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RISK CONTROL

Client Report

Quantifying Preferred Creditor Treatment by Rating Grade

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Executive Summary

The business models of Multilateral Development Banks (MDBs) depend crucially on Preferred Creditor Treatment (PCT). PCT refers to the de facto seniority that financially distressed sovereigns accord to MDBs from which they have borrowed.

In an earlier paper, Risk Control (2022), we showed, in a matched sample, that the Probability of Default (PD) of MDB sovereign loans is substantially less than those of the very same countries' international bond issues or loans from commercial banks.

This paper extends that analysis by estimating PDs for MDB sovereign loans conditional on ratings. Our results are consistent with those of the earlier paper but show, in addition, that PCT is especially strong for low rated sovereigns. These latter contribute most of MDBs' balance sheet risk.

Using the Basel Internal Ratings Based Approach (IRBA) capital formula, we show that, for loans to countries with ratings in the range crucial for MDBs of single B and CCC, PCT implies a reduction in Risk Weights (RWs) by a factor of 10 times. This may be compared with the reduction in RWs for PCT employed by Standard & Poor's and Fitch which is by a factor of approximately 2 times.

1. Introduction

Preferred Creditor Treatment (PCT) is a key feature of international development finance. Indeed, it may be said to be crucial to the business models of multilaterals lenders including Multilateral Development Banks (MDBs) and the International Monetary Fund (IMF). Because sovereign insolvencies occur outside the legal framework provided bankruptcy law, sovereigns may choose whether to continue servicing the debt of certain institutions even while they default on what they owe to other lenders. In this, they are not subject to the 'common pool' principle that underlies typical bankruptcy codes whereby the assets of a defaulted entity are placed in a pool and debtors are paid successively based on their contractual seniority.

Historical experience shows that sovereigns choose to continue servicing loans from multilateral lenders, in many cases long after they default on private sector debt or bilateral sovereign loans. Furthermore, if sovereigns do default even to multilateral lenders, when they ultimately return to the debt markets, no haircut is typically applied the unpaid interest and principal of multilateral debtors. This de facto seniority of multilateral loans, both in the timing of default and in the Loss Given Default (LGD) if insolvency occurs, not recognised explicitly in debt contracts, is the widely discussed phenomenon of PCT.

The importance of PCT is that it permits highly rated MDBs to follow the business model of issuing bonds at narrow spreads in international debt markets, lending to sovereigns at spreads much lower than these sovereigns could obtain directly in debt markets, and then to experience few defaults with minor LGD rates. Why sovereigns exert themselves so much to repay debt to multilateral lenders is discussed in Perraudin, Powell and Yang (2016), Perraudin and Yang (2018) and Cordella and Powell (2021). The motivation partly reflects the mutual nature of multilateral lenders in that many MDBs have strong borrower country representation among their shareholders (see Perraudin and Yang (2018)). Another factor is the willingness of MDBs and the IMF to 'lend into crises', continuing to finance Emerging Market and Developing Economies (EMDEs) even when other sources of finance have dried up. Hence, they are viewed by EMDEs as lenders of last resort.

PCT is widely recognised by the debt market when it price bonds issued by MDBs. Thus, the rating agencies, that act as gatekeepers for the international bond markets, allow for PCT when they assign ratings to MDBs. Specifically, Standard & Poor's employs PCT-adjusted Risk Weights (RWs) when it calculates the Risk Weighted Asset (RWA) denominator to the Risk Adjusted Capital (RAC) ratio. This latter ratio forms the centrepiece of the agency's capital adequacy assessment of MDBs. The Standard & Poor's RWs remain a black box in that they are not inferred in a clear way from PDs and LGDs (as are, for example, the Internal Ratings Based (IRB) RWs employed in the Basel III framework for commercial banks). In a comparable way, Fitch, in calculating its usable equity to assets ratio, notches up the ratings of MDB sovereign exposures which are subject to PCT and, thus, implicitly adopts modified RWs to reflect PCT.

An earlier study by Risk Control, Risk Control (2022), provides a quantification of the magnitude of PCT. The approach taken by that study is to collect a dataset consisting of 'year-sovereign' observations in which the sovereign in question has borrowed both from the international debt markets (through either bonds or bank loans) and from MDBs. The fractions of occasions in which a default has occurred after a year for the different forms of debt (MDB loan, bond or bank loan) are computed. The results suggest that, for the matched samples in question, sovereign 1-year PDs on MDB loans are 3.6 times smaller than those on international bonds.

Risk Control (2022) also calibrates sovereign MDB loan LGDs. Major MDBs have almost never written off sovereign loans. The economic cost to them of a sovereign default tends to be the lost 'interest on the interest' in that while they have almost aways had full repayment of arrears in interest and principal, the accrued interest that should be paid on deferred interest is not made good. The percentage LGD arising from unpaid interest on interest depends on the prevailing level of interest rates. But a reasonably conservative value might be taken to be in the range 5% to 10%. The latter is again between 3 and 4 times smaller than historical experience suggest for sovereign bond market LGDs.

The aim of the current paper is to build on Risk Control (2022) in adducing estimates of PDs for MDB sovereign loans *conditional on ratings*. The reasons why this is important are:

(a) Typical MDB portfolios have substantial exposure to single B and CCC sovereigns. The ratio of PCT-adjusted and sovereign bond market PDs in this range is, therefore, highly material to understanding the implications of the phenomenon.

(b) Rating agency adjustments for PCT vary considerably across ratings. For example, in the Standard & Poor's RACF, the ratio of RWs without and with PCT for sovereign exposures, are 6.33 for BBB- and 2.21 for B-. One may wish to understand whether the agencies are correct in their calibration.
(c) Rating-specific PDs are important inputs to many practical risk management calculations including provisioning, risk-based pricing and Economic Capital (EC) computation.

Past studies of PCT include the following.

- Of theoretical studies, Boz (2009) examines the dynamics of lending to sovereigns by multilateral lenders. They analyse the timing of sovereign defaults to private sector debtors and how such sovereigns decide to split borrowing between multilaterals and the private sector. Cordella and Powell (2021) analyse PCT within a game theoretic model of sovereign lending by MDBs and private sector lenders. They show that if the MDB can commit to "lend limited amounts at close to the risk-free rate under most circumstances, and [..] refrain from lending until any unpaid arrears are cleared" then MDBs are always repaid and add value.[1]

- Of empirical studies of PCT, Perraudin and Yang (2018) discuss what motivates sovereigns in according PCT to multilateral lenders and whether this might be affected if MDBs engage in risk transfer. They discuss the PD and LGD-based quantification of PCT. This is updated and made more rigorous in Risk Control (2022) which employs matched-sample analysis of MDB loan, public bond and bank loan performance for sovereign debt. Schlegl, Trebesch and Wright (2019) examine the de facto seniority of different forms of public debt (both sovereign-guaranteed and non-sovereign-guaranteed public debt) held by multilaterals, bilateral lenders, and private sector). They focus on the volume of arrears (rather than 1-year default frequencies or probabilities of default like the present study) and the fractional loss in the event of a restructuring (i.e., LGD). In any case, borrowers may be in arrears without defaulting by most definitions of default. They find that the ratio of arrears debt is lowest for multilaterals, and highest for bilateral lenders with debt to private sector being in between.

- Of studies of PCT focussed on ratings, Perraudin, Powell and Yang (2016) compares the allowance made for PCT by Standard & Poor's in its RAC ratio with what one obtains by application of a Credit Portfolio Model (CPM) in a calculation of EC. Kotecha (2019) surveys how rating agencies allow for PCT.

Finally, note that, while it is not relevant to the current study, loans by MDBs to non-sovereigns may also enjoy preferred status to a limited degree in that they are not subject to convertibility restrictions. This point is explored in Vuylsteke (1995).

The remainder of this study is organised as follows. Section 2 describes the data employed. The data include 'non-accrual' observations, outstanding balance, and historical sovereign ratings. 'In non-accrual' is the term applied by MDBs when a sovereign debt is in default. Section 3 sets out the methodology we employ. Section 4 summarises the estimation results. Section 5 concludes.

2. Data

2.1 Non-accrual data

The non-accrual data is collected from the financial statements of the following four MDBs:

1. Asian Development Bank (ADB)
2. African Development Bank (AfDB)
3. Inter-American Development Bank (IDB)
4. International Bank for Reconstruction and Development (IBRD)

For these four banks, a sovereign is placed in non-accrual status when the principal, interest or other charges are overdue to the MDB by more than 180 days (i.e., six months). This definition underlines an important

[1] Similarly, in a less formal analysis, Schadler (2014) argues, in the case of the IMF, that PCT is only sustainable if the Fund lends money strictly in line with its mandate, i.e., to "lend only in conditions when the underlying policy program (including upfront debt restructuring when necessary) is expected to restore stability and a sustainable debt burden." She argues that this was not true in the case of the IMF's lending to Greece during the European sovereign debt crisis.

difference between the present report and such studies as Schlegl, Trebesch, and Wright (2019) and Fitch (2024) which analyse the volume of arrears. Much of the arrears on which they focus would not be treated as a non-accrual event by the MDBs we study here.

The non-accrual status of the sovereigns from these regional banks is for the period 1988-2022 (35 years). We generate a list of borrowing countries from each MDB and then merge it to generate a master list[2]. For the three MDBs (ADB, AfDB and IDB), the non-accrual data is extracted from both the Ordinary Capital Resources (OCR) accounts and the Special Funds accounts. The banks use their OCR account for non-concessional lending operations and the Special Funds account for concessional lending to the poorest Developing Member Countries (DMCs). For the IBRD, we focus only on its main account, as concessional lending by the World Bank Group, is performed by the IBRD's sister organisation, the International Development Association (IDA).

ADB has employed the following three Special Funds since 1988[3] (i) Asian Development Fund (ADF), (ii) Technical Assistance Special Fund (TASF) and (iii) Japan Special Fund (JSF). In 2017, ADF's concessional lending operations were merged with the Bank's OCR account and ADF's remaining role is only to provide grants. Hence, from 2017 onwards, we only extract non-accrual observations from the OCR.

Table 2.1: Non-accrual Sovereigns

Creditor Institution	Country	First non-accrual year	Creditor Institution	Country	First non-accrual year
ADB	Afghanistan	1993, 2022	AfDB	Angola	1997
ADB	Cambodia	1990	AfDB	Burundi	2000
ADB	Marshall Islands	2006	AfDB	Central African Republic	1997
ADB	Micronesia	2009	AfDB	Chad	2000
ADB	Myanmar	1998	AfDB	Comoros	1997
ADB	Nauru	2001	AfDB	Côte d'Ivoire	2000, 2003
ADB	Solomon Islands	1995, 2002	AfDB	Democratic Republic of the Congo	1997
ADB	Vietnam	1990	AfDB	Djibouti	1997, 2002, 2005
IADB	Haiti	2002	AfDB	Gabon	1998, 2003
IADB	Honduras	1989	AfDB	Guinea	1998, 2000
IADB	Nicaragua	1988	AfDB	Guinea-Bissau	1999
IADB	Panama	1988	AfDB	Liberia	1997
IADB	Peru	1989	AfDB	Niger	1999
IADB	Suriname	1993, 2000	AfDB	Republic of Congo	1997
IADB	Venezuela	2018	AfDB	Seychelles	2000
IBRD	Bosnia and Herzegovina	1993	AfDB	Sierra Leone	1997
IBRD	Iraq	1991	AfDB	Somalia	1997
IBRD	Montenegro	1994	AfDB	Sudan	1997
IBRD	North Macedonia	1993	AfDB	Togo	1999
IBRD	Serbia	1994	AfDB	Zimbabwe	2000
IBRD	Syria	1988			

AfDB operated with the following two special funds after 1988 (i) African Development Fund (AfDF) and (ii) Nigeria Trust Fund (NTF). We extract non-accrual event data from the OCR account and the two Special Funds' accounts for the whole period 1988 to 2022.

IDB had the following three special funds with detailed financial statements in 1988: (i) Fund for Special Operations (FSO), (ii) Social Progress Trust Fund and (iii) Venezuela Trust Fund. In 2000, the Venezuela Trust terminated as it reached the maturity of the fund agreement. In 2001, publication in IDB's annual reports of the financial statements of the Social Progress Trust Fund were discontinued. In 2017, IDB merged its FSO account with the OCR account, following the call from the G20 for MDBs to optimise their balance sheets (see G20 (2015)).

[2] When a sovereign borrows from both the regional MDB and IBRD, we remove borrowing country's entry in the master list from IBRD to avoid double counting.
[3] In 2022, ADB has eight fund accounts including the three accounts observed in 1988. The non-accrual data is only taken from the OCR account from 2017.

Our non-accruals data has the dimensions of countries and years. Non-accrual status is indicated by '1' if the sovereign is in non-accrual status according to the financial statement of the year in question and otherwise equals '0'. Table 2.1 lists those sovereigns assigned to non-accrual status by the MDBs in the sample period. 46 unique countries entered arrears status during the period 1988 to 2022. In the last 10 years of the sample period, only 8 countries were assigned to non-accrual status. In 2022, Belarus and Afghanistan defaulted to IBRD and ADB, respectively.

2.2 Outstanding Balance

The non-accrual data is combined with data on an outstanding balance indicator for each sovereign and year. This indicator takes the value '1' if the sovereign has an outstanding balance to the MDB and '0' otherwise. The indicator is needed for our analysis since we wish to compute the frequencies with which countries newly enter non-accruals status given that, a year earlier, they represented an exposure to the MDB in question and were not in non-accrual status. The non-accrual status event of Nauru in 2001 is not counted as a default in this respect as there was no outstanding balance data in the corresponding period. All other entries into non-accrual status are counted as defaults.

2.3 Historical Sovereign Rating

The primary source we employ for sovereign rating data is the Standard & Poor's dataset of ratings for 165 countries covering the period 1988 to 2022. This may be obtained from Bloomberg. Ratings observations are captured for 1st January of each year. Especially before the early 1990s, however, many countries to which MDBs lend were unrated by Standard & Poor's. To construct proxy ratings, we employ ratings data provided by the Organisation for Economic Co-operation and Development (OECD). In 1997, the OECD began a system of country risk classifications based on different country risks. These data may be obtained from OECD (2023) for the period 1999 to 2022. The OECD classifies countries into a numerical rating scale from 0 to 7, with 0 being the highest rated (low risk) and 7 being the lowest (high risk).

Table 2.2: Rating Map Between OECD Rating and Standard & Poor's Rating

OECD Rating	S&P Rating
0	AAA
1	AA
2	A+
3	BBB
4	BB
5	BB-
6	B
7	CCC
-	NR

We devise a mapping from the OECD numerical rating to the Standard & Poor's rating scale as shown in Table 2.2. We start by expressing the Standard & Poor's alpha-numeric rating on an integer scale. Then, for each observed numerical OECD rating for which a Standard & Poor's alpha-numeric rating is available, we average the integer scale Standard & Poor's rating and then convert back to the alphanumeric form. We performed this for the whole sample and for 2022 and found the results for the whole sample less prudent than 2022 dataset (the low OECD ratings is mapped to a higher Standard & Poor's rating for the whole sample dataset compared to the 2022 dataset).

We use the OECD numerical ratings map (Table 2.2) produced using the 2022 dataset which is consistent with the rating map (Table 2.3) recommended by the Standardised Approach (SA) for sovereign exposures in the Basel III framework (see Table 2.3). Table 2.3 is based on the SA for commercial banks in Basel Committee on Banking Supervision (BCBS) (2023), which provides the risk weight to be used when there is an external rating and OECD rating used for the sovereign exposures.

In recent years, the raw OECD dataset has been updated approximately on a quarterly basis. We take the rating observed in January of each year as the assigned rating for that particular year. For the period from 1988 to

1998, the OECD ratings of each sovereign are assumed to be those observed in 1999. All the observations are dropped when both the Standard & Poor's and OECD rating data are absent.

Table 2.3: Rating Map Between OECD and External Rating by Basel Framework

Risk Weights	OECD Rating	External Rating
0%	0 to 1	AAA to AA-
20%	2	A+ to A-
50%	3	BBB+ to BBB-
100%	4 to 6	BB+ to B-
150%	7	Below B-

Note: The table is reproduced using the Table 1 and Table 2 from Basel Committee on Banking Supervision (2023).

Table 2.4 shows the aggregate sovereign rating data. There is a substantial increase in the number of sovereigns rated 'CCC'. This is consistent with the argument that the lower-rated countries are less likely to be rated by Standard & Poor's.

Table 2.4: Aggregate Sovereign Rating Data

S&P ratings	S&P Data	S&P Data + OECD Data
AAA	193	263
AA+	47	47
AA	86	98
AA-	120	120
A+	93	220
A	128	128
A-	156	156
BBB+	120	120
BBB	155	358
BBB-	213	213
BB+	140	140
BB	166	310
BB-	206	462
B+	247	247
B	214	790
B-	159	159
CCC+	31	31
CCC	8	1651
CCC-	3	3
CC	6	6
C	0	0
D	27	27
NR	4250	1219

3. Methodology

3.1 Default Frequencies

The three different sources of data namely: (i) Historical sovereign ratings data, (ii) MDB non-accrual data, and (iii) MDB outstanding balance data are aggregated into a 'Ratings/Non-accrual Status' table incorporating all the observed information. The value for a sovereign in each period in the table is calculated using equation (3.1). An entry of 'a/b' for a year t is the concatenation of two variables 'a' and 'b, where 'a' indicates the rating of the sovereign in the year t-1 and 'b' indicates the accrual status in year t.

In each year t, the 1-year Rating/Non-accrual Status is constructed as follows:

$$Rating = \begin{cases} 23, & if\ it\ is\ in\ non-accrual\ in\ year\ t-1 \\ rating\ in\ year\ t-1, & other\ wise \end{cases}$$

$$Non-accrual\ Status = \begin{cases} 1, non-accrual = 1\ in\ year\ t\ and\ outstanding\ balance = 1\ in\ year\ t-1 \\ 0, non-accrual = 0\ in\ year\ t\ and\ outstanding\ balance = 1\ in\ year\ t-1 \\ NA, \quad outstanding\ balance = 0\ in\ uear\ t-1 \end{cases} \quad (3.1)$$

Table 3.1 provides a sample of the Rating/Non-accrual status table for Myanmar.

Table 3.1: Myanmar's Rating/Non-accrual Status Dataset

	1988	1989-1997	1998	1999-2012	2013	2014-2017	2018	2019-2022
Rating	CCC	CCC	CCC	CCC	CCC	CCC	B	B
Non-accrual Status			1	1				
Outstanding Balance Status	1	1	1	1	0	0	1	1
Rating/Accrual Status		CCC/0	CCC/1	23/1	23/0	CCC/NA	CCC/0	B/0

Note: Myanmar's rating is derived based on OECD (2023) as it is not rated by Standard & Poor's.

Table 3.2: Observed PDs by Rating

S&P Rating	Default	Non-Default	Raw PD
AAA	0	46	0.00%
AA+	0	3	0.00%
AA	0	15	0.00%
AA-	0	27	0.00%
A+	0	68	0.00%
A	0	59	0.00%
A-	0	98	0.00%
BBB+	0	89	0.00%
BBB	0	244	0.00%
BBB-	0	157	0.00%
BB+	0	127	0.00%
BB	0	251	0.00%
BB-	1	405	0.25%
B+	0	213	0.00%
B	7	664	1.04%
B-	0	139	0.00%
CCC+	0	23	0.00%
CCC	21	1050	1.96%
CCC-	0	3	0.00%
CC	0	5	0.00%

The rating/non-accrual status table is used to obtain the raw one-year PD by rating i as shown in equation (3.2). It is estimated as the ratio of number of defaults for rating i to the total number of obligors.[4]

$$PD_i = \frac{\sum_{t=1}^{T-1} N_{t,i}^{t+1,D}}{\sum_{t=1}^{T-1}(N_{t,i}^{t+1,D} + N_{t,i}^{t+1,ND})} \tag{3.2}$$

Here, $N_{t,i}^{t+1,D}$ indicates the total number of i-rated sovereigns at time t and first non-accrual at time $t+1$. It is the sum of 'i/1' entries in the Rating/Non-accrual status table. Similarly, $N_{t,i}^{t+1,ND}$ indicates the total number of i-rated sovereigns at time t and not in non-accrual status. (it is the sum of 'i/0' entries in the Ratings/Non-accrual status table). Other entries of the table are discarded such as sovereigns which are not rated or sovereigns which have no outstanding balance to an MDB.

Table 3.2 shows the observed PDs by ratings for the MDB non-accrual data. It is expected to not find any defaults in higher ratings for 'BB' and above. The worst PD is observed for CCC at 1.96% which may reflect is due to scarcity of observations for the particular rating category. The observed PDs are not monotonically increasing as credit quality decreases.

3.2 Techniques for Low Default Portfolios

A well-behaved PD curve should satisfy two important properties:

1. Default probabilities should be monotonically increasing as credit quality decreases
2. Default probabilities should be non-zero

The observed PDs in Table 3.2 violate both above properties. The first property is violated when the observed PD for the 'B+' is lower than the observed PD for the 'BB-'. The second property is violated for all the obligors with zero default observations.

The Multilateral Development Banks (MDBs) inherently enjoy a portfolio sovereign which has a lower default instance compared to commercial bank lending to corporates. Furthermore, MDB's sovereign portfolio is strengthened because of Preferred Creditor Treatment (PCT). This combined effect leads to a few observations of default not only for the higher rating grade sovereigns but also for non-investment grade sovereigns (as seen in Table 3.2).

Such portfolios with low default observations are widely termed Low Default Portfolios (LDP). When a traditional credit rating model is applied to such LDP, it may estimate a less prudent Probability of Default (PD). One such most-used approach for LDPs is by Pluto and Tasche (2011) which includes all the observations for a rating grade equal to or below the rating grade for which the PD is estimated. This approach implicitly includes default from lower ratings in the estimation of PD for a higher rating which makes the estimate highly conservative.

Another issue with Pluto and Tasche (2011) is that it is dependent on the confidence level parameter required for the computation of the PDs. Tasche (2013) proposes to estimate using a Bayesian posterior distribution for a simple prior.

3.3 Maximum Likelihood Estimation

The logistic function form satisfies the two properties of the PD curve mentioned in section 3.2. The PD for a rating i would be according to equation 3.3.

$$PD_i(\alpha,\beta) = \frac{1}{1 + \exp(\alpha + \beta \times \phi^{-1}(F_N(x)))} \tag{3.3}$$

Here,

- $F_N(x) = \Pr[X \le x|N] = \frac{\sum_{j=1}^{x} N_j}{\sum_{j=1}^{J} N_j}$, N denotes non-default
- N_j is the total number of j-rated sovereigns, this is calculated as the sum of the 'j/0' and 'j/1' entries in the Rating/Non-accrual status table

[4] The summation of default starts with '1' which corresponds to 1988 and ends with 'T' which corresponds to '2022' which the end of period we study.

- The term $\phi^{-1}(F_N(x))$ returns a value z such that, with probability $F_N(x)$, a standard random variable takes a value less than or equal to z. This transforms the non-normal distribution of the ratings conditional on survival into an approximately normal distribution even if the underlying distribution of the rating is not continuous (see Tasche (2012))

When the ratings are discrete levels, the value of $F_N(x)$ may be equal to 1. Thus, for a discontinuous case, it is replaced by an average $\overline{F_N(x)}$ as shown in equation (3.4).

$$\overline{F_N(x)} = \frac{\Pr[X < x|N] + \Pr[X \leq x|N]}{2} \tag{3.4}$$

Tasche (2013) suggested to use Quasi Moment Matching (QMM) to solve for the parameters α and β. Yang (2017) proposes to use constrained Maximum Likelihood Estimator (MLE) which generates a rating scale leading to a more robust credit loss estimation. In this study, we apply the MLE to the logistic functional form of PD to estimate the parameters α and β.

The algorithm is implemented by maximising the log-likelihood function to estimate the parameters α and β. Let D_i and N_i denote the number of default s and the number of observations for a rating i. Let $PD_i(\alpha,\beta)$ denote the default probability for rating i, which is calculated as in equation 3.3. The default frequency is assumed to follow a binomial distribution. Then the log-likelihood of the default and non-default sample is estimated as in the equation (3.5).

$$LL = \sum_{i=1}^{I} (N_i - D_i) \times \log(1 - PD_i(\alpha,\beta)) + D_i \times \log(PD_i(\alpha,\beta)) \tag{3.5}$$

The MLE estimates of α and β are obtained by finding the values that maximise the log-likelihood function shown in equation (3.5). When we employ a 17-grade rating scale, starting from the 'AA-' and above, to 'CC', the ML parameter estimates obtained are:

- $\alpha = 5.344$
- $\beta = 1.226$

4. Results

4.1 PD Estimates

Using the ML parameter estimates described in the last section, we calculate rating-specific PDs. These are presented in column 5 of Table 4.1.

The MLE-based default probability curve (unlike the empirical PDs that appear in column 4) possesses the two properties mentioned in Section 3.2, namely that PDs be non-zero and monotonically increasing as the rating decreases. The estimated PDs shown in column 3 of Table 4.1 are comparable in magnitude to the empirical PDs except for the lowest ratings categories (e.g., CCC- and CC) for which almost no data are available.

Column 6 of the table shows the ratio of the MLE-based PDs with PCT to a smoothed set of PDs based on Standard & Poor's data (i.e., for international sovereign bonds and, therefore, without PCT).[5] This leads to changes in such entries as B+, BB and BB+ while leaving other entries, such as BBB- unaffected.

The ratios that appear in column 7 of Table 4.1 suggest that, in proportional terms, the magnitude of PCT increases as one moves down the rating scale. The increasing magnitude ceases at CCC- but almost no data are available for these ratings.

In the range BB- to B, the ratio takes the values 2.65, 4.08 and 4.23. This appears broadly consistent with the findings of Risk Control (2022). That study which used a matched dataset of country-year observations for

[5] The smoothed Standard & Poor's PDs are obtained by, for all entries in the column that are not monotonic in rating, expressing the PDs in natural logs, linearly interpolating, and then reversing the logarithmic transformation.

which sovereigns had exposure both to the bond market and to MDBs had a Weighted Average Borrower Rating of B and reported a ratio of without-PCT to with-PCT PDs of 3.6.

Table 4.1: Estimated PDs using the MLE Approach

Rating	Standard & Poor's Empirical PDs	Standard & Poor's Smoothed PDs	MDB Non-accrual Data Empirical PDs	MLE based PDs	Standard Deviation (StD)	Ratio w/o PCT to with PCT PDs	Ratio w/o PCT to with PCT PDs + 1 StD
AA- and above	0.00	0.06	0.00	0.03	0.02	2.09	1.18
A+	0.00	0.15	0.00	0.05	0.03	3.01	1.80
A	0.00	0.19	0.00	0.06	0.04	2.93	1.80
A-	0.00	0.22	0.00	0.08	0.05	2.81	1.77
BBB+	0.00	0.26	0.00	0.10	0.05	2.67	1.73
BBB	0.00	0.29	0.00	0.13	0.06	2.30	1.54
BBB-	0.33	0.33	0.00	0.17	0.07	1.98	1.37
BB+	0.17	0.50	0.00	0.20	0.08	2.57	1.82
BB	0.10	0.68	0.00	0.24	0.09	2.85	2.07
BB-	0.85	0.85	0.25	0.32	0.11	2.65	2.00
B+	0.62	1.70	0.00	0.42	0.12	4.08	3.17
B	2.54	2.54	1.04	0.60	0.14	4.23	3.43
B-	7.01	7.01	0.00	0.85	0.17	8.21	6.84
CCC+	17.01	17.01	0.00	0.92	0.18	18.47	15.46
CCC	45.26	45.26	1.96	1.71	0.34	26.53	22.16
CCC-	84.78	84.78	0.00	14.63	7.06	5.80	3.91
CC	100.00	100.00	0.00	19.57	9.96	5.11	3.39

Note: All PDs are in percent.

4.2 Rating Agency Risk Weights

It is interesting to examine the allowance that two of the major rating agencies make for PCT in their evaluations of the capital adequacy of MDBs. Both Standard & Poor's and Fitch rely heavily in this context on a capital ratio, the denominator of which is an agency-specific notion of Risk Weighted Assets (RWAs). Both agencies adjust the Risk Weights (RWs) used in calculating these RWAs for PCT.

For Standard & Poor's, the RW adjustment is explicit in that separate sets of RWs are published by the agency for loans subject to PCT and for those that are not. For Standard & Poor's, these two sets of rating-grade-specific RWs are shown in columns 2 and 3 of Panel a) of Table 4.2. Column 4 of the table shows the ratio. The ratio increases from unity for ratings AA- and above to 8.67 for BBB+ and then declines to 1.76 for the lowest non-default rating category of CC. For ratings categories that are key for MDB sovereign portfolios, BB- to CCC+, the ratios range from 3.13 to 2.06.

Fitch, rather than having explicit RWs depending on whether PCT applies or not, allows for PCT by notching coarse rating categories before it infers RWs. The result appears in Pabel b) of Table 4.2. The ratios of the pre to post PCT adjustment is between 1.5 and 2 depending on the rating category.

Note that one should not expect the RWs shown in this subsection to scale after an adjustment for PCT in just the same way as PDs. RWs and PDs are very different quantities. Even if RWs are directly inferred from a quantification of how PDs are affected by PCT, halving the PDs will not lead to a halving of RWs. An adjustment to RWs for PCT should, in any case, allow for the reduced magnitude of LGDs that one may expect to apply if PCT is applicable. As is well known, MDBs experience substantially lower LGDs in their lending to Member Countries than are observed in the international bond markets. We will attempt to untangle these various issues in the next subsection.

Table 4.2: Rating Agency Risk Weights

Panel a) Standard & Poor's

Rating	Non-PCT RW	PCT RW	Ratio Non-PCT to PCT
AA-' and above	3	3	1.00
A+	5	3	1.67
A	9	3	3.00
A-	15	3	5.00
BBB+	26	3	8.67
BBB	40	5	8.00
BBB-	57	9	6.33
BB+	76	15	5.07
BB	99	26	3.81
BB-	125	40	3.13
B+	153	57	2.68
B	185	76	2.43
B-	219	99	2.21
CCC+	257	125	2.06
CCC	297	153	1.94
CCC-	340	185	1.84
CC	386	219	1.76
D	428	257	1.67

Panel b) Fitch

Rating	Non-PCT RW	PCT RW	Ratio Non-PCT to PCT
AAA	0	0	-
AA	20	0	-
A	30	20	1.50
BBB	50	30	1.67
BB to B	100	50	2.00
CCC and lower	150	100	1.50

Note: All Risk Weights are expressed in percent.

4.3 Basel Risk Weights

The Basel Internal Ratings Based Approach (IRBA) Risk Weights (RWs) may be calculated directly using a simple formula that provides Marginal Value at Risk estimates in a Credit Portfolio Model (CPM) with the highly simplified and stylised assumption of a single asymptotic risk factor. The formula has the advantage that it yields RWs, directly and transparently, as a function of PDs and LGDs. The Standard & Poor's RWs with and without PCT described in Section 4.2 are not, as far as is known, derived from an explicit calibration based on PDs or LGDs, although the agency may employ such a methodology without making it public.

Table 4.3 shows the results of applying the Basel RW formula using without-PCT and with-PCT PDs and LGDs. When the calculations are performed without including an LGD adjustment for PCT, the ratio of without-PCT to with-PCT RWs is close to 2 in the relevant range. Indeed, since the Basel RW formula is proportional to its LGD input, whether a without-PCT LGD of 50% is used (consistent with Moody's (2023)) or a with-PCT LGD of 10% is used (consistent with the discussion in Risk Control (2022)), the ratio is identical. The righthand column in the table shows the ratio of RWs (i) when no PCT adjustments are made to either PDs and LGDs (column 2 in the table, marked as (1)), to (ii) when adjustments are made to both PDs and LGDs (column 6 in the table, marked as (4)). The RW ratios displayed in the righthand column range (for ratings important for MDB portfolios) from 15.10 for CCC+ to 9.60 for B+.

Table 4.3: Basel Risk Weights

	LGD w/o PCT (50%)			LGD with PCT (10%)			
	(1)	(2)		(3)	(4)		
Rating	PDs w/o PCT	PDs with PCT	Ratio (1)/(2)	PDs w/o PCT	PDs with PCT	Ratio (3)/(4)	Ratio (1)/(4)
AA- and above	15	8	1.75	3	2	1.75	8.77
A+	28	13	2.21	6	3	2.21	11.05
A	32	15	2.13	6	3	2.13	10.67
A-	36	18	2.04	7	4	2.04	10.20
BBB+	39	20	1.94	8	4	1.94	9.69
BBB	43	25	1.73	9	5	1.73	8.63
BBB-	46	30	1.54	9	6	1.54	7.72
BB+	58	33	1.77	12	7	1.77	8.84
BB	68	37	1.82	14	7	1.82	9.10
BB-	76	45	1.69	15	9	1.69	8.43
B+	100	52	1.92	20	10	1.92	9.60
B	115	64	1.81	23	13	1.81	9.04
B-	168	76	2.22	34	15	2.22	11.08
CCC+	237	79	3.02	47	16	3.02	15.10
CCC	245	101	2.44	49	20	2.44	12.18
CCC-	87	226	0.39	17	45	0.39	1.93
CC	-	246	-	-	49	-	-

Note: Risk Weights (RWs) are in percent. Here w/o indicates 'without'. The LGD w/o PCT is from Moody's (2023). The LGD with PCT is consistent with common MDB practice. The PDs denoted w/o PCT are those shown in column 3 of Table 4.1. Those designated with PCT are the PDs shown in column 5 of Table 4.1.

5. Conclusion

This study provides a quantification of the effects of Preferred Creditor Treatment (PCT) on the credit performance of sovereign loans by Multilateral Development Banks (MDBs). Our primary focus is on the impact of PCT on Probabilities of Default (PDs), although we discuss estimates of LGDs from other sources.

We show that the magnitude of PCT is stronger as ratings fall below investment grade and is particularly large in the range that matters most for MDB capital adequacy, namely CCC+ to B+. In this range, the ratio of PDs in the international bond market to those experienced by MDBs is between 4 for B+ and 18 for CCC+.

Our study may be helpful for investors evaluating MDB portfolios or for MDBs themselves in calibrating internal risk models. The findings could also contribute to the debate on appropriate methodologies that international rating agencies apply to assessments of MDB capital adequacy. Fitch and Standard & Poor's, in their assessment of MDBs compute capital ratios, the denominators of which equal Risk Weighted Assets.

Both these agencies adjust the RWs employed for PCT. We show that the scale of the adjustments and their pattern across different rating categories differ materially from what is suggested by what is implied by empirical evidence. Specifically, PCT is particularly strong for sovereigns with ratings in the single B and CCC range, which is key to the balance sheet risk faced by MDBs. Using a Basel capital formula, the impact of PCT is substantially greater than the allowance that the two agencies make in their capital assessments of MDBs.

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