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Exploring the Financial Profiles of Public Development Banks: An Umbrella Paper

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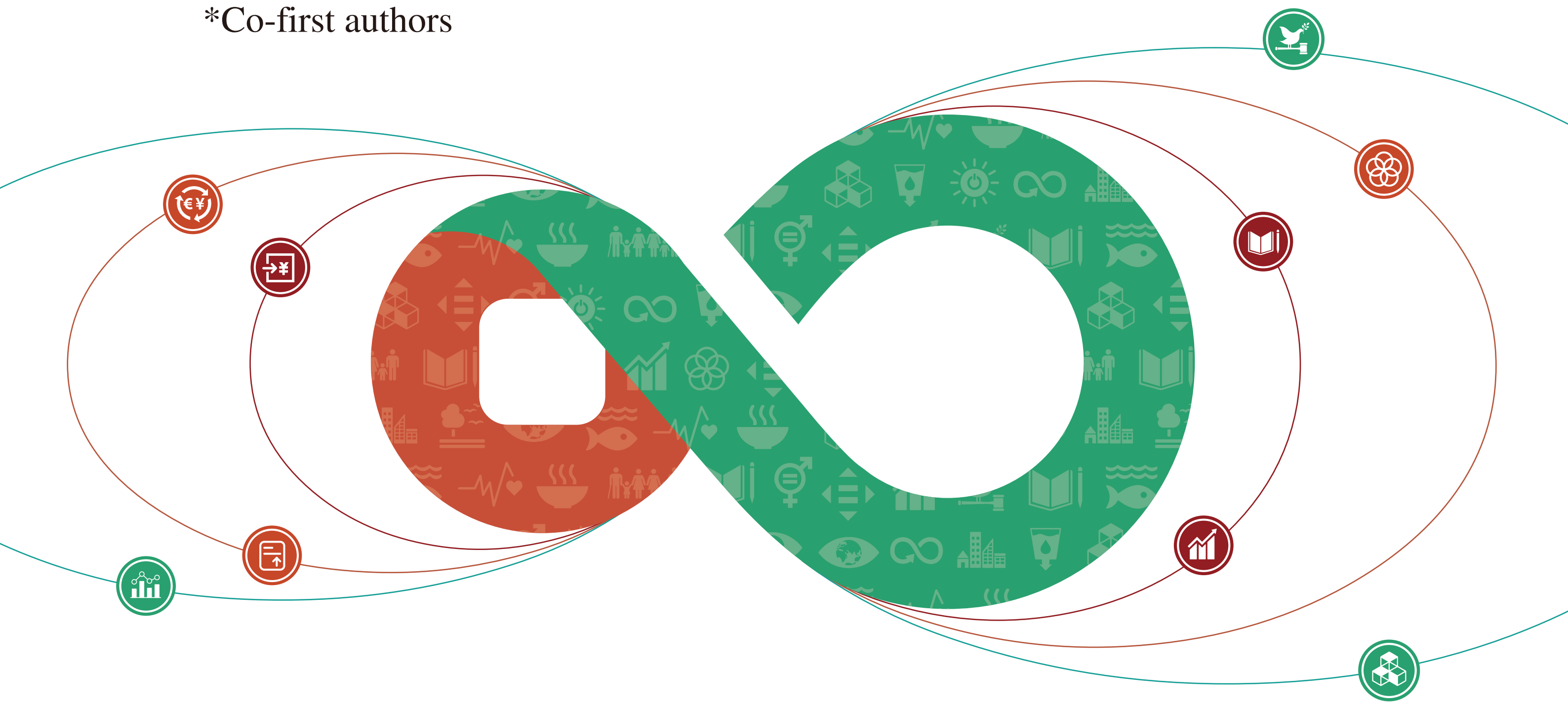

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Finance in Common

Public Development Finance Flagship Database Report Series aims to build the first comprehensive database of worldwide public development financial institutions (PDFIs) and foster original research on the rationales, operations, performance, and impact of PDFIs to improve understanding of these important institutions and achieve better development outcomes.

Public Development Finance Research Program at the Institute of New Structural Economics (INSE) and School of Health Humanities (SHH) at Peking University, the French Development Agency (Agence Française de Développement, AFD), and the Foundation for Studies and Research on International Development (Fondation pour les Études et Recherches sur le Développement International, FERDI). The report was produced by the staff of INSE, SHH, AFD and FERDI. The opinions expressed in this paper are those of the author(s) and do not reflect the position of AFD, FERDI or PKU's. It is therefore published under the sole responsibility of its author(s) or its partner institutions.

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Abbreviations and Acronyms

AGRI	Rural and agricultural development bank (mandate)
DFI	Development financing institution
EXIM	Promotion of exports and foreign trade (mandate)
FLEX	Flexible PDB (mandate)
HIC	High-income country
HOUS	Social housing (mandate)
INFRA	Infrastructure (mandate)
INTL	International financing of private sector development (mandate)
LIC	Low-income country
LMIC	Lower-middle income country
LOCAL	Local government (mandate)
MDB	Multilateral development bank
MSME	Micro-, small-, and medium-sized enterprises (mandate)
NDB	National development bank
NIM	Net interest margin
NLP	Natural language processing
PDB	Public development bank
PpE	Profit per employee
ROA	Return on assets
ROE	Return on equity
UMIC	Upper-middle income country
USD	US dollar

Abstract

Contemporary development challenges, such as climate change, and the drive for economic structural transformation have brought renewed attention to public development banks (PDBs), as illustrated by the Finance in Common Summit's creation. PDBs are critical financial intermediaries that can mobilize both public and private capital to deliver high social and economic returns, as expressed in the Sustainable Development Goals (SDGs) agenda, while remaining financially viable. This 2025 flagship database report is dedicated to collecting firsthand data on PDBs' financial profiles to examine the extent to which they can be financially viable while fulfilling public policy objectives. It provides a first-of-its-kind analysis of 259 PDBs' financial profiles over a six-year period (2018–2023). The key finding of the analysis is that the vast majority of PDBs have positive financial returns at least as presented in their profit-and-loss statements. Another preliminary finding is that observable characteristics (e.g., size, age, mandate) are weakly related to variations in financial results across PDBs. What matters for PDBs is their ability to remain financially viable in the long term, enabling them to reinvest in future development projects and to support activities and sectors that private markets often neglect. We hope that our original dataset can lay the foundation for promising research directions on PDBs' financial profiles.

I. Introduction

A critical issue remains underexplored: the compatibility of the performance of their official mandate of proactive public policy orientation with their business model's long-term viability, which requires a "reasonable" financial return.

Public development banks (PDBs) play a pivotal role in fostering sustainable development; addressing market failures; and supporting investments with significant social, economic, and environmental benefits. They have become increasingly prominent in the context of global challenges such as the green transition, which demands substantial investment to achieve climate resilience and sustainability. However, a critical issue remains underexplored: the compatibility of the performance of their official mandate of proactive public policy orientation with their business model's long-term viability, which requires a "reasonable" financial return. This acts as a cornerstone for their long-term success and sustained impact.

PDBs are distinct from private commercial banks because their primary mission is pursuing public policy objectives rather than profit maximization. These institutions are often tasked with financing projects the private sector deems too risky or insufficiently profitable, such as renewable energy infrastructure; affordable housing; and support for micro-, small-, and medium-sized enterprises (MSMEs). While such investments yield social and environmental value, they frequently generate lower financial returns or even incur losses in the short term. To the extent that PDBs are a public policy instrument addressing social needs or mitigating negative externalities (e.g., pollution at the local level or CO_2 emissions at the global level), they may require modest returns or financial subsidies to induce clients' socially optimal behavior. The financial question to address is whether PDBs can be expected to be financially viable and, at the same time, make loans that incentivize investments with positive environmental and social externalities, because such investments are not profitable enough for private finance. Nonetheless, financial viability remains essential for PDBs to continue operating effectively and fulfilling their mandates over the long term because they have dual features: on the one hand, their basic feature is to be financial institutions. Thus, they have to meet the survival constraint. On the other hand, their core feature is to proactively pursue public policy objectives that go beyond private financiers' risk appetite. This entails fiscal costs. Unlike other forms of public intervention (De Haas and Gonzales-Uribe 2024), PDBs' funding sources are expected to go beyond regular injections of public funds (Xu, Marodon et al., 2021).

PDBs' missions are multifaceted, encompassing economic development, social inclusion, and environmental sustainability. Balancing these objectives poses significant challenges. An exclusive focus on financial returns runs the risk of turning these institutions into commercial entities that crowd out private sector actors, undermining their developmental mission. Conversely, prioritizing development impact without regard for financial viability may threaten their sustainable operations, reducing them to aid-like organizations reliant on periodic government subsidies. This dual mandate necessitates a nuanced understanding of how PDBs can reconcile their core official mandate to fulfill public policy objectives with their goal of being viable financial institutions to maximize their development effectiveness.

The aim of this paper is therefore twofold: (i) to examine PDBs' financial profiles using an original worldwide database on PDBs, and (ii) to identify patterns among PDBs in terms of the variation in their financial returns.

The aim of this paper is therefore twofold: (i) to examine PDBs' financial profiles using an original worldwide database on PDBs, and (ii) to identify patterns among PDBs in terms of the variation in their financial returns. To achieve this aim, we manually and digitally collected data on key financial variables for 259 sub-national and national development banks (NDBs) over the 2018–2023 period. Three indicators of financial profiles—return on assets (ROA), return on equity (ROE), and net interest margin (NIM)—were selected for their relevance in capturing different financial health dimensions and their prominence in the existing literature (Panizza 2023). ROA measures efficiency in asset utilization, ROE evaluates shareholder returns, and NIM reflects core banking operations' profitability. Together, these metrics provide a comprehensive perspective on financial profiles, tailored to PDBs' unique characteristics.

Using the average values of ROA, ROE, and NIM over the 2018–2023 period, this study conducts a cluster analysis to explore heterogeneity in financial profiles. The analysis identifies two distinct clusters:

Cluster 1 ("Low Return"): This group comprises 218 development banks characterized by limited, albeit often positive, value of ROA, ROE, and NIM (below 2%).

Cluster 2 ("High Return"): Consisting of a small number of PDBs (41), this cluster assembles institutions having a higher value of ROA (1–12%), ROE (0.5–6.5%), and NIM (9–26%).

We further investigate whether PDBs' observable characteristics, such as size of total assets, official mandate, or location of owners, are related to their clustering. The main finding is that the financial pattern is not clearly related to one or more observed characteristics of PDBs. This suggests that key but not readily quantifiable factors—such as governance, government support policies, management practices, and alignment with social objectives—are likely to play a critical role in determining financial outcomes. This finding underscores the importance of adopting a holistic approach to explaining PDBs' financial returns, integrating quantitative and qualitative dimensions.

This paper contributes to the burgeoning PDB literature by examining their financial profiles in a nuanced and systematic manner. Existing studies often focus on comparing private and public banks (e.g., Boubakri et al. 2005; Cornett et al. 2009; Panizza 2023) and overlook the heterogeneity within public banks' and PDBs' specificity. Unlike commercial banks, PDBs do not aim to maximize financial returns but must remain financially viable to sustain their operations and impact. The recent initiative by the Institute of New Structural Economics at Peking University to build the first global database on PDBs and DFIs with the productive collaboration of French Development Agency, recently joined by the Foundation for Studies and Research on International Development and School of Health Humanities at Peking University, has addressed the definitional gaps, paving the way for focused research on these institutions. Notably, prior work has explored issues such as countercyclicality (Brei and Schclarek 2018; Gong et al. 2023) and long-term lending (Hu et al. 2022; Schclarek et al. 2023; Gong et al. 2023). This study builds on these efforts by analyzing intra-PDB heterogeneity rather than comparing PDBs with commercial banks.

In exploring these differences, we challenge the assumption that any single characteristic, such as size or country income level, is a dominant predictor of financial returns. Instead, our findings highlight the diversity within PDBs, even for those having the same observable characteristics.

In summary, this report provides an innovative analysis of PDBs' financial profile and a realistic mapping that can inform policymakers and researchers alike. By integrating cluster analysis with existing research, it lays the foundation for future work on the strategies and governance mechanisms enhancing PDBs' effectiveness and impact.

The remainder of the flagship database report is organized as follows: Sections 2 and 3 describe the data and present the variables and methodology, respectively. Section 4 presents the cluster analysis results. Section 5 concludes the report with key findings and future research directions.

II. Data

Our dataset builds on the first global database on PDBs and development financing institutions (DFIs) initiated by Xu, Marodon et al. (2021) to collect thematically focused data modules on financial profiles.[1] This publicly available database provides a worldwide list of PDBs and DFIs as well as their main characteristics (year of establishment, country of origin, official mandate, total assets, etc.). For our analysis, we completed the PDB & DFI Database by collecting financial variables on each institution using documents provided by the institutions themselves.

▪ 2.1 Data collection

The data collection procedure was divided into two parts: (i) data compilation and (ii) quality control.

Data compilation

The collection of financial data for each institution that makes up the PDBs' and DFIs' database depends on their annual reports' and financial statements' public availability. In fact, data collection began with the collection of the aforementioned documents through a systematic inspection of each institution's website. We then extracted the following financial indicators from the downloaded documents using both digital technology and manual collection:

- **Total assets,** the sum of all assets, including both current and noncurrent assets
- **Total liabilities,** including all types of current and noncurrent liabilities
- **Total equity,** the remaining interest after deducting liabilities from assets
- **Profit before tax,** the total revenue less the total expenses before tax payment
- **Net income,** pretax profit/loss minus income tax expense/benefit
    - o *Net income= profit before tax-income tax expense*
- **Net interest income,** total interest income less total interest expense
- **Number of employees,** the average number of full-time employees during the fiscal year or the number of full-time employees reported at the end of the fiscal year.

The collection of these indicators was guided by a codebook framing their specificities and indicating the corresponding variable to be reported and registered.

[1] The PDB & DFI Database is available at http://www.dfidatabase.pku.edu.cn/ (https://doi.org/10.18170/DVN/VLG6SN).

This codebook listed several equivalent terms for each indicator in multiple languages (including English, Spanish, Arabic, French, Chinese, and Russian). It also framed the conversion of financial data into US dollars and defined the choice of exchange rate. In our case, the exchange rate used was the effective rate at the end of the fiscal year[2]. Financial data were collected in their presentation currency value before being converted into USD. Manual data collection was supplemented by digital technology. For example, natural language processing was used to automatically extract variables from financial statements that followed a set of rules for standardized financial reporting.

To collect data, we relied on PDBs' publications. We compiled their annual reports and financial statements on their websites from 2018 to 2023 and extracted the financial data when available.

Quality control

To ensure the data's reliability and accuracy, a three-step quality control process was implemented. It was facilitated by corroborating evidence for each indicator per institution, which also maintained our database's credibility.

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The first round of quality control consisted of comparing our manually collected data with the data displayed in BankFocus[3]. The identified discrepancies were then subject to further verification and rectification by reviewing the supporting evidence and, where necessary, re-examining each institution's financial statements. The involved team also scrutinized, on a case-by-case basis, data not available in BankFocus.

The second round involved randomly selecting institutions from the initial database on PDBs and DFIs for review.

The third round was dedicated to a review of data quality by the (co-)principal investigators[4] in charge of the program, with a focus on resolving outstanding cases and closing the data collection process.

Our open-source database has a more comprehensive coverage than the commercial database of BankFocus.

Database with financial indicators

Among the 533 institutions listed in the PDB & DFI Database[5], some do not publish their financial statements. Table 1 shows the number of banks for which we collected the six financial indicators depending on the number of years of availability. The first column indicates that we were not able to collect data for any year for 157 institutions. However, we were able to collect financial indicators for six years (2018–2023) for 247 institutions out of the 533. For the remaining

[2] From the website www.xe.com.

[3] During the quality control process, we identified that BankFocus extracted incorrect data for several institutions, such as mistakenly pulling half-year data instead of the required information.

[4] This term refers to the three scientific directors of the three teams involved in the construction of the PDBs' and DFIs' database.

[5] PDB & DFI Database released in Q1 2024.

institutions (129), we were able to collect financial data for one year (42 institutions), two years (15), three years (13), four years (27), and five years (32).

For comparison, Table 1's second column compares our data with the data available in BankFocus. Of the 533 institutions identified in the PDB & DFI Database (Xu, Marodon et al., 2021), only 318 are available in BankFocus and only 268 have financial data available (versus 376 in our database).[6] This indicates that our open-source database has a more comprehensive coverage than the commercial database of BankFocus.

Table 1: From data collection to final sample

No. of years available	Data collection		Sample	
	All PDBs and DFIs	BF	National and Subnational PDBs	Final
0	157	50	136	0
1	42	5	30	0
2	15	13	15	0
3	13	9	7	7
4	27	16	20	19
5	32	20	29	26
6	247	205	212	207
TOTAL	533	318	449	259

Note: "All PDBs and DFIs" refers to all PDBs (including multilateral and national) and DFIs. "BF" refers to data available in BankFocus. "National and Subnational PDBs" refers to the sample after excluding multilateral development banks and DFIs. "Final" is the sample used for the analysis.

▪ 2.2 Database for the flagship report

We took the following steps to construct the sample for analysis.

First, we kept only national and subnational PDBs because comparison of their financial indicators with those of other institutions is complex given their distinct business models. In other words, we excluded equity funds, guarantee funds, and DFIs operating on the secondary mortgage market[7] from the database to keep PDBs. These funds differ significantly from PDBs in terms of their business models and balance sheet structures. These differences make direct comparisons unreliable and can introduce bias into the analysis. Further, because our aim was to assess comparable PDBs' financial return level, we also excluded multilateral development banks (MDBs). MDBs are no longer a comparable approach to NDBs. After excluding these

[6] To identify the number of PDBs and DFIs with financial data, we subtracted the number of institutions without any financial data (first line of Table 1) from the total number of PDBs and DFIs.

[7] They are the following U.S. DFIs: Freddie Mac and Fannie Mae.

different institutions, we ended up with 449 institutions (see Table 1's third column).

Second, we only kept PDBs with at least three years available. Because the aim of the flagship was to examine PDBs' financial returns, we needed to obtain a sufficient number of observations. Financial indicators are relatively volatile from year to year. This is particularly the case given the studied time frame (2018–2023), which covers the COVID-19 crisis and its aftermath. Therefore, we need a sufficient number of years to avoid biases regarding the level of financial returns of each PDB. Following this procedure, we excluded 45 PDBs, for which we had only one or two years of data, as well as 136 PDBs with no data at all (see the first three lines of Table 1's second column).

The flagship database in general reflected global patterns as in the original database, with two exceptions: this flagship database under-represented PDBs in low- and lower-middle income countries and in Africa.

Finally, we excluded outliers, defined as PDBs with a value of interest above the top percentile. This procedure excluded a limited number of observations (nine PDBs as indicated in Table 1) but ensured stabilization of the results. In fact, running the model on the sample with outliers led to unstable and unexpected results (one cluster with all PDBs and other clusters based on an outlier PDB).

The final sample therefore included 259 national and subnational PDBs, for which we had at least three years of financial data. This allowed us to compare their average financial returns over the period.

2.3 Representativeness of the flagship database report's samples

Before examining the collected financial data, we assessed the representativeness of the sample of PDBs considered. We did this by comparing the PDBs in the flagship database with the full sample of national and subnational PDBs in the original database (449 institutions). Table A1 in the appendix shows the details of the comparison. The flagship database in general reflected global patterns as in the original database, with two exceptions: this flagship database under-represented PDBs in low- and lower-middle income countries and in Africa. For other characteristics, however, there were few real differences between the characteristics of banks included in the flagship database and those included in the original database.

III. Variables and Methodology

▪ 3.1 Measures of financial returns

In line with previous work (e.g., Panizza 2023), we considered three measures of the level of financial returns: ROA, ROE, and NIM.

ROA is defined as the ratio of net income to total assets. ROE is measured as net income divided by shareholders' equity. Both measures increase with financial returns. NIM is defined as net interest income divided by total earning assets. Because of data limitations, we looked at total assets rather than total earning assets. The numerator was calculated as the difference between interest received from borrowers and interest paid to lenders.

Higher ROA and ROE indicate an ability to generate more profit for a given level of activity. A higher level of NIM reflects the bank's ability to generate income from intermediation. The comparison between ROA/ROE and NIM is instructive because it can help us understand how a bank is able to convert the income it earns from intermediation into higher profits. The bank's ability to extract rent by lending at higher rates or borrowing at lower costs can explain a high level of NIM. In this situation, we might expect higher NIM to be associated with higher ROA/ROE. However, other factors could explain why high NIM can go hand in hand with low ROA/ROE. On the one hand, inefficient banks need to generate high margins to cover their operating costs. On the other hand, margins also reflect the bank's orientation and risk profile. Banks that focus on high-risk borrowers need to internalize the risk premium in the margin.

In robustness checks, we considered two additional proxies. First, we computed the income generated by each employee. To do this, we considered profit per employee (PpE), which measures the profit generated by each employee.[8] Second, we measured the cost-income ratio, which is often used in the literature as a proxy for a bank's level of (in)efficiency. The cost-income ratio is defined as the overhead cost to net interest income.[9]

Finally, we used the average of each indicator to smooth out short-term fluctuations and better proxy long-term financial return. As Table 1 shows, we had at least six years of information available for 80% of the banks included in the analysis. Therefore, we tested whether our results were robust when we restricted the sample to banks with information for each year from 2018 to 2023.

[8] The PpE is only available for a subset of PDBs for which we were able to collect the staff number.

3.2 Characteristics of the PDBs

To examine variations in financial returns across different types of PDBs, we adopted the typologies proposed by Xu, Marodon et al. (2021). PDBs are classified according to their size (total assets), ownership, age, mandate, countries' income levels, and owners' geographical location.

Total assets were used as a criterion to classify PDBs and DFIs into five size categories: mega (more than $500 billion), large (more than $100 billion and less than or equal to $500 billion), medium (more than $20 billion and less than or equal to $100 billion), small (more than $500 million and less than or equal to $20 billion), and micro (less than or equal to $500 million). The last category assembled PDBs without collecting information on their size.

Ownership was divided into three categories: multinational (owned by entities from more than two countries), national (owned by a central government), and subnational (owned by one or several local entities). As discussed above, we excluded MDBs.

Eight different mandates were considered: general development (FLEX), rural and agricultural development (AGRI), promotion of exports and foreign trade (EXIM), social housing (HOUS), infrastructure (INFRA), international financing of private sector development (INTL), local government (LOCAL), and MSME support.

For age, we considered three categories based on the three waves of development bank implementation[10]. Old PDBs are those created before 1979, young PDBs are those created since 2000, and medium PDBs are those created between 1980 and 1999.

Finally, we exploited information on PDBs' countries of origin. We classified PDBs according to their continents (Africa, Americas, Asia, Europe, and Oceania) and the level of income of the country of their owners (based on the World Bank's income group).

3.3 Methodology

The flagship database report's main aim was to identify patterns within the financial returns of PDBs and to test

[9] Because we did not collect overhead costs directly, we approximated them by using the difference between net interest income and net income. In the absence of revenue other than interest paid by customers, the difference between net interest income and net income provides the value of overhead cost. Consider a scenario in which net interest income (defined as interest received minus interest paid) equals 5 and overhead cost equals 3. Net income is obtained by subtracting overhead cost from net interest income. In our example, net income is 2 (5-3). Because we only had information on net income and net interest income, we reversed the approach. The overhead cost is the difference between net interest income and net income. In the example, therefore, we evaluated the overhead cost according to this calculation: net interest income (= 5) - net income (= 2) = 3. The approach is similar when net income is negative. In our example, we assumed that overhead cost exceeds net interest income. For example, if overhead cost is 6, then net income is -1 (net interest income - overhead cost = 5-6). Based on the values of net interest income (5) and net income (-1), we obtained the value of overhead cost by subtracting net income from net interest income. We were unable to measure the cost-to-income ratio for four PDBs because net interest income was negative. For these banks, there was a strong issue of financial viability because they were borrowing at higher rates than they were lending. The four PDBs were as follows: Fincalabra (ITA), CDG Capital (MAR), Small Medium Enterprise Development Bank Malaysia Berhad (MYS), and Vietnam Development Bank (VNM).

[10] For age, we used the year of establishment provided in the PDB & DFI Database. Xu et al. (2021) described the dynamics of PDB creation. After World War II, the number of PDBs increased in developed countries (reconstruction) and newly independent countries. In the 1980s, PDBs came under fire because of neoliberalism's influence. The number of new PDBs declined sharply during this decade. However, the Soviet Union's collapse triggered a new wave of creation of PDBs and DFIs. More recently, the world has witnessed a new third wave after the 2008 global financial crisis, which highlighted the free market's limits and the importance of state involvement in the financial sector (World Bank, 2013). We therefore consider three categories based on the three waves.

whether some PDBs, according to their characteristics (size, age, mandate, location), were more dominant in one pattern than in others. We proceeded in three steps.

First, we used cluster analysis to isolate different patterns of PDBs according to their financial returns. Cluster analysis is a method for grouping units (here, PDBs) that share similar characteristics (here, financial returns). In the current analysis, we adopted partitioning clustering using the k-medians method. We performed cluster analysis for two to 15 clusters and selected the optimal number of clusters using the silhouette score (Hennig et al. 2015). For each institution, we considered the average of the three financial return measures: ROA, ROE, and NIM. Appendix B provides details of the cluster analysis and the choice made.

Second, we examined the characteristics of each cluster in terms of the three financial return measures considered (ROA, ROE, and NIM). The aim was to characterize each cluster's profile.

Third, we assessed the extent to which PDBs' observables features were related to different clusters. We considered several characteristics such as size, age, mandate, and location of owners according to PDBs' typology in the PDB & DFI Database.

IV. Results

The vast majority of PDBs could generate positive income and profit before tax if we looked at the average over the period of 2018-2023.

4.1 Descriptive statistics

Table 2 presents the descriptive statistics for financial values collected (Panel A) and financial ratios (Panel B).

It shows that there was a strong heterogeneity between the PDBs considered in terms of not only size (total assets, number of employees) but also returns in absolute (e.g., net profit) or relative terms (ROA, ROE, and NIM). Heterogeneity was particularly dramatic for financial returns, as shown by the interquartile ratio (the table's penultimate column). It was also observed that the mean was much higher than the median (last column). The divergence between means and medians indicated the salience of outliers in financial ratios (even after windowing).

A closer look revealed some interesting features (beyond Table 2). The vast majority of PDBs could generate positive income and profit before tax if we looked at the average over the period of 2018-2023. There were only 44 PDBs (out of 259) with a negative profit over the whole period. However, eight PDBs had negative net interest income. A special study could be conducted to better understand whether this inability to generate net interest income is a deliberate choice due to unexpected events such COVID-19, or a sign of severe inefficiency.

Second, the returns on PDBs did not seem to be very low. Despite the marked differences among them, we observed that the median PDB had an ROA of 0.61%. Interestingly, this was very close to the returns of the world largest commercial banks (0.75% in 2022)[11], despite their different mandates. Briefly, these figures ran contrary to the conventional wisdom that PDBs are inefficient institutions that cannot make earnings.

We then examined the differences in ROA, ROE, and NIM according to the PDBs' observed characteristics in Table 3. As explained above, means are not always the best summary of the distribution of financial ratios because of outliers. Therefore, we presented descriptive statistics using both the mean and median. To facilitate reading, we used a color code as follows. We highlighted

[11] See data at this link for the top 1000 commercial banks in the world: https://www.thebanker.com/Top-1000-World-Banks-2022-1656889615.

Table 2: Descriptive statistics

Variables	Obs.	Mean	Std. dev.	Min	Q1	Median	Q3	Max	Q3/Q1	Mean/ median
Panel A: Financial indicators										
Total assets	259	620,060	898,145	0	172,540	286,946	515,942	5,055,861	2.99	2.2
Equity	259	558,150	851,087	0	131,644	248,476	473,310	5,120,930	3.60	2.2
Liabilities	259	591,772	854,614	0	159,923	271,277	506,097	6,095,649	3.16	2.2
Net interest income	259	448,820	814,074	-1,608,402	27,990	175,754	372,830	6,363,180	13.32	2.6
Net income	259	348,030	706,015	-1,960,790	998	138,892	34,200	3,947,474	34.28	2.5
Profit before tax	259	445,289	842,369	-1,668,641	2,481	162,014	396,492	5,448,422	159.79	2.7
No. of employees	220	3,111	23,679	12	104	232	614	341,388	5.88	13.4
Panel B: Financial ratios										
ROA	259	26.37	280.32	-42.04	0.05	0.61	3.09	4,480.19	60.14	43.0
ROE	259	19.94	110.38	-76.77	0.11	0.86	3.19	1,154.43	30.31	23.2
NIM	259	6.36	25.15	-10.71	0.20	0.77	2.78	287.09	14.02	8.2

Note: All variables of Panel A are computed in current USD (in million), except for the number of employees. We employ exchange rates as of the fiscal year-end date. Variables in Panel B are ratios.

in green (orange) cells if mean and median for the subgroup of PDBs were above (below) the mean and median for all PDBs (as shown in the first line of the table).

We first examined how the financial returns of PDBs differed according to their size.[12] The main feature was that financial returns (ROA, ROE, and NIM) were higher for small PDBs, whereas they were lower for mega[13] and micro PDBs. Therefore, the relationship was unclear; at the very least it was nonlinear.

We then examined whether the official mandates of PDBs were related to differences in financial returns. The results were rather ambiguous because we did not find a clear pattern. Nevertheless, we showed that PDBs with a local mandate (i.e., PDBs specializing in financing local governments) tended to have higher financial ratios. By contrast, PDBs with an MSME mandate were directly associated with lower profitability ratios than their counterparts.

[12] Size categories are defined above.

[13] This finding should be treated with caution because there are only six mega-PDBs in our sample.

The descriptive statistics for the type of ownership were also unclear. However, we found that the year of establishment was correlated with different patterns of returns, albeit nonlinearly. PDBs with higher returns seemed to be those created between 1980 and 1999.

Finally, in terms of location, the most relevant feature was that PDBs in Asia had higher financial returns, whereas those in the Americas and Africa had lower returns. It was interesting to note, however, that the level of income was not clearly correlated with financial returns.

4.2 Cluster analysis

We then performed the cluster analysis using a partition approach with three variables (ROA, ROE, and NIM). We considered a number of clusters ranging from 2 to

Table 3: Descriptive statistics according to the PDB's characteristics

	Return on assets		Return on equity		Net interest margin		Obs.
	Mean	Median	Mean	Median	Mean	Median	
Total	**27.36**	**0.61**	**19.94**	**0.86**	**6.36**	**0.77**	**259**
Size							
Mega	1.02	0.38	1.37	0.60	0.77	0.39	6
Large	-0.69	0.99	1.17	0.75	12.30	1.61	16
Medium	3.13	0.68	62.54	0.69	4.04	1.08	30
Small	49.38	0.91	23.25	1.15	6.92	0.95	126
Micro	6.60	0.26	4.23	0.51	5.72	0.55	79
NI	-1.10	-1.10	-1.15	-1.15	0.37	0.37	2
Mandate							
FLEX	9.95	0.70	3.59	0.78	7.76	1.11	94
AGRI	8.08	0.65	64.94	0.42	2.45	0.76	18
EXIM	10.81	0.64	58.02	1.10	1.57	0.30	25
HOUS	20.50	0.90	9.06	1.10	7.10	1.28	21
INFRA	30.85	0.79	1.78	1.04	27.78	0.32	11
INTL	2.83	0.65	0.11	0.18	4.20	1.45	10
LOCAL	3.56	1.27	66.54	2.99	8.82	1.70	16
MSME	72.26	0.35	14.56	0.58	3.06	0.56	64

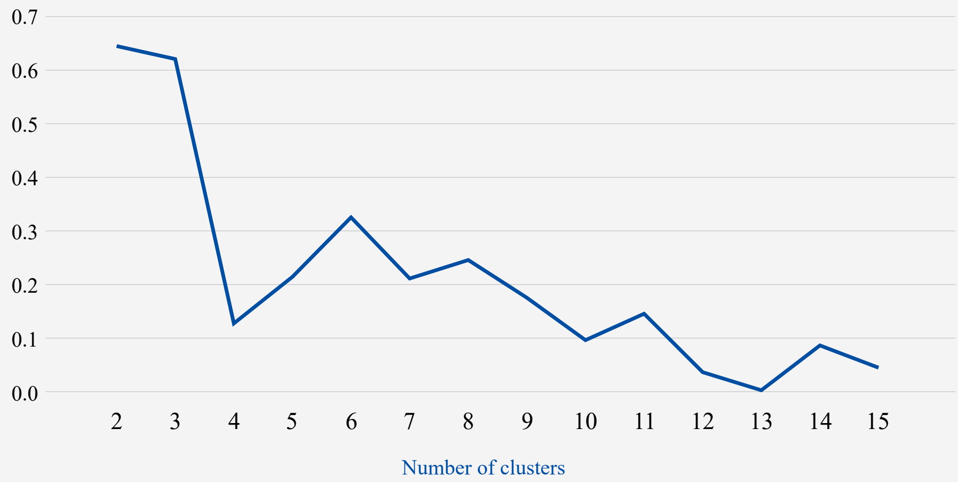
	Return on assets		Return on equity		Net interest margin		Obs.
	Mean	Median	Mean	Median	Mean	Median	
Ownership							
NATIONAL	32.08	0.64	19.67	0.86	7.27	0.79	194
SUBNATIONAL	9.34	0.56	20.73	0.89	3.63	0.77	65
Age							
Before 1980	10.64	0.55	19.89	0.80	7.09	0.75	100
1980–1999	63.44	0.98	30.57	1.17	3.38	1.14	79
2000 to today	9.44	0.42	9.50	0.62	8.39	0.56	80
Income							
HIC	4.18	0.78	27.19	0.64	4.67	0.82	99
UMIC	63.04	0.46	10.11	1.21	6.63	0.67	90
LMIC	9.70	0.70	6.26	0.98	8.97	1.24	64
LIC	20.34	3.04	193.67	0.60	2.32	1.24	6
Continent							
Africa	5.11	0.40	36.78	0.86	6.03	0.53	37
Americas	13.74	0.20	8.02	0.42	3.83	0.70	65
Asia	66.71	0.79	7.52	0.92	11.18	1.05	79
Europe	5.85	1.22	36.68	1.03	3.95	0.95	73
Oceania	10.26	0.65	1.91	1.82	0.71	0.67	5

Note: We display the mean and median values of each financial ratio for different types of PDBs. Green (orange) cells indicate that both mean and median for one sub-type of PDBs are above (below) the mean and median of all PDBs. Green (orange) value if value for a specific category is above (below) the mean and median of all PDBs (first line in bold).

15. To select the optimal number of clusters, we used the silhouette approach. The silhouette scores ranged from -1 to +1, and a higher value indicated that the object was well matched to its cluster and poorly matched to neighboring clusters. Therefore, we chose the number of clusters that maximized the value of the silhouette score. Figure 1 provides the stylized facts of the silhouette score for cluster analysis ranging from two to 15 clusters. According to the common rule, we selected the model having the highest value of silhouette score (i.e., the model with two clusters).

We categorized the two clusters as follows. Cluster 1 comprised PDBs with lower financial returns ("low return" cluster), and Cluster 2 comprised PDBs with higher financial returns ("high return" cluster).

We then summarized the characteristics of the two clusters identified in Table 4 and Figure 2 below. Based



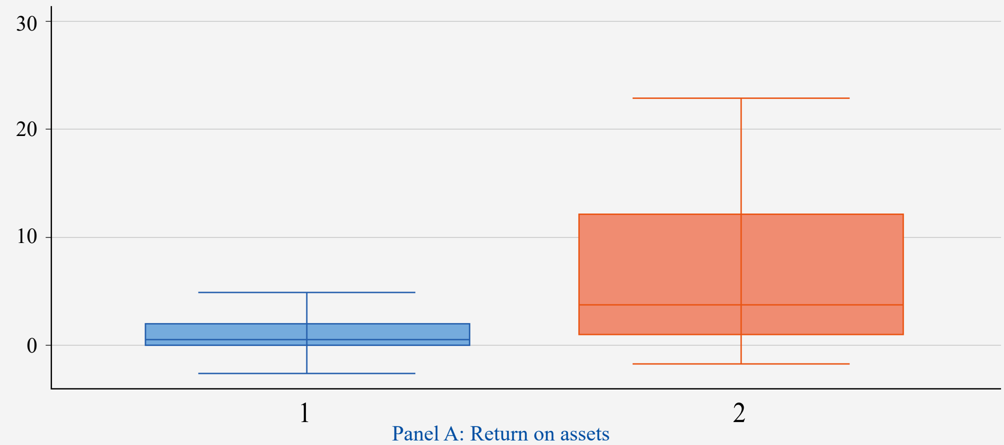
The figure displays the average value of silhouette for each clustering approach. A clustering approach with higher value indicates fewer differences within clusters and large differences between clusters.

Figure 1: Silhouette score for 2 to 15 clusters

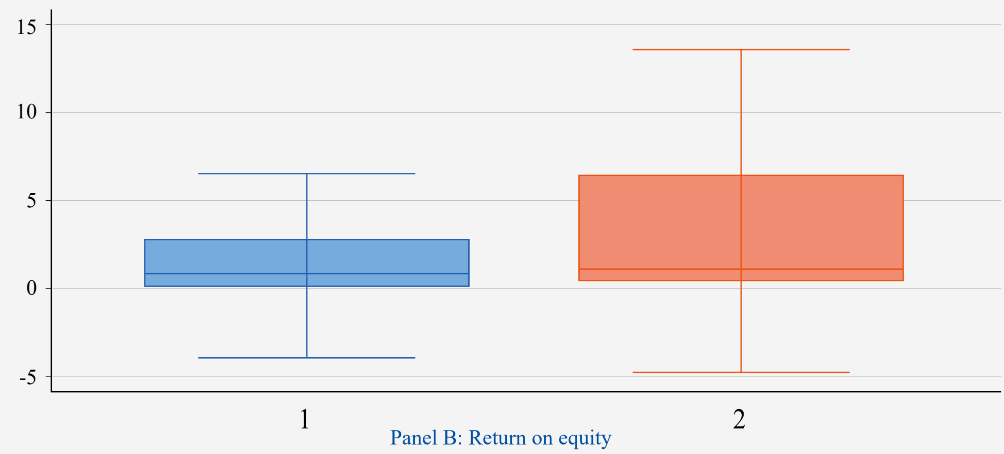
on these characteristics, we categorized the two clusters as follows. Cluster 1 comprised PDBs with lower financial returns ("low return" cluster), and Cluster 2 comprised PDBs with higher financial returns ("high return" cluster).

Table 4: Distribution of ROA, ROE, and NIM for the two clusters

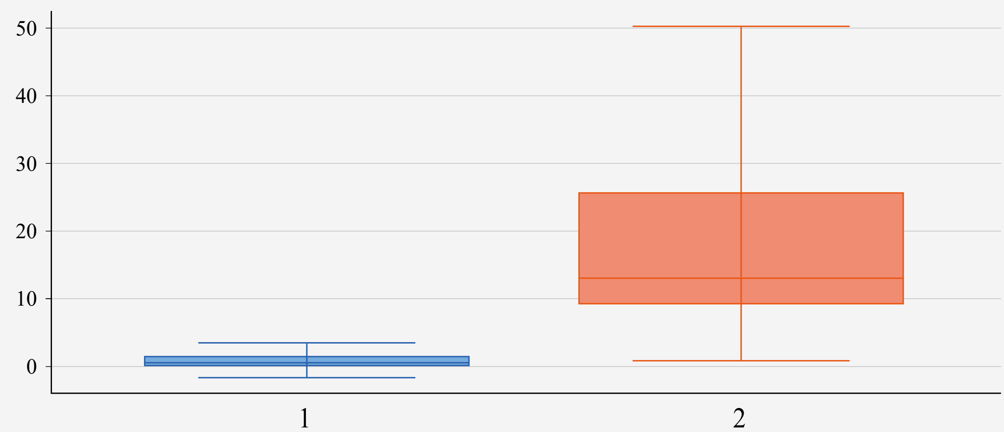
Cluster	Mean	Min	p25	p50	p75	Max	Obs.
Return on assets							
1	5.51	-42.04	0.03	0.46	2.03	243.23	218
2	137.29	-1.72	0.86	3.72	12.24	4480.19	41
All	26.37	-42.04	0.05	0.61	3.09	4480.19	259
Return on equity							
1	17.77	-76.77	0.09	0.85	2.82	1154.43	218
2	31.46	-4.76	0.42	1.11	6.49	885.06	41
All	19.94	-76.77	0.11	0.86	3.19	1154.43	259
Net interest margin							
1	0.98	-10.71	0.12	0.55	1.52	6.60	218
2	34.93	0.88	9.22	13.07	25.75	287.09	41
All	6.36	-10.71	0.20	0.77	2.78	287.09	259



Panel A: Return on assets



Panel B: Return on equity



Panel C: Net interest margin

Figure 2: Characteristics of the two clusters

To assess the validity of such a classification, we performed several robustness checks. The tables in the appendix show the results (Tables A2, A3, and A4).[14] First, we excluded mega PDBs from the analysis to avoid these institutions' specificities due to their sheer size. Second, we excluded the year 2020 because of the COVID-19 crisis, which may have seriously affected most PDBs' conduct of normal business. Third, we restricted the analysis to 207 PDBs for which we had data for the six years under consideration (2018–2023). Finally, we added some additional variables to the clustering exercise. For that, three additional procedures were followed: (a) we considered the variance of ROA, ROE, and NIM in addition to the means; (b) we performed a cluster analysis by including the cost-income ratio; and (c) we introduced PpE into the clustering exercise. Our robustness checks confirmed the results of our initial cluster analysis. The only sensitive changes observed were when we excluded the year 2020 and included PpE as a clustering variable (error rate[15] between 15% and 20% as indicated in Table A4). However, both clusters' characteristics were largely unchanged (Tables A2 and A3). For other specifications, the error rate ranged from 0% to 3%, and the results were largely unaffected. We were therefore confident enough in the cluster analysis to follow on in examining each cluster's characteristics.

4.3 Characteristics of PDBs included in each cluster

Our next step was to examine the characteristics of the PDBs of each of the two clusters. The aim was to investigate whether PDBs' observable characteristics were correlated with their financial return profile.

First, we examined the differences in the composition of the two clusters in terms of the size of the PDBs. Figure 3 shows the distribution of each size category of PDBs by cluster. The most striking feature was that both clusters were relatively similar in terms of the composition of PDBs according to their size. This finding was confirmed by a *Pearson's*-χ^2 test. We could not reject the null hypothesis (p-value = 0.74) that the differences in the distributions were due to chance.

We then examined the differences according to the age of the PDBs (Figure 4). The share of "young" PDBs tended to be higher in Cluster 1 ("low return"). In contrast, Cluster 2 was composed of more PDBs created before 1980. However, as was the case for size, the *Pearson's*-χ^2 test did not reject the null hypothesis of statistical independence (p-value = 0.40).

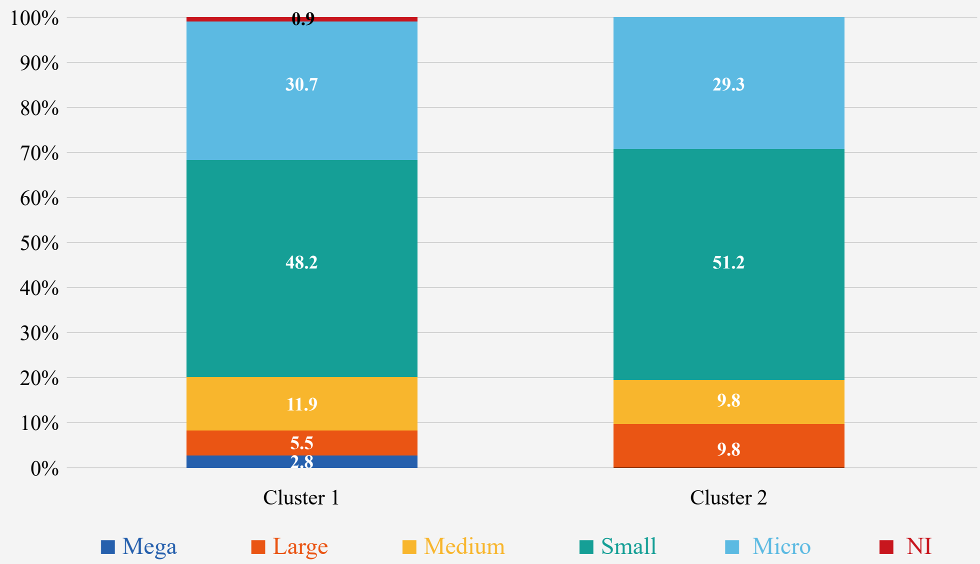
Figure 5 shows the decomposition of the number of PDBs based on their mandate. The main difference was the high share of PDBs with flexible and local mandates in Cluster 2 ("high return") and the higher share of PDBs targeting MSMEs and EXIM banks in Cluster 1 ("low return"). However, as was previously the case, these differences were not statistically different according to the results of the *Pearson's*-χ^2 test (p-value = 0.43).

Figure 6 provides a similar analysis for the share of PDBs according to their level of ownership (national or sub-national). Differences were few, as a statistical test of independence confirmed (p-value = 0.61).

In Figures 7 and 8, we addressed the differences based

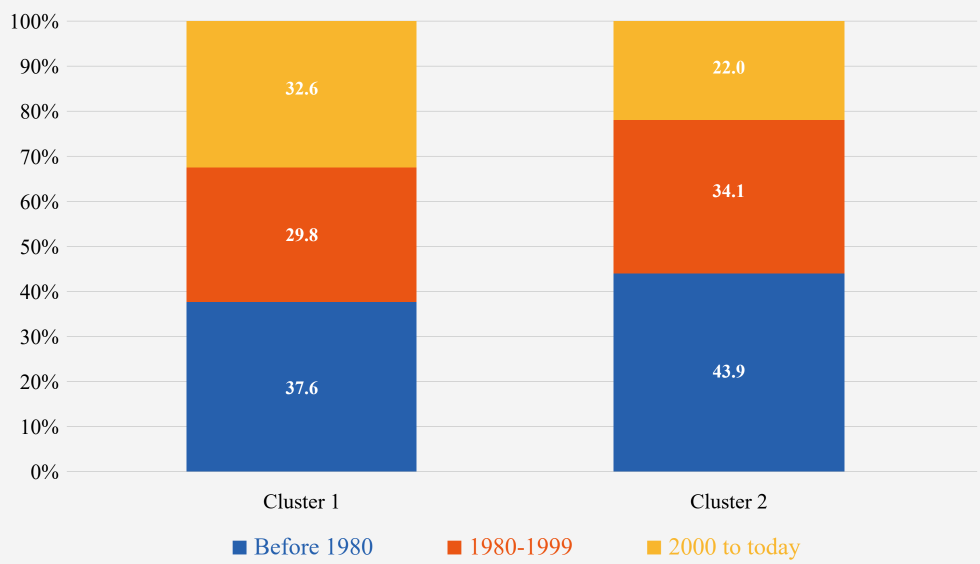
[14] Table A2 displays values for means of ROA, ROE, and NIM for each cluster in different robustness checks. Table A3 presents the medians of ROA, ROE, and NIM for each alternative cluster. Table A4 presents the number of migrations of PDBs from the initial cluster (baseline) to a new cluster after changing one parameter.

[15] The error rate is defined in Table A4 as the proportion of the number of PDBs that are classified in another cluster after the change in the total number of PDBs.



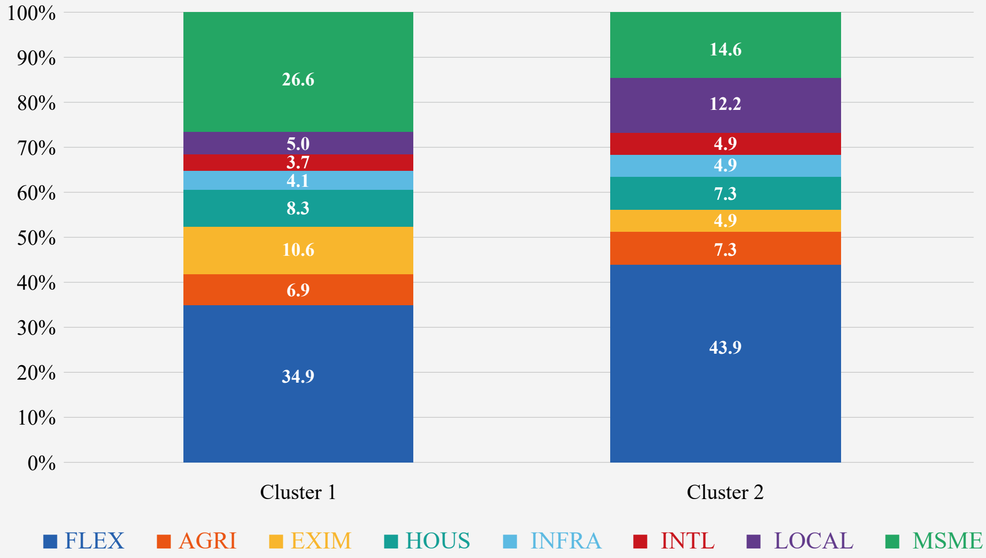
Source: Data on size categories extracted from PDB & DFI Database

Figure 3: Repartition of PDBs in clusters based on their size



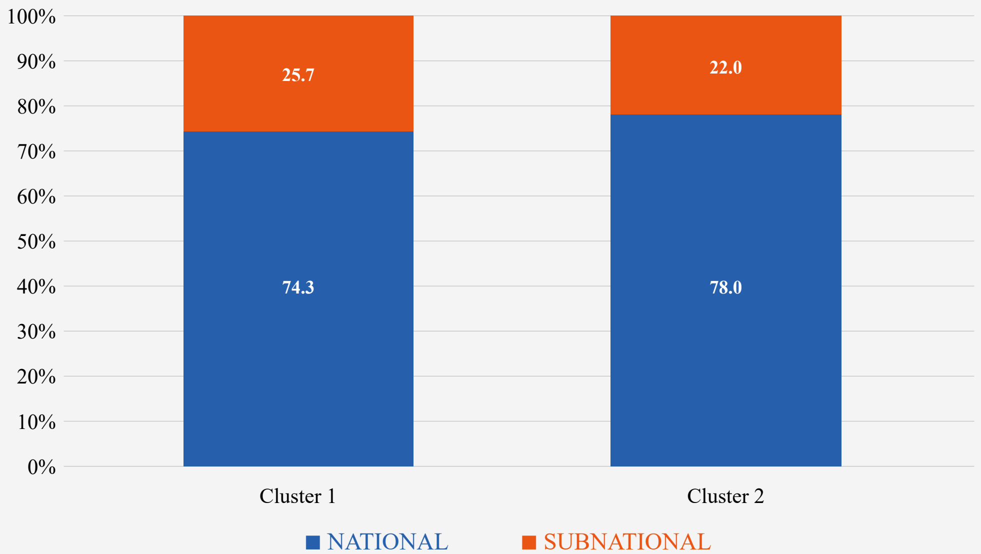
Source: Data on age extracted from PDB & DFI Database

Figure 4: Repartition of PDBs in clusters based on their age



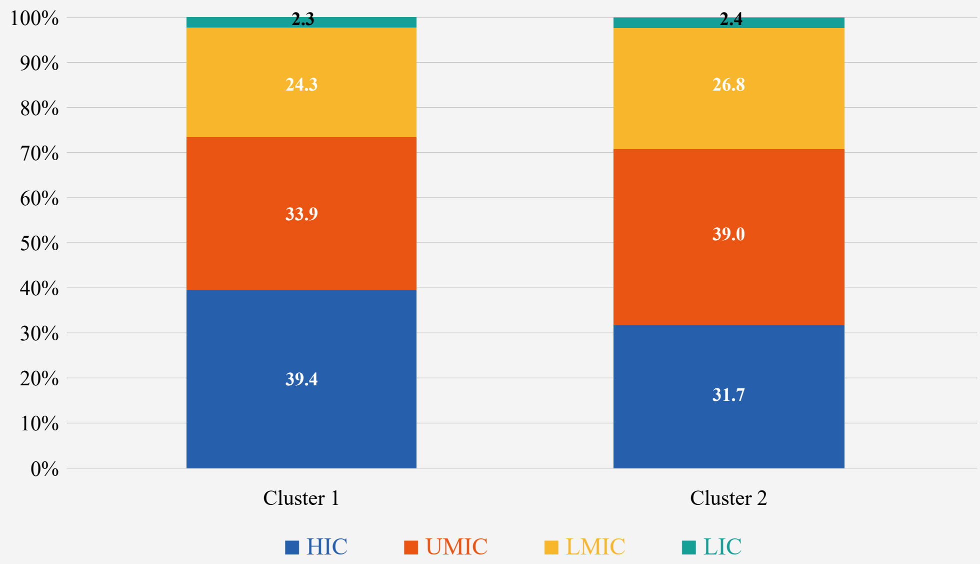
Source: Data on mandates extracted from PDB & DFI Database

Figure 5: Repartition of PDBs in clusters based on their mandate



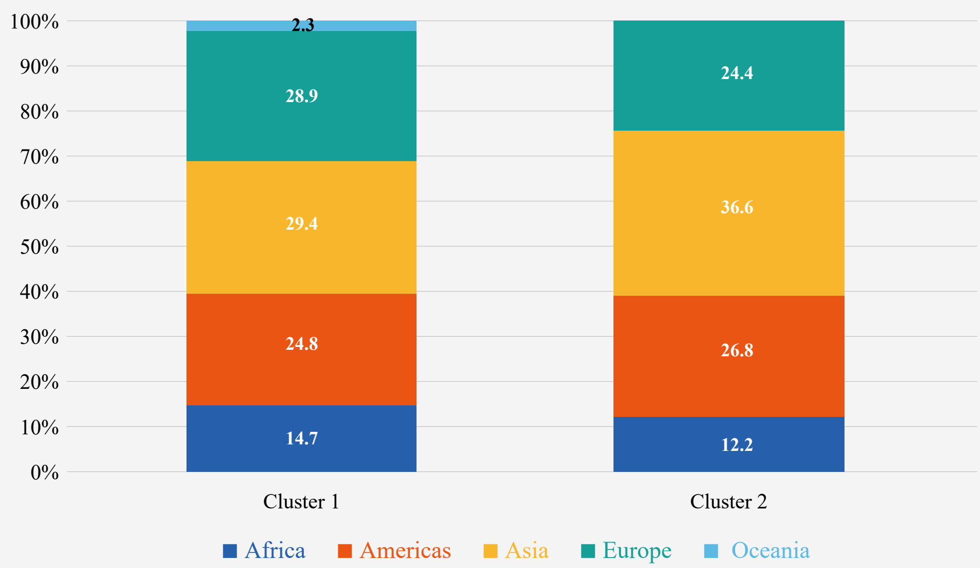
Source: Data on level of ownership extracted from PDB & DFI Database

Figure 6: Repartition of PDBs in clusters based on their level of ownership



Source: Location data by type of country extracted from PDB & DFI Database

Figure 7: Repartition of PDBs in clusters based on income group



Source: Location data by continent extracted from PDB & DFI Database

Figure 8: Repartition of PDBs in clusters based on the continent

on the location of PDBs' owners. Figure 7 depicts the share of PDBs in each cluster according to the level of income based on the World Bank classification. Figure 8 depicts the share of PDBs in each cluster according to the continent. According to Figure 7, although the share of PDBs from HIC was higher in Cluster 1 ("low return"), the differences were not statistically different from 0 (p-value = 0.83). The conclusion was similar for Figure 8.

▪ 4.4 Are characteristics of PDBs related with variations in financial returns?

The analysis presented here documented observable characteristics of PDBs (size, mandate, age, location, etc.) that were weakly correlated with the likelihood of belonging to a specific profile of financial return (low or high return cluster). Additional evidence confirms this conclusion.

First, in Appendix C, we employed a basic regression model to test whether the observed characteristics of PDBs (size, age, etc.) were correlated with differences in financial return ratios (ROA, ROE, NIM) and the likelihood of being in Cluster 1. Briefly, we documented that observed characteristics were weakly correlated with financial patterns. A few coefficients were statistically significant, and the explained variance was very low (less than 5% on average).

The analysis presented here documented observable characteristics of PDBs (size, mandate, age, location, etc.) that were weakly correlated with the likelihood of belonging to a specific profile of financial return (low or high return cluster).

Second, we focused on one particular country that had many PDBs (Brazil), which allowed us to study whether characteristics such as size, age, and mandate played a role in the same country's context. The data used in the analysis consisted of 19 Brazilian PDBs. As documented in Table 4 below, four of them belonged to Cluster 2 ("high return") and the rest to Cluster 1 ("low return"). These PDBs were quite similar because they were almost all subnational PDBs (except for one national PDB in each cluster), had similar mandates (MSME or flexible), and were micro or small (except for BNDES). In terms of age, even if relatively new PDBs were all in Cluster 1, Cluster 1 also includes old ones as Cluster 2 does.

Table 5: List of Brazilian PDBs

Cluster	Acronym	Year	Mandate	Ownership	Size	ROA	ROE	NIM
1	BNDES	1952	FLEX	National	Large	14.3	7.0	2.7
1	Banpará	1959	FLEX	Sub-	Small	1.4	4.7	0.7
1	BANDES	1969	FLEX	Sub-	Micro	0.8	-0.1	1.7
1	Badesul	1973	FLEX	Sub-	Micro	0.2	1.7	0.8
1	AFAP	1997	MSME	Sub-	Micro	-3.0	-3.9	4.3
1	Fomento Paraná	1999	FLEX	Sub-	Small	1.0	0.5	0.4
1	Badesc	1999	FLEX	Sub-	Micro	0.5	4.2	1.0
1	Goiás Fomento	2000	MSME	Sub-	Micro	0.0	0.1	0.1
1	AgeRio	2002	MSME	Sub-	Micro	0.2	0.5	0.7
1	Desenvolve MT	2003	MSME	Sub-	Micro	0.1	245.6	0.0
1	Desenvolve	2004	MSME	Sub-	Micro	-0.1	-0.1	0.1
1	Fomento TO	2005	MSME	Sub-	Micro	-0.1	-0.1	0.1
1	Desenvolve SP	2009	MSME	Sub-	Small	0.3	1.5	0.4
1	Piauí Fomento	2010	MSME	Sub-	Micro	-0.4	-0.1	0.4
1	AGE	2011	MSME	Sub-	Micro	-0.1	-0.2	0.1
2	BNB	1952	MSME	National	Small	86.5	8.1	11.9
2	BRDE	1961	FLEX	Sub-	Small	343.9	2.0	6.9
2	BDMG	1962	FLEX	Sub-	Small	13.2	4.2	10.3
2	AGN	1999	MSME	Sub-	Micro	0.0	0.0	20.8

Note: The table displays the list of Brazilian PDBs included in the analysis; their main characteristics; and the values of ROA, ROE, and NIM.

V. Conclusion and Future Research Directions

This study provides an original analysis of PDBs' financial returns, focusing on financial return indicators extracted from their financial statements. Currently, our knowledge of PDBs' financial returns is limited. The debate on these institutions has largely neglected this strategic and relevant issue. This study is an original and exploratory exercise in this direction. Specifically, it addresses two questions: (i) Can we identify the variation in the financial returns' level of PDBs? (ii) Are the broader characteristics of these institutions, such as their size, mandate, and geographical location, correlated with these variations?

We examine PDBs' financial returns using new data collected by our team. We use financial variables from 259 PDBs over the 2018–2023 period. The main finding is that the vast majority of PDBs are financially viable as far as the figures disclosed in their balance sheets are concerned — without considering explicit or implicit state support (e.g., sovereign guarantee, preferential taxation treatment) or subsidies. A total of 15% of PDBs show negative financial returns, whereas the others show positive financial returns. However, for the majority, returns are rather limited (e.g., ROA below 1%).

We then continue the investigation by identifying patterns of financial profiles using a cluster approach that considers three financial ratios (ROA, ROE, and NIM). The cluster analysis divides the PDBs into two groups. On the one hand, the vast majority of PDBs (218 out of 259) fall into a cluster characterized by limited, although often positive, financial returns (ROA, ROE, and NIM below 1% and 2%). The other cluster consists of 41 PDBs with a high level of financial returns.

Cluster 1, referred to as the "Low Return" cluster, includes 218 subnational and NDBs characterized by limited, though often positive, financial returns. The majority of PDBs in this group have ROA between 0% and 2%[16], ROE between 0% and 2.8%, and NIM between 0.1% and 1.5%, with medians of 0.5%, 0.9%, and 0.6%, respectively.

Cluster 2, the "High Return" cluster, contains 41 PDBs. The group displays slightly high financial returns, with ROA between 0.9% and 12% (median = 3.7%), ROE between 0.4% and 6.5% (median = 1.1%), and NIM between 9% and 26% (median = 13%).

In the final step, we examine whether observed characteristics of PDBs are correlated with the pattern of financial returns. We consider the following

[16] We refer to the first and third quartiles to present these figures.

characteristics: size, age, ownership, mandate, income level, and continent of origin. The analysis indicates no clear patterns in terms of the variation in financial profiles across PDBs. Our preliminary analysis finds that different characteristics of PDBs (e.g., size or mandate) are not strongly related to the different clustering of PDBs' financial profiles.

The central issue is the trade-off between pursuing public policy mandates and ensuring the minimum level of financial viability.

Because this is an exploratory exercise, one limitation is that we have to rely on figures from the PDBs' financial statements. We are thus unable to consider possible hidden support, such as government guarantees, which can significantly affect financial profiles (Lucas 2014, 2019). Additionally, a full analysis should consider risk management and investments' impact. Addressing the identified caveats and pursuing the suggested future research directions will improve our understanding of these critical institutions and their role in balancing financial viability with development goals. To enrich and deepen the analysis, future research should address several issues. The central issue is the trade-off between pursuing public policy mandates and ensuring the minimum level of financial viability. Potential research topics include the following: exploring differences in financial return indicators between development banks and commercial banks and understanding the underlying reasons, identifying appropriate indicators for measuring PDBs' financial returns, determining factors that influence PDBs' financial returns, examining how PDBs' business models reveal their financial returns, setting appropriate levels or targets for financial return measures as perceived by regulators and PDBs, and investigating the impact of compliance with financial regulatory standards on PDBs' financial returns.

A final interesting result is that this analysis could only be carried out on a limited number of PDBs. We were unable to extract financial data from a substantial number of them, raising the question of transparency. Regional associations could help PDBs improve their disclosure and facilitate knowledge sharing about these institutions. Opportunities for mutual learning about mechanisms to strengthen financial returns are vast and cover different angles: well-established practices and innovative experiences can be exchanged between "younger" and "older" PDBs, between PDBs located in different development contexts, and between PDBs of different sizes and those with a more specialized or diversified portfolio of beneficiaries.

References

01 Boubakri, Narjess, Jean-Claude Cosset, Klaus Fischer, and Omrane Guedhami. 2005. "Privatization and Bank Performance in Developing Countries." *Journal of Banking & Finance* 29, no. 8-9: 2015-2041.

02 Brei, Michael, and Alfredo Schclarek. 2018. "The Countercyclical Behavior of National Development Banks in Latin America and the Caribbean." In *The Future of National Development Banks*, Chapter 11, edited by S. Griffith-Jones and J. A. Ocampo, 278-301. Oxford, UK: Oxford University Press.

03 Cornett, Marcia Millon, Lin Guo, Shahriar Khaksari, and Hassan Tehranian. 2009. "The Impact of State Ownership on Performance Differences in Privately-Owned versus State-Owned Banks: An International Comparison." *Journal of Financial Intermediation* 19, no. 1: 74-94.

04 De Haas, Ralph, and Juanita González-Uribe. 2024. "Public Policies for Private Finance." *Annual Review of Financial Economics, Forthcoming*.

05 Gong, Di, Jiajun Xu, and Jianye Yan. 2023. "National Development Banks and Loan Contract Terms: Evidence from Syndicated Loans." *Journal of International Money and Finance 130*: 102763.

06 Hennig, Christian, Marina Meila, Fionn Murtagh, and Roberto Rocci. 2015. *Handbook of Cluster Analysis.* New-York: Chapman and Hall/CRC.

07 Hu, Bo, Alfredo Schclarek, Jiajun Xu, and Jianye Yan. 2022. "Long-term Finance Provision: National Development Banks vs. Commercial Banks." *World Development* 158: 105973.

08 Humphrey, Chris. 2014. "The Politics of Loan Pricing in Multilateral Development Banks." *Review of International Political Economy* 21, no. 3: 611-639.

09 Lucas, Deborah. 2014. "Evaluating the Cost of Government Credit Support: The OECD Context." *Economic Policy* 29, no. 79: 553-597.

10 Lucas, Deborah. 2019. "Measuring the Cost of Bailouts." *Annual Review of Financial Economics* 11: 85-108.

11 Panizza, Ugo. 2023. "State-Owned Commercial Banks." *Journal of Economic Policy Reform* 26, no. 1: 44-66.

12 Xu, Jiajun, Régis Marodon, Xinshun Ru, Xiaomeng Ren, and Xinyue Wu. 2021. "What Are Public Development Banks and Development Financing Institutions? ——Qualification Criteria, Stylized Facts and Development Trends." *China Economic Quarterly International* 1, no. 4: 271-294.

13 Xu, Jiajun, Yang Zou, and Ugo Panizza. 2025. "Comparing Financial Returns: National Development Banks vs. Commercial Banks." Beijing: Public Development Finance Research Program Working Paper, Peking University.

Appendix A – Additional tables and figures

Table A1. Comparison of flagship and original databases

	Original database		Flagship database		Cross-data share	
	Number	%	Number	%	%	Chi²
Total	**449**	**100**	**259**	**100**	**57.7**	**-**
Size						**0.00**
Mega	6	1.3	6	2.3	100.0	
Large	17	3.8	16	6.2	94.1	
Medium	33	7.3	30	11.6	90.9	
Small	160	35.6	126	48.6	78.8	
Micro	136	30.3	79	30.5	58.1	
NI	97	21.6	2	0.8	2.1	
Mandate						**0.19**
FLEX	166	37.0	94	36.3	56.6	
AGRI	33	7.3	18	6.9	54.5	
EXIM	46	10.2	25	9.7	54.3	
HOUS	31	6.9	21	8.1	67.7	
INFRA	22	4.9	11	4.2	50.0	

	Original database		Flagship database		Cross-data share	
	Number	%	Number	%	%	Chi²
INTL	16	3.6	10	3.9	62.5	
LOCAL	18	4.0	16	6.2	88.9	
MSME	117	26.1	64	24.7	54.7	
Ownership						0.77
NATIONAL	334	74.4	194	74.9	58.1	
SUBNATIONAL	115	25.6	65	25.1	56.5	
Age						0.16
Before 1980	128	28.5	100	38.6	78.1	
1980–1999	155	34.5	79	30.5	51.0	
2000 to today	166	37.0	80	30.9	48.2	
Income						0.00
HIC	171	38.1	99	38.2	57.9	
UMIC	124	27.6	90	34.7	72.6	
LMIC	137	30.5	64	24.7	46.7	
LIC	17	3.8	6	2.3	35.3	
Continent						0.00
Africa	83	18.5	37	14.3	44.6	
Americas	105	23.4	65	25.1	61.9	
Asia	131	29.2	79	30.5	60.3	
Europe	112	24.9	73	28.2	65.2	
Oceania	18	4.0	5	1.9	27.8	

Note: The table displays the distribution of PDBs in the original and flagship databases. We identify the statistical differences between both databases using a Chi² test and display in yellow (green) the under-representation (over-representation) of banks in the flagship database.

Table A2. Robustness checks and value for means of ROA, ROE, and NIM

	Baseline	W/out mega	W/out 2020	All obs.	Add variance	Add CtI	Add PpE
ROA							
Cluster 1	**5.5**	5.64	6.65	4.04	5.55	5.60	5.03
Cluster 2	**137.3**	137.3	574.3	150.7	128.1	137.3	86.2
ROE							
Cluster 1	**17.8**	18.2	6.07	21.0	18.0	18.1	6.98
Cluster 2	**31.5**	31.5	405.3	36.8	29.4	31.5	64.9
NIM							
Cluster 1	**1.0**	0.99	3.87	0.86	0.91	1.09	0.97
Cluster 2	**34.9**	34.9	75.6	27.6	33.0	34.9	17.4
Obs.							
Cluster 1	**218**	212	250	170	215	214	144
Cluster 2	**41**	41	9	37	44	41	75

Table A3. Robustness checks and value for medians of ROA, ROE, and NIM

	Baseline	W/out Mega	W/out 2020	All obs.	Add variance	Add CtI	Add PpE
ROA							
Cluster 1	**0.46**	0.46	0.57	0.45	0.44	0.44	0.26
Cluster 2	**3.72**	3.72	64.75	3.11	3.41	3.41	5.33
ROE							
Cluster 1	**0.85**	0.85	0.85	0.90	0.85	0.85	0.41
Cluster 2	**1.11**	1.11	290.08	1.17	1.14	1.14	5.18
NIM							
Cluster 1	**0.55**	0.56	0.75	0.59	0.54	0.54	0.55
Cluster 2	**13.07**	13.07	34.89	9.75	12.18	12.18	4.45
Obs.							
Cluster 1	**218**	212	250	170	215	214	144
Cluster 2	**41**	41	9	37	44	41	75

Table A4. Migrations from one cluster to another during robustness checks

Panel A: Excluding Mega-PDBs

	Robust			
Baseline	**1**	**2**	**Total**	**% errors**
1	212	0	212	
2	0	41	41	
Total	212	41	253	**0.0**

Panel B: Excluding 2020 (COVID-19)

	Robust			
Baseline	**1**	**2**	**Total**	
1	215	3	218	
2	35	6	41	
Total	250	9	259	**14.7**

Panel C: Including only banks with 6-year

	Robust			
Baseline	**1**	**2**	**Total**	
1	170	6	176	
2	0	31	31	
Total	170	37	207	**2.9**

Panel D: Add variance

	Robust			
Baseline	**1**	**2**	**Total**	
1	215	3	218	
2	0	41	41	
Total	215	44	259	**1.2**

Panel E: Add cost to income

	Robust			
Baseline	1	2	Total	
1	214	0	214	
2	0	41	41	
Total	214	41	255	**0.0**

Panel F: Add profit per employees

	Robust			
Baseline	1	2	Total	
1	143	44	187	
2	1	31	32	
Total	144	75	219	**20.5**

Appendix B – Cluster analysis

Cluster analysis consists of grouping objects according to their similarities or dissimilarities. There are several cluster analysis methods, the two main categories of which are hierarchical and partitioning (Hennig et al. 2015).

- Hierarchical methods create hierarchically related clusters through an iterative process: agglomerative hierarchical clustering starts with one group per observation and combines the two closest groups at each iteration, whereas divisive hierarchical clustering does the opposite, starting with one group that is split into two at each step of the process.

- The partitioning approach is iterative and divides data into k groups or clusters. The procedure starts with k initial group centers. Observations are assigned to the group with the closest center. The mean or median of the observations assigned to each of the groups is calculated, and the process is repeated. These steps continue until all observations remain in the same group from the previous iteration.

We chose the partitioning approach because of its stability. Each approach has its advantages and disadvantages (Hennig et al. 2015). A major limitation of the hierarchical approach for our analysis is that its results are very sensitive to the linkage method considered (e.g., single, full, or average). The results are therefore highly unstable, as our data confirmed. The different linkage methods provide very different clusters for the same dataset.

The partitioning approach proposes two main measures to determine the cluster's centroid: mean and median. We followed the latter approach (called k-medians) because means can be driven by outliers within each cluster. We measured the distance between an observation and the cluster centroids using Euclidean distance, which is the most commonly used measure.

In the analysis, we performed cluster analysis for two to 15 clusters. We used the silhouette method to determine the optimal number of clusters and maintain the correct analysis accordingly (Hennig et al. 2015). The silhouette value is a measure of how similar an object is to its own cluster (cohesion) compared to other clusters (separation). The silhouette ranges from -1 to +1, with a high value indicating that the object is well matched to its own cluster and poorly matched to neighboring clusters.

Our baseline analysis was based on our first three financial return measures: ROA, ROE, and NIM. This is because these were the only indicators for which our sample of 259 PDBs was not reduced. We took the average of each indicator over the period for each institution. Because the Euclidean distance is sensitive to the scale of the variable, we standardized the financial return variables. We then performed several robustness checks to determine whether the clusters changed when special situations were excluded from the analysis.

Appendix C – Regression analysis

In this section, we examined how observed characteristics of PDBs were correlated with financial ratios (ROA, ROE, and NIM) on the one hand and the likelihood of belonging to Cluster 1 (low return) on the other hand.

The baseline econometric model is as follows:

$$Y_i = \sum_S \beta_S I(Size = S) + \sum_A \beta_A I(Age = A) + \sum_M \beta_M I(Mandate = M) + \sum_O \beta_O I(Own = 0) + \sum_I \beta_I I(Income = I) + \sum_c \beta_c I(Cont = C) + \varepsilon_i$$

Where Y_i is the three financial ratios (ROA, ROE, or NIM) in Table C1 and a dummy equal to one if PDB i belongs to Cluster 1 in Table C2. Size, Age, Mandate, Own, Income, and Cont are dummies equal to one if PDB i belongs to size group S, age group A, has mandate M, is national, its owners are located in income country group I and in continent C.

For the analysis of the financial ratios in Table C1, we used both ordinary least squares (OLS) and least absolute deviations (LAD) models. The OLS model explains differences in means, and the LAD model explains differences in medians. Because of the importance of outliers, the latter model is well designed.

For the probability of being in the first cluster in Table C2, we used a probit model and an OLS model because of the dependent variable's binary nature.

The following tables show the results for each variable and the total variance explained by the model (R^2).

Table C1 – Linear regressions

	Return on assets				Return on equity				Net interest margin			
	OLS		LAD		OLS		LAD		OLS		LAD	
	Coef.	(Std. err.)	Coef.	(Std. err.)	Coef.	(Std. err.)	Coef.	(Std. err.)	Coef.	(Std. err.)	Coef.	(Std. err.)
Date of creation												
1980–1999	51.74	46.72	0.39	0.54	9.29	17.54	0.61	0.46	-4.50	4.15	0.57	0.36
2000 to today	-14.20	45.62	-0.12	0.53	5.27	17.13	0.05	0.45	-0.01	4.05	0.06	0.35
Size												
Large	33.63	141.69	1.01	1.64	6.58	53.20	0.27	1.40	11.36	12.57	1.64	1.10
Medium	58.46	132.12	0.34	1.53	44.93	49.60	0.39	1.31	4.35	11.72	1.22	1.03
Small	83.80	124.38	0.86	1.44	13.21	46.70	0.31	1.23	9.45	11.04	0.66	0.97
Micro	43.49	130.35	0.64	1.51	-4.97	48.94	-0.26	1.29	9.18	11.57	0.69	1.01
NI	51.07	241.20	-0.17	2.80	-35.72	90.56	-4.95	2.39**	8.22	21.40	0.54	1.88
Mandate												
AGRI	-35.10	78.17	-0.09	0.91	55.43	29.35*	-0.49	0.77	-5.61	6.94	0.05	0.61
EXIM	-56.02	70.02	-0.10	0.81	55.94	26.29**	-0.13	0.69	-5.62	6.21	-0.86	0.54
HOUS	-27.74	73.03	0.38	0.85	21.95	27.42	0.53	0.72	-3.37	6.48	0.11	0.57
INFRA	11.60	95.13	-0.02	1.10	8.91	35.72	-0.02	0.94	18.14	8.44	-0.73	0.74
INTL	1.40	104.41	-0.38	1.21	-3.48	39.20	0.23	1.03	-4.93	9.27**	0.05	0.81
LOCAL	-6.77	80.35	0.44	0.93	55.63	30.17*	1.13	0.80	1.81	7.13	0.24	0.62
MSME	67.51	48.68	-0.09	0.56	19.70	18.28	-0.09	0.48	-5.32	4.32	-0.37	0.38
Income												
UMIC	53.73	59.12	0.04	0.69	-5.66	22.20	0.93	0.59	2.87	5.25	0.33	0.46
LMIC	-43.10	69.11	0.21	0.80	-0.58	25.95	0.72	0.68	-2.20	6.13	0.65	0.54
LIC	-0.57	138.71	5.40	1.61***	184.47	52.08***	0.87	1.37	-5.36	12.31	0.77	1.08
Continent												
Americas	-32.45	69.83	0.12	0.81	-9.68	26.22	-0.40	0.69	-3.61	6.20	0.32	0.54
Asia	58.12	64.00	0.33	0.74	-18.05	24.03	-0.39	0.63	4.97	5.68	0.54	0.50
Europe	-15.25	83.94	1.27	0.97	7.03	31.51	0.11	0.83	0.13	7.45	0.86	0.65
Oceania	-30.27	142.40	0.42	1.65	0.54	53.46	0.99	1.41	-8.28	12.64	0.28	1.11
Ownership												
SUBNATIONAL	-38.85	48.28	-0.20	0.56	11.64	18.13	0.38	0.48	-3.30	4.28	0.01	0.38
Obs.	259		259		259		259		259		259	
R^2	0.0507		0.0033		0.137		0.0046		0.0713		0.0156	

*, **, *** signal significance at 10%, 5%, and 1%

Table C2 – Likelihood of being in Cluster 1

	Probit		OLS	
	Coef	Std. err.	Coef	Std. err.
Date of creation				
1980–1999	-0.13	0.25	-0.03	0.06
2000 to today	0.29	0.26	0.06	0.06
Size				
Large	-0.38	0.46	-0.33	0.18
Medium	0.26	0.41	-0.19	0.17
Small	0.05	0.25	-0.23	0.16
Micro	-	-	-0.24	0.17
Mandate				
AGRI	0.20	0.43	0.05	0.10
EXIM	0.79	0.45*	0.15	0.09
HOUS	0.45	0.39	0.11	0.09
INFRA	0.11	0.50	0.03	0.12
INTL	-0.08	0.55	-0.01	0.14
LOCAL	-0.39	0.38	-0.12	0.10
MSME	0.51	0.28*	0.10	0.06
Income				
UMIC	-0.45	0.37	-0.07	0.08
LMIC	-0.26	0.40	-0.04	0.09
LIC	-0.24	0.74	-0.02	0.18
Continent				
Americas	-0.28	0.40	-0.07	0.09
Asia	-0.41	0.36	-0.09	0.08
Europe	-0.43	0.50	-0.07	0.11
Ownership				
SUBNATIONAL	0.23	0.27	0.05	0.06
R^2	0.07		0.06	

*, **, *** signal significance at 10%, 5%, and 1%

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