclosed portfolios. Contact us to discuss how you can use this data to drive your own risk sharing business forward.

2. Optimizing CRT Portfolios: Risk vs Reward Overview

Risk-sharing investment options are driven by banks who will aim to transfer assets that contribute heavily to their Risk Weighted Asset (RWA) calculations. If these are offered “blind”, the challenge for investors is to balance return against potential diversification benefit for their existing investments.

The classic approach to asset choice is to plot risk vs return for the asset universe. Figure 2.1 shows the relationship between Option Adjusted Spread[1] (OAS) as a proxy for return and Probability of Default (PD) as a proxy for risk, for a set of 30 geographic and sector aggregates used throughout this report.

Figure 2.1 Efficient Frontier 1: Spreads vs PD for 30 Geographic / Sector Aggregates



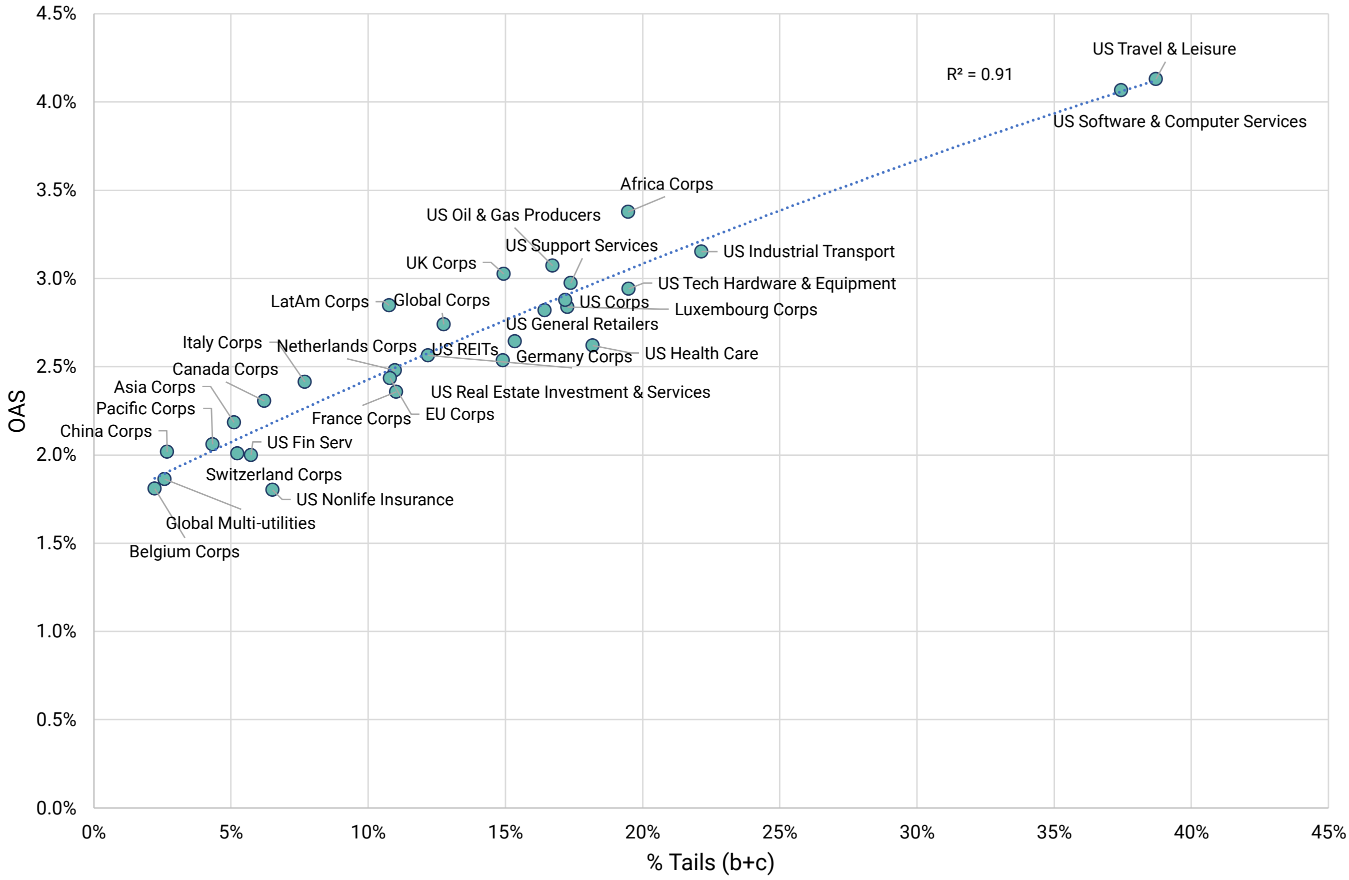
The correlation is positive and very high – so **average** credit risk for each aggregate is closely related to current OAS.

Similar correlations are likely vs CDS prices, secondary loan market rates, and most other traded credit assets, but these will be distorted by tranche structures. (At this stage, correlation between default risks is ignored – this is relaxed later in this report).

Figure 2.2 shows a similar chart with “Tail Risk” (% in **b** and **c** credit categories) as the risk measure.

[1] The Option Adjusted Spread (OAS) is derived from recent (May 2022) OAS calculated by ICE-BAML and reported on the St. Louis Fed FRED website. The credit % distribution of the aggregate constituents across 7 categories (**aaa**, **aa**, **a**, **bbb**, **bb**, **b** and **c**) are used as weights to derive a weighted average OAS for each aggregate.

Figure 2.2 Efficient Frontier 2: Spreads vs Tail Risk (% in b and c Credit Categories) - 30 Aggregates Used for Portfolio Examples

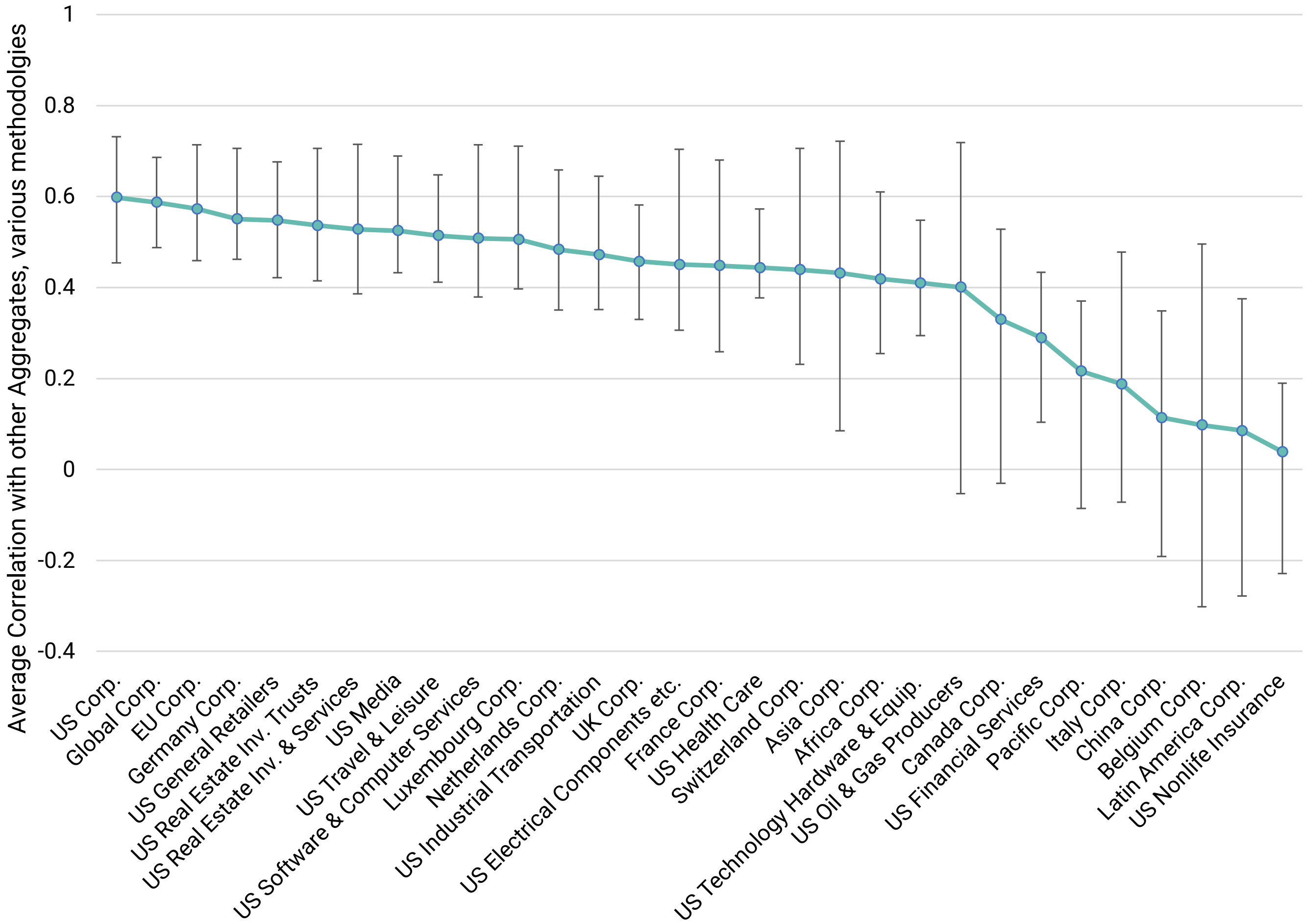


The correlation is again very high although the distribution of the aggregates in the plot is different. This suggests that any portfolio construction decisions need to use more than one risk metric.

The previous return vs risk charts ignore correlation between the various risk metrics for each aggregate. Credit Consensus data can be used to calculate correlations between PDs in terms of PD levels, PD changes, or the varying proportions of each aggregate in the tails (i.e. in the **b** and **c** credit categories).

Figure 2.3 plots the range of correlation estimates for each aggregate compared with the other 29 aggregates in the sample. Correlations use unweighted monthly data from 2016.

Figure 2.3 Most and Least Diversifying - 30 Aggregates Used for Portfolio Examples



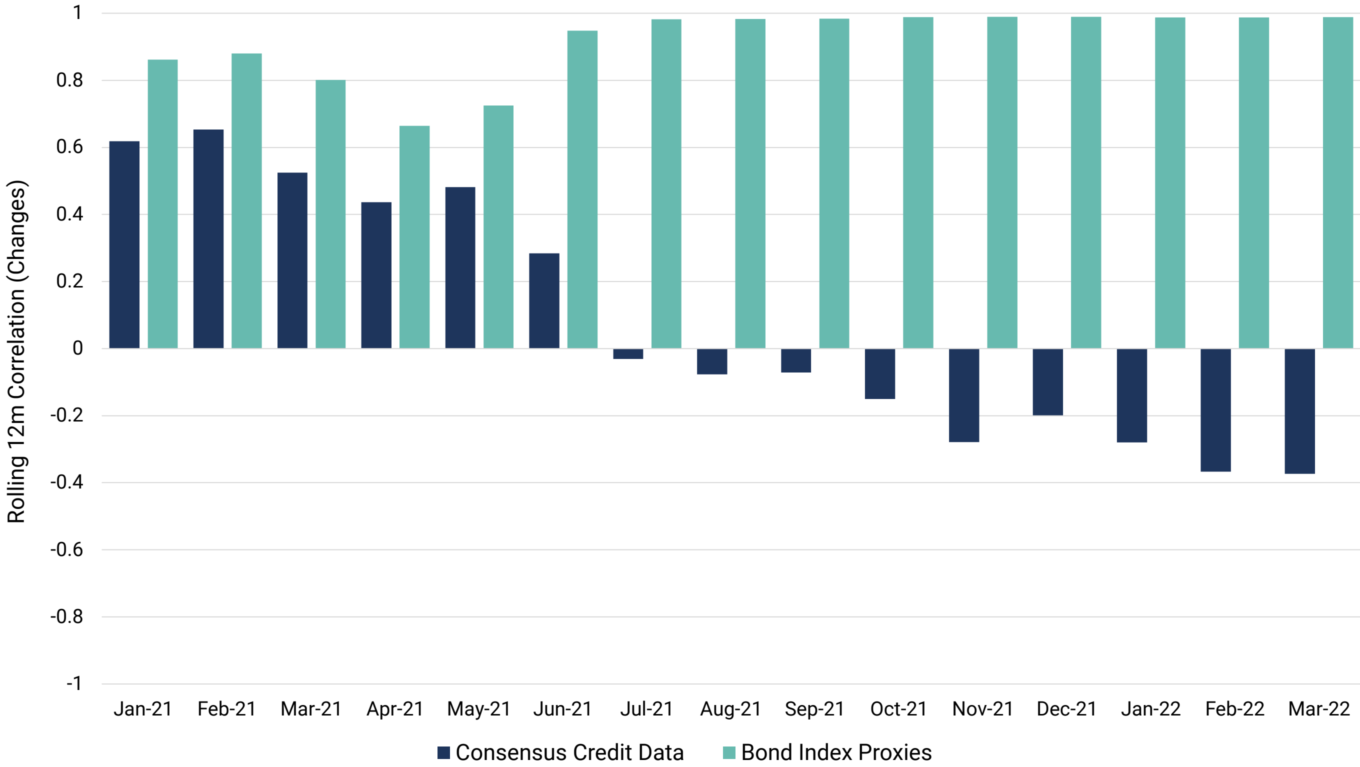
The error bars show the range of estimates using different measures of correlation – PD levels, PD Changes, and the proportion of aggregate constituents in the **b** and **c** credit categories.

US Non-Life, Latin American Corporates and Belgian Corporates are the most diversifying, although some of the error bars for these are wide. Regional and large country corporates are the least diversifying, followed by major US sectors.

Alternative sources of correlation estimates are patchy – CDS indices cover a limited range of names and many of them are illiquid; bond indices are more widely available but restricted to traded bond assets subject to the short-term swings in market sentiment and credit / liquidity risk premiums. Credit Consensus data provides a set of regular and consistent times series including risk estimates for legal entities that are not publicly traded. They are also stable over short periods, while showing trends and turning points over longer time periods.

Figure 2.4 shows rolling 12-month correlation between changes in US and European credit risk in the Healthcare sector, comparing Credit Consensus data aggregates with bond market-based proxies.

Figure 2.4 Rolling 12-month Correlation, US vs Europe Healthcare, Consensus vs Bond Indices



Credit Consensus data shows a much wider range in correlation estimates, dropping from 0.6 at the start of the period to -0.4 at the end. Over the same period, bond market proxies never dipped below 0.6 and were usually close to 1.

3. Portfolio Structures and the Typical CRT Portfolio

The sample portfolios used in this report have been selected to show how risk and return changes as the granularity of the exposures increases. This shows the value of mapping single names to aggregates, even with limited information (e.g. the country of risk is known but the industry / sector is not.)

Figure 3.1 shows allocations for each sample portfolio, with summary risk and return statistics.

Figure 3.1 Sample Portfolio Allocations and Summary Statistics

Max PD Increase 2020	18.74%	18.36%	24.86%	21.34%	30.92%	19.54%	26.87%
% Tails	10.02%	10.23%	14.80%	12.47%	13.64%	11.91%	11.60%
OAS	2.59%	2.58%	2.81%	2.74%	2.78%	2.64%	2.65%
Vol PD (CorrChg)	3.19%	3.11%	4.07%	3.45%	4.20%	3.97%	3.88%
Vol PD (Chg)	3.38%	4.23%	4.20%	3.45%	5.27%	5.74%	5.46%
Unexpected Loss	6.4%	5.4%	7.1%	7.4%	6.0%	5.3%	4.9%
PIT PD	0.83%	0.84%	0.98%	0.99%	1.04%	0.98%	0.94%
PD T=5 CTM	2.19%	2.21%	2.52%	2.57%	2.57%	2.58%	2.36%
TTC PD	0.47%	0.47%	0.55%	0.55%	0.56%	0.55%	0.51%
Aggregate	CRT AA1	CRT AA2	CRT AA3	CRT AA4	CRT AA5	CRT AA6	CRT Super
Africa Corporates		-	-	-	-	10.0%	1.1%
China Corporates		-	-	-	-	5.0%	2.1%
Asia Corporates		-	-	-	-	5.0%	5.7%
France Corporates		8.3%	-	-	-		10.5%
Belgium Corporates		8.3%	-	-	-		0.9%
Germany Corporates		8.3%	-	-	-		4.0%
Italy Corporates		8.3%	-	-	-		2.2%
Netherlands Corporates		8.3%	-	-	-		2.3%
Luxembourg Corporates		8.3%	-	-	-		1.5%
EU Corporates	50.0%	-	-	-	-	15.0%	8.7%
Switzerland Corporates	-	-	-	-	-		1.3%
United Kingdom Corporates		-	-	-	-	10.0%	15.3%
Canada Corporates		-	-	-	-	10.0%	3.2%
Global Multi-utilities		-	-	-	3.8%		2.9%
United States Financial Services		-	-	-	3.8%		1.3%
United States General Retailers		-	-	-	3.8%		3.5%
United States Health Care		-	-	-	3.8%		3.9%
United States Industrial Transportation		-	-	-	3.8%		0.4%
United States Nonlife Insurance		-	-	-	3.8%		0.4%
United States Oil & Gas Producers		-	-	-	3.8%		1.8%
United States Real Estate Investment & Services		-	-	-	3.8%		1.4%
United States Real Estate Investment Trusts		-	-	-	3.8%		5.0%
United States Software & Computer Services		-	-	-	3.8%		1.8%
United States Support Services		-	-	-	3.8%		1.7%
United States Technology Hardware & Equipment		-	-	-	3.8%		0.5%
United States Travel & Leisure		-	-	-	3.8%		2.7%
United States Corporates		-	50.0%	-	-	15.0%	9.0%
Latin America Corporates		-	-	-	-	10.0%	1.2%
Pacific Corporates		-	-	-	-	10.0%	2.3%
Global Corporates	50.0%	50.0%	50.0%	100.0%	50.0%	10.0%	1.3%
	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

CRT Asset Allocation 1 (AA1) is a low-risk mix of 50 / 50 EU and Global Corporates, and AA2 splits the EU exposure by country. AA3 is a 50 / 50 mix of US and Global Corporates, while AA4 is 100% allocated to Global Corporates. AA5 again allocates 50% to the US, but splits this by sector. AA6 is a diverse geographic mix allocated by region. The final portfolio, "CRT Super", is an approximate average of a number of disclosed portfolios – a more sector-detailed version of Figure 1.

Selection risk may be significant for any of these portfolios: aggregates cannot fully represent investor exposures in a particular sector or geography. The key issue is differences in credit behaviour between individual holdings and the typical aggregate constituent.

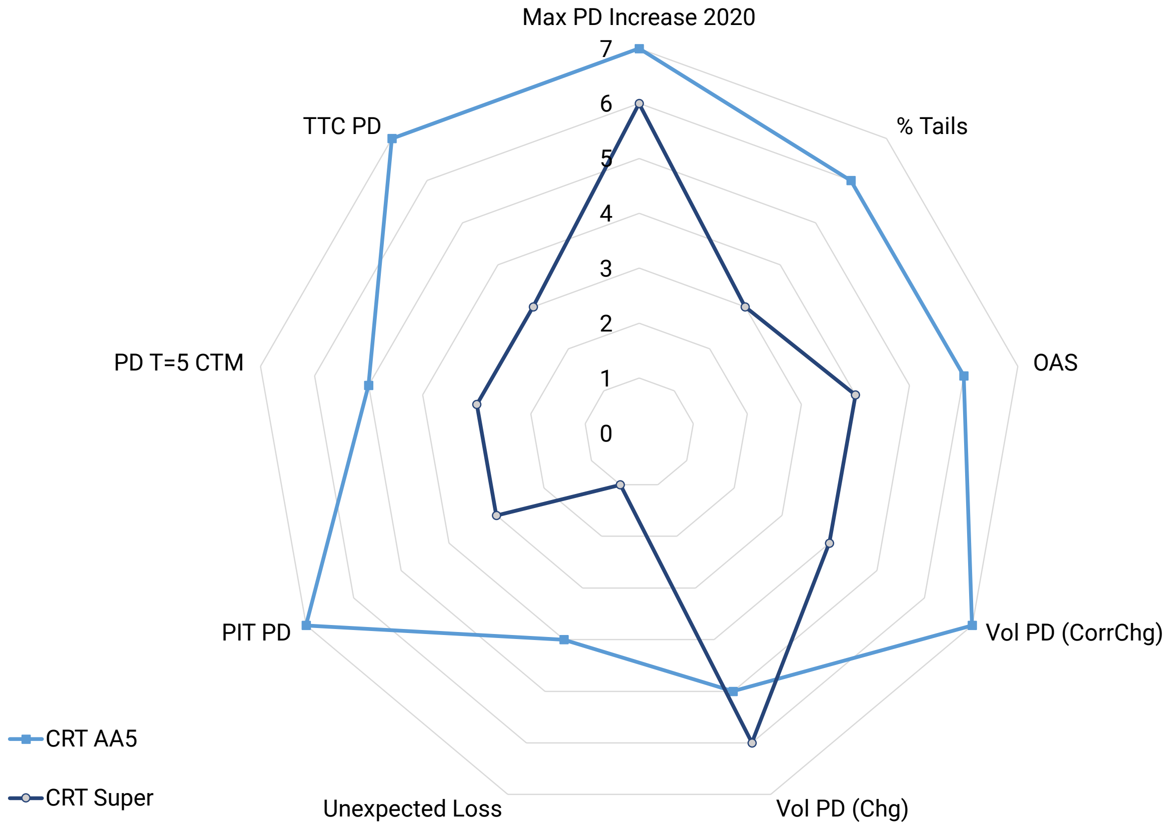
If, for example, investor exposures are all high yield in a specific sub-sector, their transition and PD change characteristics may be very different. This issue can be partly tackled by:

- Introducing "Selection" volatility and adjusting for the number of exposures (the higher the better)
- Adjusting for the % overlap between holdings and constituents (reducing the impact of maverick holdings)
- Modifying selection volatility to reflect the behaviour of the actual exposures

Selection risk is not included in these estimates but example calculations are shown in the Appendix.

Figure 3.2 graphs two of the sample portfolio on a radar chart, with each summary risk metric plotted on a different axis.

Figure 3.2 Radar Graph of Summary Risk Statistics for 2 Portfolios



This shows that – compared with the CRT Super Portfolio, the AA5 is significantly higher risk on all of these metrics except for the Volatility without the Correlation adjustment. Multiple portfolios can be compared in this way.

Glossary of summary statistics reported for each portfolio in Figures 3.1 and 3.2

TTC PD	Exposure weighted 1-year through-the-cycle ex ante probability of default.
PIT PD	Exposure weighted Point-in-Time ex ante probability of default
Vol PD (Chg)	Exposure weighted average of annualized standard deviation of TTC PD monthly changes
OAS	Credit category exposure weighted USD Option Adjusted Spread
PD T=5 CTM	TTC PD after 5th iteration of 1-year transition matrix
Unexpected Loss (UL)	Weighted average of [TTC PD * (1- TTC PD)]^0.5 (ie St.Dev. of Bernoulli distribution)
Vol PD (Corr Chg)	Exposure weighted average of annualized standard deviation of TTC PD monthly changes adjusted by monthly correlations between aggregates
% Tails	Proportion of portfolio in b and c credit categories
Max PD Increase 2020	Change in PD in 2020 if portfolio held current exposures

Case Study: Should Credit Portfolios Be Proxied by Country or by Sector?

The table below shows the summary risk statistics for two portfolios of US Corporate entities. The first maps all single names to the US Corporate aggregate; the second approximates the portfolio with 13 equally-weighted US Sector aggregates.

Risk Metric	US Corporate = 100%	US = 13 Sectors
Max PD Increase 2020	28.4%	40.5%
% Tails	17.1%	14.8%
OAS	2.88%	2.81%
Vol PD (CorrChg)	4.95%	5.26%
Vol PD (Chg)	4.95%	7.08%
Unexpected Loss	7.33%	4.96%
PIT PD	0.96%	1.09%
PD T=5 CTM	2.47%	2.56%
TTC PD	0.54%	0.56%

The 100% US Corporate portfolio has a higher % in the tails and higher implied OAS; but on all other metrics it is lower risk.

*The PD metrics are very close. PD volatility metrics are also similar **but only after adjusting for correlations between sectors.** The 2020 stress period has a much larger impact at the sector level.*

This suggests that country exposures should be split into geographically specific sectors where possible to effectively capture risk extremes.

Figures 3.3 and 3.4 shows the relationship between OAS, PD, Tail Risks and Unexpected Loss for these 7 portfolios.

Figure 3.3 Spreads, Default Risks and Tail Risks for 7 portfolios

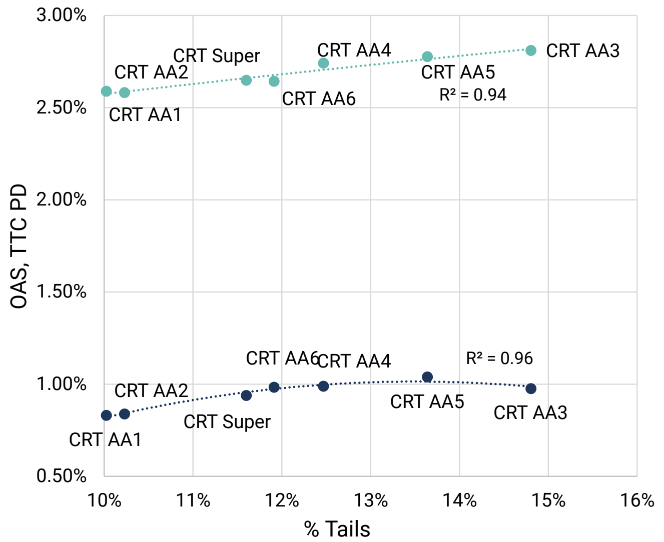
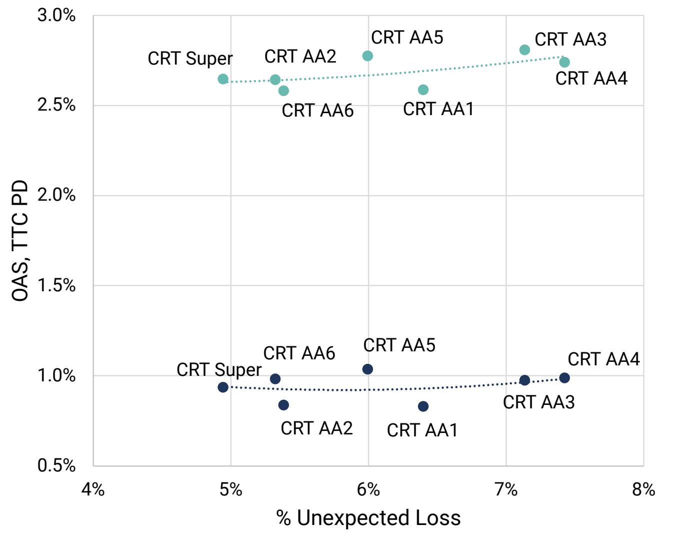


Figure 3.4 Spreads, Default Risks and Unexpected Loss for 7 portfolios



The % of aggregate constituents in the tails (**b** and **c**) are highly correlated with (1) the average PD and (2) the estimated spread.

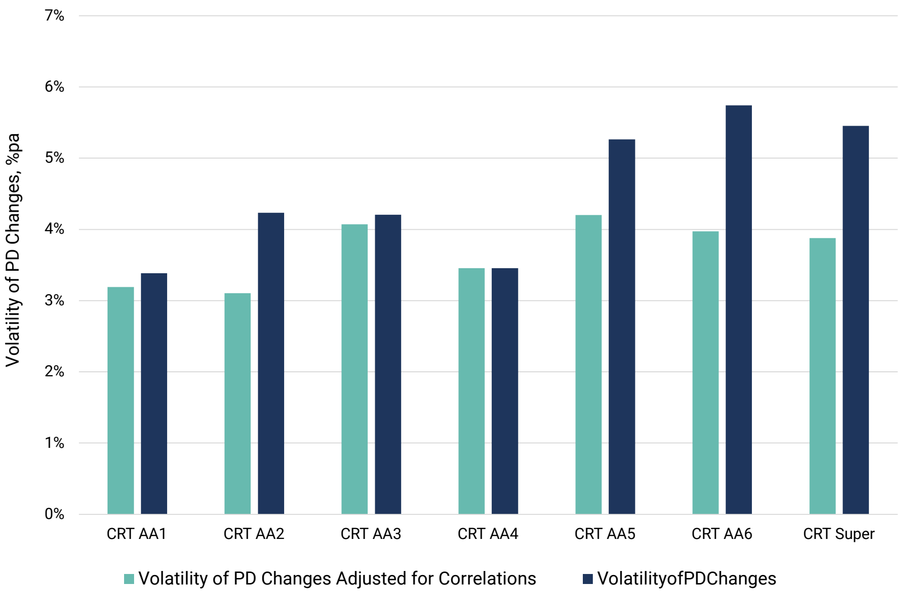
The vertical difference between these two lines is roughly proportional to the combined Credit and Liquidity risk premium, adjusted by recovery rates.

It is worth noting that the Super portfolio is close to the middle of the sample based on % in the tails, but Unexpected Loss adjusted by Correlation makes the Super portfolio lowest risk. This suggests that using PD alone (and deriving Unexpected Loss (UL) from it) may understate the portfolio risk compared with other metrics.

4. Impact of Correlation

Figure 4.1 plots the relationship between the volatility of monthly PD changes over the period 2016-2021 for each of the 7 portfolios. The green bars show the weighted average volatility of the portfolio PD after adjustment for the effect of correlations between changes in aggregate PDs.

Figure 4.1 Relationship Between Volatility of Monthly PD Changes 2016-2021



Apart from AA4, all portfolios show some reduction in PD volatility – marginal for AA3, but significant for AA5, AA6 and the "Super" portfolio.

[AA4 shows no correlation effect since it is represented by 100% exposure to Global Corporates.]

There are clear benefits to diversity and consensus aggregates can be used to quantify these.

Apart from AA4, all portfolios show some reduction in PD volatility – marginal for AA3, but significant for AA5, AA6 and the Super portfolio [AA4 shows no correlation effect, since it is represented by 100% exposure to Global Corporates.]

There are clear benefits to diversity and consensus aggregates can be used to quantify these.

Figure 4.2 shows the correlations between PD changes for the 30 aggregates used in this report. Correlations can also be calculated using Levels, % in Tails, or asymmetric changes (i.e. just the PD increases). These usually give similar but not identical results, and for specific aggregates they may be very different.

Figure 4.2 Correlation between PD Changes

Correlations	Africa Corporates	China Corporates	Asia Corporates	France Corporates	Belgium Corporates	Germany Corporates	Italy Corporates	Netherlands Corporates	Luxembourg Corporates	EU Corporates	Switzerland Corporates	United Kingdom Corporates	Canada Corporates	Global Multi-utilities	United States Financial Services	United States General Retailers	United States Health Care	United States Industrial Transportation	United States Nonlife Insurance	United States Oil & Gas Producers	United States Real Estate Investment & Services	United States Real Estate Investment Trusts	United States Software & Computer Services	United States Support Services	United States Technology Hardware & Equipment	United States Travel & Leisure	United States Corporates	Latin America Corporates	Pacific Corporates	Global Corporates
Africa Corporates	1.00	0.33	0.50	0.42	0.10	0.42	0.21	0.55	0.36	0.56	0.37	0.39	0.43	0.20	0.39	0.56	0.31	0.28	0.18	0.54	0.52	0.51	0.36	0.52	0.25	0.49	0.55	0.08	0.37	0.61
China Corporates	0.33	1.00	0.76	0.27	-0.05	0.38	0.06	0.43	0.36	0.39	0.15	0.35	0.35	0.07	0.42	0.52	0.35	0.44	0.09	0.52	0.42	0.36	0.30	0.40	0.34	0.50	0.58	0.13	0.07	0.57
Asia Corporates	0.50	0.76	1.00	0.40	0.10	0.53	0.21	0.63	0.49	0.65	0.39	0.47	0.45	0.29	0.53	0.64	0.38	0.46	0.21	0.69	0.56	0.57	0.44	0.53	0.39	0.67	0.73	0.21	0.28	0.77
France Corporates	0.42	0.27	0.40	1.00	0.21	0.55	0.19	0.43	0.35	0.69	0.39	0.34	0.60	0.21	0.43	0.49	0.41	0.35	-0.02	0.50	0.53	0.54	0.42	0.39	0.15	0.45	0.59	0.21	0.50	0.60
Belgium Corporates	0.10	-0.05	0.10	0.21	1.00	0.13	0.27	0.14	0.15	0.27	0.28	0.09	0.13	0.13	0.15	0.05	0.16	-0.15	0.09	0.08	0.03	0.11	0.10	0.06	0.13	-0.03	0.06	0.04	0.12	0.14
Germany Corporates	0.42	0.38	0.53	0.55	0.13	1.00	0.19	0.52	0.54	0.74	0.49	0.25	0.62	0.21	0.46	0.70	0.52	0.48	0.06	0.71	0.62	0.61	0.44	0.46	0.38	0.57	0.77	0.22	0.60	0.65
Italy Corporates	0.21	0.06	0.21	0.19	0.27	0.19	1.00	0.18	0.29	0.53	0.23	0.07	0.12	0.34	0.04	0.10	-0.03	0.08	0.09	0.25	0.27	0.22	0.06	0.14	-0.04	0.25	0.17	0.15	0.06	0.22
Netherlands Corporates	0.55	0.43	0.63	0.43	0.14	0.52	0.18	1.00	0.37	0.75	0.39	0.43	0.44	0.30	0.44	0.69	0.45	0.48	0.27	0.56	0.40	0.44	0.37	0.52	0.33	0.51	0.67	0.23	0.28	0.69
Luxembourg Corporates	0.36	0.36	0.49	0.35	0.15	0.54	0.29	0.37	1.00	0.61	0.52	0.19	0.66	0.39	0.37	0.48	0.25	0.44	0.09	0.67	0.59	0.59	0.20	0.39	0.40	0.52	0.66	0.19	0.21	0.56
EU Corporates	0.56	0.39	0.65	0.69	0.27	0.74	0.53	0.75	0.61	1.00	0.54	0.40	0.61	0.41	0.50	0.69	0.41	0.50	0.16	0.71	0.67	0.67	0.52	0.53	0.27	0.67	0.79	0.31	0.49	0.78
Switzerland Corporates	0.37	0.15	0.39	0.39	0.28	0.49	0.23	0.39	0.52	0.54	1.00	0.29	0.46	0.34	0.30	0.58	0.30	0.21	0.15	0.50	0.45	0.56	0.41	0.42	0.34	0.45	0.56	0.12	0.38	0.54
United Kingdom Corporates	0.39	0.35	0.47	0.34	0.09	0.25	0.07	0.43	0.19	0.40	0.29	1.00	0.42	0.43	0.38	0.48	0.31	0.26	0.24	0.40	0.32	0.38	0.37	0.34	0.16	0.35	0.46	0.20	0.25	0.79
Canada Corporates	0.43	0.35	0.45	0.60	0.13	0.62	0.12	0.44	0.66	0.61	0.46	0.42	1.00	0.42	0.65	0.67	0.55	0.39	0.27	0.69	0.71	0.61	0.49	0.45	0.40	0.45	0.77	0.12	0.58	0.73
Global Multi-utilities	0.20	0.07	0.29	0.21	0.13	0.21	0.34	0.30	0.39	0.41	0.34	0.43	0.42	1.00	0.25	0.30	0.23	0.30	0.28	0.35	0.39	0.26	0.19	0.13	0.15	0.14	0.34	0.20	0.17	0.47
United States Financial Services	0.39	0.42	0.53	0.43	0.15	0.46	0.04	0.44	0.37	0.50	0.30	0.38	0.65	0.25	1.00	0.61	0.48	0.33	0.42	0.58	0.48	0.54	0.52	0.51	0.36	0.50	0.70	0.08	0.41	0.63
United States General Retailers	0.56	0.52	0.64	0.49	0.05	0.70	0.10	0.69	0.48	0.69	0.58	0.48	0.67	0.30	0.61	1.00	0.59	0.51	0.20	0.72	0.69	0.66	0.53	0.63	0.47	0.69	0.89	0.20	0.53	0.81
United States Health Care	0.31	0.35	0.38	0.41	0.16	0.52	-0.03	0.45	0.25	0.41	0.30	0.31	0.55	0.23	0.48	0.59	1.00	0.36	0.18	0.42	0.43	0.42	0.42	0.40	0.38	0.43	0.61	0.10	0.56	0.54
United States Industrial Transpo	0.28	0.44	0.46	0.35	-0.15	0.48	0.08	0.48	0.44	0.50	0.21	0.26	0.39	0.30	0.33	0.51	0.36	1.00	-0.09	0.53	0.41	0.53	0.26	0.36	0.19	0.62	0.66	0.21	0.24	0.52
United States Nonlife Insurance	0.18	0.09	0.21	-0.02	0.09	0.06	0.09	0.27	0.09	0.16	0.15	0.24	0.27	0.28	0.42	0.20	0.18	-0.09	1.00	0.14	0.13	0.02	0.30	0.17	0.34	0.04	0.22	0.13	0.09	0.29
United States Oil & Gas Produce	0.54	0.52	0.69	0.50	0.08	0.71	0.25	0.56	0.67	0.71	0.50	0.40	0.69	0.35	0.58	0.72	0.42	0.53	0.14	1.00	0.69	0.72	0.41	0.48	0.38	0.73	0.89	0.22	0.47	0.78
United States Real Estate Investi	0.52	0.42	0.56	0.53	0.03	0.62	0.27	0.40	0.59	0.67	0.45	0.32	0.71	0.39	0.48	0.69	0.43	0.41	0.13	0.69	1.00	0.67	0.47	0.49	0.30	0.64	0.75	0.09	0.49	0.68
United States Real Estate Investi	0.51	0.36	0.57	0.54	0.11	0.61	0.22	0.44	0.59	0.67	0.56	0.38	0.61	0.26	0.54	0.66	0.42	0.53	0.02	0.72	0.67	1.00	0.34	0.49	0.28	0.82	0.78	0.06	0.44	0.69
United States Software & Compu	0.36	0.30	0.44	0.42	0.10	0.44	0.06	0.37	0.20	0.52	0.41	0.37	0.49	0.19	0.52	0.53	0.42	0.26	0.30	0.41	0.47	0.34	1.00	0.53	0.24	0.39	0.59	0.09	0.58	0.58
United States Support Services	0.52	0.40	0.53	0.39	0.06	0.46	0.14	0.52	0.39	0.53	0.42	0.34	0.45	0.13	0.51	0.63	0.40	0.36	0.17	0.48	0.49	0.49	0.53	1.00	0.42	0.58	0.66	0.07	0.41	0.59
United States Technology Hardv	0.25	0.34	0.39	0.15	0.13	0.38	-0.04	0.33	0.40	0.27	0.34	0.16	0.40	0.15	0.36	0.47	0.38	0.19	0.34	0.38	0.30	0.28	0.24	0.42	1.00	0.27	0.50	-0.03	0.24	0.39
United States Travel & Leisure	0.49	0.50	0.67	0.45	-0.03	0.57	0.25	0.51	0.52	0.67	0.45	0.35	0.45	0.14	0.50	0.69	0.43	0.62	0.04	0.73	0.64	0.82	0.39	0.58	0.27	1.00	0.81	0.11	0.43	0.68
United States Corporates	0.55	0.58	0.73	0.59	0.06	0.77	0.17	0.67	0.66	0.79	0.56	0.46	0.77	0.34	0.70	0.89	0.61	0.66	0.22	0.89	0.75	0.78	0.59	0.66	0.50	0.81	1.00	0.23	0.56	0.87
Latin America Corporates	0.08	0.13	0.21	0.21	0.04	0.22	0.15	0.23	0.19	0.31	0.12	0.20	0.12	0.20	0.08	0.20	0.10	0.21	0.13	0.22	0.09	0.06	0.09	0.07	-0.03	0.11	0.23	1.00	0.19	0.36
Pacific Corporates	0.37	0.07	0.28	0.50	0.12	0.60	0.06	0.28	0.21	0.49	0.38	0.25	0.58	0.17	0.41	0.53	0.56	0.24	0.09	0.47	0.49	0.44	0.58	0.41	0.24	0.43	0.56	0.19	1.00	0.52
Global Corporates	0.61	0.57	0.77	0.60	0.14	0.65	0.22	0.69	0.56	0.78	0.54	0.79	0.73	0.47	0.63	0.81	0.54	0.52	0.29	0.78	0.68	0.69	0.58	0.59	0.39	0.68	0.87	0.36	0.52	1.00

Extension to Tranche Correlations

Correlations between tranches can be estimated from the aggregates correlation matrix and the credit distributions of those aggregates.

If tranches are defined as Senior (**aaa**/**aa**/**a**), Senior Mezzanine (**bbb**), Junior Mezzanine (**bb**/**b**) and First Default (**c**), then a universe of aggregates can be used to proxy the correlations between tranches for a given underlying portfolio.

This first approximation can be refined by using the full universe of Credit Consensus aggregates to give more granularity, and by experimentation with the impact of defining the tranche boundaries – for example across 7 credit categories instead of three or four. See Appendix 8.1 for a description of the full universe of 800+ Credit Consensus aggregates.

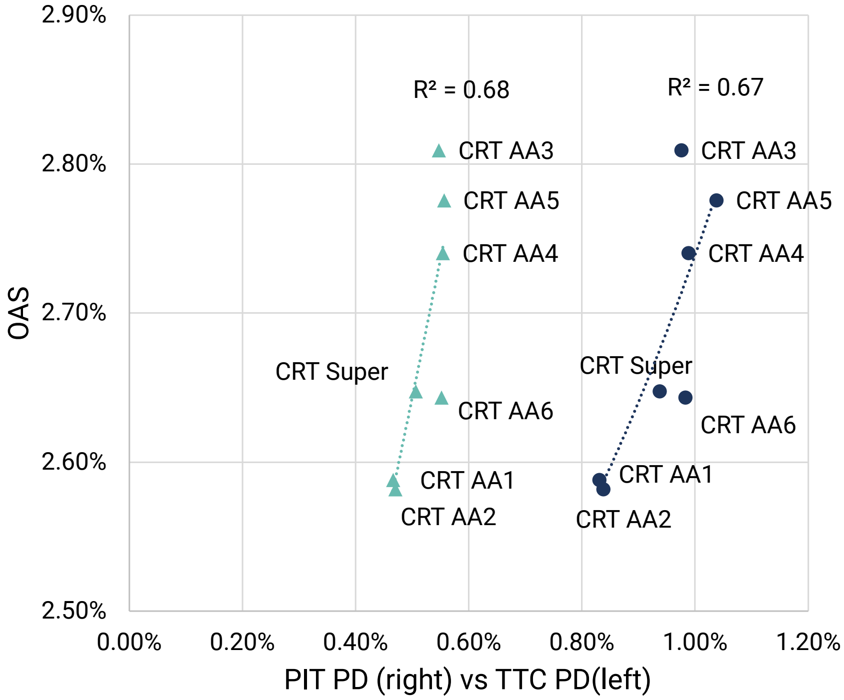
For example, a number of emerging market aggregates (African Sovereigns, Turkish Banks) as well as sectors badly hit by COVID (US Travel & Leisure) have 10% - 20% of their constituents in the **c** category; while EU Sovereigns, North American Health Care and many developed market financials (including some Pension Fund aggregates) have very high proportions in the **aa** category.

5. Impact of Point-in-Time Adjustments

In banks and non-banks, Point-in-Time (PIT) credit risk models have been developed to address the need for impairment calculations under IFRS9 / CECL. These estimates complement the main Credit Consensus dataset, with stress test metrics showing how default risk changes in a downturn. These can be used to further differentiate and accurately price risk sharing portfolios.

Figure 5.1 shows the impact of PIT adjustments, specifically based on the period of credit stress at the start of the 2020 pandemic. These adjustments vary by industry and have been cascaded to the relevant sectors for each portfolio.

Figure 5.1 Impact of PIT Stress Scenario Adjustments on Through-The-Cycle (TTC) Risk Estimates



For a given level of OAS, each portfolio is shifted to the right as the PD is scaled up under the stress scenario. The correlations between OAS and PD remain almost unchanged for both metrics.

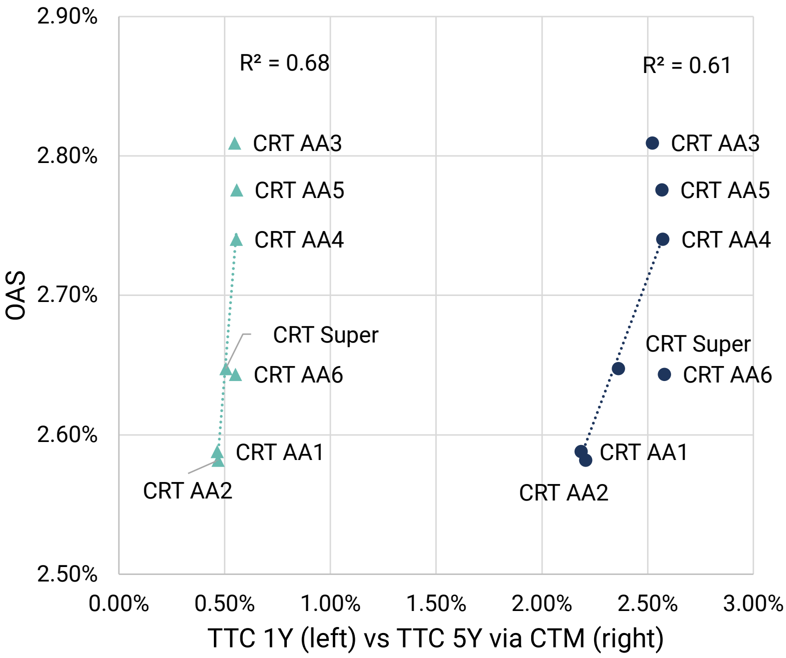
However, risk for the higher return portfolios more than doubles while risk for the lower return shows a smaller increase. The greater impact of the PIT PDs for higher return portfolios is intuitive since their exposures bring higher tail risk.

6. Impact of Transition Adjustments

The impact of rising defaults can be measured using credit transition matrices – using Credit Consensus data these can be updated monthly, supporting decisions between long term and short-term holding strategies for specific groups of loans.

Figure 6.1 shows the impact of applying typical multi-year transitions to the 1-year PDs.

Figure 6.1 Impact of 5-year CTM Adjustments on PD Estimates



As before, for a given level of OAS, each portfolio is shifted to the right as the PD is scaled up; in this case the increase is the result of repeated transformations using a 7x7 credit transition matrix.

The correlations between OAS and PD are similar but lower in the 5-year case. The AA6 portfolio shows the proportionately highest increase in risk, while the highest return (AA3) and (especially) the lowest (AA2) show lower proportionate increases. This is due to the transition matrix effect, which pulls risky entities from both ends of the credit distribution into the center. However, the most risky portfolios increase by a factor of about 5x, while the least risky increase by about 4.5x.

7. Conclusion

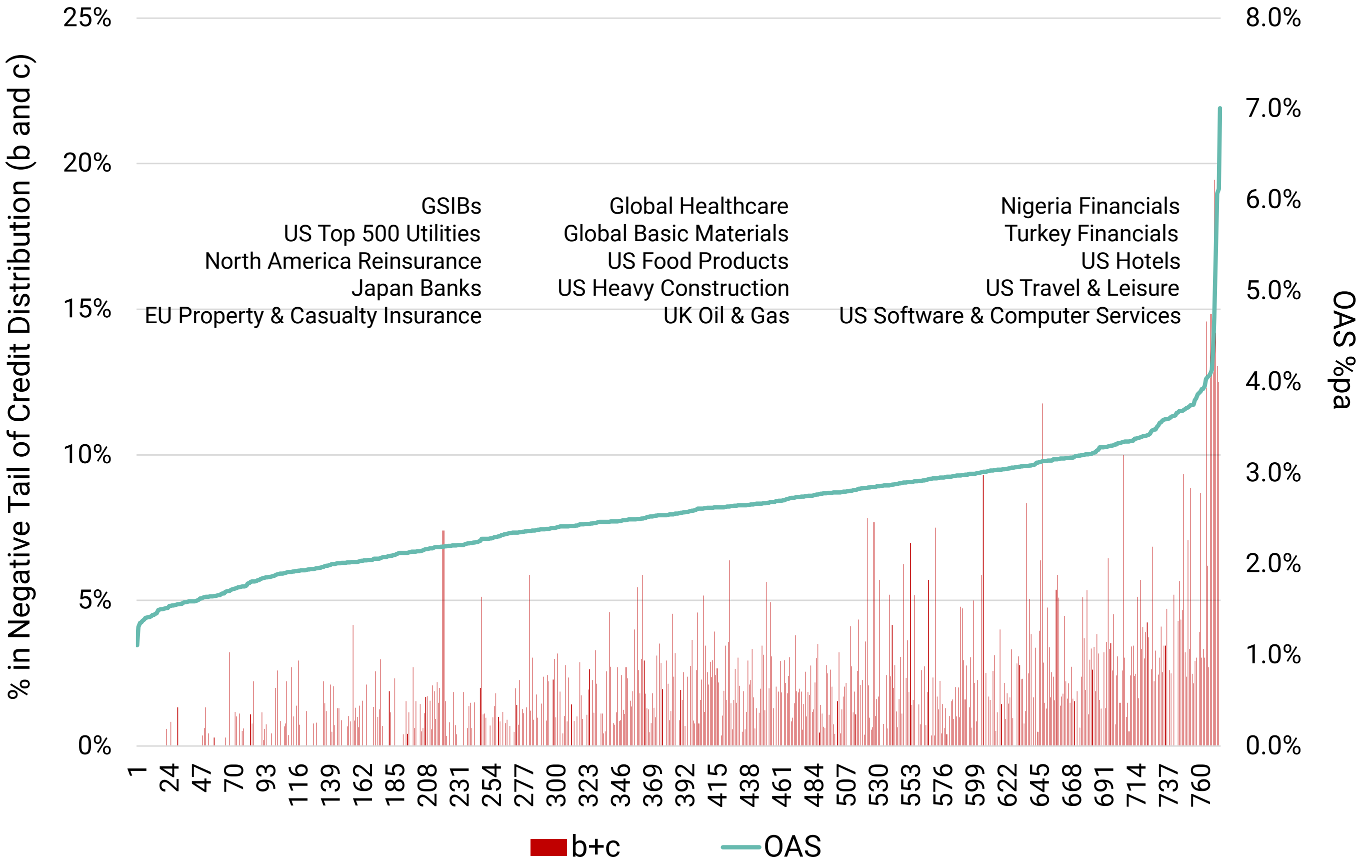
- Credit Consensus aggregates provide a detailed map of the credit market risk-reward landscape, including possible anomalies.
- Credit Consensus aggregates offer a framework and calibration for credit portfolio modelling which allows CRT investors to include the impact of undisclosed or partially disclosed portfolios by making assumptions about geographic and / or sector exposures.
- US Corporate bond spreads are closely correlated with aggregate average PDs and tail risk (% in **b** and **c** credit categories)
- US Non-Life, Latin American Corporates and Belgian Corporates are the most diversifying aggregates. Regional and large country corporates are the least diversifying, followed by major US sectors. See Appendix for a return and risk chart for all (800+) aggregates.
- Correlations between aggregates reduce measured portfolio risk in some cases by more than 20%.
- PIT adjustments approximately double the TTC default risk; the adjustment is larger for some higher risk portfolios.
- Long term transition effects increase risk by up to 5x, less for lower risk portfolios.
- NB: Credit Consensus data users can apply their own industry and sector classifications to the large universe of single names to match specific transaction types.

8. Appendices

A.1 The Consensus Aggregate Universe

Figure 8.1 compares proxy measures of risk and return for a large set of consensus credit aggregates. OAS is used for return, and Tail Risk (the proportion of each aggregate in **b** and **c** credit categories) for risk. It also shows typical aggregates from the lower, middle and upper end of the risk spectrum.

Figure A.1 Spreads vs Risk Tails (% Of Each Aggregate in b and c Credit Categories – All 800+ Aggregates



Most risky and highest yield geographic sectors include Nigerian Financials and US Travel & Leisure. Least risky and lowest yield geographic sectors include Globally Systemically Important Banks (GSIBs) and Large US Utilities

At both extremes of the distribution, there is a clear positive relationship between tail risk and OAS, but the overall correlation between these two series is low; in other words, **tail risk** is only one of various determinants of OAS.

A.2 Allocation and Selection Risk Calculations

Allocation Risk: For basic risk metrics such as PD Volatility, or Unexpected Loss, the “Allocation” portfolio risk estimate adjusting for correlation is given by:

$$Correlation\ Adjusted\ Risk = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} w_i\, w_j \sigma_i \sigma_j \rho_{ij}}$$

Where n is the number of aggregates with portfolio exposure, w_i is the portfolio weight in aggregate i, σ_i is the measure of risk for aggregate i, and r_{ij} is the assumed or measured correlation between aggregates i and j.

This assumes negligible Selection risk – i.e. the aggregate is assumed to be a close proxy for the portfolio exposures in the relevant geography / industry.

Selection Risk: If the portfolio holdings are materially different from the constituents of the aggregate, then one approach is to assume that the aggregate represents the main credit factor, and that selection risk is the exposure weighted sum of single name residual risks. Residual risk combines the effect of factor exposures (the single name credit beta effect) and single-name specific risks, which are assumed to be independent.

A range of models are possible but one convenient, robust proxy assumes that if typical annual volatility of PD Changes (in excess of aggregate volatility and any other common influences) for a single name is σ, and the portfolio has n equally weighted exposures, then selection risk can be approximated by $\sigma / \sqrt{n}$.

Overlapping names in the portfolio and the aggregate, can be handled by the “number of names equivalent” (=n*). n* is calculated as the reciprocal of the sum of squared differences between portfolio holding weights and aggregate constituent weights (A version of the Herfindahl index). Similar calculations can be used for uneven weights.

Selection risk depends on the number of names in the portfolio and their weightings, the number in the aggregate and their weightings, the overlap between them, and the typical level of excess PD volatility for an individual name in this sector.

This gives some insight into the issue of undisclosed portfolios, unmapped names, or portfolio credit distributions that do not align with the credit distribution of the aggregate. Provided the geography / sector exposures of the undisclosed portfolio are known, the allocation risk used in this report will give an initial risk estimate; and unless the aggregate and/or the portfolio are very concentrated, the selection risk will be second order. And if the portfolio is concentrated in an unusual sub-sector, it is possible to make some assumptions and adjustments to give a realistic estimate of total portfolio risk.

A.3 Marginal Contributions to Risk

A Marginal Contributions to Risk matrix can be constructed from the correlations, volatilities and portfolio exposures presented here. This can show, for example the impact of switching 1% of exposure from one geography or sector to another. It can also form the basis of an optimization algorithm. More details and examples are available on request.

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Risk professionals at banks, insurance companies, asset managers and other firms use the data to gain visibility on entities without a public rating, inform risk sharing transactions (CRT / SRT), monitor and be alerted to changes within the portfolio, benchmark, assess and analyze trends, and fulfil regulatory requirements and capital.

The data is available via the Credit Benchmark Web App, Excel add-in, flat file download, and **third-party platforms including Bloomberg.** High level credit assessments on the single name constituents of the sectors mentioned in this report can be accessed on CRPR <GO> or via CRDT <GO>.

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- The Financial Counterpart Monitor provides a unique analysis of the changing creditworthiness of financial institutions. The report, which covers banks, intermediaries, buy-side managers, and buy-side owners, summarizes the changes in credit consensus of each group as well as their current credit distribution and count of entities that have migrated from Investment Grade to High Yield.

- The Industry Monitor shows the changing creditworthiness of a selection of industries and sectors. The report shows the number of entities per category with a Credit Consensus Rating, their month-on-month changes in credit distribution, and their transitioning credit quality.

- Credit Consensus Indicators (CCIs). The CCI is an index of forward-looking credit opinions for US, UK and EU Industrials. The CCI tracks the total number of upgrades and downgrades made each month by credit analysts to chart the long-term trend in analyst sentiment for Industrials.

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