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Competitive conditions in development finance

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ABSTRACT

This paper evaluates the competitive conditions in development finance and the implications for successfully mobilising private sector finance in order to achieve the United Nations Sustainable Development Goals (SDGs). Using a market definition of cross-border development finance, the analysis uses financial data for 61 development banks from FitchConnect from 2010–2019 and applies the Panzar–Rosse test, supplemented with additional tests for market equilibrium, to gauge the competitive conditions. The key finding is that the international development finance market is in long-term equilibrium and is structured as a competitive oligopoly. The implication is that successful mobilisation of private sector finance will require more innovative structural and funding solutions. Crowding-in of private sector banks on existing terms and in large scale is likely to fall short due to lack of profitability and risk appetite. This has direct implications for the ability of the global financial system to deliver the SDGs.

1. Introduction

Mobilisation of private sector capital is a cornerstone of the international development community's strategy to achieve the United Nations Sustainable Development Goals (SDGs) and climate transition targets under the Paris Agreement. The traditional multilateral development banks (MDBs) have insufficient capital to fund the transition on their own and so are continuously seeking ways to crowd the private sector into transactions. The funding gap has been characterised as the leap from 'billions to trillions' of investment (Development Committee, 2015). The funding gap persists as the UNFSDR (United National Financing for Sustainable Development Report) reconfirmed in 2020 that the private sector will need to participate significantly in development funding if the SDGs are to be fulfilled by 2030 (United Nations, 2020).

Since the creation of the SDGs in 2015, the instructions to MDBs from international bodies to mobilise the private sector have been explicit. In July of that year, the UN launched the Addis Ababa Action Agenda which mandated development banks to mobilise long-term private capital into infrastructure investments and green finance (United Nations, 2015). At the Antalya Summit in November, the G20 then instructed major MDBs to produce an Action Plan to maximise their impact through a variety of measures to improve capital efficiency and to mobilise private capital with ongoing monitoring (G20, 2015; IATF, 2016), with particular reference to climate finance (EBRD, 2019; Multilateral Development Banks, 2018b). The G20 also established working groups with the express purpose of agreeing principles to crowd-in the private sector (G20 – IFA WG, 2017).

However, mandating an Action Plan for MDBs does not entail that private sector institutions will engage with it fully. The countries and sectors that are priorities for the MDBs in working toward the SDGs do not necessarily match the risk appetites and strategies of the large global banks in the private sector. Transactions that are demanding on bank capital such as infrastructure projects have become more expensive for the private sector (Martynova, 2015; United Nations, 2020), and the credit appetite for

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developing markets has reduced due to balance sheet constraints and compliance complexities (Starnes et al., 2016). There are also some countries in which MDBs operate that are off-limits to the private sector due to international sanctions.

The challenge to mobilising the private sector comes from the different operating mandates that MDBs are given. A common principle among these mandates is that MDBs are required to provide evidence that they are indeed crowding in the private sector and not crowding it out. This is referred to as the principle of 'additionality'. It exists as a control against the risk that an MDB might inadvertently finance deals that the private sector would have done anyway (Arvanitis et al., 2015; Carter et al., 2018). In this regard, a harmonised framework for additionality has been designed by a group of major MDBs (Multilateral Development Banks, 2018a) which makes the intention explicit:

> *'... interventions by multilateral development banks (MDBs) to support private sector operations should make a contribution beyond what is available in the market and should not crowd out the private sector.'*

In addition to demonstrating additionality, transactions need to generate sufficient financial return to attract the private sector. A critical driver of the mobilisation process is intended to be the expansion of MDBs balance sheets by the generation of more bankable projects (and more broadly by development finance institutions, DFIs), with the risk being redistributed to the private sector. Private capital can be mobilised *on a significant scale*, provided that the profitability of transactions can be maintained as the market expands.

Against this backdrop, an unaddressed question in the related body of research is whether, and how, DFIs compete in the market for development finance. The nature of this competition could affect the ability of DFIs to mobilise private capital in pursuing the SDGs. This paper defines a market for development finance by considering the cross-border activities of DFIs, and builds upon diverse strands of existing literature to explain how the activities of MDBs and other types of DFI might overlap and create competition. I evaluate the competitive conditions in the market for development finance using the Panzar–Rosse test (Panzar and Rosse, 1987), widely used by researchers and regulators for judging the market conditions in banking. The financial data from 2010 to 2019 used in the test are extracted from FitchConnect. However, as the Panzar–Rosse test alone does not necessarily provide a clear-cut representation of the market's competitive conditions, I supplement the analysis with additional tests to refine the outcomes (Bikker et al., 2012). The results demonstrate that the market for development finance is a competitive oligopoly that is in long-term equilibrium. The empirical analysis further shows that the barriers to entry in development finance are low, and that the demand curve is downward-sloping. This second aspect presents a challenge in the search for effective ways to crowd in private capital to development projects. As private sector banks incur a higher cost of funding than state-owned institutions it suggests that the market pricing for development finance is unlikely to provide sufficient incentive for private capital to participate in transactions. A further implication is that the environment may not support mobilisation of the private sector using the same financing techniques, in the same regulatory and political environment. Therefore, alternative financing mechanisms and products may be required to ensure that the SDGs are fully funded. Governments, as shareholders, will need to go further in changing the regulatory, policy and legal frameworks to permit capital to flow in sufficient quantities.

The contribution of this paper to the related literature is three-fold. First, to the best of my knowledge, this is the first comprehensive study to test for the competitive conditions in the market for development finance. Second, unlike the related body of research, I test if the market of development finance is in long-run equilibrium. Third, my research design allows for the shape of the demand curve for development finance to be inferred, leading to practical implications for the ability of DFIs to mobilise the private sector in support of the SDGs.

The structure of this paper is as follows. Section 2 provides background to explain how and why the market for development finance has been defined for this analysis. Section 3 describes the data underlying the analysis. Section 4 details the econometric models that are employed and Section 5 describes the results. Finally, Section 6 draws some conclusions and suggests future research around this topic.

2. Background: the market for development finance

Creating a shortlist of institutions to apply the Panzar–Rosse test requires some delineation of the market for development finance. This entails considering the types of institutions that are active and how they operate, their geographic coverage and the types of transactions used in private sector operations. The background given here provides the context for the entity selection in Section 3.1 and draws from a more extensive review paper on capital mobilisation (McHugh, 2021).

2.1. Types of development finance institutions

Multilateral development banks are distinctive by their ownership structures as they are controlled by a mixture of sovereign donor and recipient states. There are other development finance institutions (DFIs) such as regional and national development banks (RDBs and NDBs respectively). The national development banks generally fall into two categories — either owned by developed countries investing overseas, or local development banks that act as state-owned financial institutions.

The relationships between these different types of entities is complicated by overlaps in the definitions, and also mutual lending relationships where MDBs might be lending to NDBs in developing markets to subsequently on-lend domestically (Schclarek and Xu, 2022). For the purpose of defining the market for mobilising private sector capital and assessing the competitive conditions, the key aspect is that the institutions need to be actively involved in cross-border lending into developing markets. The MDBs alone operate with significant geographic overlaps. The Overseas Development Institute (Engen and Prizzon, 2018) calculates an average coverage range of 5.4 to 7.3 MDBs per country in developing markets (relatively more in lower income countries). Within that there is significant variation and plenty of activity in markets in which large international banks are active. There is scope for competition between MDBs even without extending the market to encompass RDBs/NDBs.

It is important to note that mobilisation focuses on private sector activities, while much of the MDBs activity is at a sovereign level. There is a rich seam of literature that discusses competition between nation states as it pertains to development lending and the international political economy with a particular focus on the relationship between China and the traditional Western MDBs (Dreher et al., 2017, 2018; Asmus et al., 2017; Swedlund, 2017; Humphrey, 2019). Concessional lending to a sovereign might affect the economic environment or the political stability in a given country to encourage more private sector activity. However, in the context of this paper, mobilisation is about the lending operations of DFIs where they invest directly into projects alongside the private sector.

DFIs are not typically considered to be overt competitors, in particular the MDBs. Much of the rhetoric in development finance is around cooperation and coordination which is seen in the number of joint reports that are produced. SDG Goal 17 (Partnerships for the Goals) is about collaboration relating to underlying targets covering finance, technology, capacity building and systemic issues. The UNFSDR cites the findings of the UN Expert Person Group that development banks should coordinate activities. The EPG recommends 'Joining up IFIs' operations, as well as with those of other development partners, to enhance development impact' (United Nations, 2020).

Although many DFIs share similar multi-lateral shareholders in the form of sovereign states, there are geographic differences, voting differences, and for bilateral development banks (i.e. NDBs) there can be specific national interests. Lending mandates for the DFIs are carefully negotiated and validated by shareholders and it is expected that funding will be deployed to the maximum based on the available capital base. This is exactly what the G20 is pressuring the MDBs to do. So, as all MDBs are under pressure to deploy capital in pursuit of the SDGs, there are reasonable grounds for believing that there is active competition.

2.2. The role of sovereigns

The fact that there are numerous MDBs in existence and that new ones are being created is seen in the context that sovereign shareholders (i.e. governments) are not satisfied with the outcomes from other MDBs that they co-own. This has led to studies on the degree of competition between China and the West in particular. The Asian Infrastructure Investment Bank and the New Development Bank are both newer arrivals with a strong Chinese presence and were set up to compensate for a perceived lack of focus on Asian issues in particular and with a different operating model to incumbent institutions (Gu, 2017; Ransdell, 2019; Kellerman, 2019). Kellerman (2019) explains the proliferation of development banks as a reaction against existing institutions when sovereign states are dissatisfied with the status quo. The ongoing creation of new development banks can be viewed as a direct result of competition between sovereign states to ensure that their interests are being attended to.

There is conflicting evidence on whether shareholder structure and attitudes affects the operation of the MDBs. Cormier (2018) take the position that MDBs have acquired sufficient agency to pursue goals somewhat independently of individual donor politics. He also considers the way in which the culture and processes of MDBs might restrict the ability of an institution to support the SDGs, something that is of material importance given the broader global goals of the G20. In contrast, Dreher et al. (2019) found a significant link between the allocation of funds from the IFC and the composition of the board. Humphrey and Michaelowa (2013) provide yet another perspective from testing the lending patterns of the World Bank, IADB and CAF, from the borrower's perspective. Rather than borrowers pursuing the cheapest loan for the required maturity, they find competitive differences in the form of the speed at which loans are approved. Also, the external pressure to conform to safeguards (eg. Environmental, Social, Governance) can be lower from institutions with less dominant donor shareholders as they are less able to impose their standards onto the MDB in question. Similarly, Yuan and Gallagher (2018) find that the provision of finance (in their case green finance to Latin America and the Caribbean) is dependent upon the attitude of the recipient country relative to the agenda of the DFI that they are seeking to borrow from.

From a systemic perspective, it is worth noting that MDB lending at a sovereign level has an affect on overall financial market stability given that MDBs can take the role of a counter-cyclical lender (Galindo and Panizza, 2018). Given that there might be an interaction between development lending, mobilisation and the health of a given country's economy, there is useful context in the literature about emerging market prudential regulation (Olszak and Kowalska, 2022), the impact of cross-border lenders (Kanga et al., 2021) and the competition-stability or competition-fragility state of an emerging market (Elfeituri, 2022; Kanga et al., 2021). However, these studies do not distinguish for development lending and it is beyond the scope of this paper to additionally assess that.

2.3. Convergence of operating models

There is a degree of convergence of operational models for MDBs that runs deeper than collaboration. This might explain the ongoing process of the creation of new DFIs over time through frustration over lending outcomes as highlighted in Section 2.2. With an unusual callable capital structure and shareholders wanting the largest MDBs to maintain AAA credit ratings the financial market effectively forces convergence on balance sheet structure and behaviour toward lending (Humphrey, 2014, 2016, 2019; Humphrey and Michaelowa, 2013). The other convergence factor is that a similar list of shareholders is generally involved in the traditional MDBs albeit in different proportions.

Additionality is also measured and calculated in similar ways across MDBs even though this requires a higher-degree of subjective decision-making into their investment decisions than the private sector. The justification of additionality requires a relative benefit calculation compared to a counterfactual baseline. This clearly might lead to investment errors at times, where projects might be over- or under-valued from so many diverse and difficult project variables (Arvanitis et al., 2015; Carmichael et al., 2016; Carter et al., 2018; Streck, 2017). An example of this is from the implementation of the Kyoto Protocol in 1997 by which the Clean Development Mechanism (CDM) would have required DFIs to consider the value of Certified Emissions Reductions (CERs) as part of a valuation assessment (Dutschke and Michaelowa, 2006; McFarland, 2011). The idea being that the trading of the subsequent CERs would justify over time the value differential. In reality, the carbon market collapsed during 2012 and into 2013 with prices falling from 2008 levels of EUR 30 per tonne to an absolute low of EUR 0.12 per tonne in the spot market in February 2013 (Ervine, 2013). Private sector banks are less likely to be able to warehouse this type of unhedgeable risk in a material size.

2.4. Financing mechanisms

The two principal financing mechanisms that DFIs use to engage with private sector banks with mobilisation as an objective are project finance and conditional lending. DFIs also lend directly to private sector companies but the deal sizes tend to be too small to need private capital in addition. Project finance is commonly used for infrastructure deals because of the contractual arrangements for such investments, and also the risk management frameworks that can be put in place (Ahiabor and James, 2019; Byoun and Xu, 2014; Hainz and Kleimeier, 2012). The use of project finance vehicles and conditionality is a mitigant for weak investor protection laws in environments with weaker legal frameworks and creditor rights and protections (Subramanian and Tung, 2016). These deals tend to be large and suit a process of debt syndication so private sector firms are brought into the transaction alongside the DFI. There is evidence that higher project risk is associated with greater involvement of MDBs and less supply of private sector syndicated debt (Byoun et al., 2013). The DFI's additionality comes from making the project 'bankable', which could derive from technical assistance or from the political umbrella that DFIs can bring in the form of Preferred Creditor Status which is seen as a useful risk mitigant (Hainz and Kleimeier, 2006; Sawant, 2010).

There is evidence of competition through the use of different types of financial instruments and structure that vary regulatory standards and layers of structural subordination (Chin and Gallagher, 2019; Shapiro et al., 2018). Further evidence of the manner in which the ownership of the institution can affect the basis for competition is given by Hernandez (2017) who finds that the presence of Chinese institutions in Africa has affected the ability of the World Bank to attach conditions to lending.

Conditional lending describes a ring-fenced bilateral lending arrangement between a DFI and a private sector bank with the intention of delivering prescribed outcomes. The loan may be made at a slight discount to the bank's usual cost of funding, but in return it is obliged to conform to a set of impact measures and targets that are linked to the SDGs. Azmi et al. (2021) find no funding benefit for emerging market banks with respect to a bank's in-house ESG efforts. In this context, 'ESG' (Environmental, Social, Governance) has become a framework with which banks operationalise the principles of the SDGs. However, conditional lending is related to client SDG/ESG metrics rather than the bank's own metrics. It is possible that there is a link between the bank internal ESG goals and its volume of sustainable lending, although the literature appears to be silent on that. As a result, there is no clear link to be made between the lack of funding benefit reported by Azmi et al. (2021) and the actual discount given to banks for accepting conditional funding from DFIs. One way to view the funding discount is as a payment for the additional monitoring and risk that the host bank takes on.

The funding discount also creates an incentive for the local bank to take more DFI funding, although currency mismatches in markets where there is less US dollar liquidity create capacity constraints (Schclarek and Xu, 2022). The diminishing returns to internal ESG activity that Azmi et al. (2021) also report are a reflection of the convex costs of the additional administrative and risk management work required. It is reasonable to expect a similar non-linear cost effect on a bank when considering the ESG metrics for the client portfolios which would limit a bank's appetite to receive conditional funding. For the DFI, this form of mobilisation is more intensive on its balance sheet than traditional syndication as it still bears the full country risk of the host bank despite not facing the SMEs directly. The convexity of monitoring costs for conditional lending, foreign currency constraints, and the more intensive balance sheet usage for the DFI suggest that there are limits to how much funding can be pushed through this channel.

The degree of leverage of mobilisation through conditional lending is consequently lower than from syndication of deals originated by the DFI itself. The syndication process is also contingent on the DFIs being able to show additionality otherwise the private sector might have funded the deals anyway. The position that MDBs have taken with respect to mobilisation enables them to focus on building a pipeline of 'bankable' projects for the private sector which is a highly granular deal generation process. Evidence from the syndicated loan markets shows that this crowding-in approach is effective even taking into account differences by country or sector (Broccolini et al., 2021; Gurara et al., 2020).

2.5. Summary

The environment for development lending contains numerous state-owned development institutions focusing on cross-border lending into developing markets. Lending objectives will align to the SDGs and may be affected by the shareholders' economic and political agendas. The institutions collaborate at an international level which aligns their approach, but also compete to extend their balance sheets to maximise lending. The range of financial structures into which the private sector can be mobilised on a significant scale is limited and has typically followed a traditional approach of lending and syndication into project finance structures. There are also capacity limits on the amount of conditional lending that can be deployed through local bank balance sheets. This is the structure of the market into which the private sector is being mobilised.

3. Data

3.1. Entity inclusion, selection and classification

The study requires the financial statements of development institutions to be collated on a comparable basis. The data to perform the analysis uses the full-year financial accounts of a selection of institutions from the FitchConnect database from 2010 to 2019. All financial figures are translated into US dollars using FitchConnect's foreign exchange data for the reporting dates of the accounts.

FitchConnect labels a large number of institutions as development banks, so in order to remain consistent with the market definition in Section 2 some filtering is required to sort out which entities should be included in the analysis.

The initial pool of entities for possible inclusion is constructed using the Fitch Identifiers for Supranationals (47), Development Banks (320) and Public Entities (432). Eliminating entities for which no accounting information exists and removing duplicates (4) results in a combined portfolio of 344 entities.

FitchConnect does not document how entities are classified, although from inspection it is clear that some authentic development banks are not included. On the grounds that members of the Association of European Development Finance Institutions (EDFI) are genuine development banks, a further 7 institutions are added for which financial information is available. Those EDFI members for which accounts are not available appear to be state-owned and integrated into sovereign accounts. The final institution added to the pool is the multi-lateral Black Sea Trade and Development Bank which is not captured anywhere else giving a total entity list of 352 development institutions.

To refine the pool further, entities are classified in 4 separate groups according to their characteristics. Using the descriptions from the ODI (Engen and Prizzon, 2018) major multilateral development banks (MDB) and regional development banks (RDB) are identified. Banks that are involved in purely concessional or sovereign activities are excluded (e.g. the IBRD) although it is acknowledged that these activities are blended for some MDBs in their some financial reporting.

The next group of entities are development banks owned by a sovereign nation operating on a cross-border basis, sometimes referred to as bilateral development banks. These are labelled in the data set as 'EDFI' or 'SOV' (for a national development bank outside EDFI) and are considered to be similar in nature. Export-import banks (EXIM) are included in the analysis as a separate category — although not formally development banks, they are involved in cross-border development projects and so are part of the competitive environment.

The remaining entities are a collection of state-owned financial institutions (SFIs). SFIs are not necessarily wholly-owned by the state and some have commercial banking operations in addition to a development mandate. Many are institutions that belong to the World Federation of Development Financing Institutions (WFDFI) which have been surveyed occasionally by the World Bank (De Luna-Martinez et al., 2018).

The WFDFI is a federation of regional geographic groups in which there are some international members although these are already captured as either MDBs, RDBs, EDFI/SOV or EXIM:

- Association of African Development Finance Institutions (AADFI)
- Association of Development Financing Institutions in Asia and the Pacific (ADFIAP)
- Association of National Development Finance Institutions (DFIs) in Member Countries of the Islamic Development Bank (ADFIMI)
- Latin American Association of Development Financing Institutions (ALIDE)

Although members of these groups do have development mandates, they do not operate cross-border and so do not fit the market definition in Section 2. In addition, MDBs engage with local governments and banks in their work for institution-building so are treated as 'customers' or a distribution channel for funding that is on-lent to customers as conditional loans as described in Section 2.4. Finally, as the World Bank observes, it is not always clear how to disentangle commercial operations (De Luna-Martinez et al., 2018). For those reasons, members of the WFDFI are also excluded from the pool of entities and any others banks that could not clearly be identified.

This final step of exclusion leaves a remaining set of 61 entities are categorised as MDB (13), RDB (9), SOV/EDFI (17) or EXIM (22). The full list of entities is in Appendix.

The descriptive statistics are summarised in Table 1. A plot of the natural logs of total income and total assets separated by grouping is shown in Fig. 1 which shows a broad size dispersion by entity type

3.2. FitchConnect API mapping

The notation and data structure used by Bikker et al. (2012) is replicated for the inputs for both dependent and independent variables. The API field mapping between the literature and the Fitch Database is shown in Table 2.

Table 1
Descriptive statistics.

Panel A: Financial variables						
Variable	Code	Obs	Mean	SD	Min	Max
$Total Operating Income$	TI	537	1,578	4,643	−178	38,387
$Total Assets$	TA	539	95,769	260,438	12	2,450,812
$Interest Expense$	IE	493	2,241	7,439	0	63,361
$Total Funding$	TF	502	87,806	242,935	0	2,219,328
$Personnel Expenses$	PE	488	239	671	−4	6,639
$Other Non-interest Expenses$	ONIE	537	697	2,223	−103	23,685
$Fixed Assets$	FA	512	1,012	4,742	0	43,332
$Loans$	LNS	510	59,947	185,369	0	1,708,540
$Other Non-earning Assets$	ONEA	539	3,919	11,745	−537	174,989
$Customer Deposits$	DPS	306	35,704	108,171	0	888,722
$Long Term Funding$	LTF	411	67,169	180,115	0	1,329,114
$Short Term Funding$	STF	411	34,943	100,796	0	925,039
$Equity$	EQ	539	10,658	21,632	8	190,413
$Operating Profit$	OP_PR	537	634	3,135	−11,316	31,522
$OpProfit/AvgTotalAssets$	OP_ROAA	529	1.5	2.7	−10.7	23.9

This table summarises the descriptive statistics of the data: number of observations (Obs), mean ($Mean$), standard deviation (SD), minimum (Min), maximum (Max). All figures are in millions of US dollars except for Op Profit/Avg Total Assets which is a ratio. All figures reported directly from FitchConnect. Each variable has an associated Code that is used for reference in Tables 2 and 3.

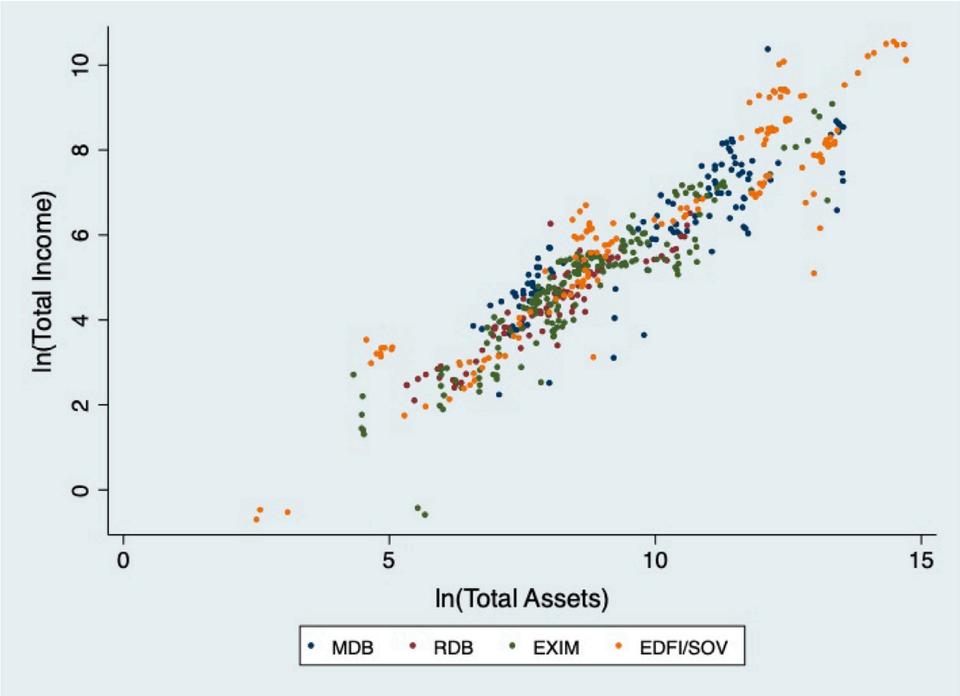

Fig. 1. Total income to total assets by entity type.

4. Methodology

Two types of test are available for measuring bank competition: structural and non-structural. Structural tests such as the Herfindahl–Hirschman Index or a simple concentration ratio require some knowledge of the underlying banking market in which the institutions operate. For development finance this seems impractical as it is not straightforward to define or circumscribe the market.

Non-structural tests include the Lerner Index, Boone Test and Panzar–Rosse test that can rely on financial parameters of firms without requiring knowledge of market structure. Of these, the Panzar–Rosse test has been chosen as the baseline test for this study which has been used extensively to test for bank competition. There is criticism in the literature of the usefulness of the Panzar–Rosse test *on a standalone basis* if the intention of the analysis is to draw conclusions on firm conduct due to market power, as the index produced is not a good measure of competitive conditions or market behaviour (Bikker et al., 2012; Elfeituri, 2022; Shaffer and

Table 2
Mapping of FitchConnect API fields.

Descriptor	FitchConnect data field
TI	FC_TOTAL_OPER_INC_BNK
TA	FC_TOTAL_ASSETS_BNK
IE	FC_TOTAL_INT_EXP_BNK
TF	FC_TOTAL_FUNDING_BNK
PE	FC_PERSONNEL_EXP_BNK
ONIE	FC_TOTAL_NON_INT_EXP_BNK
FA	FC_FIXED_ASSETS_BNK
LNS	FC_NET_LOANS_BNK
ONEA	FC_TOTAL_NON_EARNING_ASSETS_BNK
DPS	FC_DEPOSITS_BANKS_BNK
LTF	FC_TOTAL_LT_FUNDING_BNK
EQ	FC_TOTAL_EQUITY_BNK
OP_PR	FC_OPER_PROF_BNK
OP_ROAA	FC_OPERATING_ROAA_BNK
STF	Derived by [TF - LTF]

The variable codes align with the conventions in Bikker et al. (2012). The FitchConnect data field is the string required in the API formula to download the relevant data point. Short term funding (STF) is a calculated value as the difference between total funding (TF) and long-term funding (LTF).

Spierdijk, 2015, 2017). In order to mitigate this issue, Bikker et al. (2012) show that additional information is required on cost structure and market equilibrium. For this analysis the results of the test are therefore supplemented with the same additional tests as demonstrated by Bikker et al. (2012) to evaluate overall market conditions. The argument against using Panzar–Rosse also relies upon the idea that the market participants are profit-maximisers and will price to their advantage. That assumption is questionable in the context of capital mobilisation by DFIs. In this analysis we are less concerned with the competitive conduct of market participants, but rather to understand the competitive environment in which development banks operate as derived by using Panzar–Rosse supplemented with the additional tests. This environment will shape the potential market outcomes from efforts to mobilise the private sector.

4.1. The Panzar–Rosse model

The test for development finance competition is performed using the Panzar–Rosse reduced-form model. The original paper proposing the model (Panzar & Rosse, 1987) lays out the proofs for the hypotheses although the methodology for this study follows Bikker et al. as it provides a clearer starting point for the analysis as applied to banks (Bikker et al., 2012) and builds on the existing literature.

The methodology is informed by Bikker et al. (2012) using Total Operating Income (TI) of the bank as the dependent variable for regression (Eq. (1)). As fees are an integral part of banking income, an analysis restricted to Interest Income would be incomplete.

Following this method, the approach for analysing competition among commercial banks is to define the factor inputs w_p as: w_{FD} – average funding rate calculated as the ratio of interest expense to total funding (IE/TF); w_{LB} – proxy for cost of labour calculated as the ratio of personnel expenses to total assets (PE/TA); w_{FX} – proxy for the price of physical capital calculated as the ratio of other non-interest expenses to fixed assets (ONIE/FA). The subscript j refers to the control factors that are listed in Table 3.

$$\log TI_{i,t} = \beta_0 + \sum_{p=1}^{P} \beta_p \times \log w_{p,i,t} + \sum_{j=1}^{J} \gamma_j \times \log CF_{j,i,t} + u_{i,t}, \tag{1}$$

From this an index (H) is calculated as the sum of the factor inputs w_p. H is the input factor elasticity, which measures the competitive conditions in the banking market. The sum of the estimated coefficients β_p in Eq. (1) is hereafter denoted as H^r in Eq. (2).

$$H^r = \sum_{p=1}^{P} \beta_p, \tag{2}$$

Table 3 also shows the mapping of the regression parameters to the financial data collected and follows the procedure used by Bikker et al. (2012) to use bank-specific factors reflecting the risk profile. It highlights the notation used for the remainder of this paper as used in the tables of regression results.

Testing for different values of H^r can indicate the competitive conditions for a given market. Based on the revenue equation, it is shown that for a market in long-run equilibrium that H is expected to be negative for a classic monopoly or a collusive oligopoly. The argument is that the monopolist (or oligopolistic colluders) will keep marginal revenue equal to marginal cost. In the event that costs rise, the monopolist will reduce production and will experience a resulting drop in revenue. The elasticity with respect to factor inputs is therefore negative and in this case the H statistic will be negative.

Table 3
Mapping and notation of regression parameters relative to the data.

Variable	Ln(Calc)	Notation	Description
Revenue	TI		Dependent variable (Eqs. (1), (3))
Price	TI/TA		Dependent variable (Eq. (4))
w_1	IE/TF	w_{FD}	Proxy for cost of funding
w_2	PE/TA	w_{LB}	Proxy for cost of labour
w_3	ONIE/FA	w_{FX}	Proxy for cost of fixed assets
CF_1	LNS/TA	CF_{LNS}	Ratio of customer loans to total assets
CF_2	ONEA/TA	CF_{ONEA}	Ratio non-earning assets to total assets
CF_3	DPS/STF	CF_{DPS}	Ratio of customer deposits to short-term funding
CF_4	EQ/TA	CF_{EQ}	Ratio of equity to total assets
CF_5	STF/TF	CF_{STF}	Ratio of short-term funding to total funding
$logTA$ (for δ)	TA	$logTA$	Total assets (Eq. (3))

The table shows the regression parameters for each model used. The regression takes the natural logarithm of each ratio or number in the table. Revenue and Price are used as dependent variables. w_{FD} is the average funding rate calculated by dividing interest expense by total funding (IE/TF). w_{LB} is the average labour cost calculated by dividing personnel expenses by total assets (PE/TA). w_{FX} is the average cost of fixed capital calculated by dividing other non-interest expenses by fixed assets (ONIE/FA). The regression coefficients for these three factor inputs are added to produce the value for H in Eq. (2). The Notation column shows how each control factor is referenced throughout the paper.

Table 4
Summary of H statistics under various cost conditions.
Source: Adapted from Bikker et al. (2012) illustrating the different possible scenarios for Market Power.

Market Power	AC Function	H^r	H^r_s	H^p
Long-run competition	U-shaped	=1	=1	=1
Long-run competition	Flat	<0, from 0–1	=1	=1
Short-run competition	U-shaped	<0, from 0–1	>0	>0
Monopoly	U-shaped	<0	>0	>0
Monopoly	Flat	<0	>0	>0
Oligopoly	U-shaped	<0	>0	>0
Oligopoly	Flat	<0	>0	>0
Monopolistic competition	U-shaped	<0, from 0–1	>0	>0
Constant markup pricing	Flat and U-shaped	<0	=1	=1

For each case, there is an expected average cost (AC) function and predicted values of H^r, H^r_s and H^p.

In another scenario, if a market is in a state of monopolistic or oligopolistic competition, it is expected that the H statistic for the revenue equation will be positive but in the range of 0 to 1. The reasoning is that near substitutes will create economic competition and that participants will behave in a more competitive manner. In the context of development finance, a 'near substitute' for a development loan could be risk offset through a bank guarantee or insurance contract, or a traditional private sector bank lending relationship with associated ancillary services such as cash management, foreign exchange or liquidity facilities.

The last case is for a perfectly competitive market in long-run equilibrium where the H statistic is expected to be equal to 1. Increases in factor prices can be passed on fully suggesting a flat demand curve and where competitors can freely enter and exit the market. Further tests are explained in Section 4.2 that consider what happens if these assumptions are relaxed.

The Bikker et al. (2012) study reviews the application of the Panzar–Rosse model across 31 different previous papers. They identify different treatments of the dependent variable $R_{i,t}$ and also for the control factors. Two further variations of Eq. (1) are also tested but adjusted for scaling which is not part of the original theoretical model. The first of these is where an additional control factor is added to control for scale using the natural log of Total Assets (Eq. (3)). The second variation uses a price measure calculated by dividing Revenue by Total Assets (Eq. (4)). It can be shown that the H statistics calculated by these different approaches will invariably be greater than 0 which changes the way in which the results can be interpreted.

$$\log TI_{i,t} = \beta_0 + \sum_{p=1}^{P} \beta_p \times \log w_{p,i,t} + \sum_{j=1}^{J} \gamma_j \times \log CF_{j,i,t} + \delta \log TA_{i,t} + u_{i,t}, \tag{3}$$

$$\log(TI/TA)_{i,t} = \beta_0 + \sum_{p=1}^{P} \beta_p \times \log w_{p,i,t} + \sum_{j=1}^{J} \gamma_j \times \log CF_{j,i,t} + u_{i,t}, \tag{4}$$

These two equations give separate competition measures for respectively scaled revenue (H^r_s) and price (H^p). Table 4 shows the range of potential market power scenarios for different combinations of the three types of H statistic but also puts them into context with questions regarding the nature of competition in the market and the shape of the average cost curve.

These additional market factors can affect the interpretation of the results and so require further investigation with some additional tests and analysis.

4.2. Additional tests and analysis

Bikker et al. (2012) propose an additional test to supplement the Panzar–Rosse model in order to determine whether the market is in a long-term structural market equilibrium. Provided there is free market entry, economic forces should make RoA equal for all market incumbents and therefore insensitive to input prices. An additional regression test using Eq. (5) produces a similar sum of coefficient H^{RoA}. If we cannot reject $H^{RoA} = 0$ then we also cannot reject that the market is in equilibrium, and that marginal costs are equal to average costs.

$$\log(RoA)_{i,t} = \beta_0 + \sum_{p=1}^{P} \beta_p \times \log w_{p,i,t} + \sum_{j=1}^{J} \gamma_j \times \log CF_{j,i,t} + u_{i,t}, \tag{5}$$

A final step is to consider average costs in the market to visualise the average cost curve. This also helps to characterise the competitive position and market power. The approach that has been taken is to use the sum of the factor inputs (refer to Table 3 for IE, PE, ONIE) and compare this to the 'unit of production' which is the size of the balance sheet (TA). The graph of this is shown in Fig. 2.

4.3. Expectations with regard to the model

The operating model for development banks is highly dependent upon wholesale funding and maintaining top-quality credit ratings. As a result, increases in funding costs will be more affected by the general level of interest rates than by credit spreads. Conversely, the customers of MDBs are lower-quality rated and so lending rates will be affected primarily by credit spreads rather than wholesale market interest rates. A negative coefficient for w_{FD} would suggest that MDBs are unable or unwilling to pass on changes in their funding costs to their borrowers.

The cost of administering development work can be high and a significant portion of non-interest expenses pertain to people and consultants which should be evident from w_{LB}. As this factor input is also disconnected from the lending rates to customers, w_{LB} should have a similar directional impact to w_{FD} so the coefficient should have the same sign. Given that the balance sheet structure of development banks is not reliant upon customer deposits it is not clear how economically relevant the price of physical capital w_{FX} would be. Rather than maintaining branch networks, MDBs do often maintain a physical presence in countries in which they operate and so the operating model is more similar to an investment banking operation. A similar argument applies to either the inability or reluctance to pass on cost increases and again it would be expected for the coefficient of w_{FX} to be similar to the other input factor prices.

The control factors that ought to have a significant impact on revenue will relate to the efficiency with which capital is deployed. To that end, the equity to asset ratio (CF_{EQ}) should have a strong influence, as might the ratio of customer loans to total assets (CF_{LNS}). Given the lack of significant branch networks, the relevance of non-earning assets is expected to be limited (CF_{ONEA}). As the large DFIs are not reliant on customer deposits to function, controlling for this is unlikely to be meaningful (CF_{DPS}). Instead of customer deposits, controlling for the proportion of short to long term funding could show an alternative sensitivity to capital structure (CF_{STF}).

Each of the three models (revenue, scaled revenue, price) are run using pooled OLS with the control factors as specified, and controlling for entity type. Additional robustness checks are included in Section 5.5.

4.4. Alternative estimation methods

The OLS estimation methodology described in this section is the standard implementation of the Panzar–Rosse model because the derivation of the original work is based on a static equilibrium framework. This estimation method is standard in the related literature, which is also recognised by Bikker et al. (2012).

There are variety of arguments against using a static linear regression model that have been put forward. A criticism of the use of OLS for the Panzar–Rosse test is that markets do not re-adjust instantaneously and that a dynamic model is a more realistic framework with which to estimate the H statistic. Goddard and Wilson (2009) argue that if the market is dynamic, then the fixed-effects estimator would bias the H statistic toward zero. Along similar lines, Hsieh and Lee (2010) argue that even if a static model with fixed effects might control for the characteristics of individual entities, it would still not take endogenous variables and dynamic adjustment into account. Delis et al. (2008) make the case for using GMM by respecifying the Panzar–Rosse model in a dynamic format and comparing the results from OLS and GMM side-by-side. In their study, they find that OLS can potentially *understate* the degree of market power.

When the dynamic nature of relationships is ignored, the predictable variation in the dependent variable is captured by serial correlation in the random disturbance term. In order to explore the potential of a dynamic model specification, the data was tested for serial correlation as proposed by Wooldridge and implemented by Drukker (2003) for each of the specified models for H^r, H^r_s and H^p. In all cases the null hypothesis holds that there is no serial correlation in the data, which suggests that the panel might not be dynamic in nature.

Even though the static framework appears to be supported by the data, the complexity of the market for development finance constitutes an opportunity for future research and this is addressed in Section 6.

Table 5
OLS regression for revenue (H^r) and scaled revenue (H^r_s).

Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) H^r	(9) H^r-	(10) H^r_s	(11) H^r_s-
w_{FD}	−0.550***	−0.490***	−0.550***	−0.679***	−0.511***	−0.723***	0.0474	−0.490***	−0.591***	0.385***	0.172***
	(0.108)	(0.105)	(0.109)	(0.172)	(0.105)	(0.112)	(0.0388)	(0.162)	(0.105)	(0.0598)	(0.0459)
w_{LB}	−0.830***	−0.826***	−0.829***	−0.658***	−0.521***	−0.753***	0.303***	−0.386***	−0.417***	0.239***	0.149***
	(0.0897)	(0.0833)	(0.0953)	(0.125)	(0.105)	(0.0996)	(0.0528)	(0.146)	(0.0975)	(0.0636)	(0.0518)
w_{FX}	−0.242***	−0.286***	−0.242***	−0.424***	−0.188***	−0.245***	0.00349	−0.431***	−0.256***	0.156***	0.0736**
	(0.0492)	(0.0539)	(0.0504)	(0.0778)	(0.0533)	(0.0579)	(0.0259)	(0.0987)	(0.0682)	(0.0437)	(0.0292)
CF_{LNS}		−0.257*						−0.640***	−0.600***	0.122*	0.0853
		(0.132)						(0.229)	(0.166)	(0.0644)	(0.0573)
CF_{ONEA}			−0.00151					0.105	0.139**	0.121***	0.113***
			(0.0638)					(0.0868)	(0.0685)	(0.0344)	(0.0284)
CF_{DPS}				−0.117**				−0.102*		0.0256	
				(0.0498)				(0.0567)		(0.0252)	
CF_{EQ}					−0.705***			−0.934***	−0.857***	0.318***	0.349***
					(0.126)			(0.217)	(0.148)	(0.0856)	(0.0591)
CF_{STF}						0.0123		−0.118	−0.142**	0.165***	0.113***
						(0.0504)		(0.107)	(0.0589)	(0.0441)	(0.0256)
$logTA$							0.878***			1.006***	0.945***
							(0.0241)			(0.0366)	(0.0303)
Const.	−0.582	−0.423	−0.583	0.0574	0.105	−0.769	−0.771***	0.337	0.0786	0.0320	−0.658***
	(0.550)	(0.533)	(0.551)	(0.753)	(0.579)	(0.546)	(0.236)	(0.872)	(0.572)	(0.293)	(0.223)
Obs.	419	406	418	221	419	350	419	213	337	213	337
R-sq.	0.340	0.344	0.340	0.239	0.394	0.316	0.882	0.371	0.418	0.888	0.891

Notes: This table summarises the coefficient estimates of the panel data models, outlined in Eqs. (1) and (3). The model is estimated by means of the Pooled OLS estimation method. Robust standard errors are indicated in round parentheses. The dependent variable is total operating income (TI). The key explanatory variables are defined as follows. w_{FD} is the average funding rate calculated by dividing interest expense by total funding (IE/TF). w_{LB} is the average labour cost calculated by dividing personnel expenses by total assets (PE/TA). w_{FX} is the average cost of fixed capital calculated by dividing other non-interest expenses by fixed assets (ONIE/FA). The control variables are defined as follows. CF_{LNS} is the ratio of customer loans to total assets, CF_{ONEA} is the ratio of non-earning assets to total assets, CF_{DPS} is the ratio of customer deposits to short-term funding, CF_{EQ} is the equity to total assets ratio, CF_{STF} is the ratio of short-term funding to total funding, and $logTA$ denotes total assets. The sample period runs from 2010 to 2019. The cross-sectional dimension comprises multilateral development banks (MDBs), regional development banks (RDBs), development banks owned by a sovereign nation that operate on a cross-border basis (SOV/EDFI), as well as export-import banks (EXIM). Robust standard errors are reported in parenthesis.

***Denote the 1% significance level.

**Denote the 5% significance level

*Denote the 10% significance level.

5. Results

Following the methodology in Section 4, the Panzar–Rosse test uses standard OLS regression techniques.

5.1. OLS regression analysis

The full range of regression results are shown in Table 5 for the revenue model and revenue scaled by total assets. Robust standard errors are shown in brackets under each coefficient. Table 5 shows the coefficients for the factor inputs w_{FD}, w_{LB} and w_{FX} with various combinations of control factors in order to observe individual effects (models 1 to 7). The models for Eq. (1) (model 8) and Eq. (3) (model 10) are very similar and only differ from the inclusion of a control factor for total assets (CF_{TA}) and so are both presented in this table. As MDBs generally do not collect customer deposits, the impact of CF_{DPS} (the ratio of customer deposits to short-term funding) is potentially unreliable and so in models 9 and 11 this control factor is removed and is the preferred model. The exclusion of this control factor allows additional observations to be included and would otherwise exclude some important MDBs from the analysis such as the IFC and the EBRD. It is notable that including CF_{DPS} approximately halves the number of observations (Models 4, 8 & 10). All models are shown for completeness throughout but greater reliance will be place on results excluding CF_{DPS}. This slightly reduced model is shown with a minus sign (eg. H^r compared to H^r-). The removal of this control factor does not significantly affect the fully-specified model.

A key observation in Table 5 is that the sign of all three price factors is negative in all the revenue models without scaling as a control factor (Models 1–6, 8–9). The statistical significance is very high at less than 1% across the board and is substantially unaffected by individual control factors. The elasticities for w_{FD} and w_{LB} are of similar magnitude and the effect of w_{FX} is strongly statistically significant but of lower magnitude.

Models 8 shows a fully specified Panzar–Rosse revenue model, model 9 shows the same minus the control factor CF_{DPS}. It is striking that in both cases the two strongly statistically significant control factors are the ratios of loans to total assets (CF_{LNS}) and the ratio of equity to total assets (CF_{EQ}). Both show strongly negative coefficients. The intuition for a negative coefficient for CF_{EQ} seems clear, a proportionately higher percentage on the balance sheet suggests a less leveraged business which would result in lower

Table 6
OLS regression for price (H^p).

Models								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	H^p	H^p-
w_{FD}	0.131***	0.121***	0.133***	0.357***	0.116***	0.250***	0.379***	0.216***
	(0.0378)	(0.0379)	(0.0372)	(0.0583)	(0.0377)	(0.0453)	(0.0573)	(0.0409)
w_{LB}	0.461***	0.472***	0.407***	0.394***	0.348***	0.379***	0.235***	0.182***
	(0.0445)	(0.0475)	(0.0440)	(0.0495)	(0.0561)	(0.0450)	(0.0597)	(0.0481)
w_{FX}	0.0377	0.0491*	0.0495*	0.107**	0.0182	0.102***	0.152***	0.0928***
	(0.0293)	(0.0290)	(0.0299)	(0.0474)	(0.0264)	(0.0346)	(0.0455)	(0.0307)
CF_{LNS}		0.0727					0.117**	0.125***
		(0.0441)					(0.0547)	(0.0478)
CF_{ONEA}			0.116***				0.121***	0.112***
			(0.0257)				(0.0343)	(0.0285)
CF_{DPS}				0.0628***			0.0249	
				(0.0203)			(0.0240)	
CF_{EQ}					0.258***		0.310***	0.420***
					(0.0625)		(0.0815)	(0.0591)
CF_{STF}						0.0736***	0.164***	0.128***
						(0.0219)	(0.0415)	(0.0243)
Const.	−0.797***	−0.722***	−0.712***	−0.398	−1.049***	−0.748***	0.0338	−0.701***
	(0.250)	(0.270)	(0.239)	(0.276)	(0.260)	(0.250)	(0.291)	(0.230)
Obs.	419	406	418	221	419	350	213	337
R-sq.	0.353	0.359	0.382	0.318	0.389	0.352	0.426	0.472

Notes: This table summarises the coefficient estimates of the panel data models, outlined in Eq. (4). The model is estimated by means of the Pooled OLS estimation method. Robust standard errors are indicated in round parentheses. The dependent variable is total operating income divided by total assets (TI/TA). The key explanatory variables are defined as follows. w_{FD} is the average funding rate calculated by dividing interest expense by total funding (IE/TF). w_{LB} is the average labour cost calculated by dividing personnel expenses by total assets (PE/TA). w_{FX} is the average cost of fixed capital calculated by dividing other non-interest expenses by fixed assets (ONIE/FA). The control variables are defined as follows. CF_{LNS} is the ratio of customer loans to total assets, CF_{ONEA} is the ratio of non-earning assets to total assets, CF_{DPS} is the ratio of customer deposits to short-term funding, CF_{EQ} is the equity to total assets ratio and CF_{STF} is the ratio of short-term funding to total funding. The sample period runs from 2010 to 2019. The cross-sectional dimension comprises multilateral development banks (MDBs), regional development banks (RDBs), development banks owned by a sovereign nation that operate on a cross-border basis (SOV/EDFI), as well as export-import banks (EXIM). Robust standard errors are reported in parenthesis.

***Denote the 1% significance level.

**Denote the 5% significance level.

*Denote the 10% significance level.

total revenue. This is perhaps not surprising given that a bank's capital ratio is at the heart of its business model. However, for DFIs this is particularly important because of the need to maintain the best possible credit ratings. It seems that a binding constraint for development finance could be the credit assessment criteria that are imposed upon them.

The strong negative coefficient for CF_{LNS} is both economically significant and has implications for capital mobilisation. The data suggests that the higher the proportion of the balance sheet is dedicated to customer loans, the lower that total income would be. A possible explanation for this would be if DFIs that endeavour to stretch the balance sheet more for clients are lending at inferior marginal rates. In other words, potentially pushing to the limit to maximise the balance sheet. This would be a bad omen for mobilising private sector institutions as it suggests that the universe of bankable projects might be right at the viable limit. The last variable for revenue model 9 is a 5% significance for control factor CF_{STF} which relates to the ratio of short term funding to total funding. This shows a small negative coefficient that intuitively makes sense if a greater proportion of short-term funding is a sign of a less flexible balance sheet, and hence less longer term and more profitable lending.

The fully specified models linked to scaled revenue (10–11) introduce total assets (CF_{TA}) as a key control factor. The positive coefficients for the factor inputs w_{FD}, w_{LB} and w_{FX} when controlling for scale is a consistent result with the expectations of Bikker et al. (2012) that scaling turns the coefficients positive. The control factor for total assets (CF_{TA}) shows very strong significance at the 1% level and a very significant economic impact of approximately 1. This is not very surprising given the pattern shown in Fig. 1 as this shows a strong relationship between size and revenues. A coefficient of 1 shows that revenue is proportionate to total assets. That being said, the control factors that appear to be significant for these models are the ratio of other non-earning assets to total assets (CF_{ONEA}) which is statistically significant at the 1% level but not economically large at 0.113 (model 11). The stronger effects come from CF_{EQ} which is the same as for the revenue model and reflects the equity position of the balance sheet, and also CF_{STF} relating to short term funding. The link to short-term funding is statistically significant in the same direction as for the revenue models, but not very economically significant. One extra unusual feature of these models is a very high r-squared of 0.89 which suggests unusually good explanatory power and is consistent with previous research on the used of scaled models for the Panzar–Rosse test.

Table 6 is a similar analysis where the dependent variable is the ratio of total income to total assets (the price model in Eq. (4)). Models 7 and 8 are the fully specified models albeit with model 8 dropping the customer deposit control factor CF_{DPS}. These models again show very high levels of statistical significance for nearly all the factors except for CF_{DPS}. The direction of the effects

Table 7
OLS regression by entity type.

Models	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	H^r	H^r_s	H^p	H^r-	H^r_s-	H^p-
w_{FD}	0.197**	0.508***	0.513***	−0.302***	0.214***	0.237***
	(0.0863)	(0.0639)	(0.0610)	(0.0830)	(0.0476)	(0.0438)
w_{LB}	−0.661***	0.0776	0.0885	−0.504***	0.0900*	0.116***
	(0.0853)	(0.0791)	(0.0566)	(0.0769)	(0.0507)	(0.0434)
w_{FX}	0.0893	0.202***	0.204***	−0.158***	0.0970***	0.108***
	(0.0720)	(0.0388)	(0.0400)	(0.0481)	(0.0286)	(0.0282)
CF_{LNS}	−0.214*	0.0630	0.0671	−0.161	0.0887*	0.0998**
	(0.119)	(0.0604)	(0.0561)	(0.123)	(0.0494)	(0.0459)
CF_{ONEA}	0.114**	0.104***	0.104***	0.0346	0.0893***	0.0917***
	(0.0490)	(0.0305)	(0.0304)	(0.0462)	(0.0261)	(0.0259)
CF_{DPS}	0.159***	0.0665***	0.0652***			
	(0.0473)	(0.0213)	(0.0214)			
CF_{EQ}	−0.0259	0.775***	0.786***	−0.659***	0.575***	0.630***
	(0.198)	(0.109)	(0.112)	(0.116)	(0.0668)	(0.0629)
CF_{STF}	0.150**	0.0763**	0.0752*	0.0407	0.104***	0.107***
	(0.0713)	(0.0436)	(0.0432)	(0.0374)	(0.0231)	(0.0227)
$logTA$		0.985***			0.958***	
		(0.0578)			(0.0331)	
RDB	−2.375***	−0.272	−0.241	−1.849***	−0.0220	0.0590
	(0.263)	(0.253)	(0.233)	(0.159)	(0.138)	(0.126)
SOV/EDFI	−2.615***	0.617**	0.664***	−2.188***	0.420***	0.536***
	(0.254)	(0.288)	(0.245)	(0.158)	(0.137)	(0.120)
EXIM	0.758**	0.967***	0.970***	0.0771	0.581***	0.603***
	(0.327)	(0.251)	(0.251)	(0.174)	(0.120)	(0.117)
Constant	4.870***	−0.0933	−0.166	2.315***	−1.007***	−1.154***
	(0.520)	(0.423)	(0.361)	(0.444)	(0.253)	(0.254)
Observations	213	213	213	337	337	337
R-squared	0.790	0.909	0.533	0.705	0.903	0.536

Notes: This table summarises the coefficient estimates of all models both fully-specified (Models 1–3), and minus the CF_{DPS} control for customer deposits (Models 4–6). The baseline entity type is multi-lateral development banks (MDB). The model is estimated using the Pooled OLS estimation method. Robust standard errors are indicated in parentheses. The explanatory variables are as follows. w_{FD} is the average funding rate calculated by dividing interest expense by total funding (IE/TF). w_{LB} is the average labour cost calculated by dividing personnel expenses by total assets (PE/TA). w_{FX} is the average cost of fixed capital calculated by dividing other non-interest expenses by fixed assets (ONIE/FA). The control variables are defined as follows. CF_{LNS} is the ratio of customer loans to total assets, CF_{ONEA} is the ratio of non-earning assets to total assets, CF_{DPS} is the ratio of customer deposits to short-term funding, CF_{EQ} is the equity to total assets ratio and CF_{STF} is the ratio of short-term funding to total funding. The sample period runs from 2010 to 2019. Additional controls for entity type show regional development banks (RDBs), development banks owned by a sovereign nation that operate on a cross-border basis (SOV/EDFI), as well as export-import banks (EXIM). Robust standard errors are reported in parenthesis.

***Denote the 1% significance level.

**Denote the 5% significance level.

*Denote the 10% significance level.

is similar between these price models and the scaled revenue models. This again is predicted by Bikker et al. (2012) in their analysis of the various Market Power scenarios in Table 4.

5.2. OLS regression controlling for entity type

The next step is to consider the impact that controlling for entity type could have on the fully specified models. Table 7 shows 6 models for the revenue, scaled revenue and price equations and either fully-specified or reduced in the preferred model to exclude control factor CF_{DPS} linked to customer deposits. The number of observations increases significantly with the exclusion of CF_{DPS} from 213 to 337 which on balance reduces the robust standard errors and having a material effect on the coefficients. This discussion will focus on models 4–6 which are the preferred set of models. It is notable that controlling for entity type increases the r-squared for the revenue model (4) to 0.705 (from 0.418) and the price model (6) to 0.537 (from 0.472).

The revenue model (model 4) shows strongly statistically significant coefficients for the factor inputs w_{FD}, w_{LB} and w_{FX} which is consistent with previous results. The impact of the proportion of equity on the balance sheet (CF_{EQ}) is also consistent with the previous results and is strongly negative. This reflects the loss of revenue from running a balance sheet that has a large proportion of equity capital. None of the other control factors (CF_{LNS}, CF_{ONEA}, CF_{STF}) show any significance in model 4. However, the entity type does appear to differentiate for RDBs and SOV/EDFI when compared to the base case of the MDBs. The coefficients for RDBs and SOV/EDFI of −1.849 and −2.188 respectively suggests that these entities make less revenues than MDBs and EXIMs when controlling for other factors. When considering the scaled revenue (Model 5) and price models (Model 6), RDBs look very similar to the base case of MDBs, but both SOV/EDFI and EXIM have statistically significant positive coefficients respectively of 0.420 and

Table 8
Panzar–Rosse test values — all models.

Models		(1) H^r	(2) H^r_s	(3) H^p	(4) H^r-	(5) H^r_s-	(6) H^p-
Panzar–Rosse	H	−0.3748	0.7880	0.8052	−0.9643	0.4006	0.4612
	p (H = 0)	0.0164	0.0000	0.0000	0.0000	0.0000	0.0000
	p (H = 1)	0.0000	0.0408	0.0091	0.0000	0.0000	0.0000

The values for H shown in this table are from a full model controlling for entity type as in Table 7. H is the sum of the three factor input coefficients: w_{FD} is the average funding rate calculated by dividing interest expense by total funding (IE/TF). w_{LB} is the average labour cost calculated by dividing personnel expenses by total assets (PE/TA). w_{FX} is the average cost of fixed capital calculated by dividing other non-interest expenses by fixed assets (ONIE/FA). The probability of H = 0 or H = 1 is tested in each case.

0.581 for Model 5, and 0.536 and 0.603 for Model 6. This suggests that these entities produce more revenue per unit of assets than the MDBs.

Using risk appetite as a lens with which to view the results could explain some of the relative differences to MDBs. For models 5 & 6, the fact that SOV/EDFI and EXIM achieve higher revenues per unit of total assets could be that they seek higher margins for lending than MDBs/RDBs. Given that some of the data for MDBs/RDBs might contain some concessional activity that would make sense. In model 4, it suggests a reduction in total revenues from being an RDB or SOV/EDFI. It is less easy to see the intuition with this in a way that is consistent with the previous argument on risk. It would suggest that these entities lend to less risky projects overall. Is it probable that SOV/EDFIs can lend more profitably to less risky projects compared to other types of institutions? It is possible, but it suggests that a more forensic analysis of loan data is needed to unpack what is happening. It is also fair to note that there are relatively few entities in the model per entity category which could result in some over-fitting and high r-squared results.

Using the fully specified model and controlling for entity, the H statistics can be recalculated. Table 8 shows the sum of the factor inputs w_{FD}, w_{LB} and w_{FX} to calculate the H statistic for all three models, including and excluding the control factor for customer deposits. The preferred models (4, 5 & 6) show very clear results. For the revenue model (4) the H statistic is −0.9643 and is significantly different to 0. The scaled revenue model (5) and the price model (6) show H statistics of 0.4006 and 0.4612 that are statistically significantly at the 1% level in the range of 0 to 1 which will assist later when evaluating the Market Power case as described in Table 4. There are additional tests that need to be performed in order to narrow down the potential competitive conditions.

5.3. Additional regression tests

The tests for market equilibrium using H^{RoA} are described in Section 4.2 and the results are shown in Table 9. Results are shown for a fully specified model and the preferred model dropping CF_{DPS} as it relates to customer deposits (models 1 & 2). The same two models are then shown using entity type as an additional control factor (models 3 & 4). The key test is that if H^{RoA} is zero, the market can be considered to be in long-term equilibrium. A negative result would suggest that the market is only in short-term equilibrium and that market entrants might still be anticipated, or that the market is monopolistic or oligopolistic.

For the two models including CF_{DPS} (models 1 & 3), the H statistic for return on assets is not significantly different from 0 which suggests that the development finance market is in long-term equilibrium. For the two models excluding CF_{DPS} (models 2 & 4) which allow more observations to flow, model 2 cannot be rejected at the 1% level and model 4 cannot be rejected at the 5% level. However, as the H statistic estimate is a positive number it is most unlikely to be negative in practice and imply any potential instability. So, while the test is not conclusive, a positive H statistic does not suggest that the market is therefore in disequilibrium.

The final test required in order to place the analysis in the context of Table 4 is to estimate the average cost curve for DFIs. It is not practical to observe this directly. In order to build a picture of what it might look like, a reasonable option is to run regression of the log of average costs controlling for entity type as shown in Table 10. As with the previous analyses, results are given both including and excluding CF_{DPS} for reasons previously stated.

The key coefficient for this regression is to refer to total assets ($logTA$) as this is the metric for the quantity of 'production', being the size of the bank balance sheet. There is a significant negative coefficient as measured by the t-statistic which indicates that the negative relationship is statistically significant at the 1% level. A test for a quadratic relationship by taking the square of $logTA$ was also statistically significant at the 1% level although does not materially increase average costs. It does, however, imply that there are major economies of scale with regard to costs. This can be seen by inspection of the data, the linear regression and the STATA lowess estimate as shown graphically in Fig. 2. There is a flatting out of the estimated cost curve for larger institutions but there is no evidence to suggest that the average cost curve could be U-shaped.

5.4. Assessing the competitive environment

The final step is to pull all the different tests together to evaluate the overall competitive conditions. Table 11 is an extension of Table 4 showing the range of potential market environments based upon prior research and the propositions that they put forward in their paper. This table contains two extra columns to show clearly whether a Market Power scenario is rejected and the reasons to justify this rejection.

In this analysis cases are rejected for the following reasons:

Table 9
Return on Asset regression models.

Models	(1)	(2)	(3)	(4)
w_{FD}	0.251***	0.141*	0.269***	0.124
	(0.0934)	(0.0748)	(0.0906)	(0.0775)
w_{LB}	0.111	0.158**	0.0918	0.0717
	(0.0711)	(0.0780)	(0.0848)	(0.0803)
w_{FX}	0.00849	0.00850	0.0332	0.0617*
	(0.0401)	(0.0320)	(0.0516)	(0.0334)
CF_{LNS}	0.0106	0.0663	0.0280	0.0934
	(0.0693)	(0.0671)	(0.0739)	(0.0658)
CF_{ONEA}	0.00253	−0.00891	−0.00463	−0.0461
	(0.0507)	(0.0458)	(0.0531)	(0.0471)
CF_{DPS}	0.0241		0.0352	
	(0.0320)		(0.0339)	
CF_{EQ}	0.208	0.427***	0.248	0.588***
	(0.129)	(0.0947)	(0.201)	(0.121)
CF_{STF}	0.185***	0.189***	0.197***	0.191***
	(0.0674)	(0.0457)	(0.0703)	(0.0432)
RDB			0.0692	0.417**
			(0.346)	(0.202)
SOV/EDFI			0.0222	0.404*
			(0.330)	(0.209)
EXIM			0.168	0.794***
			(0.361)	(0.210)
Constant	2.144***	2.462***	2.100***	1.573***
	(0.392)	(0.386)	(0.511)	(0.486)
Observations	193	304	193	304
R-squared	0.174	0.259	0.178	0.307
H^{RoA}	0.3702	0.3069	0.3939	0.2570
p (H = 0)	0.0031	0.0079	0.0019	0.0309
DF	184	296	181	293

Notes: This table summarises the coefficient estimates of four model variations with Return on Assets as the dependent variable. The model is estimated by means of the Pooled OLS estimation method. The key explanatory variables are defined as follows. w_{FD} is the average funding rate calculated by dividing interest expense by total funding (IE/TF). w_{LB} is the average labour cost calculated by dividing personnel expenses by total assets (PE/TA). w_{FX} is the average cost of fixed capital calculated by dividing other non-interest expenses by fixed assets (ONIE/FA). The control variables are defined as follows. CF_{LNS} is the ratio of customer loans to total assets, CF_{ONEA} is the ratio of non-earning assets to total assets, CF_{DPS} is the ratio of customer deposits to short-term funding, CF_{EQ} is the equity to total assets ratio and CF_{STF} is the ratio of short-term funding to total funding. The sample period runs from 2010 to 2019. Additional controls for entity type show regional development banks (RDBs), development banks owned by a sovereign nation that operate on a cross-border basis (SOV/EDFI), as well as export-import banks (EXIM). H^{RoA} is the sum of the three factor input coefficients with RoA as the dependent variable. The probability of H = 0 is tested in each case. DF is the degrees of freedom. Robust standard errors are reported in parenthesis.

***Denote the 1% significance level.

**Denote the 5% significance level.

*Denote the 10% significance level.

- Both long-run competition cases require the H statistics for H_s^r and H^p to be equal to 1, as does the last case for constant markup pricing. The evidence from Table 8 does not support this;
- The case for short-run competition seems highly unlikely. Bikker et al. (2012) suggest that H^{RoA} ought to be negative if there is short-run competition. In this instance, the H^{RoA} test is statistically positive at the 5% level using the preferred model and reinforces the idea that there are significant economies of scale in development lending. The average cost analysis also appears to rule this out;
- The analysis for the shape of the average cost curve seems conclusive enough to permit the U-shaped AC Function to be ruled out;
- The monopoly case seems unrealistic given that DFIs are generally active in many countries and there is significant overlap in operations.

This process of deduction leave a single most likely outcome which is that the development finance market is an oligopoly with a downward sloping demand curve. That of itself is not necessarily an anti-competitive environment, but it does have implications for crowding in private sector finance which will be addressed in Section 6.

5.5. Further statistical considerations and robustness

The development bank financial data has two characteristics that have the potential to reduce the value of introducing fixed effects for individual institutions into a panel data analysis. The first characteristic is that the data is relatively static over time at

Table 10
Average Cost regressions.

Log of Avg. Cost	Coef.	Robust Std Err.	t	P>t	95% Conf Int.	
CF_{LNS}	−0.0418	0.0518	−0.8100	0.4200	−0.1438	0.0603
CF_{ONEA}	0.0674	0.0293	2.3000	0.0220	0.0096	0.1252
CF_{DPS}	0.0074	0.0210	0.3500	0.7260	−0.0340	0.0487
CF_{EQ}	−0.1137	0.0724	−1.5700	0.1180	−0.2565	0.0291
CF_{STF}	0.0161	0.0408	0.3900	0.6940	−0.0644	0.0966
$logTA$	−0.1468	0.0313	−4.6900	0.0000	−0.2084	−0.0851
RDB	−0.2893	0.1913	−1.5100	0.1320	−0.6665	0.0879
SOV/EDFI	−0.3849	0.2202	−1.7500	0.0820	−0.8190	0.0492
EXIM	0.1392	0.1875	0.7400	0.4590	−0.2305	0.5089
Constant	−1.7462	0.4084	−4.2800	0.0000	−2.5513	−0.9411
Log of Avg. Cost	Coef.	Robust Std Err.	t	P>t	95% Conf Int.	
CF_{LNS}	−0.0008	0.0534	−0.0100	0.9880	−0.1058	0.1042
CF_{ONEA}	0.0663	0.0236	2.8100	0.0050	0.0199	0.1127
CF_{EQ}	−0.2548	0.0619	−4.1200	0.0000	−0.3766	−0.1330
CF_{STF}	0.0252	0.0273	0.9200	0.3570	−0.0286	0.0790
$logTA$	−0.1887	0.0180	−10.4800	0.0000	−0.2241	−0.1533
RDB	−0.1680	0.0834	−2.0200	0.0450	−0.3319	−0.0040
SOV/EDFI	−0.4061	0.0938	−4.3300	0.0000	−0.5905	−0.2216
EXIM	0.1565	0.0911	1.7200	0.0870	−0.0226	0.3357
Constant	−1.5997	0.1798	−8.9000	0.0000	−1.9534	−1.2460

The regression uses a dependent variable of the natural log of Average Costs (AC is the sum of interest expenses (IE), personnel expenses (PE) and other non-interest expenses (ONIE)), against all factors in the fully specified model. The base case entity is multi-lateral development banks. The lower table removes CF_{DPS} from the regression. The log of Total Assets ($logTA$) is the key coefficient as this represents the 'quantity' of production and the chart of AC. The log–log graph of AC against TA is shown in Fig. 2. The sample period runs from 2010 to 2019. Robust standard errors are reported in column 3. P>t shows the probability of a coefficient being equal to zero. The 95% confidence interval is shown in the final two columns.

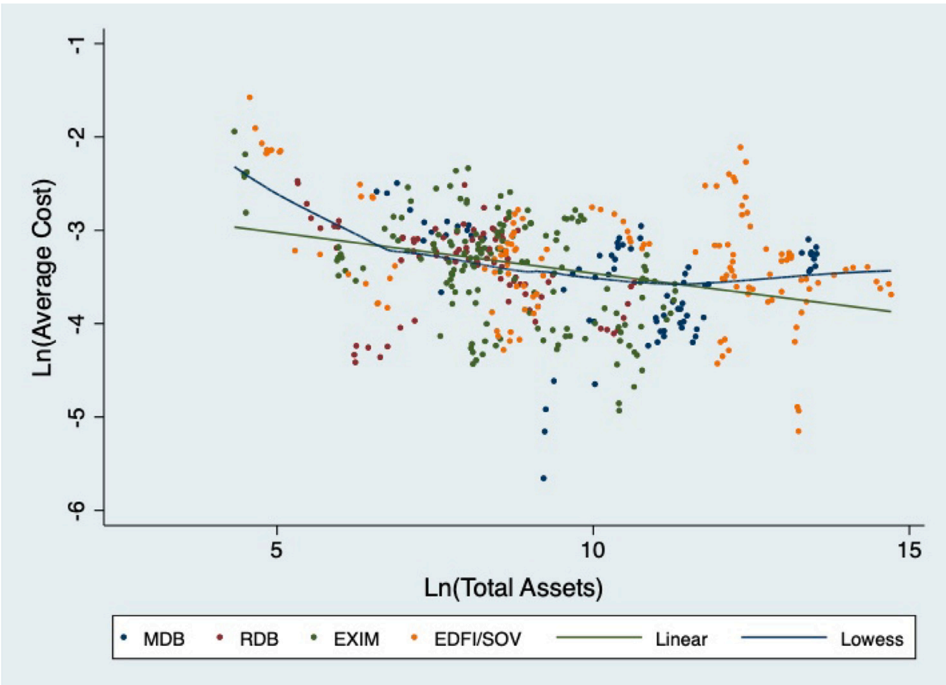

Fig. 2. Average cost to total assets by entity type.

the level of an individual bank. This is because the long-term nature of development loan portfolios leads to slower turnover of assets on the balance sheet. Income in any given year is stems mainly from loans made in previous years. For instance, Fig. 1 is indicative of significant variations between institutions, albeit a limited variation over time for a given bank. The second reason to doubt

Table 11
Evaluation of Market Power scenarios based on modelled values for the H statistics.

Market Power	AC Function	H^r	H_s^r	H^p	Reject	Reason
Long-run competition	U-shaped	=1	=1	=1	Yes	H≠1
Long-run competition	Flat	<0, from 0–1	=1	=1	Yes	H≠1
Short-run competition	U-shaped	<0, from 0–1	>0	>0	Yes	RoA stable, AC flat
Monopoly	U-shaped	<0	>0	>0	Yes	AC flat
Monopoly	Flat	<0	>0	>0	Yes	Multiple firms exist
Oligopoly	U-shaped	<0	>0	>0	Yes	AC flat
Oligopoly	Flat	<0	>0	>0	–	–
Monopolistic competition	U-shaped	<0, from 0–1	>0	>0	Yes	AC flat
Constant markup pricing	Flat & U-shaped	<0	=1	=1	Yes	H≠1

Notes: This table is an extended version of Table 4 and includes two extra columns to explain whether a Market Power case is rejected and the reasons for doing so. For each Market Power case, there is an expected average cost (AC) function and predicted values of H^r, H_s^r and H^p. The Reject column states whether scenario 2 is consistent with a given market power case and it can be shown that only one case is valid. The final column 'Reason' explains the grounds for rejection of a given market power. Only one case (Oligopolistic competition, flat AC curve) can be valid for scenario 2 because: 'H' values are not equal to 1, the RoA test shows the market to be in long run equilibrium, the 'AC' function is not U-shaped, there are multiple firms in the market.

the value of using fixed effects owes to the operational convergence of business models as described in Section 2.3. Convergence between entity types can increase multicollinearity in the data undermining the value of the fixed-effects estimation method. The differences between banks are more likely to be apparent when comparing across entity types, meaning that MDBs or NDBs could function similarly as a groups, but each group has its own distinctive operating characteristics.

A variety of robustness checks were performed by changing the mix of entity types in the regression, by applying fixed effects, separating the data set into pre- and post-2015 and finally by controlling for the regional location of the DFIs' headquarters. The significance of 2015 as highlighted in Section 1 is that this was the year of the Antalya Summit at which the G20 instructed major MDBs to mobilise private sector capital. Controlling by region of domicile accounts for the possibility that there might be different regional imperatives even though many of the MDBs share similar sovereign shareholders.

Table 12 contains a full set of H statistics for the six models shown with robust standard errors and controlling for entity type (as in Table 7). The R^2 and F-test are reported for each model and scenario.

Focusing on H^r initially in models 1 & 4, H is broadly negative across all scenarios. For the preferred model 4, H is statistically less than zero in all scenarios except for Fixed Effects (scenario D). For model 1, there are other cases where H is not significantly different from zero although as this model controls for customer deposits and therefore excludes several major DFIs it is a less reliable representation of development finance. For fixed effects (model 4, scenario D), the R^2 (within) is estimated at 0.0422 and the F-test probability is 0.1643. This suggests that controlling for specific entities is not statistically helpful and perhaps unreliable as explained above.

The results are broadly similar for H_s^r and H^p in that both measures are statistically between 0 and 1 with a couple of exceptions. For scenario C (MDB/RDB only), H_s^r turns negative which is not consistent with the theory and H^p is not statistically different from zero. For scenario D (Fixed effects) model 5 estimates a value for H_s^r that is not statistically different from zero. Breaking the data set into the periods before and after the events of 2015 (scenarios E & F) makes no real difference to the outcome, and neither does separation of the DFIs by region of domicile (scenario G).

The landscape of values for H is broadly consistent with the basic pooled OLS model which shows that H^r is statistically negative, and that H_s^r and H^p are generally between 0 and 1. This gives further support the conclusion drawn in Table 11 about the potential competitive conditions in development finance. The results for fixed effects leave a question mark over whether there is an improvement that can be made to a model that considers fixed effects by entity. However, this might require a different approach to using Panzar–Rosse to test for competitive conditions and is beyond the scope of this analysis.

6. Conclusions

The international community has committed to delivering the United Nations Sustainable Development Goals by 2030 and delivering under the Paris Agreement on climate change. The financial world has been left in no doubt that the private sector needs to be part of the solution. The G20 has made that explicit and the MDBs are actively cooperating to mobilise private capital in support of those goals. Motivating private capital to participate in development finance on the scale that is required according to the United Nations ('billions to trillions') will require a realignment of economic incentives, potential adjustments of risk appetite and changes in regulation and government policy.

Reshaping the development finance market on such a grand scale requires a clear view of the competitive economic forces affecting it. This research addresses this challenge directly. The competitive conditions for development finance will affect the probability of succeeding in mobilising the private sector using existing tools and techniques. This paper shows that the best explanation for the competitive conditions in development finance is a state of competitive oligopoly in long-term equilibrium which would be characterised by a downward-sloping demand curve.

The traditional implications of a competitive oligopoly would be that incumbent firms can tacitly cooperate and stifle competition. This could result in limited new market entrants, less innovation and higher prices.

Table 12
H statistics and standard errors with varying scenarios.

	Models	(1)		(2)		(3)		(4)		(5)		(6)	
Scenario		H^r	$\sigma(H^r)$	H^r_s	$\sigma(H^r_s)$	H^p	$\sigma(H^p)$	H^r-	$\sigma(H^r-)$	H^r_s-	$\sigma(H^r_s-)$	H^p-	$\sigma(H^p-)$
A: All entities	H	−0.3748	0.1549	0.7880	0.1029	0.8052	0.0739	−0.9643	0.1212	0.4006	0.0784	0.4612	0.0587
	p(H = 0)	0.0164		0.0000		0.0000		0.0000		0.0000		0.0000	
	p(H = 1)	0.0000		0.0408		0.0091		0.0000		0.0000		0.0000	
	R^2	0.7901		0.9090		0.5328		0.7047		0.9035		0.5364	
	Prob > F	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
B: All minus EXIM	H	−0.0996	0.1914	0.7768	0.1651	0.8410	0.1269	−0.7884	0.1250	0.2430	0.0980	0.3754	0.0803
	p(H = 0)	0.6038		0.0000		0.0000		0.0000		0.0140		0.0000	
	p(H = 1)	0.0000		0.1793		0.2130		0.0000		0.0000		0.0000	
	R^2	0.7792		0.8839		0.5534		0.7686		0.8950		0.5481	
	Prob > F	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
C: MDB/RDB Only	H	−1.8790	0.4227	−0.6666	0.5763	0.0875	0.3485	−1.0875	0.1428	−0.3410	0.1056	0.1226	0.1309
	p(H = 0)	0.0001		0.2548		0.8031		0.0000		0.0017		0.3510	
	p(H = 1)	0.0000		0.0064		0.0126		0.0000		0.0000		0.0000	
	R^2	0.8710		0.8896		0.6597		0.8300		0.9024		0.4281	
	Prob > F	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
D: All entities Fixed Effects	H	−0.1138	0.1829	0.2286	0.2475	0.2869	0.2376	−0.0048	0.1372	0.2189	0.1394	0.2656	0.1445
	p(H = 0)	0.5388		0.3635		0.2369		0.9723		0.1236		0.0729	
	p(H = 1)	0.0000		0.0041		0.0055		0.0000		0.0000		0.0000	
	R^2 (within)	0.0796		0.3215		0.1121		0.0422		0.3526		0.1787	
	Prob > F	0.0000		0.0000		0.0000		0.1643		0.0000		0.0000	
E: All entities < 2015	H	−0.2400	0.2636	0.8344	0.1410	0.7933	0.1124	−0.9543	0.1683	0.4308	0.1136	0.4948	0.0792
	p(H = 0)	0.3649		0.0000		0.0000		0.0000		0.0002		0.0000	
	p(H = 1)	0.0000		0.2428		0.0690		0.0000		0.0000		0.0000	
	R^2	0.7795		0.9236		0.5877		0.7230		0.9215		0.6287	
	Prob > F	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
F: All entities>= 2015	H	−0.2486	0.1668	0.7824	0.1850	0.9130	0.1296	−0.9895	0.1653	0.3537	0.1090	0.4188	0.0913
	p(H = 0)	0.1397		0.0001		0.0000		0.0000		0.0014		0.0000	
	p(H = 1)	0.0000		0.2426		0.5039		0.0000		0.0000		0.0000	
	R^2	0.8412		0.9007		0.5088		0.7118		0.8871		0.4444	
	Prob > F	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
G: By Region	H	−0.9913	0.2875	0.7571	0.0911	0.7374	0.0810	−0.7942	0.1870	0.4896	0.0713	0.5852	0.0670
	p(H = 0)	0.0007		0.0000		0.0000		0.0000		0.0000		0.0000	
	p(H = 1)	0.0000		0.0083		0.0014		0.0000		0.0000		0.0000	
	R^2	0.4218		0.9111		0.5433		0.4807		0.9070		0.5440	
	Prob > F	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	

The values for the Panzar–Rosse H statistic shown in this table are for all models controlling for entity type as in Table 7 with robust errors. The probability of H = 0 or H = 1 is tested in each case. The R^2 is reported in each case and the F-test for the overall model. The first set of values for H shown in this table are replicated from Table 8. Scenarios A, B & C vary the mix of entity types included in the test. Scenario D tests for fixed effects. Scenarios E & F separate the data into pre- and post-2015. Finally scenario G controls for region in which they are headquartered.

Although, from this analysis, we have the economic conditions of an oligopoly, there is no obvious anti-competitive intent. MDBs collaborate together to try and increase the volume of bankable projects and are positively encouraging private sector banks to enter the development finance market. The barriers to entry would ideally be as low as possible to encourage more competition and lending. However, the barriers are not just economic (eg. pricing, capital), technical (e.g. contracts, legal systems) or from MDBs solving for information asymmetries. The large international private sector banks also need to have a vested interest to lend into developing countries in line with their corporate strategy and in support of their chosen client base. That is a harder gap to bridge.

Another practical economic implication of a downward-sloping demand curve is that the market is unlikely to support crowding-in of private sector capital on the scale that is required to meet the SDGs by relying on traditional loan syndication where MDBs take a similar economic position to private sector banks. Expanding loan funding on a significant scale for development finance could be counterproductive as increased competition might depress pricing and actively discourage private sector firms to participate. This could inhibit, rather than encourage, mobilisation. It suggests that the stock of ‘bankable’ projects is too limited and that something more innovative will be required to scale the necessary private sector financial investment.

The answer seems to point toward MDBs focusing more on how they can make different contributions to transactions. This suggests that efforts to create co-investment funds and similar ‘vertical’ risk sharing structures are less likely to succeed. Conversely, ‘horizontal’ risk sharing structures such as credit enhancement or securitisation do create differentiated economic roles for IFIs and the private sector, although we should recognise that these also have their limitations and will not always be the correct solution.

The Harmonised Framework for Additionality in Private Sector Operations (Multilateral Development Banks, 2018a) is a useful guide for how all IFIs could choose to allocate their resources toward direct and indirect efforts to mobilise the private sector. Indirect mobilisation perhaps has the most scope for IFIs to leverage their special position as it has the least impact on a bank’s balance sheet. Direct mobilisation is a useful mechanism for IFIs to pilot new ideas and test them in the markets.

It should be stressed that many IFIs/MDBs are already focused on mobilisation and striving to discover how to increase private sector mobilisation. At the same time we should also acknowledge that as long as a significant funding shortfall exists, there are still more solutions to be discovered. DFIs and governments are likely to continually have to refine their approach including considering more aggressive government intervention through regulation or fiscal policy to deal with economic externalities. There is certainly scope for future research into the interaction between mobilisation methods and competitive structures.

This type of competitive analysis has not been applied to development finance before even though it has frequently been used for assessing competition in domestic financial markets. This might be because non-structural tests have often been used to assess potential issues of market conduct and efficiency and DFIs are not thought of in that context. DFIs do not collude in the way that bank regulators are concerned about commercial banks and abuse of market power. MDBs in particular certainly cooperate and coordinate given that they are mandated to do so by the G20. They aim to work as a group with common goals and avoid competition, but this is not a market conduct issue in the sense that would apply to private sector banks. Do DFIs actively compete? There are certainly pressures for DFIs to deploy finance internationally where their operations can overlap which might create competition to lend. On the other hand, the coordination of activity might mitigate this risk. This is inconclusive and needs further research. As highlighted in Section 2.2, development lending at both a sovereign and private sector level cannot really be separated from local macroeconomic and regulatory conditions. Further research could evaluate the impact of DFI mobilisation (through syndicated and conditional lending) relative to the debate around market competition-stability versus competition-fragility.

Another important finding that this analysis reinforces is the dependence that DFIs have on their capital structure. Throughout Section 5 we see that the ratio of equity to total assets has a highly significant impact on the financial outcomes for DFIs. The combination of credit rating assessment methods, a desire to maintain the highest rating possible and the risk profile of lending portfolios with regard to concentrations and country risk conspire together to make this a binding constraint. It is not clear that private sector lenders and investors would be able to share the burden or diversify away this type of risk which is another potentially significant challenge for mobilising private capital. This argues for a more detailed study of risk appetite in developing markets across the public and private sector.

As noted in Section 4.4, the data appears to support a static model although the complexity of development finance presents opportunities for future research. This could involve the exploration of more advanced models from the conceptual/theoretical perspective, which might, for instance, account for less tangible drivers of competitive conditions, such as corporate governance in MDBs, the preferred creditor status of MDBs, political interests embedded in development finance projects, or strategic considerations of the governments of donor countries.

These conclusions point to an operating model where the distinct roles of DFIs and private sector banks are maintained. More thought should be given as to how additionality can be leveraged. We already see this in project finance transactions and conceptually this comes through the 'political umbrella' that the DFIs bring to financing and preferred creditor status. However, we still do not know enough about how these intangible qualities are valued and treated by the private sector which is beyond the scope of this paper and would be a worthy subject for future study.

CRediT authorship contribution statement

Christopher A. McHugh: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share data.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. List of entities selected from the methodology outlined in Section 4.

Category	Name	Fitch ID
MDB	International Finance Corporation	135922
MDB	Multilateral Investment Guarantee Agency	1007550
MDB	African Development Bank	107349
MDB	Asian Development Bank	140172
MDB	Asian Infrastructure Investment Bank	1473722
MDB	European Bank for Reconstruction and Development	140235
MDB	European Investment Bank	104895
MDB	European Investment Fund	143426
MDB	Inter-American Development Bank	108096
MDB	Inter-American Investment Corporation (IDB Invest)	108098
MDB	Islamic Corporation for the Development of the Private Sector	1006044
MDB	Islamic Development Bank	108116
MDB	New Development Bank	1493075
RDB	East African Development Bank	140227
RDB	Fondo Financiero para el Desarrollo de la Cuenca del Plata	1068915
RDB	Black Sea Trade and Development Bank	107585
RDB	Banque Ouest Africaine de Developpement	1461858
RDB	Central American Bank for Economic Integration (CABEI)	140218
RDB	Corporacion Andina de Fomento (CAF)	116633
RDB	Eastern and Southern African Trade and Development Bank (TDB)	1003581
RDB	Eurasian Development Bank	1104338
RDB	Gulf Investment Corporation G.S.C.	115002
SOV	Development Bank of Japan Inc.	1003299
SOV	Agence Francaise de Developpement (AFD)	112173
SOV	Caisse des Depots et Consignations (CDC)	111731
SOV	Cassa depositi e prestiti SpA	1009074
SOV	China Development Bank	112981
SOV	Industrial Bank of Korea	111716
SOV	KfW	108758
SOV	Korea Development Bank	111757
EDFI	Societe De Promotion Et De Participation Pour La Cooperation Economique	108421
EDFI	CDC Group PLC	1002134
EDFI	Compania Espanola de Financiacion del Desarrollo, COFIDES S.A., S.M.E.	1002580
EDFI	DEG - Deutsche Investitions- und Entwicklungsgesellschaft mbH	1003162
EDFI	Norfund	1384351
EDFI	Oesterreichische Entwicklungsbank AG	1286750
EDFI	SOFID-Sociedade Para O Financiamento Do Desenvolvimento - Instituicao Financeira De Credito, S.A.	1464072
EDFI	Simest SpA	1497740
EDFI	Nederlandse Financierings-Maatschappij voor Ontwikkelingslanden N.V.	107969
EXIM	AB Svensk Exportkredit	105940
EXIM	Arab Trade Financing Program	1000794
EXIM	Export Development Bank of Egypt S.A.E	112386
EXIM	Export Development Bank of Iran	1003956
EXIM	Export Development Canada	1003154
EXIM	Export-Import Bank of Romania-EximBank S.A.	1501503
EXIM	Exportno-Importna Banka Slovenkej Republiky	1003967
EXIM	KLP Kreditt AS	1008305
EXIM	National Export-Import Bank of Jamaica	1003964
EXIM	The Export-Import Bank of the Republic of China	1003691
EXIM	Trade and Investment Development Corporation of the Philippines	1094810
EXIM	African Export-Import Bank (Afreximbank)	1000130
EXIM	Export-Import Bank of India (EXIM)	150393
EXIM	Export-Import Bank of Malaysia Berhad	1003961
EXIM	Export-Import Bank of Thailand	112104
EXIM	Finnvera plc	1004277

EXIM	Hungarian Export-Import Bank Private Limited Company	108065
EXIM	Lembaga Pembiayaan Ekspor Indonesia	1003713
EXIM	MFB Hungarian Development Bank Private Limited Company	1007172
EXIM	The Export-Import Bank of China	1003975
EXIM	The Export-Import Bank of Korea	112445
EXIM	Turkiye Ihracat Kredi Bankasi A.S.	1011472

References

Ahiabor, F.S., James, G.A., 2019. Domestic lead arranger certification and the pricing of project finance loans. Int. J. Finance Econ. 24 (1), 150–167. http://dx.doi.org/10.1002/ijfe.1654.

Arvanitis, Y., Stampini, M., Vencatachellum, D., 2015. Balancing development returns and credit risks: project appraisal in a multilateral development bank. Impact Assess. Project Apprais. 33 (3), 195–206. http://dx.doi.org/10.1080/14615517.2015.1041837.

Asmus, G., Fuchs, A., Angelika, M., 2017. BRICS and foreign aid of work. AidData Working Paper No. 43, AidData, Williamsburg, VA, Available at: https://www.aiddata.org/publications/brics-and-foreign-aid. (Accessed 9 September 2022).

Azmi, W., Hassan, M.K., Houston, R., Karim, M.S., 2021. ESG activities and banking performance: International evidence from emerging economies. J. Int. Financ. Mark. Inst. Money 70, http://dx.doi.org/10.1016/j.intfin.2020.101277.

Bikker, J.A., Shaffer, S., Spierdijk, L., 2012. Assessing competition with the panzar-rosse model: The role of scale, costs, and equilibrium. Rev. Econ. Stat. 94 (4), 1025–1044. http://dx.doi.org/10.1162/REST_a_00210.

Broccolini, C., Lotti, G., Maffioli, A., Presbitero, A.F., Stucchi, R., 2021. Mobilization Effects of Multilateral Development Banks. World Bank Econ. Rev. 35 (2), 521–543. http://dx.doi.org/10.1093/wber/lhz049.

Byoun, S., Kim, J., Yoo, S.S., 2013. Risk management with leverage: Evidence from project finance. J. Financ. Quant. Anal. 48 (2), 549–577. http://dx.doi.org/10.1017/S0022109013000082.

Byoun, S., Xu, Z., 2014. Contracts, governance, and country risk in project finance: Theory and evidence. J. Corp. Finance 26, 124–144. http://dx.doi.org/10.1016/j.jcorpfin.2014.03.003.

Carmichael, D.G., Lea, K.A., Balatbat, M.C.A., 2016. The financial additionality and viability of CDM projects allowing for uncertainty. Environ. Dev. Sustain. 18 (1), 129–141. http://dx.doi.org/10.1007/s10668-015-9630-5.

Carter, P., Van de Sijpe, N., Calel, R., 2018. The elusive quest for additionality. Working Paper No. 495, Center for Global Development, http://dx.doi.org/10.2139/ssrn.3310521.

Chin, G.T., Gallagher, K.P., 2019. Coordinated Credit Spaces: The Globalization of Chinese Development Finance. Dev. Change 50 (1), 245–274. http://dx.doi.org/10.1111/dech.12470.

Cormier, B., 2018. Analyzing if and how international organizations contribute to the sustainable development goals: Combining power and behavior. J. Organ. Behav. 39 (5), 545–558. http://dx.doi.org/10.1002/job.2163.

De Luna-Martinez, J., Vicente, C.L., Arshad, A.B., Tatucu, R., Song, J., 2018. 2017 Survey of National Development Banks. Technical Report, World Bank, (Accessed: 9 September 2022).

Delis, M.D., Staikouras, K.C., Varlagas, P.T., 2008. On the Measurement of Market Power in the Banking Industry. J. Bus. Finance Account. 35 (7–8), 1023–1047. http://dx.doi.org/10.1111/j.1468-5957.2008.02098.x.

Development Committee, 2015. From Billions to Trillions: Transforming Development Finance. Available at: http://pubdocs.worldbank.org/en/622841485963735448/DC2015-0002-E-FinancingforDevelopment.pdf. (Accessed: 9 September 2022).

Dreher, A., Fuchs, A., Parks, B.C., Strange, A.M., Tierney, M.J., 2017. Aid, China, and growth: Evidence from a new global development finance dataset of work. AidData Working Paper No.46, AidData, Williamsburg, VA, Available at: https://www.aiddata.org/publications/aid-china-and-growth-evidence-from-a-new-global-development-finance-dataset. (Accessed: 9 September 2022).

Dreher, A., Fuchs, A., Parks, B., Strange, A.M., Tierney, M.J., 2018. Apples and Dragon Fruits: The Determinants of Aid and Other Forms of State Financing from China to Africa. Int. Stud. Q. 62 (1), 182–194. http://dx.doi.org/10.1093/isq/sqx052.

Dreher, A., Lang, V.F., Richert, K., 2019. The political economy of International Finance Corporation lending. J. Dev. Econ. 140, 242–254. http://dx.doi.org/10.1016/j.jdeveco.2019.05.003.

Drukker, D.M., 2003. Testing for serial correlation in linear panel-data models. Stata J. 3 (2), 168–177.

Dutschke, M., Michaelowa, A., 2006. Development assistance and the CDM - How to interpret 'financial additionality'. Environ. Dev. Econ. 11 (2), 235–246. http://dx.doi.org/10.1017/S1355770X05002780.

EBRD, 2019. Joint Report on Multilateral Development Banks' Climate Finance. Available at: http://www.ebrd.com/2018-joint-report-on-mdbs-climate-finance. (Accessed: 9 September 2022).

Elfeituri, H., 2022. Banking stability, institutional quality, market concentration, competition and political conflict in MENA. J. Int. Financ. Mark. Inst. Money 76, http://dx.doi.org/10.1016/j.intfin.2021.101476.

Engen, L., Prizzon, A., 2018. A guide to multilateral development banks. Available at: https://odi.org/en/publications/a-guide-to-multilateral-development-banks/. (Accessed: 9 September 2022).

Ervine, K., 2013. Carbon Markets, Debt and Uneven Development. Third World Q. 34 (4), 653–670. http://dx.doi.org/10.1080/01436597.2013.786288.

G20, 2015. G20 Leaders' Communiqué Antalya Summit. Available at: http://www.g20.utoronto.ca/2015/151116-communique.html. (Accessed: 9 September 2022).

G20 – IFA WG, 2017. Principles of MDB's strategy for crowding-in Private Sector Finance for growth and sustainable development. Available at: https://www.bundesfinanzministerium.de/Content/EN/Standardartikel/Topics/world/G7-G20/G20-Documents/Hamburg_reports-mentioned/Principles-of-MDBs-strategy.pdf?__blob=publicationFile&v=3. (Accessed: 9 September 2022).

Galindo, A.J., Panizza, U., 2018. The cyclicality of international public sector borrowing in developing countries: Does the lender matter? World Dev. 112, 119–135. http://dx.doi.org/10.1016/j.worlddev.2018.08.007.

Goddard, J., Wilson, J.O.S., 2009. Competition in banking: A disequilibrium approach. J. Bank. Financ. 33 (12), 2282–2292. http://dx.doi.org/10.1016/j.jbankfin.2009.06.003.

Gu, B., 2017. Chinese multilateralism in the AIIB. J. Int. Econ. Law 20 (1), 137–158. http://dx.doi.org/10.1093/jiel/jgx006.

Gurara, D., Presbitero, A., Sarmiento, M., 2020. Borrowing costs and the role of multilateral development banks: Evidence from cross-border syndicated bank lending. J. Int. Money Finance 100, http://dx.doi.org/10.1016/j.jimonfin.2019.102090.

Hainz, C., Kleimeier, S., 2006. Project Finance as a Risk-Management Tool in International Syndicated Lending of Work. Governance and the Efficiency of Economic Systems (GESY), SFB/TR 15, Discussion Paper No 183, http://dx.doi.org/10.2139/ssrn.567112, (Accessed: 9 September 2022).

Hainz, C., Kleimeier, S., 2012. Political risk, project finance, and the participation of development banks in syndicated lending. J. Financ. Intermediation 21 (2), 287–314. http://dx.doi.org/10.1016/j.jfi.2011.10.002.

Hernandez, D., 2017. Are ''New'' Donors Challenging World Bank Conditionality? World Dev. 96, 529–549. http://dx.doi.org/10.1016/j.worlddev.2017.03.035.

Hsieh, M.F., Lee, C.C., 2010. The Puzzle Between Banking Competition and Profitability can be Solved: International Evidence from Bank-Level Data. J. Financ. Serv. Res. 38 (2–3), 135–157. http://dx.doi.org/10.1007/s10693-010-0093-4.

Humphrey, C., 2014. The politics of loan pricing in multilateral development banks. Rev. Int. Political Econ. 21 (3), 611–639. http://dx.doi.org/10.1080/09692290.2013.858365.

Humphrey, C., 2016. The Invisible Hand: Financial Pressures and Organisational Convergence in Multilateral Development Banks. J. Dev. Stud. 52 (1), 92–112. http://dx.doi.org/10.1080/00220388.2015.1075978.

Humphrey, C., 2019. 'Minilateral' Development Banks: What the Rise of Africa's Trade and Development Bank says about Multilateral Governance. Dev. Change 50 (1), 164–190. http://dx.doi.org/10.1111/dech.12467.

Humphrey, C., Michaelowa, K., 2013. Shopping for Development: Multilateral Lending, Shareholder Composition and Borrower Preferences. World Dev. 44, 142–155. http://dx.doi.org/10.1016/j.worlddev.2012.12.007.

IATF, 2016. Inter-Agency Task Force on Financing for Development. Available at: https://developmentfinance.un.org/about-iatf. (Accessed: 9 September 2022).

Kanga, D., Murinde, V., Soumaré, I., 2021. How has the rise of Pan-African banks impacted bank stability in WAEMU? J. Int. Financ. Mark. Inst. Money 73, http://dx.doi.org/10.1016/j.intfin.2021.101364.

Kellerman, M., 2019. The proliferation of multilateral development banks. Rev. Int. Organ. 14 (1), 107–145. http://dx.doi.org/10.1007/s11558-018-9302-y.

Martynova, N., 2015. Effect of Bank Capital Requirements on Economic Growth: A Survey of Work. De Nederlandsche Bank Working Paper No. 467, http://dx.doi.org/10.2139/ssrn.2577701, (Accessed: 9 September 2022).

McFarland, B.J., 2011. Carbon Reduction Projects and the Concept of Additionality. Sustain. Dev. Law Policy 11 (2), 15.

McHugh, C.A., 2021. Mobilising Private Funding of Development Finance. J. Dev. Stud. 57 (12), 1979–2001. http://dx.doi.org/10.1080/00220388.2021.1945042.

Multilateral Development Banks, 2018a. Harmonized Framework for Additionality in Private Sector Operations. Available at: https://www.ebrd.com/our-values/additionality.html. (Accessed: 9 September 2022).

Multilateral Development Banks, 2018b. Mobilization of Private Finance 2017 By Multilateral Development Banks and Development Finance Institutions. Available at: https://www.adb.org/documents/mobilization-private-finance-mdbs-dfis-2017. (Accessed: 9 September 2022).

Olszak, M., Kowalska, I., 2022. Does bank competition matter for the effects of macroprudential policy on the procyclicality of lending? J. Int. Financ. Mark. Inst. Money 76, http://dx.doi.org/10.1016/j.intfin.2021.101484.

Panzar, J.C., Rosse, J.N., 1987. Testing For ''Monopoly'' Equilibrium. J. Ind. Econ. 35 (4), 443–456.

Ransdell, J., 2019. Institutional innovation by the Asian Infrastructure Investment Bank. Asian J. Int. Law 9 (1), 125–152. http://dx.doi.org/10.1017/S2044251318000176.

Sawant, R.J., 2010. The economics of large-scale infrastructure FDI: The case of project finance. J. Int. Bus. Stud. 41 (6), 1036–1055. http://dx.doi.org/10.1057/jibs.2009.63.

Schclarek, A., Xu, J., 2022. Exchange rate and balance of payment crisis risks in the global development finance architecture. J. Int. Financ. Mark. Inst. Money 79, http://dx.doi.org/10.1016/j.intfin.2022.101574.

Shaffer, S., Spierdijk, L., 2015. The Panzar-Rosse revenue test and market power in banking. J. Bank. Financ. 61, 340–347. http://dx.doi.org/10.1016/j.jbankfin.2015.09.019.

Shaffer, S., Spierdijk, L., 2017. Market Power: Competition Among Measures. Elgar Publishing.

Shapiro, D.M., Vecino, C., Li, J., 2018. Exploring China's state-led FDI model: Evidence from the extractive sectors in Latin America. Asia Pac. J. Manag. 35 (1), 11–37. http://dx.doi.org/10.1007/s10490-017-9526-z.

Starnes, S., Kurdyla, M., Alexander, A., 2016. De-Risking By Banks in Emerging Markets – Effects and Responses for Trade. Available at: https://openknowledge.worldbank.org/handle/10986/30350. (Accessed: 9 September 2022).

Streck, C., 2017. Ensuring New Finance and Real Emission Reduction: A Critical Review of the Additionality Concept. Carbon Clim. Law Rev. 5 (2), 158–168. http://dx.doi.org/10.21552/cclr/2011/2/176.

Subramanian, K.V., Tung, F., 2016. Law and Project Finance. J. Financ. Intermediation 25, 154–177. http://dx.doi.org/10.1016/j.jfi.2014.01.001.

Swedlund, H.J., 2017. Is China eroding the bargaining power of traditional donors in Africa? Int. Affairs 93 (2), 389–408. http://dx.doi.org/10.1093/ia/iiw059.

United Nations, 2015. Addis Ababa action agenda of the third international conference on financing for development. Available at: https://www.un.org/esa/ffd/ffd3/. (Accessed: 9 September 2022).

United Nations, 2020. Financing for Sustainable Development Report 2020, Available at: https://developmentfinance.un.org/fsdr2020. (Accessed: 9 September 2022).

Yuan, F., Gallagher, K.P., 2018. Greening Development Lending in the Americas: Trends and Determinants. Ecol. Econom. 154, 189–200. http://dx.doi.org/10.1016/j.ecolecon.2018.07.009.