Multilateral Development Bank Ratings and Preferred Creditor Status

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Abstract[1]

This paper analyzes influences on the credit standing of Multilateral Development Banks (MDBs). We focus on the quality, diversification and single name concentration of their portfolios, and on the market practice known as Preferred Creditor Status (PCS). PCS refers to the fact that sovereigns which default on other debt rarely fail to meet their obligations to MDBs. The paper examines how rating agencies assess MDB ratings, looking, in particular, at how Standard & Poor's (S&P) evaluates capital adequacy. We benchmark the agency's approach against an industry-standard, ratings-based Credit Risk Model (CRM). We implement the approaches for a specific MDB: the Inter-American Development Bank (IDB).The paper shows that S&P's approach is highly conservative in its treatment of single name concentration risk and makes insufficient allowance for PCS. Calibrating the CRM with risk-neutral distributions, we examine the effect of PCS on MDB funding spreads.

Executive Summary

Multilateral Development Banks (MDBs) play an important role in international financial markets, raising money by issuing bonds and lending to their borrowing member countries.

In so doing, they benefit from a market practice known as Preferred Creditor Status (PCS). PCS refers to the fact that sovereign borrowers typically continue to service their loans from MDBs even in the unlikely event that they default on other claims. This confers on the loans of MDBs a type of de facto seniority.

The business model followed by MDBs requires that they maintain a high credit standing. For this reason, their assessment by ratings agencies is an important consideration in MDB decision making and agency ratings are widely perceived as a constraint on their lending.

In evaluating MDB credit standing, one influential rating agency, Standard & Poor's (S&P), relies on a transparent quantitative measure: the Risk-Adjusted Capital (RAC) ratio. The RAC ratio equals forecast common equity divided by the MDB's Risk Weighted Assets (RWAs). To be judged by S&P as having a strong capital position, an MDB must maintain a RAC ratio greater than a given target value. If the level of common equity is given, this requires that the MDB limit its RWAs.

S&P's measure of RWAs equals a weighted sum of assets (with weights dependent on rating and jurisdiction). This weighted sum is adjusted for three factors: diversification (across countries and sectors), Single Name Concentration (SNC) and PCS. The assumptions adopted by S&P in making these adjustments are important in determining whether S&P's credit risk evaluation constrains an MDB's lending.

In this paper, we analyze S&P's methodology. We look, in particular, at the approaches the agency employs in adjusting for i) diversification, ii) SNC and iii) PCS. We focus on a particular MDB, the Inter-American Development Bank (IDB), and investigate possible alternatives to the adjustments employed by S&P. Our analysis suggests that S&P's treatments of SNC and PCS are extremely conservative in the case of the IDB.

To benchmark the S&P approach, we formulate an industry-standard, ratings-based Credit Risk Model (CRM) and apply this to the IDB's portfolio. By design, the CRM rigorously allows for diversification and SNC. To adjust for PCS we consider adjustments to CRM inputs, specifically to the recovery rates on sovereign loans in the IDB's portfolio.

In rating Collateralized Debt Obligations (CDOs), S&P employs target probabilities of default (PDs) associated with different maturities. Using the CRM and the target PDs, we are able to deduce the capital levels that the IDB needs to obtain a AAA rating. (The analysis abstracts from additional, qualitative criteria applied in the rating process.)

For the IDB to obtain a rating of AAA, the CRM suggests it should hold capital in excess of $14-15bn. One may compare this to the figure of $33bn that is required for the IDB to achieve the highest S&P category of capital adequacy. (Note that our calibration is based on December 2014 data and does not allow for the steps IDB has recently taken i) to consolidate different balance sheets and ii) to exchange assets with other MDBs. These steps have reduced the degree to which the RAC ratio constrains IDB lending.)

The CRM may also be simulated using risk-adjusted distributions in order to assess the "risk-adjusted probability" that the IDB will exhaust its capital. Assuming a recovery rate, and working out the expected loss under such a risk adjusted distribution, permits the estimation of the spreads that the market would charge the IDB to borrow. This calculation may be performed with and without adjustment for PCS. The effect of PCS may then be inferred by comparing these two estimates. We find that before the PCS adjustment, the IDB's market spread equals 19 to 37 basis points (bps), depending on maturity. After adjustment, the spread falls to 7 to 14 bps.

To conclude, the paper indicates that S&P's approach is highly conservative in its treatment of single name concentration risk and makes insufficient allowance for PCS.

1. Introduction

Multilateral Development Banks (MDBs) play an important role in international financial markets. Owned by groups of countries that provide equity capital, MDBs raise money by issuing bonds in global capital markets and lend to their borrowing member countries. Income from lending is either reinvested in the business by boosting capital or used to pay for grant financing, concessional lending, technical assistance, salaries and other expenses.[2]

Over time, the role of MDBs has evolved. For example, the World Bank initially acted as a facilitator of post-war reconstruction and has subsequently assumed a mandate of alleviating worldwide poverty. Similarly, the European Bank for Reconstruction and Development (EBRD) was created to foster a transition to a market economy but has since taken on a wider role of furthering development; see Buiter and Fries (2002), Clemens and Kremer (2016) and Ravallion (2016). Academics and others have discussed the value of the activities in which MDBs engage,[3] including knowledge creation and diffusion, pure financing (including counter-cyclical and crisis lending) and the provision of incentives through loans for countries to pursue reforms.[4]

In this paper, we examine the creditworthiness of MDBs and analyze the levels of capital they must hold to achieve high credit status. MDBs are capital constrained in that they cannot, of themselves, issue new capital instruments without going through complex negotiations with shareholders. Hence, the scale of their activities and the level of risk that they can assume are limited by the market's view of their solvency as reflected in credit spreads and agency credit ratings.

In analyzing MDB creditworthiness, we focus on a particular institution, the Inter-American Development Bank (IDB). We examine and apply the approach to calculating credit

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[2] MDBs do not typically pay dividends to their shareholders.

[3] Gilbert, Powell and Vines (1999) argued that the World Bank i) needed to transition from a reliance on conditionality to a knowledge bank with lending focused more on countries with sound economic policies and ii) that its value-added came from the bundling of lending and knowledge services and attempts to unbundle these activities were misplaced. Boz (2011) studies the nature of emerging market borrowing from international financial institutions, including MDBs. The author finds that such borrowing tends to be counter-cyclical and smaller in magnitude than borrowing from private sector sources and that lending for budget or balance of payments support tends to come with strings attached in the form of conditionality arrangements.

[4] For a general discussion, see Chapter 6 in Inter-American Development Bank (2006). Wezel (2004) presents evidence that MDB lending gives borrowing countries an incentive to honor commitments and thereby reduces agency costs, stimulating private sector financing flows in parallel to the MDB loans. Perraudin and Sibert (2000) analyze bargaining on conditionality between an MBD and a sovereign borrower under asymmetric information. Buiter and Fries (2002) emphasize the useful mechanisms that MDBs have for monitoring and enforcing loans and applying subsidies, and argue that MDBs should not be agencies for allocating grants or effecting redistribution internationally.

risk capital employed by the rating agency Standard & Poor's (S&P). S&P is prominent in assessing MDBs, and the agency's methodology relies to a significant degree on a transparent quantitative assessment of capital adequacy. Our analysis compares results obtained using S&P's approach with those implied by an industry-standard, credit portfolio model. We also look at bond market perceptions of MDB risk as revealed by relative MDB and sovereign bond spreads.

We focus on particular factors influencing credit standing of MDBs, specifically diversification and the market practice known as Preferred Creditor Status (PCS). PCS describes the phenomenon that, when sovereigns default on claims to private institutions, they commonly continue to service debt held by official creditors including MBDs. PCS means that loans made by MDBs are effectively senior to private commercial debt and often to bilateral official debt. One popular database lists22 recent bond exchanges, 13 of which involved a reduction in principal with an average haircut of 48.3 percent; none of these include any reduction in the face value of debt from MDBs.[5]

Such favorable loss experience suggests that PCS should play a large role in credit assessments of MDBs and, hence, has important implications for the capital MDBs must hold to achieve high ratings. The ratings agencies adjust for PCS in rating MDBs, but whether they do so to the extent justified by the actual loss experience of MDB institutions is controversial.

Consider the example of the IDB: S&P reduces its estimate of the IDB's risk weighted assets (and hence of the capital it must hold to achieve a given standalone credit standing) by 10 percent to reflect the beneficial effects of PCS. Such a small reduction might be questioned in the light of the IDB's loss experience. According to IDB estimates of those occasions in its entire history on which its borrowers have defaulted on commercial debt, the IDB itself has suffered non-accrual events on only about 11 percent of those occasions. Moreover, even in the cases of these non-accrual events, the IDB did not experience any write-offs or write-downs from its ordinary capital.[6]

Another important determinant of MDB credit quality is the degree to which MDB portfolios are diversified or concentrated. Like conventional commercial banks, the degree of diversification across geographical regions and sectors is an important influence on key credit

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[5] See Cruces and Trebesch (2013) and the 2014 update of the dataset available at:
https://sites.google.com/site/christophtrebesch/data
[6] This abstracts from those low income countries that obtained debt relief through the internationally negotiated Multilateral Debt Relief Initiative (MDRI).

quality measures such as the probability of default. Unlike most commercial banks, some MDBs have, in addition, significant single name concentration risk in that they have relatively high proportionate exposures to particular sovereigns. We examine different approaches to assessing diversification and single name concentration risk and illustrate the sensitivity of S&P's rating assessment to the choice of approach in the case of the IDB.

In our analysis of IDB portfolio risk using an industry standard credit portfolio model, we allow explicitly for PCS and compare our findings with the allowance made for PCS by S&P. Our model also allows for diversification and single name concentration risk in a rigorous and consistent fashion, so we are again able to check the accuracy of the approximations and methodological choices adopted by S&P.

We do not attempt to adjust for the impact of MDBs' callable capital. Some allowance is made for this by ratings agencies, but it is difficult to assess through calculation whether their approach is conservative or not. By performing comparisons that make no allowance at all for callable capital, we ensure that our conclusions are highly conservative in this regard.

The spreads demanded of MDBs that borrow from the international bond market shed light on the credit quality of these institutions as perceived by the bond market. To examine the impact of PCS on bond market pricing, we implement a variant of our portfolio credit risk model using risk adjusted (rather than historical) distributions. We show that implied spreads with no allowance for PCS are higher than those observed in the market whereas, when PCS is introduced, model-implied spreads more closely resemble market levels.

The paper is organized as follows. Section 2 presents evidence of MDB credit standing and discusses the nature of PCS and how one might expect it to influence MDB solvency risk. Section 3 sets out the methodologies we employ in analyzing the portfolio risk of our example MDB, the IDB. We present S&P's methodology for rating MDBs, providing interpretation and comments on the quantitative modeling approach the agency employs. We also present the ratings-based credit portfolio model that we apply to the IDB's portfolio.[7] Section 4 describes the IDB's portfolio and how we mapped it into appropriate inputs for the portfolio analysis. Section 5 presents the results of our analyses, and Section 6 concludes.

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[7] This latter model is i) multi-period, so one may employ it to analyze risk over multiple horizons, and ii) may be run using either historical or risk-adjusted distributions extracted from spreads. So, one may both analyze appropriate capital and infer market spreads at which the IDB could borrow under different assumptions about the nature of its portfolio.

2. MDB Credit Status

Multilateral Development Banks (MDBs) provide finance to developing countries for projects in virtually all sectors and general budget support normally linked to policy reforms. One may think of MDBs as risk-poolers. Non-borrowing MDB member countries face a choice between lending directly to a borrowing country (in which case they may select projects or countries that accord with their specific development or political objectives) or may provide capital to an MDB. In the latter case, the non-borrowing country gains scale in its lending (through the leverage of the MDB) and may gain technical expertise and diversify its own risks.[8]

Table 1. Key Risk Indicators for MDBs

Bank	Est.	Share-holders	S&P Rating	S&P SACP	Net Loans	Total Assets	Share-holders' equity	Equity to Assets Ratio	Total Liabilities	RAC	Adjusted RAC
IDB	1959	48	AAA	aa+	74,215	106,299	23,697	0.23	82,602	31	16
EIB	1958	28	AAA	aa+	524,078	656,650	73,327	0.11	583,323	17	15
EBRD	1991	68	AAA	aaa	23,593	63,546	17,130	0.27	46,416	22	15
IBRD	1946	188	AAA	aaa	154,861	351,634	37,078	0.11	314,556	25	30
ADB	1966	67	AAA	aaa	55,925	115,660	16,938	0.15	98,722	29	17
IFC	1956	184	AAA	aaa	22,536	91,246	24,035	0.26	67,211	16	29
CEB	1956	41	AA+	aa	15,263	30,927	3,081	0.09	27,846	32	18
AfDB	1964	78	AAA	aa+	17,618	32,335	8,980	0.28	23,354	24	18
CAF	1968	19	AA-	aa-	18,999	30,495	8,763	0.29	21,731	26	14
CABEI	1960	13	A	a	5,236	7,537	2,268	0.30	5,269	25	12

Note: Data are taken from the 2015 S&P Ratings Direct reports. All figures are in millions of U.S. dollars. The euro-dollar conversion rate used for EIB, EBRD and CEB data is the rate on 31 December 2014. For AfDB, we used the SDR-USD conversion rate of December 30, 2013. EBRD shareholders include the EU and the EIB. Most institutions shown in the table lend to both public and private sectors. Institutions such as the IFC focus exclusively on lending to the private sector. The lack of PCS for private lending, diversification issues, and its use of equity investments make the IFC somewhat different from MDBs such as the IDB or IBRD. Note that these 2015 figures for the IDB do not include the positive impacts of the recent Argentina upgrade nor other recent changes that improve capital ratios.

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[8] Bobba and Powell (2006) argue in favor of this trade-off and present empirical results to illustrate the inferred preferences of non-borrowing countries given the pattern of their bilateral aid. Bobba and Powell (2007) show that politics (proxied by the voting correlations at the United Nations) does play a role in the cross-country distribution of bilateral aid and using this as an instrument show aid extended to countries with the closest alignments in voting patterns tends to be less effective.

The ability of MDBs to leverage through their borrowing in international capital markets is significantly enhanced by their high credit standing.[9] Table 1 shows the rating of the primary MDBs as of June 2015. Only one MDB has a rating of less than AA-, while just three have current ratings below AAA. Table 1 also documents the long, stable track record of lending of many MDBs, most of which were established in the late 1950s or early 1960s.

The financial data contained in Table 1 illustrate the sources of MDBs' high credit standing, particularly their strong equity capitalization. Equity to assets ratios (shown in column 9 of Table 1) are higher than those observed in commercial banks, being mostly in the range 20-30 percent. The exceptions are the IBRD (which has a diversified lending book and an accounting treatment of swaps quite different from that employed by other MDBs[10]), and the two European institutions, EIB and CEB (the assets of which mainly comprise relatively high-quality loans to developed-country borrowers).

Two other sources of financial strength from which MDBs benefit are i) shareholder support through callable capital and ii) Preferred Creditor Status (PCS).

On i), MDBs enjoy promises of additional capital injections from their shareholders should the MDB in question experience financial difficulties. There is some variation across member countries as to how automatic such additional contributions would be if the capital were actually called or whether these contributions would have to be ratified by some political process. Rating agencies tend to allow some proportion of this additional callable capital to count as actual capital, but it is less than 100 percent. In particular, for MDBs aiming for an AAA rating, S&P only makes allowance for callable capital promised by shareholders that have AAA S&P ratings.[11]

To appreciate the impact of i) on rating agency evaluations of callable capital, one may examine the fifth column of Table 1, which shows S&P's Stand Alone Credit Profile (SACP) for

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[9] The degree to which ratings add information has been studied by numerous authors. Cavallo, Powell and Rigobón (2008) find that sovereign ratings and outlooks, controlling for current spreads, improve predictive power and so add information. Eijffinger (2012) shows that spreads led ratings and outlook changes in the 2010-2011 sovereign debt crisis in Europe. Kiff, Nowak and Schumacher (2012) present evidence that rating agency assessments affect the cost of funding of sovereign issuers and argue that this fact raises financial stability concerns. Baum, Karpava, Schäfer and Stephan (2013) show that, at least in periods of crisis, sovereign ratings affect exchange rates and the borrowing terms that sovereigns face.

[10] The IBRD includes swaps on a gross basis in its accounts, which boosts the size of its balance sheet substantially.

[11] This notably excludes promises of callable capital from the US. Ignoring callable capital from non-AAA-rated shareholders implies that changes in shareholder ratings may trigger somewhat questionable MDB downgrades or upgrades. Promises of callable capital from lower rated shareholders are taken into account if the MDB aims for a lower rating than AAA.

the different MDBs. This measure, expressed in a lower-case version of the agency's main issuer rating scale, reflects S&P's view of the credit standing a given MDB would have in the absence of additional capital support from its shareholders. One may observe that, in practice, the allowance S&P makes for callable capital boosts its rating assessment by one notch for four of the 10MDBs shown.[12]

On ii), as explained in the introduction, PCS is a market practice whereby distressed sovereigns service their obligations to some lenders even while defaulting on other debts. This practice results in an effective increase in seniority of MDB claims compared to claims that would otherwise have the same seniority.[13] One should note that there is no legal basis for PCS. It constitutes a market practice attributable to the incentives faced by distressed sovereign borrowers. PCS may reflect the concern of defaulting sovereigns to remain on good terms with multilateral institutions that maintain lending when private sector funding dries up. Unlike IMF loans, however, MDB lending is not made in periods of private or bilateral debt renegotiations, and some have questioned whether loans by MDBs are counter-cyclical; see Perry (2009).

What explains the phenomenon of PCS? First, it is reasonable to expect that distressed sovereign debtors will favor lenders that continue to lend even through very difficult economic times. MDBs have traditionally played such a role, acting as counter-cyclical providers of funding, and hence, one might expect them to enjoy PCS.[14]

Second, the mutual nature of some MDB institutions is likely to encourage PCS. One may note that the degree of mutuality varies across MDBs. At one extreme, the CAF (Latin

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[12] The boost could be up to three notches according to the methodology, but only if the Business Profile is "Extremely Strong" in which case the institution is unlikely to need it.

[13] The case of Argentina is instructive in several respects. Following its 2002 default on commercial debt and despite a severe economic crisis, Argentina remained current on all payments to the IDB and fully repaid IMF loans in advance of their final maturity. Furthermore, during the recent court case of Argentina vs. NML Capital Ltd. (NML) (one of the hold-out investors that did not accept the terms of the 2005 or 2009 offers), while NML sought to disrupt Argentina's international payments and eventually succeeded in preventing Argentina from paying bondholders that agreed to the restructurings, MDBs' preferred creditor status was apparently not questioned.

[14] PCS has been extensively discussed in the context of the International Monetary Fund (IMF). PCS was not mentioned in the IMF's articles of agreement but, in 1988, the IMF's board of governors' interim committee "urged all members within the limits of their laws to treat the Fund as a preferred creditor" (see Boughton, 2001). Martha (1990) examines whether international law offers guidance in setting priorities in external debts settlements and in particular what this implies for Preferred Creditor Status of the IMF. He concludes that the IMF PCS could be placed on a more explicit legal basis through recognition in debt contracts. Raffer (2009) also makes the case for more explicit legal recognition of PCS. Schadler (2014) argues that the IMF's PCS is threatened by the effective relaxation in lending criteria that occurred when it lent to Greece in 2010. "The IMF's PCS is well-justified, provided the IMF is charged with, and capable of, carrying out its role as a catalyst of market finance or, when market access has been totally closed down, as a facilitator of early return to market access."

America's Development Bank) has a board that only includes borrowing countries.[15] At the other extreme, at the World Bank (specifically the IBRD), non-borrowing countries hold the majority of equity. The IDB is intermediate between these two cases in that, of its 48 member countries, the United States holds the largest equity share but its 26 borrowing member countries[16] own a majority of the institution's equity.[17]

While the ratings agencies take PCS into account in evaluating MDB credit standing, one may question whether they do so to an appropriate extent. Moody's and Fitch rate MDBs using methodologies that are comparatively qualitative and are not fully disclosed to the market. However, S&P uses a relatively transparent and largely quantitative approach to rate MDBs. The S&P approach includes a specific adjustment for PCS. Below, we examine the magnitude of the S&P PCS adjustment in the case of the MDB on which we focus our analysis, the IDB.

Table 2. Example MDB Spreads

	IBRD spreads in bps			
	1 year	3 year	5 year	10 year
2015	27	20	16	31
2014	28	13	7	47
2013	33	34	24	46
2012	21	31	51	75
All years	27	26	26	48
	IDB spreads in bps			
	1 year	3 year	5 year	10 year
2015	28	21	19	26
2014	17	14	14	43
2013	28	16	18	58
2012	41	23	21	60
All years	30	19	18	47

Note: Entries in the table are average daily spreads (annualized and in basis points) over US Treasury benchmarks. "All years" refers to the average across the years.
Source: Reuters.

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[15] Ocampo and Titelman (2009) and Seatzu (2014) describe the relatively successful development of multilateral financial institutions within Latin America.

[16] The most recent members include Korea and China. Haiti is a borrowing member country, although it currently receives only grant financing from the IDB and no loans. See http://www.iadb.org/en/about-us/how-the-inter-american-development-bank-is-organized,5998.html

[17] Humphrey and Michaelowa (2013) discuss the relationship between MDB shareholder structures and how they are used as a source of funding by borrower countries while Humphrey (2014) analyzes how MDB shareholder arrangements affect the ways in which MDBs price their loans.

Bond market spreads are also important indicators of credit standing. Table 2 shows estimates of spreads on MDB bond issues for two example institutions, IBRD and the IDB. Short and medium maturity spreads have varied over time as concerns about emerging market borrowers have evolved but for both institutions, typical spreads have been in the range 20 to 30 basis points. Below, we show what an analysis of the IDB portfolio implies for spreads on the bank's debt and obtain estimates broadly consistent with the figures shown in Table 2.

3. Methodologies

3.1 Two Methodologies

In this section, we describe two methodologies for assessing MDB credit quality and the impact of PCS. We apply these methodologies to data from a particular example MDB, namely the Inter-American Development Bank (IDB). The first approach is that employed by the rating agency, Standard & Poor's (S&P). The S&P methodology for rating MDBs relies heavily on the Risk Adjusted Capital (RAC) ratio that the agency developed for assessing commercial banks. In broad terms, for a given bank, the RAC is the ratio of its forecast equity (based on specific S&P definitions) to its risk weighted assets (where the weights are defined by S&P).[18]

The second approach described in this section, consists of a ratings-based, credit risk model. Models of this type are widely used by large banks in calculating their own economic capital and also for Pillar II concentration risk analysis. The technique consists of simulating the correlated ratings of the bank's exposures up to a given horizon and then valuing the exposures conditional on their ratings. The approach yields Monte Carlo estimates of the distribution of the bank's portfolio value at future points in time (typically one year hence) from which risk measures such as Value at Risk (VaR) or default probabilities may be readily calculated.

3.2 The S&P Approach

Here, we provide a concise description of S&P's methodology for rating MDBs. The agency's approach is set out in Standard & Poor's (2012a). It builds on the methodology the agency employs in rating commercial banks, as detailed in Standard & Poor's (2010).[19]

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[18] S&P states that the RAC ratio has a weighting of just 25 percent in the rating assessment of an MDB. However, if multiple indicators are combined and one has greater variability than others, then it is possible for that indicator to dominate the determination of the ranking even if it only has a relatively small weight.
[19] See also Standard & Poor's (2012b).

A schematic description of S&P's approach to rating MDBs appears in Figure 1. The methodology combines judgmental assessments of the MDB's business profile with an evaluation of its financial profile. The financial profile combines analysis of i) the capital and earnings position of the bank and ii) its funding and liquidity position.

The starting point for S&P's methodology is the agency's Risk Adjusted Capital (RAC) ratio (see Standard & Poor's, 2010). This ratio consists of the bank's forecast future capital resources (current capital adjusted for projected earnings) divided by its Risk Weighted Assets (RWAs). RWAs comprise the bank's exposure multiplied by exposure-class-specific Risk Weights (RWs) devised by S&P. We describe how S&P calculates RWAs in detail below.

Having calculated the RAC ratio of a given MDB, S&P uses the ranges in Table 3 to determine a capital adequacy category. For the highest category of Extremely Strong, an MDB must attain an RAC ratio in excess of 23 percent. Combining the capital adequacy category with an assessment of the bank's funding and liquidity position, based on the mappings in Table 4, the agency determines the MDB's financial profile (which takes one of seven possible values).

Figure 1. Standard& Poor's Approach to Rating MBDs
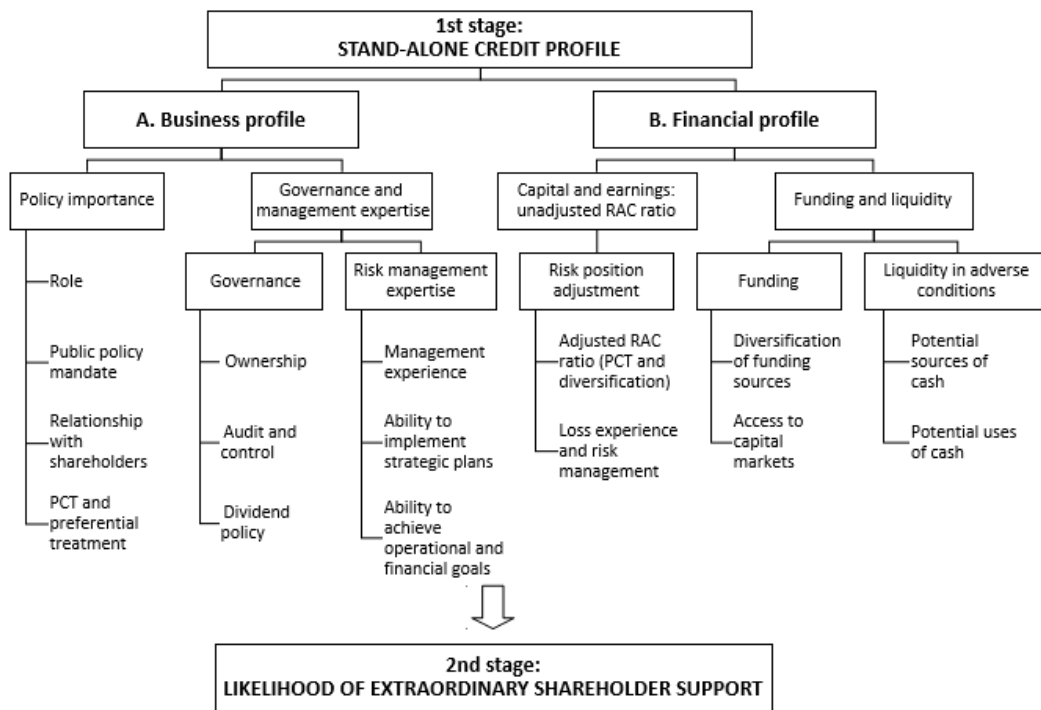
Note: The figure shows the decision process followed by S&P in assigning ratings to MDBs. The process determines the Standalone Credit Profile combining a Business Profile score and a Financial Profile score, the latter evaluation depending heavily on the Risk Adjusted Capital ratio (adjusted for additional factors).

Table 3. RAC Ratio Thresholds for Different Capital Adequacy Categories

Assessment	The RAC Ratio is:*
Extremely Strong	Above 23%
Very Strong	Above 15% and up to 23%
Strong	Above 10% and up to 15%
Adequate	Above 7% and up to 10%
Moderate	Above 5% and up to 7%
Weak	Above 3% and up to 5%
Very Weak	Lower than 3%

Note: This table shows how S&P categorizes the capital and earnings profile of an MDB based on its RAC ratio. If the RAC ratio is within 10 percent of a particular threshold, S&P incorporates qualitative forecast in assigning the MDB to a financial profile category.
Source: Standard & Poor's (2012a).

Table 4. Combining Capital and Funding and Liquidity Scores to Obtain Financial Profile

		Capital Adequacy						
		Extremely Strong	Very Strong	Strong	Adequate	Moderate	Weak	Very Weak
Funding and Liquidity	Very Strong	Extremely strong	Extremely strong	Very strong	Strong	Adequate	Moderate	Weak
	Strong	Extremely strong	Very strong	Strong	Adequate	Moderate	Weak	Very weak
	Adequate	Very strong	Strong	Adequate	Moderate	Weak	Very weak	Very weak
	Moderate	Strong	Adequate	Moderate	Weak	Very weak	Very weak	Very weak
	Weak	Moderate	Moderate	Weak	Very weak	Very weak	Very weak	Very weak
	Very Weak	Weak	Weak	Very weak	Very weak	Very weak	Very weak	Very weak

Note: This table shows how S&P combines capital adequacy and funding and liquidity scores to obtain the financial profile of a multilateral development bank.
Source: Standard & Poor's (2012a).

Lastly, the agency combines the financial profile with a judgmental assessment of the MDB's business profile using the mappings in Table 5 to obtain a (lower case) letter rating.

Table 5. Combining the Financial and Business Profile

		Financial Profile						
		Extremely Strong	Very Strong	Strong	Adequate	Moderate	Weak	Very Weak
Business Profile	Extremely Strong	aaa	aaa/aa+	aa+/aa	aa/aa-	a+/a	a-/bbb+	bbb/bbb-
	Very Strong	aaa/aa+	aa+/aa	aa/aa-	a+/a	a/a-	bbb+/bbb	bb+/bb
	Strong	aa+/aa	aa/aa-	a+/a	a/a-	bbb+/bbb	bbb/bbb-	bb/bb-
	Adequate	aa/aa-	a+/a	a/a-	bbb+/bbb	bbb/bbb-	bb+/bb	b+/b
	Moderate	a+/a	a/a-	bbb+/bbb	bbb/bbb-	bb+/bb	bb-/b+	b/b-
	Weak	a-/bbb+	bbb+/bbb	bbb/bbb-	bb+/bb	bb/bb-	b+/b/b-	ccc+/ccc/ccc-
	Very Weak	bbb+/bbb	bbb/bbb-	bb+/bb	bb/bb-	b+/b/b-	ccc+/ccc/ccc-	cc

Note: This table shows how S&P combines the business and financial profiles of a multilateral development bank in order to form its Stand-Alone Credit Profile (SACP).
Source: Standard & Poor's (2012a).

3.3 Methodologies Applied by Other Ratings Agencies

The S&P methodology in rating MDBs may be compared with those employed by other ratings agencies. Of these, the DBRS approach resembles that of S&P most closely, with ratings being based on a combination of scores for intrinsic assessment and support assessment. The intrinsic assessment relies in part on a capital to Risk Weighted Assets ratio, but in the DBRS approach the RWAs are a slightly modified version of the Basel RWAs.

Fitch issues intrinsic and support ratings for each MDB. The approach mixes qualitative and quantitative indicators via a scoring system. Fitch does not employ a notion of Risk Weighted Assets. It measures capital adequacy using three ratios: i) Shareholders' equity/total assets and guarantees (15.0 percent of the total rating evaluation), ii) Paid-in capital/subscribed capital (3.5 percent) and iii) Outstanding debt/shareholders' equity (12.5 percent).

Like Fitch, Moody's (2013) employs a scorecard approach. Capital adequacy and liquidity factors are used to infer Intrinsic Financial Strength. This is then combined with a scoring of Member Support to obtain a final rating range. Capital adequacy is assessed using the following indicators: i) Position (weighted 50 percent) comprising two indicators: Asset Coverage Ratio and Leverage as measured by Debt as percentage of Usable Equity; ii) Asset Quality (weighted 40 percent) comprising two indicators: Borrower Quality (based on Weighted Average Borrower Rating) and Non-Performing Assets (expressed as NPLs as a percentage of Total Loans); and iii) Profitability (weighted 10 percent) comprising two indicators: Return on Assets (in percent), Net Interest and Dividend Margin-to-Earning Assets (in percent). These are then subject to the following Adjustment Factors ranging from -3.5 to +1 notches based on three factors: Portfolio Concentration, Operating Environment and History. No use is made of Risk Weighted Assets.

3.4 S&P's Risk Adjusted Capital Ratio

To calculate its RAC ratio, S&P employs a set of Risk Weights (RWs) for the various asset classes that banks hold.[20] These weights depend on the ratings of the claims as well as on the asset class in question. Detail on the various RWs may be found in Standard & Poor's (2012a).

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[20] The risk weights (RWs) employed by S&P are represented by the agency as comparable to, but currently, somewhat different from Basel regulatory RWAs. S&P suggests that the two may move closer over time as Basel III rules are progressively implemented. In fact, as we explain below, the S&P RWs are quite different in conception from the Basel RWs, and it would be highly surprising if the two sets of risk weights converged.

For MDBs that primarily lend to sovereigns, the most important weights are those shown in Table 6. The weights depend on the rating of the sovereign and on the fraction of multilateral debt in total external debt.

Table 6. Central Government Risk Weights

	Share of multilateral debt in the total external debt			
	<25%	25%-50%	50%-75%	>75%
AA- and above	3	3	3	3
A+	3	3	3	5
A	3	3	5	9
A-	3	5	9	15
BBB+	5	9	15	23
BBB	9	15	23	34
BBB-	15	23	34	47
BB+	23	34	47	62
BB	34	47	62	79
BB-	47	62	79	99
B+	62	79	99	122
B	79	99	122	146
B- and below	99	122	146	173

Note: This table shows how S&P calculates risk weights to account for PCS, depending on the sovereign long-term foreign currency credit rating. Entries are in percent. The right hand column contains risk weights applied to debt par values when multilateral debt is so large that the agency expected PCS to play no role. For given ratings, weights in other columns are lower to reflect the effect of PCS.
Source: Standard & Poor's (2012a).

The latter dependence is intended to reflect how one might expect PCS to influence loss experience.[21] When all debt is multilateral (i.e., borrowings from MDBs and comparable institutions like the IMF), a sovereign that wishes to lighten its debt burden by defaulting will be unable to treat MDB loans as senior. On the other hand, a sovereign that has borrowed only a

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[21] Heavy reliance on PCS debt may distort outcomes in some cases. Steinkamp and Westermann (2014) examine the implications of the increase in the fraction of some countries' debt that is owed to lenders enjoying PCS. Increasing public lending may have the effect of increasing interest rates on private financing which becomes highly subordinated. PCS may be seen as an element within the broader arrangements and conventions for restructuring sovereign debt. These are discussed by Brooks et al. (2015), who propose various reforms.

fraction of its debt from multilateral institutions will be able to treat this debt preferentially if it so chooses and still achieve a reduction in its debt burden.

When S&P wishes to calculate RWs for sovereign exposures not allowing for PCS, it employs the weights in the far-right column in Table 6. The adjustment for PCS that S&P then suggests is to calculate total portfolio RWAs using this far-right column for sovereign exposures minus portfolio RWAs when the weights contained in all the columns of the table are employed.[22]

The RAC ratio as described above using the far-right column of Table 6 is termed "unadjusted" by S&P. By this, the agency means that the simple RAC is not adjusted for concentration or diversification or for PCS. To arrive at an "adjusted RAC," S&P adjusts for PCS as just described as well as adjusting for four types of dependence: i) country/region concentration/diversification, ii) sector concentration/diversification, iii) business line concentration/diversification, and iv) individual obligor concentration.

RWA dependence adjustments for a, b and c are calculated using the same approach. The adjustment is calculated by applying assumptions of correlations among different geographies, sectors and business lines. Consider one of these three dimensions of dependence, s, where s is one of a, b, or c. The adjustment for dimension s is calculated as follows:

$$
\begin{array}{c} RWA \\ adjustment \\ for\ dimension\ s \end{array} \equiv \sqrt{ \begin{pmatrix} K_1^{(s)} \times C_1^{(s)} \\ \vdots \\ K_{J_s}^{(s)} \times C_{J_s}^{(s)} \end{pmatrix}^T \begin{pmatrix} 1 & \cdots & R_{1,J_s}^{(s)} \\ \vdots & \ddots & \vdots \\ R_{J_s,1}^{(s)} & \cdots & 1 \end{pmatrix} \begin{pmatrix} K_1^{(s)} \times C_1^{(s)} \\ \vdots \\ K_{J_s}^{(s)} \times C_{J_s}^{(s)} \end{pmatrix} } - RWA^{(u)} \quad (1)
$$

Here, $K_j^{(s)}$ is the unadjusted-RAC RWA for category j under dependence dimension s, i.e. the weighted sum of exposure amounts in a particular category j where the weights are those specified by S&P in Standard & Poor's (2012a). For example, if s were a, i.e., the adjustment in question was for geographical regions, $K_j^{(s)}$ would be the RWAs for a particular country.

The weight $C_j^{(s)}$ that appears in equation (1) is referred to by S&P as the concentration factor for category j under dependence dimension s, while the constant $R_{i,j}^{(s)}$ is the correlation of

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risk categories i and j under dependence dimension s. S&P uses separate correlation matrices for geographic regions, industries and business lines. For geographic regions and industries correlations, S&P estimates these correlations using MSCI equity indexes. Business line correlations are derived judgmentally by the agency.

In formula (1), $RWA^{(s)}$ is the RWA after the adjustment for diversification under dependence dimension s. The difference between the RWA after adjustment and the RWA before adjustment is the adjustment for diversification. The adjusted RWA for all three dimensions, denoted $RWA^{(a,b,c)}$ is then defined as:

$$RWA^{(a,b,c)} \equiv RWA^{(u)} + \sum_{s\in\{a,b,c\}}\left(RWA^{(s)} - RWA^{(u)}\right) \tag{2}$$

Note that the geographic diversification adjustment is applied to *both* sovereigns and non-sovereigns. The sector diversification adjustment, in contrast, is applied to non-sovereign exposures only. In our analysis below, we make no adjustments for business line diversification.

The last adjustment, in this case for individual exposure concentrations, is implemented using very different and somewhat less consistent assumptions. (The reasoning above is consistent in that RWAs are all based on volatilities and correlations.) For the top 20 exposures, an adjustment to RWAs is made by adding a quadratic, scaled version of an upper bound for concentration risk suggested by Gordy and Lütkebohmert (2007). The adjustment for corporate exposures, following the Gordy and Lütkebohmert notation, is as follows:

$$Corporate\ concentration\ adjustment = 11.7 \times Y^2 + 0.19 \times Y \tag{3}$$

Here,

$$Y \equiv \frac{1}{2K}\sum_{i=1}^{m} s_i^2 C_i Q_i + \bar{s}\left((\delta - 1)(K - K_m^*) + \delta(R - R_m^*)\right) \tag{4}$$

where

$s_i = \frac{EAD_i}{Total\ EAD}$, is the share of the total portfolio corresponding to exposure i.

$\bar{s} = \max(s_i, i = 1, \dots, m)$, is the largest s_i among the top m exposures.

$Q_i = \delta \times (K_i + R_i) - K_i$, is used for notional convenience and $\delta = 4.83$.

$C_i = \frac{LGD^2 + 25\% \times LGD \times (1 - LGD)}{LGD}$, can be viewed as a stressed LGD using its normalized variance.

$$K_i = \left[LGD \times \Phi \left(\frac{\Phi^{-1}(PD_i)}{\sqrt{1-\rho}} + \sqrt{\frac{\rho}{1-\rho}} \Phi^{-1}(\alpha) \right) - PD_i \times LGD \right] \times Maturity\ adjustment,\ \text{is}$$

the Basel II unexpected loss for exposure i.

$R_i = PD_i \times LGD$, is the expected loss for exposure i.

$K_m^* = \sum_{i=1}^{m} K_i$, is the cumulative unexpected loss for the m largest exposures.

K is the RAC charge for the entire corporate portfolio.

$R_m^* = \sum_{i=1}^{m} R_i$, is the cumulative expected loss for the m largest exposures.

R is the S&P normalized loss for the entire corporate portfolio.

For sovereign exposures, the adjustment is simplified to:

$$Sovereign\ concentration\ adjustment = \frac{1}{2K} \sum_{i=1}^{n} s_i^2 C_i Q_i \tag{5}$$

As noted above, the single name concentration risk adjustment is based on a different modelling paradigm than the diversification adjustments employed by S&P. We will show in the results section below that the agency's approach produces results that are much more conservative than those obtained using a simple alternative approach, which is more in the spirit of S&P's diversification adjustment.

To adjust for PCS, as explained in the context of Table 6, S&P calculates the unadjusted RAC with lower central government risk weights than those included in the standard RAC methodology. (The lower risk weights, which appear in Table 6 in columns other than the rightmost, depend both on the sovereign's rating and on the share of multilateral debt in the sovereign's total external debt.) The decrease in the RWA induced by this change in the risk weights is then subtracted from the fully adjusted RWAs to obtain a final PCS-adjusted RWA.[23]

3.5 Theoretical Justification for the S&P Methodology

To understand the theoretical underpinnings of the S&P approach, suppose that an institution defaults when its capital at a future date 1 (denoted X_1) falls below a level γ. The probability of default at date 0 may be written as:

$$p_d = Prob(X_1 < \gamma) \tag{6}$$

---

[23] This builds on Martin and Wilde (2003) and Gordy (2004).

Suppose that future capital has a distribution such that:

$$p_d = F\left(\frac{\gamma - X_0 - \mu}{\sigma_A}\right) \tag{7}$$

where X_0 is initial capital and μ equals the forecast increase in capital over the period in question and σ_A is the standard deviation of risky assets and F is a monotonically increasing function. Distributions consistent with these assumptions include the family of elliptical distributions with finite second moments such as Gaussian and Student's t distributions.

If $\gamma = 0$, inverting the above gives a relationship between the ratio of forecast capital, $X_0 + \mu$ to total asset volatility, σ_A, and the default probability.

$$\frac{Forecast\ capital}{Total\ asset\ volatility} = -F^{-1}(p_d) \tag{8}$$

If one associates different ratings grades with different maximum default probabilities, given a distribution, F, one may determine ratings using minimum forecast-capital to total-asset-volatility ratios.

To make such an approach operational, one must have ways of calculating the numerator and denominator in the ratio on the left side of equation (8). Current capital plus forecast retained earnings and net capital issues imply the numerator. Estimating the denominator in a simple fashion is more challenging.

To understand the approach taken by S&P, suppose a bank invests in N asset classes, and its holding of asset class i is A_i. Then, σ_A may, in general, be written as:

$$\sigma_A = \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} \rho_{i,j,A} A_i\ \sigma_{i,A} A_j \sigma_{j,A}} \tag{9}$$

Here, the parameters $\rho_{i,j,A}$ and $\sigma_{i,A}$ are asset correlations and volatilities, respectively. Note that asset value volatility here is a quadratic expression and cannot be expressed as a weighted sum of asset exposure values, i.e., as RWAs.

If all the asset class returns are perfectly correlated, however, (i.e., $\rho_{i,j,A} = 1$), then:

$$\sigma_A = \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} A_i\ \sigma_{i,A} A_j \sigma_{j,A}} = \sqrt{\sum_{i=1}^{N} A_i\ \sigma_{i,A} \sum_{j=1}^{N} A_j \sigma_{j,A}} = \sum_{j=1}^{N} A_j \sigma_{j,A} \tag{10}$$

Alternatively, suppose the portfolio is made up of many assets that are not perfectly correlated but which have shares of risk ($\sqrt{\xi}$) on a single risk factor and on idiosyncratic shocks

$(\sqrt{1-\xi})$ that wash out in a large portfolio. In this case, the total portfolio volatility would equal $\sqrt{\xi} \sum_{j=1}^{N} A_j \sigma_{j,A}$. Hence, when returns are perfectly correlated (or alternatively, when the only non-diversified risk in a large portfolio is exposure to a single risk factor), total portfolio volatility equals a form of risk weighted assets or RWAs.

The diversification adjustments employed by S&P are fully consistent with the above formulation. In equation (1), the $K_j^{(s)}$ equals the risk weighted assets corresponding to a single asset class (leaving aside diversification across multiple risk factors). Such single-asset-class RWAs are combined using a correlation matrix for the multiple risk factors. This is consistent with the RWAs being proportional to total asset volatility.

3.6 Comments on the S&P Methodology

Several aspects of the S&P methodology deserve comment. First, the sequential adjustment for different dimensions of diversification a, b and c as described above is only approximate. To calculate diversification effects rigorously across different dimensions (such as geographical regions, sectors and business lines), one must expand the correlation matrices employed by S&P. To be specific, for each region a full set of matrix rows corresponding to sectors and business lines should be present in this expanded matrix. Using the notation of equation (1) and for simplicity, abstracting from business lines, one would then perform a diversification adjustment using a correlation matrix with $J_{(a)} \times J_{(b)}$ rows and columns.

Given two matrices say for sector and region, banks use several different approaches to infer a larger dimensional matrix. A common approach is to suppose that each obligor has an exposure to one common factor which is a weighted sum of two factors, specifically the sector and region factors corresponding to the sector and the region of the single exposure. While the relative weight of the sector and region factors for each individual exposure is sometimes estimated, at least some banks simplify by supposing that the composite factor for each individual exposure is an equal weighted sum of a global sector and a region/country factor. A second approach that is used by some banks to generate the larger dimensional correlation matrix is to assume that it equals the Kronecker or tensor product of the two smaller matrices. Below, in order to study the conservatism or otherwise of the S&P approximation, we apply these two approaches to expanding the matrices.

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Second, it is notable that the S&P diversification adjustments are made without themselves being PCS-adjusted. PCS reduces the risk of defaults affecting not just the base case unadjusted RWA, but also the deviations from this base case attributable to diversification. One might consider it more appropriate, instead of following the S&P order of calculation, to calculate the so-called unadjusted RAC ratio inclusive of PCS adjustments and then to introduce diversification adjustments. Again, below, we evaluate the conservatism or otherwise of the S&P approach.

Third, one may enquire whether the adjustment in risk weights for PCS made by S&P is appropriate in magnitude. The above discussion suggests that one may assess this issue by looking at the relative volatility of debt that enjoys PCS status from that which does not. Volatility for debt enjoying PCS status is not directly measurable as it is not publicly traded. However, one may calibrate the differences in default probability and infer an adjustment in the volatility of value. We shall perform such a calibration below, simulating the IDB portfolio with and without PCS adjustments and then comparing the relative portfolio volatilities.

Fourth, one may consider alternative approaches to allowing for single name concentration risk. The approach taken by S&P appears quite inconsistent with the other adjustments that the agency includes for correlation. While its diversification adjustments are based on asset volatility adjustments, S&P employs for single name concentration the adjustment described in equations (3)-(5) above, which is taken from Gordy and Lütkebohmert (2007). These authors develop a granularity (or single name concentration) adjustment based on an asymptotic expansion of the CreditRisk+ model (devised by CSFP, 1997). Their analysis builds on Wilde (2002) which derives such adjustments for CRMs more generally.

CreditRisk+ is a default mode model and in any case the asymptotic expansion is only valid locally. The examples that Gordy and Lütkebohmert provide involve adjustments in capital of between 2 percent and 15 percent. When applied to the IDB portfolio, the adjustment to capital amounts to well over 100 percent. One may doubt whether a local approximation is appropriate in this case.[24] Below, we examine an alternative approach to adjusting for single name concentration which is more in the spirit of the other adjustments S&P adopts for diversification effects.

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[24] One may also question whether using an adjustment based on a default mode model is appropriate. Basel RWAs as Gordy and Lütkebohmert (2007) note are derived from an economic-loss mode model.

To summarize, several aspects of the S&P methodology merit further investigation and, in the results section below, we return to these issues and evaluate the implications for MDB ratings using the credit standing of the IDB as an example.

3.7 Portfolio Credit Risk Modeling

The second methodology that we apply to examine the credit standing of our primary example MDB, the IDB, follows industry-standard credit risk modeling approaches. This approach, widely used by banks and ratings agencies, consists of simulating the evolution of ratings using techniques based on the Ordered Probit model employed in statistical analysis of discrete choice data. Correlated random factors are simulated using Monte Carlo methods and these are mapped into changes in the ratings of individual obligors based on a set of cut-off points. The cut-off points are inferred from estimates of ratings transitions matrices.

To understand more precisely how the model works, first consider the random behavior of a set of ratings for individual loans. Suppose there is a set of I credit exposures denoted by $i = 1, 2, \cdots, I$. Assume that at date t, exposure i has a rating, R_{it}, taking one of K values, $1, 2, \cdots, K$. Here, K indicates the default state, while state 1 indicates the highest credit quality category.

Since we need to analyze the actual ratings dynamics and perform pricing calculations, we must distinguish between actual and risk-adjusted distributions of ratings changes. Assume that under both actual and risk-adjusted probability measures, R_{it} evolves as a time homogeneous Markov chain. The actual and risk-adjusted $K \times K$ transition matrices are denoted: M and M^* respectively. The (i, j)-elements of M and M^* are $m_{i,j}$ and $m_{i,j}^*$ respectively. Let $m_{i,j,\tau}$ and $m_{i,j,\tau}^*$ denote the (i, j)-elements of the τ-fold products of the matrices M and M^*, i.e. M^τ and $(M^*)^\tau$.[25]

---

[25] The actual transition matrix, M, may be estimated from historical data on bond ratings transitions. The risk-adjusted transition matrix M^* may be deduced from bond market prices, in particular, from spread data on notional pure discount bonds with given ratings. To see how one may achieve this, note that if credit risk and interest rate risk are independent and spreads only reflect credit risk (i.e., there are no tax or liquidity effects), the τ-maturity spread on a pure discount bond with initial rating i, denoted S_τ^i, satisfies:
$\exp(-S_\tau^{(i)}\tau) = m_{i,K,t}^*\gamma, K, tm_{i,K,t}^*)$
Here, γ is the expected recovery rate in the event of default.
Let $\Gamma \equiv \tau_1, \tau_2, \equiv t\tau_d$ denote a set of integer-year maturities. To infer the risk-adjusted matrix, we may choose $m_{i,j,o}^*$ for $i, j = 1, 2$, a set and tan to minimise:
$\min_{m_{i,j,m}^*} \sum_{\tau \in \Gamma} \sum_{i=1}^{K=1} (S_\tau^{(i)} - (m_{i,K,m}^*\gamma, K, mm_{i,K,m}^*)))^2$

We have just described a theoretically consistent set of the actual and risk-adjusted marginal distributions of ratings for our set of I exposures. Now consider how one may simulate changes in ratings incorporating dependence between ratings changes for different obligors.

We employ the Ordered Probit approach widely used in ratings-based portfolio credit risk models. For any row of M (say the jth row), one may deduce a set of cut-off points $Z_{j,k}$ for $k = 1, 2, \cdots, K - 1$ by recursively solving the equations:

$$
\begin{aligned}
m_{j,1} &= \Phi(Z_{j,1}) \\
m_{j,2} &= \Phi(Z_{j,2} - Z_{j,1}) \\
&\vdots \quad \vdots \quad \vdots \\
m_{j,K} &= 1 - \Phi(Z_{j,K-1})
\end{aligned}
\tag{11}
$$

Here, $\Phi(\cdot)$ is the standard normal cumulative distribution function. Doing this, we obtain a set of ordered cut off points: $Z_{j,1} \leq Z_{j,2} \leq \cdots \leq Z_{j,K-1}$.

Given an initial rating, j, to simulate a change in the rating from t to $t + 1$ for exposure i, we draw a random variable $X_{i,t+1}$. If $Z_{j,k-1} < X_{i,t+1} \leq Z_{j,k}$ (where by convention $Z_{j,1} = -\infty$ and $Z_{j,K} = \infty$), exposure i's rating at $t + 1$ is k.

The latent variables $X_{i,t}$ that determine changes in ratings are assumed to be standard normal random variables. To include dependency between the ratings changes of different exposures, assume that the $X_{i,t}$'s, for exposures $i = 1, 2, \cdots, I$, satisfy a factor structure, in that:

$$
X_{i,t} = \sqrt{1 - \beta^2} \sum_{j=1}^{J} a_{i,j} f_{j,t} + \beta_i \, \varepsilon_{i,t}
\tag{12}
$$

Here, the $f_{j,t}$ are factors common to the latent variables associated with the different credit exposures and the $\varepsilon_{i,t}$ are idiosyncratic shocks. The $f_{j,t}$ and the $\varepsilon_{i,t}$ are standard normal and the weights $a_{i,j}$ are chosen so that the total factor component for exposure i denoted: $f_{I(i),t}^* \equiv \sum_{j=1}^{J} a_{i,j} f_{j,t}$, is also standard normal.

If one knows the risk-adjusted probabilities of default for individual exposures and assumes that defaults, recovery rates and shocks to interest rates are independent, the valuation

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Here, note that the $m_{i,K,}^*$ are implicitly functions of the $m_{i,k}^*$. (Note, we attach penalties to the objective function if entries in the transition matrix become negative in the course of minimization. This ensures the resulting risk adjusted matrix is well-behaved.)

In performing this calculation, we assume that the recovery rate γ is 50 percent and that the maturities in Γ are $1, 2, \ldots, 8$ years. The spread data we employ are time averages of pure discount bond spreads calculated by Bloomberg based on price quotes for bonds of different ratings and maturities issued by industrial borrowers.

of individual exposures at some future date conditional on ratings is straightforward. For example, under these assumptions, the price $V_{t,R}$ of a defaultable fixed rate bond with initial rating R, coupons c, and principal Q is:

$$V_{t,R} = \sum_{i=1}^{N} c \exp[-r_{t,t+i}i] \left((1 - m_{R,K,i}^*) + \gamma\, m_{R,K,i}^*\right) + Q \exp[-r_{t,t+N}N] \left((1 - m_{R,K,N}^*) + \gamma\, m_{R,K,N}^*\right) \tag{13}$$

Here, $r_{t,t+i}$ is the i-period interest rate at date t. It is simple to derive pricing expressions for floating rate loans and many other credit sensitive exposures under these assumptions as well.

Drawing together the various elements described above, one may simulate dependent ratings for all *I* exposures. The steps involved are the following:

1. Draw the $f_{j,t}$ and $\varepsilon_{i,t}$ and calculate the latent variables for each exposure and each period using equation (12).
2. Deduce the time path followed by the ratings by comparing the latent variable realizations with the cut-off point intervals $Z_{j,k-1} < X_{i,t+1} \le Z_{j,k}$.
3. Conditional on the rating at the chosen future date, price and *I* exposures.
4. Repeat the exercise many times to build up a data set of value and rating realizations.

The above list of steps explains how one may simulate the value of a portfolio of credit risk instruments in order to calculate risk statistics such as Value at Risk or Expected Shortfall. To simulate the portfolio value to estimating price, one may perform a comparable simulation by using the risk adjusted transition matrix, M^*, instead of the actual transition matrix, M, as the basis for the probabilities of transitions from one rating category to another. The price of any security is then the expected payoff on that security calculated using these risk adjusted distributions.

4. Data and Calibration

This section describes the IDB portfolio that we evaluate using both the S&P RAC ratio and ratings-based CRM methodologies and the calibration we employ in the latter analysis. Table 7 summarizes the credit risk portfolio data as it is broken down for use in the S&P RAC ratio calculation. One may observe the dominant role of Government and Central Bank credit

exposures, contributing 88 percent of credit exposures by par value.[26] Financial institutions contribute another 8 percent.

Table 7. Credit Risk Portfolio Data

Credit risk category	Exposure amount
Gov. and Central Banks	106,951
Institutions	10,269
Corporate	3,721
Securitization	482
Other Assets	482
Total	121,905

Note: Exposure amounts are in millions of USD and are based on June 2015 information.
Source: IDB.

In its own internal portfolio classification, the IDB breaks its credit risk exposures into three broad categories: Sovereign (SG) loans, Non-sovereign (NSG) loans and Investments. SG loans contribute 67 percent of the total credit portfolio, NSG loans account for 5 percent and Investments represent 28 percent. For the credit exposures described in Table 7, 74 percent of Government and Central Bank exposures fall into SG loans, while 24 percent fall into Investments. Some 27.4 percent of Institution exposures belong to NSG loans, while 72.6 percent belong to Investments. Almost all corporate exposures (97 percent) consist of NSG loans, the rest being Investments. All securitizations belong to Investments. We leave aside consideration of Other Assets, which represent only a very small fraction of total assets.

Table 8 shows the distribution of IDB's exposures to central government as a fraction of its portfolio broken down by the share of indebtedness to multilateral lenders in its total external debt. The figures in Table 8 should be compared with S&P's central government risk weights (by rating and exposure to multilateral lenders) shown in Table 6. A significant share of the IDB's portfolio consists of central government loans with ratings in the vicinity of BBB. For such ratings, the risk weights without allowance for PCS (as shown in the far-right column of Table 6) are around two to three times higher than when allowance is made.

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[26] Some MDBs lend extensively to the private sector on a non-sovereign-guaranteed basis. Romero and Van de Poel (2014) describe such activities. In contrast, the IDB's portfolio consists mostly of sovereign loans.

Table 8. Portfolio Distribution

Rating	Shares in total multilateral debt			
	<25%	25% - 50%	50% - 75%	>75%
AA- and above	0.6%	0.0%	0.0%	0.0%
A+	0.0%	0.0%	0.0%	0.0%
A	0.0%	0.0%	0.0%	1.1%
A-	0.0%	0.0%	0.0%	0.0%
BBB+	17.5%	3.2%	0.0%	0.0%
BBB	2.5%	12.0%	0.0%	0.4%
BBB-	20.7%	0.0%	0.0%	0.0%
BB+	0.0%	0.0%	0.0%	0.0%
BB	0.0%	1.5%	5.6%	0.0%
BB-	0.0%	3.3%	0.0%	0.5%
B+	0.0%	0.0%	7.6%	0.0%
B	0.0%	2.0%	0.6%	1.4%
B- and below	3.4%	16.1%	0.0%	0.0%

Note: The table shows the shares of IDB's portfolio of credit exposures to central governments broken down by i) rating and ii) groups of countries for which multilateral debt comprises percentages of total external debt falling into particular ranges. The data pertain to June 2015. Entries before rounding sum to 100 percent.

To enter the SG loans, NSG loans and Investments into exposure types within our CRM, we adopt the assumptions described below.

All SG loans are modelled as Sovereign Floating Rate Notes (SFRN) with fixed spreads over LIBOR. We assume that the coefficient on the idiosyncratic factor in equation (12), denoted β, equals zero. The mean and volatility of the recovery rate for SG exposures are assumed to equal 0.5 and 0.25 respectively.[27] The assumed duration of SG loans was calculated using IDB's country-specific SG loan amortization schedules. The CRM requires that we specify the cash flow characteristics of exposures. We assume a 115 bps spread and 50 bps commitment fee except one outstanding Ecuador DSL which is another type of Contingent Loan. For this DSL, the spread is 165 bps and commitment fee is 75 bps.[28]

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[27] These values are consistent with standard credit risk modelling assumptions for senior unsecured corporate bonds and are conservative when applied to sovereign exposures.

[28] Note that the IDB portfolio consists of relatively simple financial instruments. Credit exposures are almost all conventional loans, bonds or deposits. Some authors have argued that MDBs should take on somewhat less standard

NSG loans are modeled as defaultable Floating Rate Notes (FRNs). We employ a detailed database of all NSG loans outstanding at June 2015 consistent with RAC ratio calculation data.[29] We assume the same commitment fees as the SG loans.

For NSG loans, the credit quality is driven by a single country factor, a single industry factor and idiosyncratic risk. The industry-country ratio is assumed to be 0.5 and the idiosyncratic risk weight is 0.5. The mean recovery rate is assumed to depend on the loan's seniority. Senior debt is assumed to have 0.5 mean recovery rate and sub-debt is assumed to have 0.3 recovery rate. Both seniorities have a recovery volatility of 0.25.[30]

Investments comprise exposures to Government and Central Banks, Institutions, Corporates and Securitizations (ABS-MBS). All investments are modeled as Fixed Rate Bond/Loan exposures except Cash, which is modeled as a default-free bond with a 1 percent interest rate. We assume a 5 percent coupon rate for all other Fixed Rate Bond/Loan exposures and a 4 year maturity.

Exposures to Government and Central Banks are modeled as Fixed Rate Sovereign Bond. ABS-MBS, Institutions (excluding cash) and Corporates investments are treated as diversified pool exposures.[31]These exposures are assumed to be driven by a single country factor and idiosyncratic risk. The idiosyncratic risk weight is assumed to be 0.5.

As there is no country/region information available for ABS-MBS, we assume ABS-MBS is equally distributed in the regions Europe and North America. The diversified pool exposures are assumed to be driven by a single country factor and idiosyncratic risk. The idiosyncratic risk weight is assumed to be 0.5 for all diversified pool exposures.

5. Results

5.1 S&P Analysis of IDB

We begin by examining S&P's analysis of the IDB RAC ratio in Table 9. Column 2 of the table sets out the agency's calculation. Column 3 shows our replication of this calculation based on the

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exposures. MDBs typically operate with relatively conservative loans and commitments. For example, Humphrey and Prizzon (2014) suggest that MDBs could extend their operations to include a wider use of guarantees. See also Fitch Ratings (2006).

[29] In one or two cases, where data is missing we interpolate using other data on similar loan-country combinations.

[30] The recovery rate means and volatilities are consistent with those implied by Moody's historical recoveries data.

[31] The diversified pool exposures we employ consist of infinitely granular loans pools modelled using a multi-period generalization of the Vasicek loss distribution. Individual loans are assumed to default or not in each period and parameters include period-by-period actual and risk adjusted default probabilities (the latter being used in pricing calculations).

parameters given in Standard & Poor's (2012) and an estimate of the correlation matrices used by S&P to perform the diversification adjustment. These matrices are not made public by S&P, so we have estimated suitable correlation matrices based on MSCI equity indices. The diversification adjustment we obtain is reasonably close but not identical to that of S&P.[32]

The results shown in Columns 2 and 3 of Table 9 are notable in several regards. Firstly, IDB's dominant exposure category is Government and Central Banks. This category contributes $64 billion to IDB's total of $72 billion unadjusted credit risk RWAs. Secondly, the PCS adjustment appears very small considering the bank's own loss experience. Considering cases where sovereigns have defaulted on other debt since 1960, in only 11 percent of those cases was there a non-accrual event for the IDB.[33] Thirdly, the Industry and Geographical Region diversification appears relatively small, reflecting the fact that the portfolio has significant concentration to South American sovereigns. Fourthly, the single name concentration adjustment is extremely large, leading almost to a tripling of credit risk RWAs after adjustment for diversification and PCS.

We wish to examine the issues with the S&P methodology raised in Section 3. These issues include: i) sequential adjustment for diversification adjustments, ii) the fact that diversification and Single Name Concentration (SNC) adjustments are performed before adjustment for PCS, iii) the magnitude of PCS adjustments, and iv) the approach S&P takes in adjusting for SNC. We analyze these issues in the next four subsections. The results of sensitivity analyses of these issues are reported in Table 9.

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[32] There remain some aspects of the S&P calculation that are opaque. For example, it is unclear how exposures to government bodies are treated in the sector diversification adjustment. We have made the assumption that they are dropped, but this may not correspond to what S&P is actually doing in its calculation.

[33] See "Annex – IDB's PCT Adjustment Methodology" to "Regulations Governing the Implementation of the Capital Adequacy Policy" (unpublished document prepared by IDB Finance Department). Most non-accrual events imply delayed payments of interest. So the only "losses" to the IDB in these cases is interest on those interest payments (which is not charged) or penalty interest rates that might typically be included in a commercial loan contract.

Table 9. Replication of S&P RAC Ratio Calculations

	RWA (S&P calculation)	RWA (RCL calculation)	Sequential adjustment for diversification dimensions	Diversification and SNC after PCS adjustment	The magnitude of PCS adjustments	SNC concentration
Credit Risk						
Gov. and Central Banks	64,116	64,116				
Institutions	2,550	2,550				
Corporate	4,859	4,859				
Securitization	302	302				
Other Assets	542	542				
Total Credit Risk	72,368	72,368	72,368	72,368	72,368	72,368
Total Operational Risk	4,295	4,295	4,295	4,295	4,295	4,295
RWA before adjustments	76,663	76,663	76,663	76,663	76,663	76,663
MLI Adjustments						
Industry and Geo Diversifications	-8,310	-8,066	-8,112	-4,816	-8,066	-8,066
PCS	-15,909	-15,909	-15,909	-15,909	-42,478	-15,909
SNC	92,138	91,025	91,025	78,098	91,025	19,168
High Risk Exposure Cap	-8	-8	-8	-8	-8	-8
Total MLI Adjustments	67,911	67,042	66,995	57,365	40,473	-4,815
RWA after adjustments	144,573	143,704	143,658	134,028	117,136	71,848
Adjusted common equity (ACE)	24,719	24,719	24,719	24,719	24,719	24,719
RAC Before Adjustments	32.24%	32.24%	32.24%	32.24%	32.24%	32.24%
RAC After Adjustments	17.10%	17.20%	17.21%	18.44%	21.10%	34.40%
AAA Callable	12,095	12,095	12,095	12,095	12,096	12,095
RAC After Adjustments and AAA callable	25.46%	25.62%	25.63%	27.47%	31.43%	51.24%

Notes: Figures are in millions of US dollars unless otherwise specified. In the first block, when comparing the unadjusted RWA, we use the same data set as used in the IDB RAC ratio calculation. Our unadjusted RWA calculation for each credit risk category is identical to what IDB has obtained. In the second block, when calculating the industry diversification and single name concentration for NSG, we use a slightly different data set, as we need to know the single sector information for individual obligor which is not provided in the IDB RAC ratio calculation Excel work book. This is why we obtained slightly different numbers for Industry Diversification and SNC adjustments. Figures do not include the impact of the recent Argentina upgrade.

5.2 Sequential Adjustment for Diversification Dimensions

Firstly, we examine the effects of the approximation involved in the sequential adjustment for different dimensions of diversification. As noted in Section 3, the S&P approach involves an approximation in that adjustment for diversification in multiple dimensions and is made sequentially as a series of separate adjustments rather than making a single global adjustment. To examine the impact of this approximation for region and sector diversification (we ignore business line diversification), we estimate large dimensional correlation matrices and perform a single diversification adjustment across region and sector simultaneously.

We generate large dimensional matrices using two approaches common in the industry: i) a Kronecker or tensor product approach and ii) a Weighted-Sum-of-Indices technique. Approach i) consists of estimating separate correlation matrices for region factors and for sector factors and then constructing a large dimensional matrix as the Kronecker product of the two separate matrices. Approach ii) consists of estimating a correlation matrix of region and global sector factors and then generating a larger dimensional matrix consisting of the correlation matrix of all possible pairs of a single region factor and a single sector factor.

We compare the results of these two approaches with the S&P sequential adjustment approach. The portfolio standard deviation is in each of the three approaches calculated as follows:

1. The Kronecker product approach

   The correlation is estimated as:

   $$\Sigma = \Sigma^{(R)} \otimes \Sigma^{(S)} \tag{14}$$

   Here, $\Sigma^{(R)}$ is the region correlation matrix and $\Sigma^{(S)}$ is the sector correlation matrix.

   The standard deviation of a portfolio is then estimated as:

   $$sd = \sqrt{w'\Sigma w} \tag{15}$$

2. The Weighted-Sum-of-Indicators Approach

   The $(N_s(i-1)+j, N_s(k-1)+l)^{\text{th}}$ entry of the correlation is estimated as:

   $$\Sigma_{(N_s(i-1)+j, N_s(k-1)+l)} = \text{Cov}\left(\frac{f_i^{(R)}+f_j^{(S)}}{2}, \frac{f_k^{(R)}+f_l^{(S)}}{2}\right) = \frac{1}{4}\left(\Sigma_{(i,k)}^{(R)} + \Sigma_{(i,l)}^{(R,S)} + \right.$$
   $$\left. \Sigma_{(k,j)}^{(R,S)} + \Sigma_{(j,l)}^{(S)}\right) \tag{16}$$

   Here, $\Sigma^{(R,S)}$ is the region sector correlation matrix.

   The standard deviation is estimated in the same way as in equation (15).

3. The S&P sequential adjustment approach

   The S&P approach is as follows:

   $$sd = 1 + \left(\sqrt{w^{(R)'}\Sigma^{(R)}w^{(R)}} - 1\right) + \left(\sqrt{w^{(S)'}\Sigma^{(S)}w^{(S)}} - 1\right) \tag{17}$$

In each of the above approaches, the correlation matrices $\Sigma^{(R)}, \Sigma^{(S)}$ and $\Sigma^{(R,S)}$ are estimated from MSCI equity indices.

Table 10 presents a comparison of portfolio standard deviations obtained under the three methods. The portfolio weights employed are those from the IDB's NSG portfolio. As one may observe (and this remains true for other portfolios that we examined), the S&P approach yields lower portfolio standard deviations than the more rigorous approaches of working with a larger dimensional correlation matrix and adjusting for diversification across multiple dimensions in a single step. In the case of the IDB NSG portfolio, the S&P approach yields results that are only slightly less conservative. With other portfolios, one may find cases in which the S&P approach is markedly less conservative than the more rigorous approaches.

Table 10. Estimated Standard Deviation Using Actual Weights[34]

	sd from Kronecker product of correlations	sd from average of correlations	S&P adjusted sd
Actual weights (IDB NSG only)	0.81	0.84	0.80

Note: The table shows the standard deviation of the IDB portfolio adjusted in three different ways for diversification. The undiversified portfolio standard deviation is normalized to unity. The three approaches consist of i) creating a large correlation matrix from a region and a global sector matrix (both being estimated using MSCI equity indices) by taking the Kronecker product of the two; ii) creating a large correlation matrix by supposing that each factor corresponding to a region-sector pair comprises the equally weighted sum of a region and a global sector index; and iii) adjusting sequentially for region and sector correlations using the S&P approach. The portfolio weights employed are those of the IDB NSG portfolio.

To evaluate the impact of the S&P sequential diversification adjustment on the IDB's RAC ratio calculations, we scale up the industry and geographic diversification adjustment for the NSG portfolio only by the ratio: $\frac{sd\,from\,average\,of\,correlations}{S\&P\,adjusted\,sd}$. (The change only affects the NSG portfolio because only this is broken down both by region and sector.) The result is a small

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[34] We also estimate the standard deviation using randomly simulated weights. We generate a random, uniformly distributed weight *w* to each combination of country and sector; the portfolio weights are then normalized. The estimated standard deviations for the three different approaches are 0.68, 0.8 and 0.65.

increase in the diversification adjustment. The corresponding adjustments and RAC ratios are given in the fourth column of Table 9.

5.3 The Order of Calculation of the PCS Adjustment

The second issue we examine is the order of calculation of the PCS adjustment. One may question whether it is appropriate to calculate the unadjusted RAC ratio without allowing for PCS. This is material because the diversification and single name concentration adjustments are calculated as deviations from a base (unadjusted) RWA figure. It would seem more reasonable to calculate adjustments as deviations from an RWA figure that is inclusive of the PCA adjustment.

Column 5 of Table 9 shows the results of using the PCS-adjusted RWA as the base case for the diversification and single name concentration adjustments. The lower base means that the magnitudes of adjustments as deviations from the base tend to be lower. The reduction in RWA reflecting diversification falls from $8.1bn to $4.8bn when the PCS-adjusted base is used instead of the unadjusted base. In this respect, the order of calculation implicit in the S&P adjustment for diversification is not conservative.

On the other hand, the adjustment for single name concentration falls by $12bn from $90.5bn to $78.1bn. The RAC ratio after using the post-PCS-adjustment base case is 27.5 instead of 25.7.

5.4 The Magnitude of PCS Adjustments

Thirdly, one may question the magnitude of PCS adjustments. We performed a Monte Carlo (MC) simulation in our CRM to examine the impact on portfolio volatility of adjusting for PCS. The portfolio we used in MC simulation is IDB SG portfolio only. With PCS adjustments, we assume the default probabilities of sovereign loans are reduced by 80 percent. Given that the IDB's loss experience is that it incurs losses on only 11 percent of occasions on which its borrowers default, an 80 percent reduction seems reasonable. In this case, the SG portfolio volatility drops by a factor of 3.04 from 1,458 to 480. This may be compared to the proportional reduction in SG RWA assumed by S&P of 1.34.

The RWA from the S&P calculation and the portfolio volatility from MC simulation are given in Table 11.The corresponding RAC ratio estimates are presented in column 6 of Table 9. If one applies the CRM scaling factor of 3.04 to the S&P SG RWAs, one obtains a reduction in

RWA attributable to PCS of \$42.5bn instead of \$15.9bn. This leads to the RAC ratio after all adjustments of 31.6 instead of 25.7.

Table 11. S&P RWA and RCL Volatility

	S&P RWA	RCL volatility
Before PCS	63,326	1,458
After PCS	47,417	480
Ratio	1.34	3.04

Note: The table shows S&P's RWAs and the volatility of the IDB's portfolio value calculated using the CRM described in Section 3. The results "Before PCS" adjustment are estimated using the baseline calibration. The "After PCS" results are calculated after reducing the default probability of sovereign credit exposures by 80 percent. The ratio of pre- to post-PCS-adjustment results is 1.34 for the S&P RWAs but 3.04 for the CRM volatilities. Figures do not include the impact of the recent Argentina upgrade.

5.5 Single Name Concentration Risk

Lastly, one may question the adjustment for single name concentration employed by S&P. This approach is not consistent with the rest of the methodology which involves adjustments for the impact of different factors on total portfolio volatility. Instead, S&P apply the analysis of Gordy and Lütkebohmert (2007). This is developed on the basis of an approximation to a default mode CreditRisk+ model, which is very different from the basic S&P methodology which derives capital inclusive of diversification effects assuming that losses are elliptically distributed.

As an alternative to the S&P, CreditRisk+ approximation, one may develop a simple volatility adjustment for single name concentration. We describe this adjustment below and then apply it in the case of the IDB portfolio. Suppose that RWA are proportional to total portfolio volatility. Assume that each exposure has a random return R_i defined as follows:

$$R_i = \sigma_i\left(\sqrt{\rho}f + \sqrt{1-\rho}\epsilon_i\right) \tag{18}$$

Here, σ_i is the volatility of the individual position, f and ϵ_i are factor and idiosyncratic risk components respectively, and their relative contribution to total asset return risk is reflected in the parameter ρ.

Consider a large, granular portfolio in which idiosyncratic risk is diversified away. This corresponds to the case with no single name concentration. In this case,

$$Var(\sum_{i=1}^{N} w_i R_i) = Var\left(\sum_{i=1}^{N} w_i \sigma_i \sqrt{\rho} f\right) = \rho(\sum_{i=1}^{N} w_i \sigma_i)^2 \tag{19}$$

One may consider this as proportional to the base or unadjusted RWA for the portfolio.

If idiosyncratic risk is not diversified away,

$$Var\left(\sum_{i=1}^{N} w_i R_i\right) = Var\left(\sum_{i=1}^{N} w_i \sigma_i \sqrt{\rho} f\right) + Var\left(\sum_{i=1}^{N} w_i \sigma_i \sqrt{1 - \rho} \epsilon_i\right)$$
$$= \rho\left(\sum_{i=1}^{N} w_i \sigma_i\right)^2 + (1 - \rho) \sum_{i=1}^{N} w_i^2 \sigma^2 \tag{20}$$

Using equations (19) and (20), one may deduce a scaling adjustment for base case RWA to reflect single name concentration.

$$RWA \ adjusted \ for \ SNC = Base \ RWA \times \sqrt{\frac{\rho + (1 - \rho)\lambda}{\rho}} \tag{21}$$

The adjustment depends on the factor share parameter, ρ, and λ which is the Herfindahl index of shares of RWAs in individual asset classes:

$$\lambda = \frac{\sum_{i=1}^{N} w_i^2 \sigma^2}{\left(\sum_{i=1}^{N} w_i \sigma_i\right)^2} = \frac{\sum_{i=1}^{N} (Base \ RWA_i)^2}{\left(\sum_{i=1}^{N} Base \ RWA_i\right)^2} \tag{22}$$

We estimate λ using the RWAs calculated from IDB top 20 SG and the top 20 NAG single names. The unadjusted RWAs are shown in Table 12.

One may calculate the scaling factor:

$$\sqrt{\frac{\rho + (1 - \rho)\lambda}{\rho}} \tag{23}$$

for different values of the factor risk share parameter ρ ranging from 0.05 to 0.5 using the above estimated λ parameter. The resulting scaling factor estimates are shown in Table 13.

Considering Table 13, one should note that the scaling factor increases as the ρ parameter decreases. What is a plausible value for this parameter? The Basel single risk factor model assumes that corporate asset values have coefficients on common risk factors ranging from 12 percent to 24 percent. Assuming ρ equals 20 percent, one obtains a scaling of RWA of 1.3. Scaling up the base RWA by 1.3 to reflect single name concentration, one obtains the RAC ratios shown in column 7 of Table 9, i.e., 51.2 instead of 25.7.

Table 12. Top 20 SG RWA and Top 20 NSG Single Names RWA

Country	RWA	NSG single name	RWA
Argentina	22,391	Panama Canal Expansion Program	435
Brazil	7,892	Costa Rica Reventazon Hydroelectric Power Plant	317
Ecuador	5,021	Peru LNG Project	284
Venezuela	4,828	Argentina IMPSA Wind Energy Investment Program	262
Mexico	3,276	Mexico Etileno XXI	261
Dominican Republic	2,621	Costa Rica ICE Debt Refinancing	231
Colombia	2,568	Argentina AUSA Road Safety and Urban Mobility Program	203
El Salvador	2,472	Regional Isolux Corporate Loan	184
Jamaica	2,191	Uruguay Montes del Plata	164
Guatemala	1,846	Brazil Pécem Thermoelectric Power Plant Project	136
Honduras	1,192	Peru Chaglla Hydroelectric Power Project	136
Costa Rica	991	Regional Hidrovias Transport	132
Paraguay	946	Paraguay Promoting Soybean Industrialization in Paraguay	120
Bolivia	833	Regional IIG Regional Trade Finance Facility	105
Nicaragua	759	Ecuador Quito International Airport	99
Uruguay	738	Regional Central American Mezzanine Infrastructure Fund	95
Panama	689	Brazil Embraport Project	93
Peru	601	Jamaica Transjamaican Highway Project	91
Barbados	434	Brazil Delba Vessel	87
Suriname	425	Dominican Republic Boulevard Turístico del Atlántico Toll Roa	80

Note: The table shows the IDB's largest exposures in USD millions to single names. Specifically, the data consist of the largest 20 exposures to central governments and the largest 20 exposures to corporates. Figures do not incorporate the effect of the recent Argentina upgrade.

Table 13. Scaling Factors

rho	scaling factor
0.05	2.0
0.1	1.5
0.2	1.3
0.3	1.2
0.4	1.1
0.5	1.1

Note: The table shows the scaling factor defined in equation (23). The parameter λ (estimated using IDBs base-case S&P RWAs) equals 0.15. The results are shown for different values of the factor share parameter, ρ.

5.6 Credit Portfolio Model Analysis

The previous sections have examined approximations and adjustments in the S&P RAC ratio methodology. In some cases, we have employed the CRM described in Section 3 to calibrate particular aspects of the RAC ratio calculations.

The CRM may alternatively be used directly to calculate capital appropriate for the IDB portfolio that we use as the example for our analysis of MDB credit quality. Through its flexible Monte Carlo approach, the CRM rigorously deals with diversification, single name concentration and PCS adjustments. When calibrated using risk adjusted rather than historical distributions, the CRM may also be used to link the analysis of credit risk to bond market spreads.

We produced results for the following two cases: i) using a non-PCS adjusted calibration for SG, and ii) using a PCS-adjusted calibration for SG. As noted above, PCS effectively boosts de facto seniority in that when defaults occur, sovereigns generally continue to service their debts to MDB. We, therefore, adjust for PCS by assuming a reduced expected Loss Given Default rate.

To illustrate, if the recovery rate for market borrowings unaffected by PCS is 50 percent and defaulting sovereigns maintain their servicing of MDB debt half the time, the adjusted LGD would be 25 percent, corresponding to an adjusted recovery rate of 75 percent. For the PCS-adjusted and non-adjusted cases, we perform our calculation using actual transition matrices and risk adjusted transition matrices (RATM).

*5.6.1 Results with a Non-PCS Adjusted Transition Matrix for SG*

Figure 2 and Figure 3 are the portfolio value distribution histograms using a non-PCS adjusted transition matrix for SG. We focus on 2.3, 11.9 and 98.8 basis point VaR quantiles. These confidence levels correspond to the 1-year, 3-year and 10-year default probabilities that are thresholds for AAA status according to a table of idealized default probabilities provided by S&P. The mean values of the total portfolio and the VaRs at 1-year, 3-year and 10-year horizons are shown in Table 14. These VaRs may be interpreted as the capital levels that the bank would have to exceed in order to keep its default probability below the idealized default probabilities associated with AAA status.

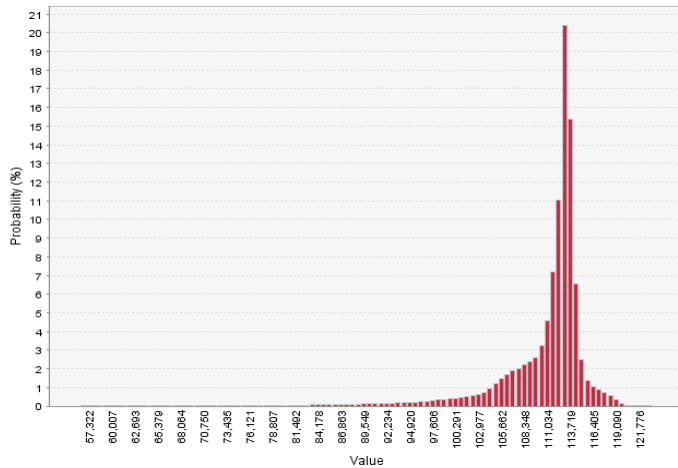# Figure 2. Portfolio Value Distributions without PCS Adjustment

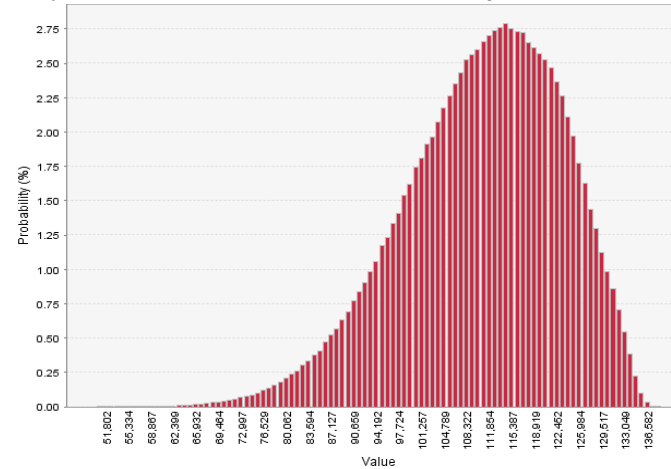1-year horizon, actual TM without PCS adjustment
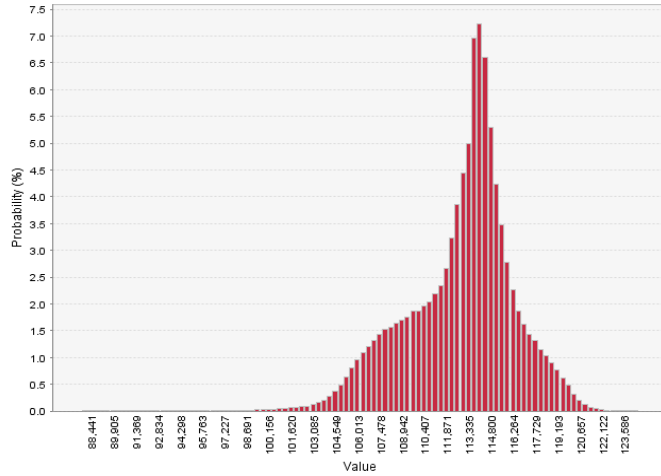
10-year horizon, actual TM without PCS adjustment
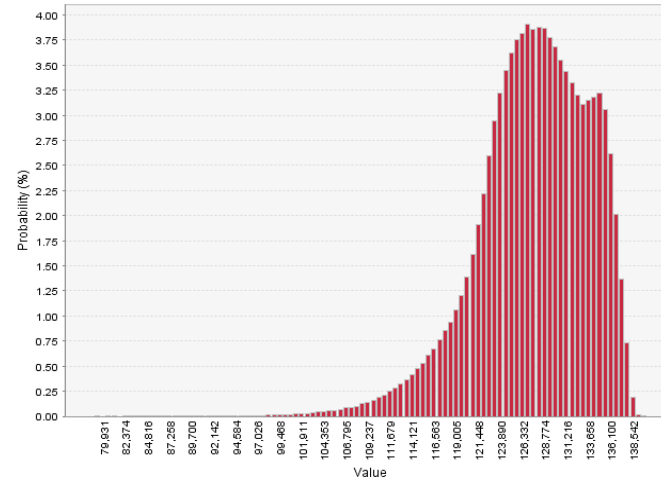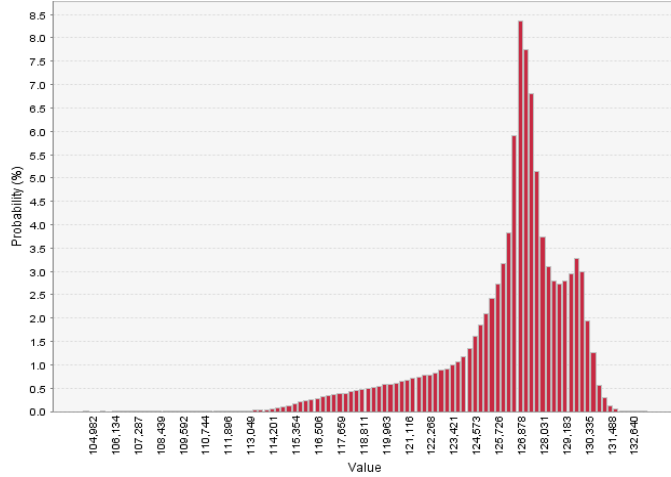
1-year horizon,RATM without PCS adjustment
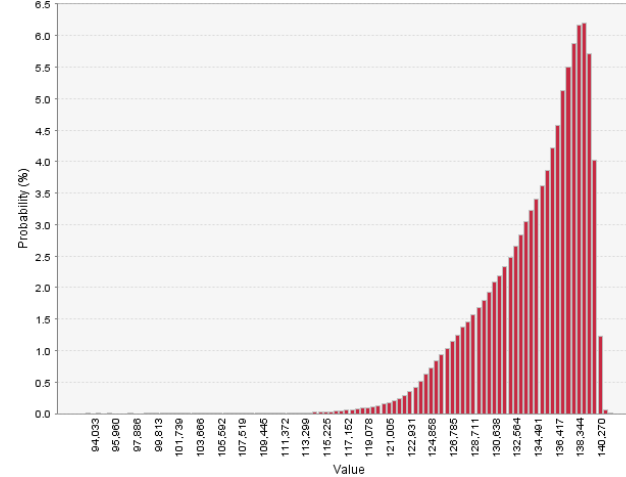
10-year horizon, RATM without PCS adjustment

Note: The figure displays the distributions of total portfolio value at 1 and 10 year horizons (left and right-hand panels, respectively). The data employed are from the IDB's portfolio as of June 2015. The upper and lower pairs of panels show the distributions using actual and risk-adjusted transition matrices respectively.

37

Figure 3. Portfolio Value Distributions with PCS Adjustment (reduce LGD by 50 percent)
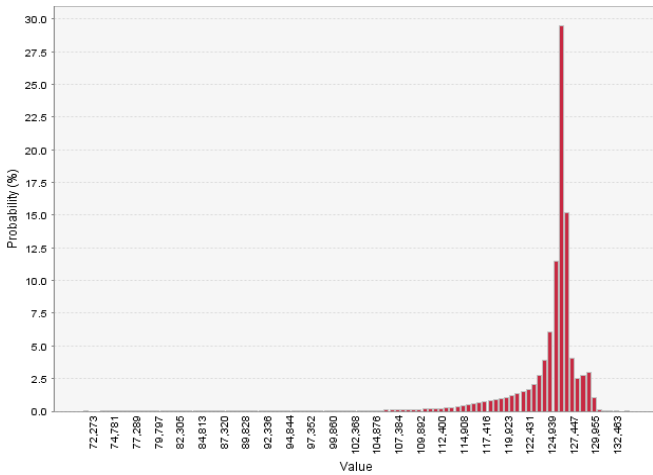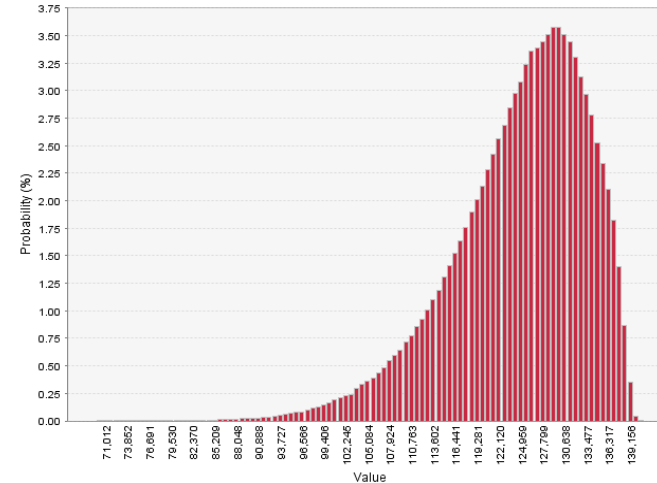
1-year horizon, PCS-adjusted actual TM

10-year horizon, PCS-adjusted actual TM

1-year horizon, PCS-adjusted RATM

10-year horizon, PCS-adjusted RATM

Note: The figure displays the distributions of total portfolio value at 1 and 10-year horizons (left and right-hand panels, respectively) inclusive of adjustments for Preferred Creditor Status (default probabilities are reduced by 80 percent). The data employed is that of the IDB's portfolio as of June 2015. The upper and lower pairs of panels show the distributions using actual and risk-adjusted transition matrices, respectively.

38

Table 14. Portfolio VaR

	Actual transition matrix		
	1-year horizon	3-year horizon	10-year horizon
Mean value	113,228	117,093	128,196
VaR 98.8bp			18,387
VaR 11.9bp		18,038	
VaR 2.3bp	17,163		

Note: This table shows risk statistics including expected portfolio value and Value at Risk (VaR) for the IDB's portfolio over 1, 3 and 10 year horizons and using actual and risk-adjusted transition matrices. The results are expressed in USD millions. The confidence levels of the VaRs employed (2.3, 11.9 and 98.8 basis points) correspond to those used by S&P as thresholds for achieving AAA rating status for 1, 3 and 10 year maturity bonds respectively. These thresholds come from a table of idealized rating-specific default probabilities distributed to S&P to structures in the CDO market.

The actual IDB capital (adjusted common equity) in June 2015 was $24.7bn. One may compare this capital level to the required VaR capital numbers of $17.2bn, $18bn and $18.4bn that the Table 10 results suggest would be required to obtain a rating of AAA over the three horizons of 1, 3 and 10 years. (Note again that these capital estimates are made so far with no adjustment for PCS.) Again, one may compare this with the capital of $33.3bn that S&P would require (see Tables 4 and 9) to designate IDB as having an "Extremely Strong" RAC ratio.

Table 15 shows the default probabilities implied by the simulations. These represent the share of occasions on which, at the VaR horizon, the simulated portfolio value falls below the mean value of the portfolio minus the bank's capital. The respective default probabilities are 0.01, 1.1 and 24.8 basis points for the three horizons of 1, 3 and 10 years. One may simulate the model using risk adjusted distributions and calculate the risk adjusted default probabilities. Using the formula shown in equation (24), one may calculate the spread on the bank's debt.

$$S = -\frac{log(PD \times \gamma + (1-PD))}{Maturity} \tag{24}$$

Here, γ is the recovery rate for IDB debt which is assumed to be 0.5. The spreads implied by these calculations are 37.2, 35.34 and 18.79basis points for the maturities of 1, 3 and 10 years,

respectively. These spreads appear high compared to the actual spreads that MDBs face. The calculations so far make no allowance for PCS, which may explain why the spreads are high.

Table 15. Distribution Implied PD, Rating and Spread

	Actual transition matrix			Risk adjusted transition matrix		
	Mean - capital	PD	Implied rating	Mean - capital	PD	Implied spread(bps)
1-year horizon	88,508	0.0001%	AAA	87,078	0.7425%	37.20
3-year horizon	92,374	0.0113%	AAA	87,420	2.1090%	35.34
10-year horizon	103,477	0.2480%	AAA	87,967	3.7223%	18.79

Note: The table shows default probabilities (PDs) for IDB based on Monte Carlo exercises employing the CRM. The PDs are generated by calculating the share of iterations for which the portfolio value at the simulation horizon is less than the initial mean portfolio value minus the IDB's capital. The implied rating is then inferred by comparing the PD (based on actual transition matrices) with the threshold PDs in the idealized default probability table circulated by S&P to CDO structurers. To achieve an AAA rating, 1, 3 or 10 year obligations must have PDs less than 2.3, 11.9 and 98.8 basis points, respectively. The implied spreads are calculated using equation (24), assuming a recovery rate of 50 percent, and the PDs based on risk adjusted transition matrices.

5.6.2 Results with a PCS Adjusted Transition Matrix for SG

To adjust for PCS, we suppose the LGD of sovereign loans are reduced by 50 percent. As noted above, the IDB has experienced losses on only 11 percent of the occasions on which its borrowers have defaulted. As an adjustment for PCS, therefore, one may view an 50percent reduction in LGD as quite conservative.

Table 16. Portfolio VaR (PCSadjusted)

	Reduce LGD by 50%		
	1-year horizon	3-year horizon	10-year horizon
Mean value	126,530	128,874	134,793
VaR 98.8bp			13,675
VaR 11.9bp		15,059	
VaR 2.3bp	14,928		

Note: See notes to Table 14. The table shows results comparable to Table 14 except that the transition matrices employed in the CRM Monte Carlo exercises to generate the risk statistics are adjusted for Preferred Creditor Status (PCS) in that default probabilities for central government credit exposures are reduced by 80 percent and 50 percent.

Table 16 shows the capital required to achieve AAA status if, in adjusting for PCS, we reduce the LGD by 50 percent. Specifically, for the three horizons, 1, 3 and 10 years, the capital necessary to achieve AAA according to the S&P look-up table of idealized default probabilities is \$14.9bn, \$15.1bn and \$13.7bn, respectively.

Table 17 shows the probabilities (for 1, 3 and 10 year horizons) that the portfolio value will fall below the mean value minus the bank's capital inclusive of PCS adjustments. With a PCS adjustment to the LGD, calculating with risk adjusted distributions and assuming a recovery rate of 75 percent, one obtains spreads of 7 to 14 basis points. Note that our analysis uses paid up equity capital not adjusted for callable capital. Including this latter would reduce the implied spreads further.

Table 17. Distribution Implied PD, Rating and Spread (PCS adjusted)

	Actual transition matrix			Risk adjusted transition matrix		
	Mean - capital	PD	Implied rating	Mean - capital	PD	Implied spread(bps)
	Reduce LGD by 50%					
1-year horizon	101,810	0.0000%	AAA	100,778	0.2810%	14.06
3-year horizon	104,155	0.0019%	AAA	100,854	0.8099%	13.53
10-year horizon	110,074	0.0308%	AAA	100,861	1.3245%	6.64

Note: See notes to Table 15. The table shows results comparable to Table 15 except that the transition matrices employed in the CRM Monte Carlo exercises to generate the risk statistics are adjusted for Preferred Creditor Status (PCS) in that default probabilities for central government credit exposures are reduced by 80 percent and 50 percent.

6. Conclusion

The ability of MDBs to realize their international development objectives is limited in practice by the need to maintain access to low cost financing in international debt markets. Even though many MDBs currently enjoy highly favorable borrowing terms, they regard their agency ratings as placing constraints on the volume and riskiness of the loans they can offer. The importance for public policy of the limits placed by rating agency views on MDB activity is emphasized by Group of Twenty (2015)[35]and Humphrey (2015).[36]

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[35] Griffith-Jones, Griffith-Jones and Hertova (2008) also argue for the importance of MDBs in achieving policy objectives and advocate the creation of new regional development banks.

[36] It is interesting to compare the debate on capital limits faced by MDBs by ratings agencies with the parallel debate on the appropriate level of capital for commercial banking determined by regulators. For example, Baker and

This paper examines in greater detail the methodology applied by the most influential ratings agency for MDBs, Standard & Poor's (S&P), taking as an example the evaluation of the Inter-American Development Bank (IDB). To benchmark S&P's approach (which contains several approximations and proprietary calibrations), an industry-standard, ratings-based Credit Portfolio Model (CRM) is applied to the IDB portfolio.

The paper identifies two areas in which S&P's practice appears extremely conservative. First, Preferred Creditor Status (PCS) is an important factor reducing the risk of MDB portfolios. The magnitude of the S&P adjustment for PCS appears much smaller than that justified by the loss experience of the IDB and other MDBs. Moreover, employing the cost of IDB borrowing and backing out the market perceived value of PCS (motivated by the fact that PCS is a market practice) also indicates that a much larger adjustment would be warranted. Second, the Single Name Concentration (SNC) risk adjustment employed by S&P more than doubles the IDB's Risk Weighted Assets (RWA) according to S&P's approach. The adjustment deployed by S&P is based on a particular methodology which is not directly consistent with other aspects of the agency's approach. An alternative, more consistent approach leads to a smaller adjustment.

Using an industry-standard portfolio CRM conservatively calibrated, we calculate the capital necessary to maintain the IDB's default probability lower than threshold idealized default probabilities. This model avoids many of the approximations implicit in the S&P methodology.

We perform these calculations with and without adjustments for PCS. We find that without adjustment for PCS, the IDB would need around $17bn in capital to achieve a rating of AAA. This compares with the bank's actual capital of $24bn.[37]Including PCS adjustments, the capital required to achieve AAA drops to $14-15bn. This may be compared to the capital of $33bn that S&P would require in order to designate the IDB as having an "Extremely Strong" RAC ratio. Clearly, the bank faces risks in addition to the credit risk that we analyze but these calculations also make no allowance for callable capital.

Wurgler (2013) discuss whether capital requirements have any economic impact on bank behavior or whether Modigliani-Miller-style capital neutrality holds.

[37] These figures do not include the impact of the recent Argentina upgrade or other changes that have improved the IDB's capital ratios.

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