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Lending over the technology lifecycle: Strategies for information search by banks in renewable energy project finance

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ABSTRACT

Commercial bank credit is pivotal for the development of large-scale assets. However, technological immaturity may hinder access to bank capital, particularly when banks lack information on a new technology's history and investment risk profile. We currently lack an understanding of how the banking sector can overcome this hurdle. Thus, this study examines the strategies banks use to gather information and develop a financial understanding of emerging technologies. Using two-part fractional response models and data on 7826 project finance deals in renewable energy, we find that, under technological uncertainty, banks gain confidence through brownfield lending, syndication, and information sourcing from borrowers until a strong banking network is formed. Furthermore, ownership and past lending relationships influence bank decisions. The dynamic results emphasize the importance of early bank entry and relationship building. The study concludes with policy implications, underscoring the need for greater coordination of public finance and formation of intermediation platforms.

1. Introduction

A substantial body of research underscores the central role that renewable energy technologies must play in addressing climate change (Bolton & Kacperczyk, 2023; Klaaßen & Steffen, 2023; McCollum et al., 2018). This necessitates swift and substantial financing with low-cost, long-term capital (Đukan et al., 2023; Steffen & Schmidt, 2021). One pivotal source of such capital is bank credit, which provides developers with low-interest funds, often for as long as the operational lifespan of renewable energy assets (Amuakwa-Mensah & Näsström, 2022; Egli et al., 2018; Polzin et al., 2019; Xin et al., 2017).

Bank credit though is not immediately accessible and requires active intermediation, particularly when technologies are being improved even as they get deployed (Kerr & Nanda, 2015a). In this early phase, banks may hesitate to lend due to variety of reasons (Böttcher, 2020) as technology assets' performance may not clear resulting in high information asymmetry. The improvement potential of the technology may also be uncertain resulting in potential cannibalization of early projects (Markard, 2020). The technology developers, operators or equipment providers may not have an adequate track record, reputation, or pre-existing banking relationships (Böttcher, 2020; Hombert & Matray, 2016; Geddes et al., 2018). Additionally, banks themselves may not have experience or expertise in such assets and, therefore, in the event of asset distress, may not know how to manage recovery (Höwer, 2016).

How, and from whom, do banks then learn or gather confidence about new technologies? To the best of our knowledge, this question has not been addressed in the academic finance literature even though global climate goals depend on large-scale financing of innovative, or yet to be innovated, low-carbon technologies. The provision of external credit to such technologies requires information gathering on the part of banks that establish certainty for issuing low-cost long-term credit. A better understanding of this issue can contribute to deciphering bank behavior and elucidate how policymakers can appropriately incentivize or regulate banks even as success is found in standalone policy instruments such as fixed remuneration schemes, guarantees (Steffen, 2018), and priority sector lending mandates (Ahmed, 2010).

We identify from the finance and banking literature three general strategies that allow banks to gather information, de-risk their investments, and increase market share. First, banks, much like firms, can invest through the acquisition or refinancing of brownfield assets of a

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technology. In such case the cost and revenue uncertainties are mitigated by developers before the banks get involved (Greig et al., 2023; Grosvenor Clive, Stokes. 2019; Gumber, Zana, et al., 2024; Vermeulen & Barkema, 2001). Investing in such de-risked assets allows banks access to operating performance, develop relationships with borrowers, ascertain the quality of non-financial actors such as operators and equipment providers, and build benchmarks for comparable future lending.

Second, banks can lend to greenfield assets through syndicates, where the lending amount (and therefore the risk) is reduced and information is exchanged between the syndicate members (Dennis & Mullineaux, 2000; Ivashina, 2009; Ivashina & Scharfstein, 2010; Sufi, 2007). Third, banks can gather and diffuse information from and to the ecosystem of technology lenders and borrowers independently of specific deals to gain confidence over time and find lending opportunities (Alperovych et al., 2022). Financial literature has devoted less study to the last strategy than the first two. It finds that in opaque networks, such as those in renewable energy project finance, banks diffuse information into their network to join future syndicates and source more information to recognize borrowers to whom they can lend. This strategy relies on the assumption that information regarding each deal or transaction is passed on in the network of investors connected by their prior experience of lending or investing together. 3.4.1 provides detailed methodology on how this strategy is empirically applied with its interpretation.

In extant research, each of these strategies is examined from a static perspective. Banks are considered to make decisions, such as those to syndicate, irrespective of the maturity of the underlying assets' technology or the bank's experience with the technology. Additionally, each of these strategies is studied separately or on a standalone basis, and thus shed no light on the importance of one over the other or on their collective importance, especially with the passage of time and increasing technology maturity. Furthermore, to our knowledge, none of these strategies are examined in the context of project financing (Alperovych et al., 2022; Boot, 2000; Bruche et al., 2020; Degryse & Van Cayseele, 2000). Much research focuses on patent led corporate lending that is affected by exogenous policy regulations on innovation disclosure or readability of borrowers' financial disclosures (Hoffmann & Kleimeier, 2021; Hoffmann et al., 2019). Such characteristics though crucial for obtaining information on bankability of firms, do not reflect the banks' willingness to lend to off-balance sheet or project financed assets.

Moreover, prior research typically conducts single-country analyses, specifically of the US financial system (Bento & Fontes, 2015; Stoneman & Battisti, 2010), whereas diffusion or sourcing of information on a technology is a global phenomenon. Finally, such prior analysis of banking relationships is typically confined to bank networks (Alperovych et al., 2022; Dennis & Mullineaux, 2000), whereas information flows may pass from one bank to another through other financial intermediaries and borrowers (Massa & Rehman, 2008).

To broaden our understanding of the strategies in light of progress in emerging technologies, we address the above shortcomings by analyzing bank lending between 1997 and 2023 in 31 countries for three renewable energy technologies. These include solar photovoltaic (PV) plants, onshore wind turbines, and offshore wind turbines. These three renewable energy technologies are the largest deployed low-carbon technologies that matured during our analysis period and are most often financed using project finance structures (Steffen, 2018). To shed light on which strategy is preferred over the technology lifecycle, we collectively examine the strategies. We examine the differences in the strategies by conducting a dynamic analysis, controlling the maturity of the technologies and the entry of the banks into any market. Finally, we examine global information flows between investors in the 31 countries. We utilize reporting from Bloomberg New Energy Finance, which provides the most comprehensive transaction information on borrowers (Gumber, Zana, et al., 2024; Larosa et al., 2022; Mazzucato & Semieniuk, 2017, 2018; Rickman et al., 2022; Steffen et al., 2018; Steffen et al., 2019). We are able to benefit from this comprehensive reporting to conduct a network-based information flow analysis, as proposed by Banerjee et al. (2013), that includes all borrower transactions and a sample of bank lending transactions. The information flow analysis estimates information centralities, which proxy for how often banks source information from other actors in the network and how often they diffuse information to the network.

Our analysis differs from others in literature that have examined the significance of each of the three strategies from a standalone and static perspective. We find that bank behaviors differ with respect to technology opening and bank entry—specifically, not all strategies play out equally. Most importantly, we find that brownfield lending, syndication, and information sourcing from borrowers are crucial in the early stages of technology. In contrast, once technology is mature and bank networks are well established, information diffusion is an important factor.

Our results expand the understanding of bank lending and contribute to less-examined areas of project finance. Our results also contribute to the ongoing efforts to understand how bank credit can be accelerated to promote innovation, especially in the case of technologies deemed important by policymakers (Hsu et al., 2014; Rajan & Zingales, 1998). Additionally, our research advances current work by integrating three different strategies previously examined in isolation and differentiate with respect to the importance of each with the passage of time. Finally, our research also advances upon recently developed network analysis techniques (Banerjee et al., 2013; Banerjee et al., 2019) to shed light on the importance of information flows in opaque networks of new lending sectors.

The paper proceeds as follows. In 2, we examine the technology lifecycle and lending strategies followed by banks during different phases of technology as we develop our research framework. In 3, we discuss our case selection of renewable energy technologies, the data sourced from Bloomberg, the network topology of the data and our statistical method. In 4, we discuss the empirical results of the research and, in Sections 5 and 6, conclude with implications, limitations, and prospects for future research.

2. Lending over the technology lifecycle

Technology's lifecycle is like the business lifecycle, represented by an S-curve starting with the formative phase, followed by growth, maturity, and eventual decline (Geroski, 2000; Kanger, 2021; Markard, 2020). Advancement to the maturity phase, especially in the case of technologies reliant on external credit, requires finance and financialization for greater deployment that result in the creation of learning opportunities (Amore et al., 2013; Benfratello et al., 2008; Geddes & Schmidt, 2020; Naidoo, 2020; Nykvist & Maltais, 2022; Rajan & Zingales, 1998). In the absence of adequate credit, governments can direct funds via regulation or intermediation that motivate banks to shift their portfolios toward greener technologies (Andersson et al., 2017; Deleidi et al., 2020; Edler & Georghiou, 2007; Edler & Yeow, 2016; Mazzucato & Semieniuk, 2017).

However, technologies during their formative and initial growth phases are not fully proven. Thus, banks must devote extensive effort to understand the risk profile of underlying technology assets (Egli et al., 2018) irrespective of government or stakeholder pressure to do so. Understanding the risk profile is fundamentally a task of information gathering to reduce information asymmetry and mitigate risks—either through better selection or risk sharing and dispersal (Bofondi & Gobbi, 2006; Crawford et al., 2018; Sharpe, 1990).

In this section, we first discuss the risks prevailing for banks during a technology's lifecycle, the strategies deployed by banks to gather information and lend, and how the strategies evolve with technological maturity. We present our research framework to develop our hypothesis to evaluate strategies that prove useful throughout the technology lifecycle.

2.1. Technology lifecycle and lending strategy

We take cues from the technology innovation literature to understand the phases of technology maturity. Within the general innovation literature, we specifically refer to the widely used technology innovation systems (TIS) literature (Bergek et al., 2015; Bergek et al., 2008; Gumber, Egli, et al., 2024), which provides a meso understanding of the evolution of the system that advances the technology. We overlay TIS on the existing banking literature.

The TIS literature examines technology through four lifecycle phases: the formative, growth, maturity and decline phases (Markard, 2020). TIS analytically examines the phases using three core dimensions, namely, size & actor base, institutional structure & networks, and technology performance & variation (Markard, 2020). We depict these dimensions and their effect on bank information asymmetry in Table 1.

The size & actor base reflects the degree of activity such as entrepreneurial effort or market transactions using proxies such as size and base of actors, change in size due to entry and exit, types and roles of actors, size of network, and number of projects. The institutional structure & networks reflect the different technology institutions, and their impacts examined using analysis of types of influential institutions, sophistication of intermediaries and inter-organization networks. Technology performance & variation reflects the maturity of the technology and its direction of development using proxies such as level of technological performance, degree of technological variation, and emergence of dominant design. We apply these dimensions through the four phases to contextualize the risks faced by banks when lending on the assets of a technology. We also depict the first three phases which are important to our analysis in Table 1.

The *formative phase* refers to the early years when none of the core dimensions exhibit strong performance. For instance, technology sales and therefore the asset size are close to zero, there are few growth prospects, and there is high uncertainty in technology performance parameters. Performance is unclear or lower than existing technology with no clear sight of a dominant design (Anderson & Tushman, 2018; Taylor & Taylor, 2012). Additionally, the technology system is characterized by large information asymmetry between innovators and lenders as it is dominated by a few small actors with low entry and exit rates. Institutional structures such as policy regulations on innovation disclosure are not well developed, and networks between actors are loose or incomplete (Bento & Fontes, 2019). In such a situation, the projects (or assets) of technology are small and built on highly uncertain assumptions and prospects of growth. The projects are also developed by a few developers and suppliers who may often be small and confined in their business to the specific technology with little or no history with financial markets (Böttcher, 2020). Furthermore, formal institutions, either those of policy or industry associations, may not be well established, and sourcing of any information about the technology and its developers by banks may be out of reach or prohibitively expensive (Dell'Ariccia & Marquez, 2004).

Table 1
Technology innovation system dimensions and bank strategies.

Technology Innovation System Dimensions	**1. Formative Phase**	**2. Growth Phase**	**3. Maturity Phase**
Size & actor base	*Low sales, small asset size* *Few actors, low entry and exit rates*	*Increasing sales and asset size* *Some experienced actors*	*High sales, large assets* *Several experienced actors, high barriers to entry*
Institutional structure & networks	*Weak institutions with uncertain regulations* *Loose and weak actor networks*	*Formalization of institutions with emerging (maybe still uncertain) regulations* *Emerging actor networks*	*Developed institutions with low uncertainty in regulation* *Well-developed actor networks*
Technology performance & variation	*Performance uncertainty* *No dominant design*	*Performance modestly certain* *Emergent dominant design*	*Performance stable* *Dominant design*
Bank Information Asymmetry	***Very high***	***High to Modest***	***Low***
Bank Strategy	***Brownfield Lending*** *(for technological information; no construction risk)* ***Syndication*** *(with government investment banks/ development banks)* ***Diffuse information*** *(to banks)*	***Brownfield Lending*** *(for technological information; no construction risk)* ***Syndication*** *(increased screening and monitoring)* ***Diffuse & Source information*** *(to banks and from borrowers)*	***Brownfield Lending*** *(for market share)* ***Syndication*** *(to reduce size risk)* ***Source information*** *(from borrowers)*

In such a phase, banks desiring to enter the financing of technology in the early stages may lend to pre-existing assets devoid of construction risk to gather primary technological information, albeit only if any such assets are available to lend. They may also seek to syndicate with other banks to reduce information costs (Ivashina, 2009) or lend on the backs of other established investors (provided they find some). In this situation, they may also seek support from government agencies, such as development banks, to reduce exposure and gain from the latter's in-house technical expertise (Degl'Innocenti et al., 2022; Gurara et al., 2020). They may also diffuse information about their intent to other banks to form syndicates (Alperovych et al., 2022). In the next section, we discuss information flows through which the diffusion or spread of information occurs. Finally, they may also extend loans—albeit backed by corporate balance sheets and not necessarily the technology assets—to pre-existing borrowers with whom they share a relationship (Bharath et al., 2007).

The *growth phase* refers to the mezzanine period when technological performance becomes clearer. Variations or uncertainties in design and implementation decrease, a dominant design emerges, and along with technical certainty, so does the demand or future prospect for the technology and the number and variety of actors who form a collaborative network. Alongside this, policy institutions and industry associations also begin to emerge and formalize (Markard, 2020). A key highlight of the growth phase is the rapid initial growth that helps a technology escape its demise, what is known as the valley of death (Nemet et al., 2018). During the growth phase, as larger assets begin to be developed by a variety of developers, bank lending begins to materialize. However, lending may be confined to a few developers who manage to develop a history of developing smaller projects and raising early-stage investments from reputed investors.

As the phase progresses, information on technology assets past performance and return realization is generated alongside greater dissemination of information on future lending possibilities. However, this crucial phase is a transition phase unlike the other phases—it resembles change toward certainty during which time banks may be hesitant to lend and may derisk or wait, that is, they may adopt strategies to limit their risk unless more information is available or simply not invest. Strategies to derisk and gather information can include the following three: lending against fully developed (constructed) assets where cost and construction uncertainties are mitigated and revenue potential is adequately known (Greig et al., 2023), syndicating with other banks so that the lending amount is reduced and assets are screened and monitored along with partner banks, and gathering and diffusing information from and to the technology actors and other lenders (Dennis & Mullineaux, 2000; Meuleman et al., 2009). Gathering information from non-financial actors, specifically potential borrowers, provides a means of identifying potential lending opportunities, and diffusing information to the rest of the banking network provides access to syndicated lending opportunities by informing other banks of the intent to join in on similar loans (Alperovych et al., 2022). Diffusing also acts as a means of creating bank reputation among other banks, so that less-reputed banks are inclined to approach the lead bank for future syndications.

The *maturity phase* refers to the period when technology sales are high, performance may be stable or increasing with potential for branching into new applications,[1] growth prospects are lower than in the growth phase, medium or large actors exist, there is a high degree of specialization along the supply chain with varied options, barriers to entry are high, and networks and institutions are well developed (Anderson & Tushman, 2018; Markard, 2020; Taylor & Taylor, 2012). In this phase, technology is well known in the market, with a recorded history of the return generation from dependable borrowers, and risks are considered manageable. During this phase, banks that have a track record of lending for the technology may not necessarily seek information on its track record but to increase their access to lending opportunities or newer markets (Berger & Dick, 2007). Hence, they may lend alone (without syndicates), except for lending to exceptionally large projects or to new markets, or they may lend on brownfield assets to increase market share and source information from borrowers but limit their diffusion to other banks. However, banks that enter late into the technology or the market, especially once the technology is mature, may exercise strategies like the growth phase until they achieve adequate confidence to manage the risk entirely alone or develop a method of accessing future deals, that is, by sourcing or diffusing information.

Finally, the *decline phase* refers to the period when technology sales are below maximum and declining, performance is questioned vis-à-vis other comparable opportunities, growth prospects are low, actors exit at high rates, and institutions and networks begin to break down (Markard, 2020). During this phase, lenders are locked into stranded assets and may begin to reduce their exposure (Curtin et al., 2019). Banks with no exposure may refrain from entering the technology but nevertheless exercise the option to lend in the case of profitable ventures, for example in the case of distressed asset recovery.

In the four phases discussed above, the relevance of the strategies applied by banks to gather information, gain confidence, and finally build their market share in a new technology will vary. While during the formative phase brownfield lending may not be feasible due to a mere lack of pre-existing assets, it may take precedence in the growth phase. Similarly, syndication may be the preferred option in the formative and early parts of the growth phase; it may decrease over time as banks compete to increase market share. Additionally, information flows may exhibit dichotomous trends. Banks may wish to diffuse more information, especially if they seek to form syndicates either during the early phases of the technology or to access larger projects. Over time, they may attempt to reduce information diffusion, especially if they lead in market share and seek to prevent competition. On the other hand, they will seek more information from borrowers to access new future opportunities.

Finally, banks may not act alike while adopting different strategies. Some banks, such as those that are state or government owned, may be required or asked to lend at the behest of their public shareholders into priority assets (Ahmed, 2010). Such regulations may include new technology assets serving social policy, such as decarbonization. Moreover, some banks may have greater access to development finance capital than others to lend on new technology assets. Some banks may only lend to more reputed borrowers or those with whom they have had pre-existing relationships (Hellmann et al., 2007). Some banks may be large enough to take such risks or, conversely, small enough to risk capital in new technology assets to generate the excess returns required for the bank's growth. We discuss these factors as controls in the Research framework and Methods sections.

2.2. Research framework

Three key aspects aid in developing our method: First, we are interested in conducting a dynamic analysis. Second, we are concerned with information flows, and third, we are interested in the relative share of banks, that is, how they perform relative to other banks and gain market share.

Since we are interested in understanding time-varying bank behavior vis-vis technology maturity, we model our research along three-time variables, two of which include technology maturity and bank entry, as depicted in Fig. 1. The time variables include, first, the calendar year along which we aggregate the analysis to form a time series and control for time effects that affected all countries (such as the global financial crisis). The second includes "time since technology opening," a count in years of the time since the first technology asset was financed. This provides a measure of how long the technology has existed and acts as a proxy for the maturity of the technology innovation system, assuming that the technology matures with passage of time (Steffen et al., 2018). The time to full maturity is uncertain, with no consensus on finer points regarding when technology matures. Therefore, we conduct our analysis by varying the time since technology opening; we conduct the analysis for 5, 10, and 15 years. The zone in Fig. 1 highlighted in green depicts the time since technology opening, with the lighter shade depicting the uncertainty surrounding when a technology matures.

The third time variable includes "time since bank entry," which provides us with a count in years of the time since the first technology asset was financed by a particular bank. Like the previous variable, this also acts as a proxy for how confident a particular bank is with a technology; that is, the longer a bank has invested in the technology, the more comfortable it will be as cost of gathering information reduces notwithstanding internal bank frictions. As with the previous variable, there is no consensus on how long is adequate. So, we include three possibilities—first, when the bank entered before the technology matured and technology was in the growth phase; second, when the bank entered before the technology matured but is now mature; and third, when the bank entered after the technology matured. In the first case, banks are in a period of technological uncertainty, whereas in the latter two, they are beyond technological uncertainty but face growing competition or the opening of new markets.

Next, we are interested in information flows, which we examine using the different strategies discussed previously as proxies. First, we consider the brownfield assets that a bank has lent to. We use higher brownfield lending as a proxy for higher access to primary information on technology performance and access to borrowers, equipment suppliers, and other actors in the technology supply chain. Next, we examine syndication with other banks, which we consider a means of

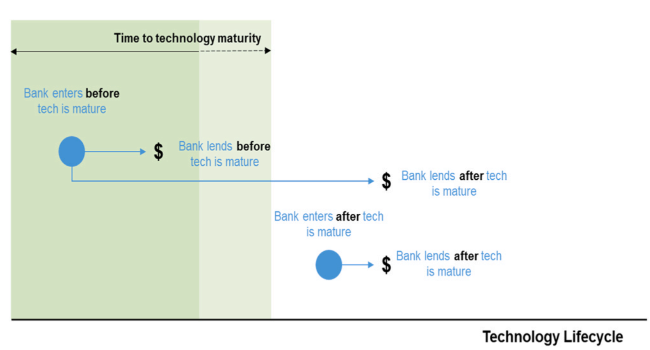


Fig. 1. Illustration of time since technology opening and bank entry.

[1] Please note that the maturity phase may experience spells of growth that may not be linearly fashioned Roussel, P. A. (1984). Technological Maturity Proves a Valid and Important Concept. *Research Management*, *27*(1), 29–34. https://doi.org/10.1080/00345334.1984.11756815.

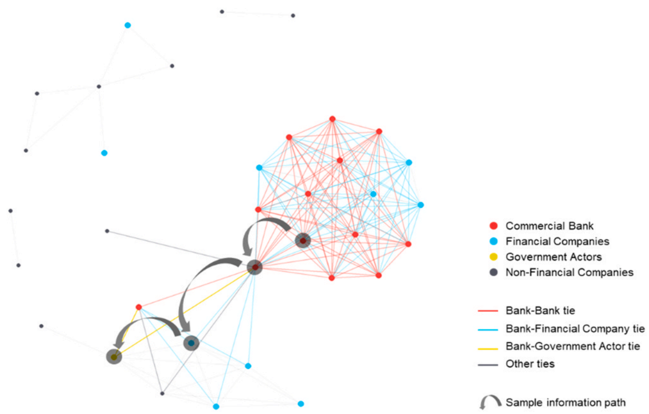


Fig. 2. Example of information transmission in a renewable energy investment network.
The network illustrates a hypothetical network wherein, at each transaction, the information is transmitted from one actor to another with a probability until the entire network is saturated. The highlighted path in gray is shown as an example.

exchanging information during transactions and bookkeeping, thereby building the history of asset and borrower performance necessary to make decisions on future deals. Last, we consider information flows to other banks and from borrowers, which we regard as a means of dispersing intent to lend and gathering information on potential borrowers, respectively. We measure information flows following the method developed by Banerjee et al. (2013, 2019) and applied by Alperovych et al. (2022), where it is assumed that the information generated at one bank is passed stochastically through the network until the network is saturated with that information. Fig. 2 provides a depiction of information flow, and the next section explains the method we apply to calculate information diffusion and sourcing and how these differ from conventional social network tools previously applied in research.

Finally, we are interested in the relative market shares that a bank manages to achieve using the strategies. Particularly, we examine lending on greenfield assets that carry technology-related risks and for which banks must gather as much information as possible. Since technology innovation often results in information exchange, learning, and building confidence across borders, we calculate market share globally in this step. Accordingly, the time since technology opening and bank entry is also calculated for the first global technology project in any country. However, we evaluate our results for regulatory and behavioral differences between countries and find that our results are robust to controlling for bank country of origin.

3. Data and methods

3.1. Data

To evaluate bank strategies, we source data from Bloomberg New Energy Finance (BloombergNEF, 2024b) for three technologies, namely, solar photovoltaic (PV), wind onshore, and wind offshore. We chose to study renewable energy technologies, as they are at the forefront of government decarbonization policy, and specifically chose three technologies, as they moved beyond their technical innovation phase in the past two decades while generating numerous profitable lending opportunities. Accordingly, we source a total of 69,170 transactions. These are those that achieved final investment decisions between 1997 and 2023 (27 years). Among these, transactions where an organization's names are not reported or for which their type (bank, financial company, etc.) cannot be recognized are removed. In addition, transactions with unreported capacities[2] are removed. Furthermore, countries with at least 30 transactions reporting bank details in the case of solar PV and onshore wind are selected, and in the case of offshore wind, only six countries—Belgium, France, Germany, the Netherlands, Taiwan, and the United Kingdom—are selected. This reduces the total transactions in the chosen countries to 63,900. Among the 63,900 transactions, only 7826 contained information on commercial banks, representing 12.25 % of the total transactions in the database.[3]

Table 2 summarizes the available data, and Figure A1 and A3 in Appendix A depicts the share of transaction capacity (banded by size in MW) for which bank information is available. We use capacity (reported in MW) as a proxy for the investment amount. We find that maximum reporting occurs in the case of refinancing, followed by new-build greenfield transactions. Furthermore, in Figures A2 and A4 in Appendix A, we see that the mean value of the transactions (in MW) for which bank information is available is slightly higher than those for which information is not reported, however, the variation (as seen with standard deviation in Figure A4) with respect to financed technologies and transaction sizes is low, albeit small and tilted slightly in favor of larger deals. While a sample selection bias with respect to unobservable characteristics cannot be fully ruled out (as generally is the case in comparable studies, see footnote 3), technology and transaction size are the key variables concerning banks' decision to engage in financing of a certain asset type, providing confidence in the representativeness of the sample.

The transaction data includes financial information, including names of investors (sponsors/borrowers and lenders), the capacity financed for each transaction, transaction country, technology, and the final investment date, with each transaction categorized as new build, acquisition, or refinancing. A new build transaction occurs when financing for a project is arranged for the first time. This is treated as a "greenfield" transaction. An acquisition occurs when a project is acquired by someone or changes ownership, and refinancing occurs when a project has a new lender who provides it with debt. Acquisition and refinancing are collectively treated as "brownfield" transactions from a lending perspective.

The transactions database is complemented with the BNEF organizations database (BloombergNEF, 2024a) that includes organization tickers, if assigned by Bloomberg, the activities undertaken by the organization, the organization's headquarters, and parent reporting entity. Furthermore, we apply the Bloomberg Industry Classification System (BICS) to classify organizations into one of the following four types of companies. These include commercial banks, financial companies, government actors, and non-financial companies. If BICS classification is unavailable, we utilize the activities of the organization listed in the BNEF organizations database to classify them. The parent reporting entity along with company classification into four types is used to recognize whether a bank is publicly owned (by state or government).

3.2. Network topology

Fig. 3 depicts the network topology of a renewable energy infrastructure investment system where different banks and other investors come together to finance an asset of the technology. Fig. 3(a) depicts the different investors who may be involved in a transaction at different stages of a project's or an asset's deployment. In each transaction, there are investors, which we classify as commercial banks, financial

[2] Capacities are reported for renewable technology assets in MW, proxying for the size of the transaction.

[3] Alperovych et al. (2022) work with 2414 LBO transactions between 1986 and 2012 in the USA. Sufi (2007) uses 12,672 syndicated loans to all non-financial institutions between 1992 and 2003 in the USA. Ivashina & Kovner (2011) use 1590 LBO loans between 1993 and 2005.

Table 2
Summary data of transactions and investors involved in the transaction networks between 1997 and 2023.

	Transactions				Number of Unique Investors				
	New Build	Acquisitions	Refinancing	Total	Commercial Banks	Financial Companies	Non-Financial Companies	Government Actors	Total
Renewable Energy Network – All Technologies	53,448 [5755]	7354 [468]	3098 [1603]	63,900 [7826]	1002 [1002]	2054 [747]	13,180 [2377]	459 [76]	16,725 [4202]
Solar PV	32,902 [4098]	3976 [224]	1656 [778]	38,534 [5100]	860 [860]	1527 [494]	9261 [1597]	361 [50]	12,009 [3001]
Wind Onshore	20,235 [1594]	3113 [219]	1383 [776]	24,731 [2589]	429 [429]	824 [337]	5131 [907]	188 [42]	6572 [1715]
Wind Offshore	311 [63]	265 [25]	59 [49]	635 [137]	159 [159]	143 [99]	263 [96]	26 [17]	591 [371]

Figures mentioned in brackets refer to transactions or investors present in deals with at least one commercial bank.

companies, government actors, and non-financial companies. Financial companies include venture capital firms, private equity firms, and asset managers. Government actors include government agencies, state investment banks, multilateral development banks, and sovereign wealth funds. Non-financial companies include utilities, energy companies, and other companies unclassified in other categories.

As investors look to invest in an asset, they may invest in two stages. The first is when the project is conceptualized. In this case, the project is "greenfield," and the transaction is classified in the data as "new built." Second, when the project is already built but undergoes acquisitions or refinancing, the project is "brownfield", and the transaction is classified in the data as "acquisition" or "refinancing." Through a mix of the above transactions, also possibly in different geographies, investors obtain information regarding the performance and profitability of the technology and therefore obtain confidence for future transactions. Accordingly, banks and other investors represent individual nodes of the network through whom the information is transmitted.

Finally, Fig. 3(b) depicts the next layer of technology on top of Fig. 3 (a), which depicts that investors may also invest in different technologies as they place themselves as sectoral leaders, that is, in the renewable or energy infrastructure sector space. Fig. 3(c) summarizes the logical hierarchy we employ to examine this network. At the top is technology, which is our key distinguisher of investor behavior. Next is the market in which the technology assets are deployed. The market is global in our analysis. Thereafter, it is the asset that forms the next hierarchy on which different transactions are conducted by different participating actors. Investors exchange knowledge during these transactions, either with those investing in the asset or from those who are already invested in the asset. Furthermore, such collaboration during transactions results in the formation of the network of investors (nodes) connected by the transactions they conduct together, which is later used to diffuse and source information.

The network described above is not static and changes composition over time. Therefore, the network evolves either with the entry or exit of the actors. Moreover, it also changes composition with changing shares of transactions, that is, the number of times two investors engage. Accordingly, we examine the evolution of this network with 3-year, 6-year, and 9-year intervals (reference periods) with the network weighted by the number of transactions a pair of actors engage in, following similar approaches as Engelberg et al. (2012). We choose to analyze three reference periods to avoid the potential of reverse causality wherein strategy and success co-evolve, and banks depict recency bias in favor of one strategy.

While information is exchanged among all types of investors, we specifically analyze the information exchanged by commercial banks with other commercial banks and borrowers. We analyze information exchange by generating two information centralities. The first is for information diffused by commercial banks to other commercial banks, and the second is for information sourced by commercial banks from potential borrowers. We call the first diffusion centrality and the second sourcing centrality. Diffusion centrality is a proxy for the information that is diffused into the network by a bank and indicates how likely banks are to be invited to syndicate with other banks in the future, thereby increasing their market share (Alperovych et al., 2022). Sourcing centrality is a proxy for the mean number of times information is sourced by a bank from non-financial actors. It is a proxy for the information heard on average by banks about borrowers. Banks will invest in borrowers whom they have heard about, and hence, if they hear more on average, they will lend more often to more borrowers. In both cases of diffusion and sourcing, we expect the bank's market share to increase with higher information diffusion or sourcing. The mechanics of information diffusion and sourcing and the calculation of the resulting centralities are discussed in the methods section.

3.3. Network and data summary

In conducting our analysis, we are limited by the share of information reported by BNEF. In many transactions, information on the lender is missing. However, taking the sample network where only commercial banks transact omits key information flows among other investors. Therefore, we work with a full network of investors for the three technologies, as summarized in Table 2. Fig. 4 depicts the country-wise breakdown of new build or greenfield transactions where commercial bank information is available. Figure A5 in Appendix A depicts the breakdown of Fig. 4 by technology.

3.4. Method

The research framework under 2.2 motivates Eqs. 1 and 2, wherein we apply a two-part fractional response model developed by Papke and Woolridge (Papke & Wooldridge, 2008; Wulff, 2019) to examine the average mean effect of the *strategies* on bank greenfield market share. In the two-part analysis, we first examine whether the strategies affect whether the banks participate through a logit analysis (Eq. 1) and thereafter conduct the fractional response on those who do participate and what impact the strategies have on the market share (Eq. 2). We also introduce the c*ontrols* mentioned in the previous section and discuss their calculations ahead. *T* refers to calendar time, *ref_period* refers to the past reference period over which the strategies are computed, *tech_open* refers to years since technology opening, and *bank_entry* refers to years

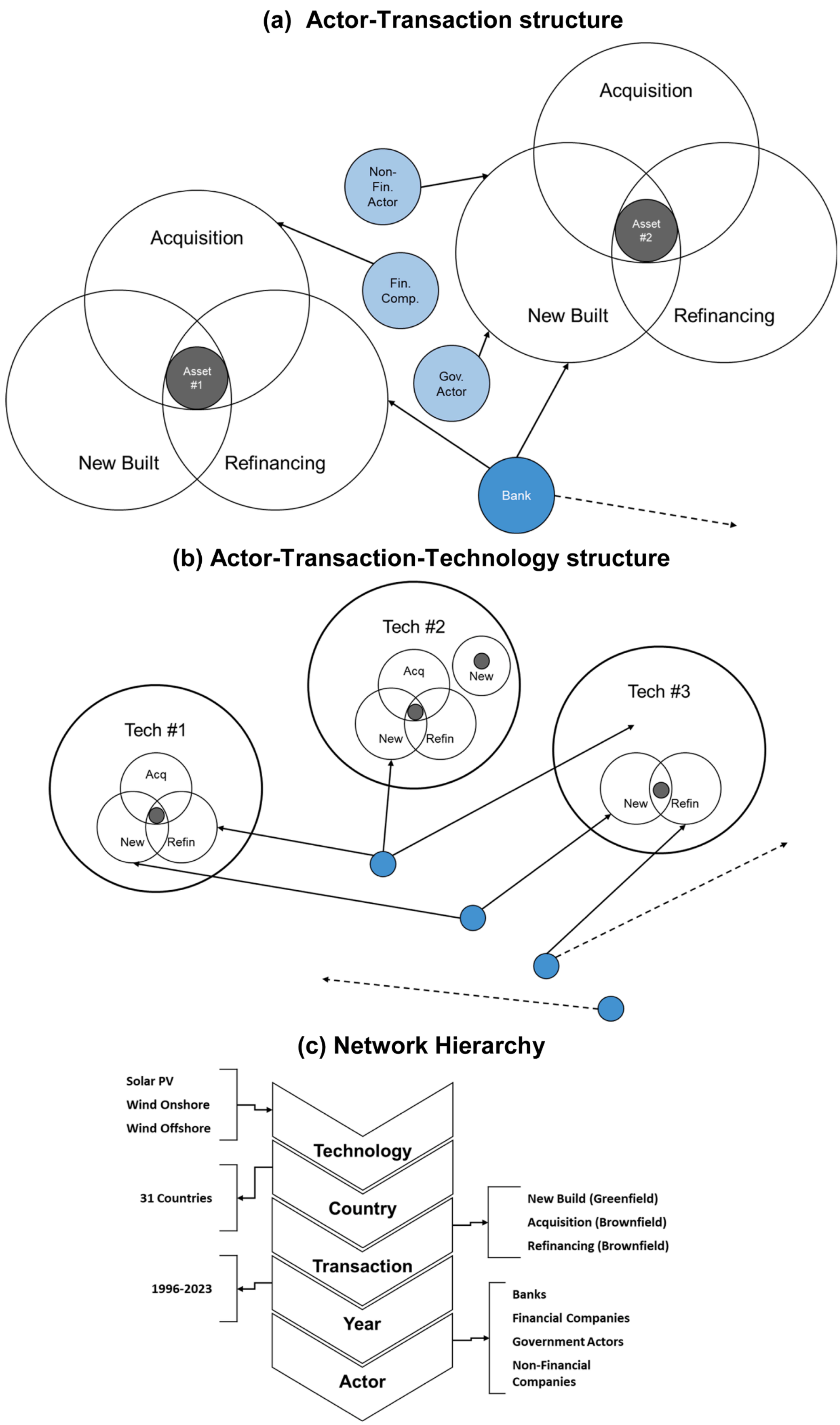
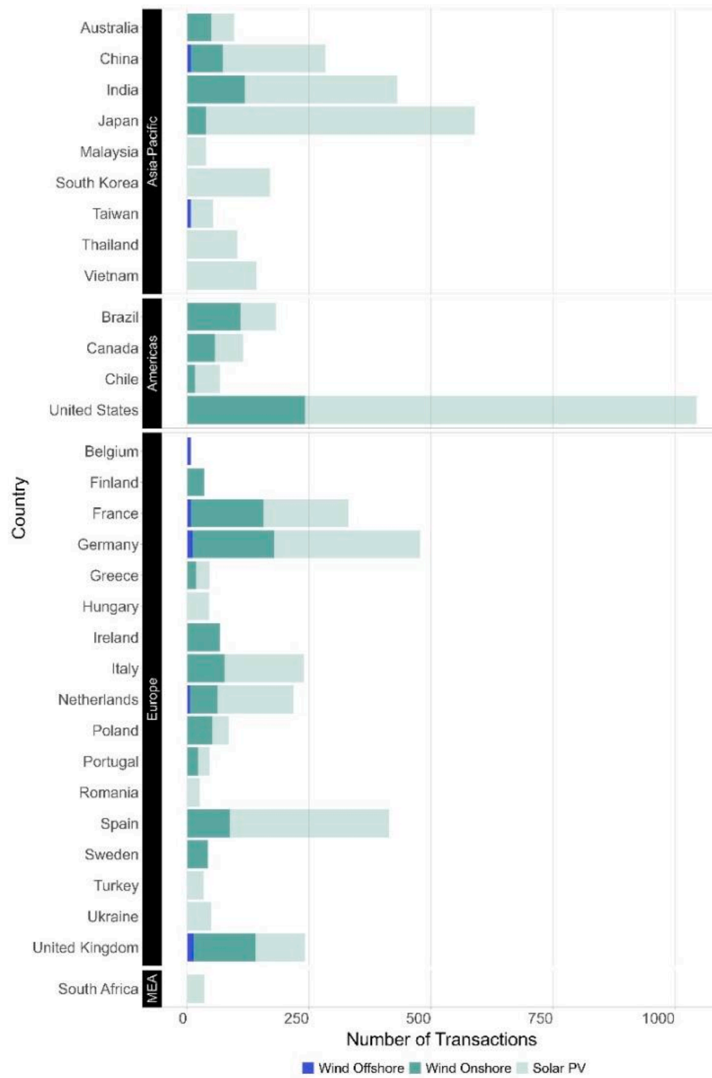


Fig. 3. Network topology of energy infrastructure investment system.



MEA refers to Middle East & Africa

Fig. 4. Transaction summary of new build (greenfield) transactions by country between 1997 and 2023.

since bank entry in the technology.

$$\begin{aligned} \mathit{Bank\ Greenfield\ Participation}_{t,tech\_open,bank\_entry} = {} & \beta_o \\ & + \mathit{Strategies}_{(t-1)-(t-ref_{period}),tech\_open,bank\_entry} + \mathit{Controls} + \varepsilon_{t,tech\_open,bank\_entry} \end{aligned} \tag{1}$$

$$\begin{aligned} \mathit{Bank\ Greenfield\ Share}_{t,tech\_open,bank\_entry} = {} & \beta_o \\ & + \mathit{Strategies}_{(t-1)-(t-ref_{period}),tech\_open,bank\_entry} + \mathit{Controls} + \varepsilon_{t,tech\_open,bank\_entry} \end{aligned} \tag{2}$$

In both equations, we regress the market share as the dependent variable, which is a continuous variable between 0 and 1. Due to the bounded nature of the dependent variable, we apply a two-part fractional response model and compute the average marginal effects of the explanatory variables (Wulff, 2019). In the first part, we apply a logit model to examine whether banks participate (1 if they participate, 0 if they do not) in any year, as banks often invest once and then pause for subsequent years until the next transaction. This step is important, as we have several zero market shares after bank entry, the exclusion of which would bias the result for banks that enter but do not participate in subsequent years. This allows us to deal with nonparticipation rather than omitting bank shares for years in which they do not lend (Ramalho et al., 2010). Thereafter, in the second part, we apply the fractional model to analyze the share of banks that do participate.[4]

Due to the nature of the data where exact shares of lending with transactions by banks are not available, we compute the market share as the bank's share of deals of overall deals in the market (deal share) or as the bank's share of capacity invested as a percent of overall capacity invested by banks in the market (capacity share). The market is the global market (i.e., the 31 countries examined in our database). The deal share counts the same project multiple times, as two or more banks may be present in one transaction. The capacity share splits the weight of each transaction equally among the participating banks. Capacity is

[4] We conduct our analysis in R (version 4.2.3) and compute our results using the fixest package (version 0.11.2) and marginaleffects package (version 0.18.0).

equally split between participating banks, as the exact share of investments is not available in Bloomberg, an approach commonly found in the literature (Mazzucato & Semieniuk, 2018; Rickman et al., 2022). We acknowledge that splitting equally may underweight the risk taken by lead banks (lead arrangers). Yet, equally splitting the transaction capacity is a conservative estimate—overweighting banks with lower lending and underweighting those with higher lending. The overall capacity share is thus dependent on lead banks doing more deals or transactions. Regressing both types of market share therefore provides us with robustness check and contributes nuance on whether banks act differently in larger, less-syndicated transactions; that is, the capacity share provides us with an insight into whether the weight of the transactions is relevant and whether banks should engage in larger transactions for future growth.

Furthermore, we control for time and technology fixed effects and compute our dependent and explanatory variables over the calendar year and by technology, respectively. The country fixed effects are dropped, as our analysis is global. However, fixed effects for bank country, or the country of the bank headquarters, are evaluated to determine whether regulatory differences between countries and behavioral differences between banks due to their country of origin affect bank strategies in any way. The results presented in Appendix E (see Tables E8, E9, and E10) show that they do not, and therefore the manuscript depicts models with time and technology fixed effects. The fixed effects allow us to control exogenous differences, such as macroeconomic shocks with time or technology differences.

Finally, we vary three-time variables. First, we compute the explanatory variables over three different *reference periods*. The reference period is the time in years prior to the calendar year of analysis for which the market shares or dependent variables are computed. The reference periods are 3-year, 6-year, and 9-year periods prior to the analysis year. We conduct such an analysis to identify any impact of the variance of the past experience of banks, such as information flows or their past lending on brownfield assets. Second, as mentioned in 2.2, we vary "time since technology opening" and conduct partial regressions to analyze the difference between periods when a technology was new in the market (time since technology opening). We conduct this for 5, 10, and 15 years. Third, we finally vary "time since bank entry" and analyze the three variations that can exist vis-à-vis "time since technology opening," that is, banks entered before technology maturity and the technology is not mature, banks entered before technology maturity and the technology is mature, and banks entered after technology maturity.

3.4.1. Variables

3.4.1.1. Dependent variable. Since we are concerned with understanding whether banks invest in a technology vis-vis other banks, the dependent variable we examine is the bank's market share in calendar year *t*. The market share is either calculated as the bank's share of deals (deal share) of overall deals in the market in year *t* or the bank's share of capacity invested as a percent of overall capacity invested by banks in the market (capacity share). The dependent variable is calculated only for new build transactions or greenfield transactions. For the first part, that is, the logit regression, if the share is greater than 0, the variable is marked as 1. Each of the variables discussed below are also listed in a tabular format in Appendix F.

3.4.1.2. Explanatory variables. For each of the following three strategies—that is, brownfield lending, syndicating with other banks, or exchanging information—we compute the following variables for the three *reference periods* described above. Our base analysis is conducted for 6-year periods (*t-1 to t-6)*, with robustness conducted for 3-year and 9-year periods.

<u>Brownfield lending</u> – We calculate the bank's share in the market for brownfield lending in the reference period. We calculate the deal and the capacity share as the dependent variable, that is, the share of deals or capacity, as a percent of total brownfield deals and capacity. The variables computed are between 0 and 1.

<u>Syndication</u> – We calculate the bank's share of deals syndicated with other banks in the reference period. Like the dependent variable, we calculate the share of deals as well as the share of capacity, albeit the transaction's full capacity instead of the bank's share only, that was syndicated. The syndication share takes a bank's own transactions in greenfield assets as the denominator, hence calculating what percentage of the bank's own deals were syndicated.

<u>Information exchange</u> – We calculate information exchange using two information centralities discussed under network topologies in 3.2 and as determined by Alperovych et al. (2022). To arrive at the centralities, we consider the full network of banks and other investors and develop adjacency matrices for prior reference periods (*t–1 to t-reference period)*. Accordingly, adjacency matrices are built on rolling bases for each year globally for each technology. Further, the adjacency matrices are weighted by the number of transactions conducted by two nodes (banks and other investors). So, if two investors appear together on four transactions, their link is weighted by four.

In the adjacency construction, it is assumed that the information generated at one node is passed stochastically from neighbor to neighbor with some probability *p*, along with the details of the node, to recognize who originated the information. Thus, at $T = 1$ (different from t above), the immediate neighbors *j, k, …,* of node *i* hear about the information generated from node *i,* and thereafter, at time $T = 2$, the neighbors of those neighboring nodes *j* and *k* will hear about the same information with the same probability *p*. The process continues for T time periods until the information saturates the network. Accordingly, Banerjee et al. suggest using $T = \mathrm{diam}(A_t)$, where diam is the diameter of matrix A_t. This implies that the information will spread until the last node in a fully connected network hears the information. This restricts the information from echoing (if $T > \mathrm{diam}(A_t)$) or deteriorating before saturating the network (if $T < \mathrm{diam}(A_t)$). Furthermore, the probability *p* can be approximated by $1/\mathrm{E}[\lambda_1(A_t)]$, which is the inverse of the largest eigenvalue of the adjacency matrix A_t. Accordingly, the information matrix for a technology, market, and transaction type can be represented by equation 3.

$$I(A_{tech-mar-tran-t}, \quad p, T) = \sum_{T=1}^{diam(A_t)} \left(pA_{tech-mar-tran-t}\right)^T \tag{1}$$

After the calculation of the information matrix, also NxN in dimension, the diffusion is estimated as the sum of the rows of matrix I across columns that represent banks; that is, diffusion of a bank to other banks only. The sum represents the number of times information originating at one bank node is heard by other bank nodes. Similarly, sourcing is calculated as the mean of the non-financial actor or borrower columns, as that represents the average number of times a bank node is likely to hear information from other borrower nodes. In calculating each of the centralities, we can distinguish between information diffused to commercial banks and information sourced from non-financial companies.

Overall, the two centrality measures provide us with a proxy for a bank's ability to disseminate information to other banks or provide us with a proxy for a bank's exposure to borrowers. The measures do not reflect a bank's active effort in seeking information, as is also the case with other social network centralities such as degree or eigenvector centrality often used to depict reputation (Ivashina & Kovner, 2011). We cannot distinguish between what a bank actively or passively diffuses or sources, nevertheless we can study information spillovers that other network measures have not allowed before.

3.4.1.3. Controls. Based on our discussion in 2.1, we introduce the following controls:

<u>Whether a bank is state or government owned</u> – Since state- or government-owned banks may be motivated by government policy, they

may exhibit a higher market share. For instance, in India, banks are mandated to direct their lending to priority sectors, which include renewable energy (Kumar. J & Majid, 2020). Accordingly, we recognize whether a bank is state or government owned by mapping each entity to its parent company. With iterative mapping of parents, we can recognize the topmost parents and whether they are government actors. If a bank is owned by a government actor at the parent level, we consider the bank to be state or government owned; otherwise, it is privately owned. Appendix B provides a summary of the state- or government-owned banks by country.

Share of deals with government actors – Government actors, including development banks and public agencies, are mandated to crowd in investments in renewable energy (Steffen & Schmidt, 2019; Waidelich & Steffen, 2024). They co-invest with banks to reduce risks in early investments so that banks can later risk more themselves (Geddes et al., 2018). Hence, a higher share of co-investment representing a bank's deal or capacity share in the reference period will reflect the bank having a higher share in the market with the passage of time. However, the share of co-investments will decrease as the bank succeeds at making more deals; hence, the relationship we will witness is negative. We calculate the share of deals with government actors in the same way as we calculate the share of syndicated deals—both for share of deals and share of capacity.

Reputation of the borrower – Often, banks lend to reputed borrowers or provide them with lenient covenants (Ivashina & Kovner, 2011). In addition, highly reputed borrowers, who are well known in the market, may attract lenders, as the borrowers may be highly rated for the technology assets. Accordingly, we control for the reputation of the borrower in the analysis year. Reputation is calculated using network variables of eigenvector centrality (in a deal-weighted network) that proxy for the reputation of borrowers (Ivashina & Kovner, 2011). Alternatively, reputation can also be calculated using degree centrality; however, the degree, unlike eigenvector centrality, does not account for the reputation of those with whom the banks are connected. Hence, eigenvector centrality is chosen for our analysis. The calculation of degree and eigenvector centralities is explained in Appendix C. The variable is calculated for preceding reference years prior, as is the case for other explanatory variables. Thereafter, the mean reputation of a bank's borrowers is calculated. If a transaction involves multiple borrowers to whom a bank may have lent in a particular transaction, the maximum reputation of a borrower in a particular transaction is taken in calculating the mean. Higher lending to reputed borrowers will positively correlate with the dependent variable.

Recurrent lending to the same borrowers – Irrespective of borrower reputation or information sourcing from the network, banks are also more likely to lend to those with whom they have an existing relationship. Accordingly, we estimate the share of deals in analysis year *t*, where banks lent to borrowers with whom they had an existing relationship in the reference period. The calculation is conducted in the same way as syndication, both for share of deals and share of capacity.

Finally, the regression setup for evaluating the effects on the dependent variable is split according to the nature of the dependent variable—that is, whether it is calculated as a deal share or as a capacity share. Tables 3 and 4 provide summary statistics of all variables computed for the 6-year reference period. Table D1 in Appendix D provides the correlations for each variable.

4. Results

We divide our results into static and dynamic analyses. In the former, we do not account for the time since technology opening and bank entry and explain the significance of the strategies for the full sample. The dynamic analysis splits the sample by the time since technology and bank market opening to examine how the factors' influence varies along the technology lifecycle and the experience of the bank.

4.1. Static results

Table 4 depicts the static regression results split into two parts of the fractional response model. The first part depicts logit results explaining how the variables affect whether a bank participates in the market (Models 1 and 2), and the second part depicts fractional results explaining how the variables affect bank market share once banks decide to participate (Models 3 and 4).[5] Furthermore, Models (1) and (3) in Table 5 show the results when the bank's market share is calculated using its deal share, whereas Models (2) and (4) show the results when the bank's market share is calculated using its capacity share.

The static analysis in Table 5 is conducted with a reference period set to 6 years. Table E1 in Appendix E depicts the same results for the 3-year and 9-year reference periods, and Table E8 depicts the model with bank country fixed effects. The robustness of the results across reference periods indicates that while learning from lagging effects is important, the length of the prior period does not materially change our analysis.

4.1.1. Strategies for bank participation

The results from Models (1) and (2) in Table 5 depict negative or insignificant influence except for *information diffusion*. *Brownfield lending* yields insignificant results. Higher *syndication* results in less market participation and does so with respect to deal share and capacity share. This result is contrary to our expectations. Higher syndication should result in higher exchange of information between banks, leading to higher future risk taking. However, our results suggest that banks who syndicate are risk averse and unwilling to increase their participation in future deals. This could be due to idiosyncratic behavior on the part of banks who follow other riskier banks but never take on the technological or infrastructure-related risks associated with renewable energy projects.

Among the information centralities, *information diffusion* depicts expected directionality, and *information sourcing* depicts insignificant influence. In the case of *information diffusion,* the result concurs with previous studies that found that banks diffuse more information to make themselves recognizable to other lenders with whom they can potentially syndicate and obtain future lending opportunities (Alperovych et al., 2022). This is likely because technology knowledge is circulated globally, and several banks are keen on developing a global market share in our dataset. Thus, among the three strategies, only the strategy to diffuse information to other banks increases bank participation in new renewable energy asset lending.

The control variables under Models (1) and (2) in Table 5 produce mixed results. They yield insignificant results for state or government ownership and opposite results in the case of deals with government actors. The negative influence of share of deals with government actors exhibits behavior like that of syndication—banks unlikely to increase lending receive support from government actors, potentially in the hope that they will increase their future participation. Whether this is a policy mismatch requires further investigation and is beyond the scope of this research because we cannot comment on the policy goal—whether it is increasing future lending on part of banks who receive government support on deals, or it is to crowd-in investment only on few transactions irrespective of future outcomes.

[5] The two columns for Models (3) and (4) depict the coefficient from the fractional model and the average marginal effect (AME) on the dependent variable with significance of the AME estimated with a two-tailed z-test. The AME allows us to meaningfully interpret the results of the fractional model by explaining the effect on the dependent variable with a one-unit change in the explanatory variable. Only the variable of state or government owned is restricted to a 0 or 1 with 1 indicating that the bank is owned by a state or a government. Therefore, the average change in the case of state or government owned is restricted to two states.

Table 3
Summary statistics (reference period = 6 years), including years when banks do not participate after entry into the technology.

	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Bank Greenfield Market Capacity Share	11722	0.330	0.470	0	0	1	1
Bank Greenfield Market Deal Share	11722	0.330	0.470	0	0	1	1
Bank Brownfield Market Capacity Share	11722	0.003	0.014	0	0	0.001	0.460
Bank Brownfield Market Deal Share	11722	0.003	0.011	0	0	0.002	0.250
Share of Banks' Greenfield Transaction Capacity Syndicated	11722	0.370	0.450	0	0	0.970	1
Share of Banks' Greenfield Deals Syndicated	11722	0.330	0.430	0	0	0.830	1
Bank Diffusion Centrality (to other banks)	11722	0.110	0.260	0	0	0.069	2.800
Bank Sourcing Centrality (from non-financial companies)	11722	0.000	0.001	0	0	0.000	0.067
Bank is State/Government Owned (in time t)	11722	0.140	0.350	0	0	0	1
Share of Bank Transaction Capacity with Government Actors	11722	0.100	0.270	0	0	0	1
Share of Bank Deals with Government Actors	11722	0.094	0.250	0	0	0	1
Mean Eigen Centrality of Bank Borrowers in Year-t	11722	0.019	0.061	0	0	0	0.640
Share of Bank Transaction Capacity in Year-t with Past Borrowers	11722	0.031	0.150	0	0	0	1
Share of Bank Deals in Year-t with Past Borrowers	11722	0.031	0.150	0	0	0	1
Years Since Technology Opening in Market	11722	16.000	5.000	0	12	19	26
Years Since Bank Entry in Technology in Market	11722	5.900	4.600	0	2	9	26

Statistics calculated for individual technologies in global network

Table 4
Summary statistics (reference period = 6 years), excluding years when banks do not participate after entry into the technology.

	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Bank Greenfield Market Capacity Share	3904	0.016	0.046	0	0.001	0.015	1
Bank Greenfield Market Deal Share	3904	0.016	0.042	0.002	0.004	0.014	1
Bank Brownfield Market Capacity Share	3904	0.006	0.019	0	0	0.004	0.410
Bank Brownfield Market Deal Share	3904	0.006	0.016	0	0	0.004	0.250
Share of Banks' Greenfield Transaction Capacity Syndicated	3904	0.380	0.440	0	0	0.900	1
Share of Banks' Greenfield Deals Syndicated	3904	0.310	0.400	0	0	0.670	1
Bank Diffusion Centrality (to other banks)	3904	0.190	0.370	0	0	0.180	2.800
Bank Sourcing Centrality (from non-financial companies)	3904	0.000	0.002	0	0	0.000	0.067
Bank is State/Government Owned (in time t)	3904	0.140	0.350	0	0	0	1
Share of Bank Transaction Capacity with Government Actors	3904	0.099	0.240	0	0	0	1
Share of Bank Deals with Government Actors	3904	0.087	0.220	0	0	0	1
Mean Eigen Centrality of Bank Borrowers in Year-t	3904	0.045	0.087	0	0	0.054	0.640
Share of Bank Transaction Capacity in Year-t with Past Borrowers	3904	0.092	0.260	0	0	0	1
Share of Bank Deals in Year-t with Past Borrowers	3904	0.093	0.250	0	0	0	1
Years Since Technology Opening in Market	3904	14	5	0	11	17	26
Years Since Bank Entry in Technology in Market	3904	4.600	4.900	0	0	8	24

Statistics calculated for individual technologies in global network

4.1.2. Strategies when banks participate

The results from Models (3) and (4) in Table 5 provide the fractional response of those who participate. The result now produces expected directionality, as hypothesized in the case of *brownfield lending* (in capacity share), *syndication*, and *information diffusion* and *information sourcing*. Larger market share in terms of capacity share in brownfield lending results in a subsequent larger market share in greenfield lending. However, merely lending on a higher number of brownfield assets (Model (3)) does not yield any increase in the greenfield deal share. Hence, a bank's brownfield lending on larger assets or lending on many assets with high cumulative capacity increases their ability to lend more for future greenfield assets. This is crucial to subsequently generate information based on asset size, as the risk differs in larger transactions.

Similarly, higher syndication in terms of capacity share also results in a subsequent larger market share in greenfield transactions. The deal share depicts no significance. Since syndication share is calculated for prior greenfield lending, the results suggest that lending on larger assets where bank syndicates lend together results in those syndication banks gaining larger market share with respect to capacity. Thus, banks that gain information and experience on larger assets are consequently able to gain future capacity shares.

The information variables, on the other hand, depict positive and significant effects on deal and capacity share. Higher diffusion centrality, measured as the total time banks hear of another bank, increases the market share of a bank if they are heard more often. The diffusion of one's own information to other banks, as researched, increases the likelihood that a bank will be invited into syndicates by other banks for future lending. The marginal effects, as seen with the AME, are slightly higher at the deal level (Model (3)) than the capacity level (Model (4)). Thus, this strategy is particularly useful in gaining deal share rather than capacity share. In this regard, it is useful for banks to obtain more lending opportunities, even if they involve smaller assets.

Similarly, higher sourcing centrality, measured as the average number of times a bank hears from a potential borrower, also increases the market share of a bank if they heard more often. The marginal effects as seen with the AME are the same at the deal level (Model (3)) and the capacity level (Model (4)), thereby rendering no advantage of lending on larger assets.

Finally, the controls also provide several insights. First, state- or government-owned banks, as hypothesized, lend more and exhibit a larger share once they decide to participate. They present a 0.4 % higher share in deals and a 0.5 % higher share in capacity than privately held banks. Second, the share of deals or capacity with government actors has a negative effect on both deal and capacity share, contrary to expectations. Government actors often co-invest or co-lend with inexperienced banks in the hope that future lending from such banks will occur once they learn from government-led derisking investments. However, our finding suggests one of the two things—either banks that are unlikely to invest in renewable energy assets conduct one-off investments since government support is available, or banks do not manage to learn adequately through past experiences since many of the risks are absorbed by the government actors.

Third, the reputation of the borrower measured with Eigen centrality also exhibits negative significance. This finding indicates that banks lend

Table 5
Static regression results.

	Logit		Fractional Response			
Dependent Var.:	**Bank Greenfield Market Deal Share**	**Bank Greenfield Market Capacity Share**	**Bank Greenfield Market Deal Share**		**Bank Greenfield Market Capacity Share**	
reference_period	**6-year**	**6-year**	**6-year**		**6-year**	
Model #	**(1)**	**(2)**	**(3)**	***ame***	**(4)**	***ame***
Brownfield Lending						
Bank Brownfield Market Deal Share	−3.955		0.015 (1.173)	0		
	(4.642)			(0.017)		
Bank Brownfield Market Capacity Share		−1.687			2.215***	0.033***
		(2.420)			(0.481)	(0.007)
Syndication						
Share of Banks' Greenfield Deals Syndicated	−1.025***		0.056 (0.090)	0.001		
	(0.140)			(0.001)		
Share of Banks' Greenfield Transaction Capacity Syndicated		−0.756***			0.324***	0.005***
		(0.148)			(0.076)	(0.001)
Information Diffusion and Sourcing						
Bank Diffusion Centrality *(to other banks)*	2.206***	2.046***	0.748***	0.011***	0.635***	0.009***
	(0.368)	(0.331)	(0.088)	(0.001)	(0.102)	(0.002)
Bank Sourcing Centrality *(from non-financial companies)*	−54.674	−57.621	62.544**	0.93**	62.518**	0.93**
	(43.351)	(50.087)	(20.444)	(0.311)	(21.734)	(0.329)
Controls						
Bank is State/Government Owned *(in time t)*	−0.015	−0.010	0.253**	0.004**	0.327**	0.005**
	(0.049)	(0.048)	(0.080)	(0.001)	(0.099)	(0.002)
Share of Bank Deals with Government Actors	−0.445**		−0.784***	−0.012***		
	(0.157)		(0.200)	(0.003)		
Share of Bank Transaction Capacity with Government Actors		−0.429***			−0.982***	−0.015***
		(0.127)			(0.212)	(0.003)
Mean Eigen Centrality of Bank Borrowers in Year-t	12.513***	12.395***	−1.634***	−0.024***	−1.929***	−0.029***
	(2.032)	(1.980)	(0.410)	(0.006)	(0.491)	(0.007)
Share of Bank Deals in Year-t with Past Borrowers	244.957***		0.267**	0.004***		
	(8.482)		(0.081)	(0.001)		
Share of Bank Transaction Capacity in Year-t with Past Borrowers		2065.814***			0.177	0.003.
		(68.861)			(0.106)	(0.002)
Fixed-Effects:						
Year of Close	Yes	Yes	Yes		Yes	
Technology	Yes	Yes	Yes		Yes	
S.E.: Clustered	by: Year of Close	by: Year of Close	by: Year of Close		by: Year of Close	
Observations	11718	11718	3903		3903	
RMSE	0.40264	0.40444	0.02524		0.03206	
Pseudo R2	0.22285	0.21618				

Signif. codes:'***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
ame = average marginal effects

to less-reputed borrowers to increase their market share. This is a result of the growing renewable energy market, where new entrants with low reputations demand bank credit and banks without many alternate options lend to such new entrants. Fourth, shares of deals with past borrowers show positive significance. This result is as expected; it suggests that banks lend to known borrowers. However, the dynamics of new entrants and relationship lending are temporal. We discuss these in the dynamic analysis next.

4.2. Dynamic results

In the dynamic analysis, we present the fractional model (part 2 of all regressions) of our analysis for the banks that participate in lending. The logit results are provided in Appendix E, Tables E2–E3. The outcomes of the logit results are discussed when relevant and dissimilar to those found in the static results. Additionally, only results of the 6-year reference period are discussed in the main manuscript, but results with 3-years and 9-years reference period are provided in tables E4, E5, E6 and E7 in Appendix E. Different reference periods are analyzed to address the potential of reverse causality wherein strategy and success co-evolve. This is banks select a strategy because of their recent success with that strategy. Overall, we find our results remain robust.

We divide our analysis along the two, time variables. First, we study the time since technology opening or when the technology is mature. In this case, we study variance in the time needed for the technology to mature. Second, we study the time since bank entry. In this case, we distinguish between the behavior of banks by when they enter a technology, that is, before or after the technology is mature.

4.2.1. Variance in technology maturity

Table 6 depicts the analysis with 6-years reference period for data for transactions that occurred within 5 years, 10 years, and 15 years of technology opening globally, that is, from the first technology transaction in our database. Models (1) to (3) depict the results for market share calculated using deal share, and Models (4) to (6) depict the results using capacity share.

In the case of *brownfield lending*, the results are mostly in line with the static results. Overall, lending on larger assets or lending on many assets with high cumulative capacity increases a bank's greenfield capacity share. However, we also find two differences. First, increasing deal share in brownfield lending results in higher greenfield deal share for the 10-year period (Model (2)), though the effect is also present for 5-year period if we use reference period as 3 years (see Table E4 in Appendix E). Second, the AME for brownfield lending decreases over time in the case of capacity share (Models (4), (5), (6)). The second difference indicates a rapid increase in the asset size of a technology during its growth phase, which prompts lenders to gather information on larger assets that reflect the risk of future lending opportunities.

Next, *syndication* exhibits a positive influence for both deal share and capacity share. This departs from the static findings, where deal share

Table 6
Partial fractional response models by technology with variations in years since technology opening.

Dependent Var.:	Bank Greenfield Market Deal Share						Bank Greenfield Market Capacity Share					
reference_period	**6-year**		**6-year**		**6-year**		**6-year**		**6-year**		**6-year**	
Time Since Technology Opening	**5-year**		**10-year**		**15-year**		**5-year**		**10-year**		**15-year**	
model #	**(1)**	***ame***	**(2)**	***ame***	**(3)**	***ame***	**(4)**	***ame***	**(5)**	***ame***	**(6)**	***ame***
Brownfield Lending												
Bank Brownfield Market Deal Share	2.996	0.307	3.228**	0.049***	0.755	0.01 (0.013)						
	(2.028)	(0.208)	(0.862)	(0.014)	(0.974)							
Bank Brownfield Market Capacity Share							2.320**	0.238**	2.842***	0.043***	2.170***	0.028***
							(0.729)	(0.074)	(0.567)	(0.009)	(0.564)	(0.007)
Syndication												
Share of Banks' Greenfield Deals Syndicated	0.824.	0.084*	0.377*	0.006*	0.243*	0.003*						
	(0.409)	(0.042)	(0.157)	(0.002)	(0.095)	(0.001)						
Share of Banks' Greenfield Transaction Capacity Syndicated							0.716*	0.074*	0.519**	0.008**	0.420***	0.005***
							(0.307)	(0.032)	(0.156)	(0.003)	(0.099)	(0.001)
Information Diffusion and Sourcing												
Bank Diffusion Centrality *(to other banks)*	0.172	0.018	0.005	0 (0.002)	0.382**	0.005***	0.359*	0.037**	0.259	0.004	0.380**	0.005**
	(0.210)	(0.021)	(0.150)		(0.102)	(0.001)	(0.138)	(0.014)	(0.194)	(0.003)	(0.118)	(0.002)
Bank Sourcing Centrality *(from non-financial companies)*	19.522**	1.998***	39.479*	0.601**	49.562*	0.64* (0.255)	12.785*	1.313**	37.752*	0.574*	49.586*	0.64* (0.266)
	(4.313)	(0.447)	(15.300)	(0.228)	(19.894)		(4.242)	(0.442)	(16.360)	(0.241)	(20.982)	
Controls												
Bank is State/Government Owned *(in time t)*	0.289	0.03 (0.023)	0.214.	0.003.	0.176.	0.002.	0.422	0.044	0.180	0.003	0.216.	0.003.
	(0.220)		(0.114)	(0.002)	(0.094)	(0.001)	(0.255)	(0.027)	(0.141)	(0.002)	(0.116)	(0.002)
Share of Bank Deals with Government Actors	−1.376*	−0.141**	−0.710**	−0.011**	−0.642**	−0.008***						
	(0.486)	(0.05)	(0.228)	(0.004)	(0.178)	(0.002)						
Share of Bank Transaction Capacity with Government Actors							−1.337**	−0.137**	−0.915**	−0.014**	−0.974***	−0.013***
							(0.406)	(0.042)	(0.277)	(0.004)	(0.207)	(0.003)
Mean Eigen Centrality of Bank Borrowers in Year-t	−2.149.	−0.22.	−0.382	−0.006	−0.449	−0.006	−2.349*	−0.241*	−0.411	−0.006	−0.921	−0.012
	(1.126)	(0.115)	(0.754)	(0.011)	(0.505)	(0.006)	(0.927)	(0.095)	(0.940)	(0.014)	(0.654)	(0.008)
Share of Bank Deals in Year-t with Past Borrowers	1.040	0.106	0.546**	0.008***	0.302**	0.004**						
	(0.646)	(0.066)	(0.153)	(0.002)	(0.105)	(0.001)						
Share of Bank Transaction Capacity in Year-t with Past Borrowers							0.960*	0.099*	0.301	0.005	0.268.	0.003.
							(0.370)	(0.038)	(0.248)	(0.004)	(0.149)	(0.002)
Fixed-Effects:												
Year of Close	Yes		Yes		Yes		Yes		Yes		Yes	
Technology	Yes		Yes		Yes		Yes		Yes		Yes	
S.E.: Clustered	by: Year of Close		by: Year of Close		by: Year of Close		by: Year of Close		by: Year of Close		by: Year of Close	
Observations	163		938		2350		163		938		2350	
RMSE	0.0388		0.02881		0.02499		0.0723		0.04428		0.03467	

Signif. codes:'***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
ame = average marginal effects

effects of syndication were not significant. Furthermore, the AME of higher syndication decreased in both cases over time. This indicates that syndication is a means of gathering information and derisking investments to gain confidence, especially early on, when technology risks are high. The same decreasing trend is also observed in the coefficients of the logit models in Table E2 in Appendix E, which explains whether the strategies induce bank participation. However, as found in the static logit analysis, syndication in Table E2 also does not induce participation, but the negative influence decreases with time. Those who syndicate are unlikely to participate again, but they are likely to not participate in earlier years.

Next, *information diffusion* is not as beneficial as found in the static analysis. The effects gain significance only in year 15 (Models (3) and (6)), although information diffusion to other banks is positively significant in the case of capacity share in Model (4). This is potentially because networks are not well developed in early years, as seen by the low number of banks in Fig. 5. Also, networks are also likely to be influenced by brownfield transactions. Accordingly, we include interaction between brownfield lending and diffusion centrality in Appendix E, table E11 where significance of strategies holds but with weaker significance. Thus, diffusing information to a small set of lenders potentially helps attain near-term, larger opportunities for those banks in the market. However, given the higher AME in the static analysis, diffusion is seen to be beneficial in years beyond year 15 of the technology when banking networks become well established.

Last, *information sourcing* from borrowers remains significant as found in the static analysis but depicts higher AME during the 5-year analysis period (Models (1) and (4)) and lower AME subsequently than the AME in the static analysis. This has two outcomes. First, information sourcing is more important in the first 5 years than in the first 10 and 15 years, respectively. This is likely because of the disproportionately higher number of borrowers, as seen in Fig. 5. Second, information sourcing gains importance after year 15 in our data (due to the higher AME of the complete dataset in the static analysis).

Among the controls, the evident difference is in the behavior of state- or government-owned banks, which exhibit weak significance for years 10 and 15 and none for year 5, unlike in the static analysis (Table 4). Even the logit results for the same in Table E2 in Appendix E suggest that state- or government-owned banks participate once the technology is 10 or 15 years old. Thus, once they participate, they lend to larger projects.

4.2.2. *Variance in bank entry*

As in the previous sections, Table 7 shows analyses for time since technology entry for banks. In this case, we discuss three possibilities. First, both the technology and banks are new. Second, the technology is not new or mature, but the bank is new, and third, both the technology and bank are not new. In Table 7, we take Models (2) and (5) from Table 6 as the base case for this analysis. Accordingly, the time since technology opening is fixed to 10 years, and the time since bank opening varies.

In the case of *brownfield lending* as a strategy, the results are consistent with respect to the capacity share analysis vis-à-vis the static results. Overall, lending on larger assets or lending on many assets with high cumulative capacity increases a bank's greenfield capacity share. However, the results are positively significant with respect to deal share (Models (1) and (3), Table 7). Those banks who lend on brownfield assets of a technology early (tech <10, bank <10) and remain as lenders to such brownfield assets (tech >10, bank >10) also increase their deal share in greenfield assets in the future. Furthermore, banks who join late (tech >10, bank <10) manage to increase their capacity share with lending on higher capacity brownfield assets only.

With respect to *syndication*, the results differ substantially. First, banks gain from syndication with respect to deal share and capacity share if they are early to the technology (tech <10, bank <10). This conforms with the early-stage strategy of gathering information via syndicates and reducing risk exposure. However, these early banks who stick around lose deal share if they continue to syndicate in later years (tech >10, bank >10; Model (3)). This reflects the potential loss of the dominant position of lead banks with experience in case they decide to syndicate and share their knowledge with other banks. On the other hand, banks who enter late ((tech >10, bank <10) increase their capacity share by syndicating on larger capacity assets. They do not exhibit any significant increase or decrease from syndicating on more deals.

Next, *information diffusion* to other banks is positively significant only once the technology is mature or a large enough banking network is formed (see Fig. 5). Thus, banks who enter early and stick around, or those who enter late to the technology, benefit from diffusing information to other banks to access future greenfield lending opportunities. Finally, *information sourcing from borrowers* plays a positively significant role in the early years when the technology is new, and so is the bank (Models (1) and (4)). This is a corollary of banks depending on information sourced from borrowers rather than from other banks or via other strategies. Furthermore, information sourcing from borrowers negatively affects capacity share among those banks who enter the technology late or once it is mature (tech >10, bank <10). In the absence of strong bank networks, lenders may rely on sourcing information from borrowers, but once bank networks are developed, sourcing higher information from borrowers may not yield benefits. This conforms with recent research that suggests that diffusing information to banking networks is crucial for banks to gain market share (Alperovych et al., 2022), albeit we recognize that higher information flow may stem from past success and reinforce a bank's information centrality.

Among the controls, state- or government-owned banks display positive and significant results for periods when the technology is not

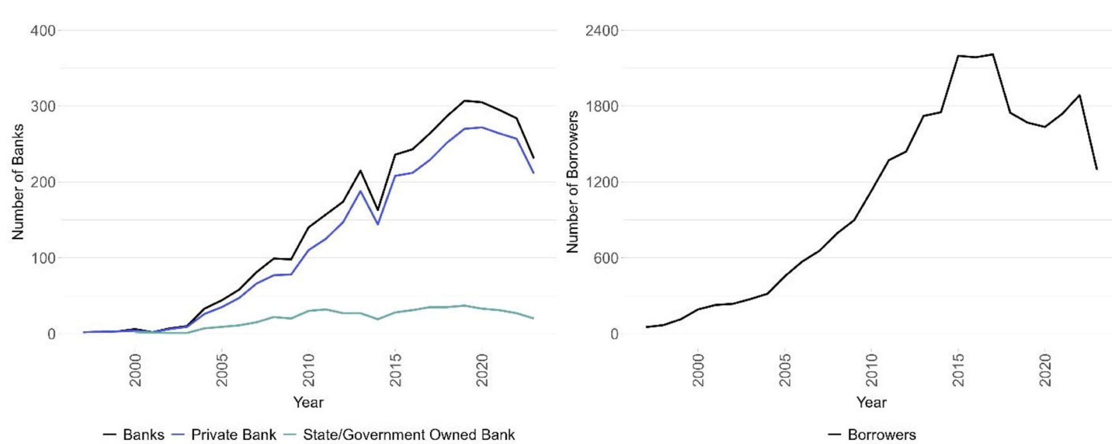


Fig. 5. Number of banks and other firms participating each year.

Table 7
Partial fractional response models by technology with variations in years since bank entry.

Dependent Var.:	**Bank Greenfield Market Deal Share**						**Bank Greenfield Market Capacity Share**					
reference_period	**6-year**		**6-year**		**6-year**		**6-year**		**6-year**		**6-year**	
Time Since Technology Opening	**< =10-year**		**> 10-year**		**> 10-year**		**< =10-year**		**> 10-year**		**> 10-year**	
Time Since Bank Entry	**< =10-year**		**< =10-year**		**> 10-year**		**< =10-year**		**< =10-year**		**> 10-year**	
model #	**(1)**		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**	
		ame		***ame***		***ame***		***ame***		***ame***		***ame***
Brownfield Lending												
Bank Brownfield Market Deal Share	3.228**	0.049***	4.791	0.047	14.869***	0.201***						
	(0.862)	(0.014)	(2.881)	(0.029)	(2.916)	(0.036)						
Bank Brownfield Market Capacity Share							2.842***	0.043***	5.403* (2.042)	0.053*	10.132***	0.142***
							(0.567)	(0.009)		(0.021)	(1.877)	(0.031)
Syndication												
Share of Banks' Greenfield Deals Syndicated	0.377*	0.006*	0.044	0 (0.001)	−0.332.	−0.004*						
	(0.157)	(0.002)	(0.058)		(0.161)	(0.002)						
Share of Banks' Greenfield Transaction Capacity Syndicated							0.519**	0.008**	0.339**	0.003**	0.182 (0.150)	0.003
							(0.156)	(0.003)	(0.087)	(0.001)		(0.002)
Information Diffusion and Sourcing												
Bank Diffusion Centrality *(to other banks)*	0.005	0 (0.002)	0.666***	0.007***	0.443***	0.006***	0.259	0.004	0.739***	0.007***	0.472*	0.007**
	(0.150)		(0.146)	(0.001)	(0.081)	(0.001)	(0.194)	(0.003)	(0.176)	(0.002)	(0.203)	(0.002)
Bank Sourcing Centrality *(from non-financial companies)*	39.479*	0.601**	−96.300	−0.954	161.266	2.18 (2.016)	37.752*	0.574*	−251.036.	−2.446*	139.995	1.966
	(15.300)	(0.228)	(86.986)	(0.828)	(147.931)		(16.360)	(0.241)	(119.304)	(1.145)	(282.726)	(4.177)
Controls												
Bank is State/Government Owned *(in time t)*	0.214.	0.003.	0.213**	0.002**	0.417***	0.006***	0.180	0.003	0.387* (0.178)	0.004.	0.622***	0.011***
	(0.114)	(0.002)	(0.059)	(0.001)	(0.045)	(0.001)	(0.141)	(0.002)		(0.002)	(0.100)	(0.002)
Share of Bank Deals with Government Actors	−0.710**	−0.011**	0.006	0 (0.001)	−0.386*	−0.005*						
	(0.228)	(0.004)	(0.123)		(0.149)	(0.002)						
Share of Bank Transaction Capacity with Government Actors							−0.915**	−0.014**	−0.429*	−0.004*	−0.162	−0.002
							(0.277)	(0.004)	(0.185)	(0.002)	(0.239)	(0.003)
Mean Eigen Centrality of Bank Borrowers in Year-t	−0.382	−0.006	−0.443	−0.004	−0.787	−0.011	−0.411	−0.006	−1.122.	−0.011.	−0.297	−0.004
	(0.754)	(0.011)	(0.520)	(0.005)	(0.746)	(0.01)	(0.940)	(0.014)	(0.627)	(0.006)	(0.734)	(0.01)
Share of Bank Deals in Year-t with Past Borrowers	0.546**	0.008***	0.143*	0.001*	−0.052	−0.001						
	(0.153)	(0.002)	(0.063)	(0.001)	(0.159)	(0.002)						
Share of Bank Transaction Capacity in Year-t with Past Borrowers							0.301	0.005	0.242. (0.117)	0.002*	−0.257.	−0.004.
							(0.248)	(0.004)		(0.001)	(0.131)	(0.002)
Fixed-Effects:												
Year of Close	Yes		Yes		Yes		Yes		Yes		Yes	
Technology	Yes		Yes		Yes		Yes		Yes		Yes	
S.E.: Clustered	by: Year of Close		by: Year of Close		by: Year of Close		by: Year of Close		by: Year of Close		by: Year of Close	
Observations	938		2408		557		938		2408		557	
RMSE	0.02881		0.0093		0.01649		0.04428		0.01652		0.01825	

Signif. codes:'***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
ame = average marginal effects

new (tech > 10). State- or government-owned banks also show positive and weak significance with respect to deal share in Model (1). This suggests that publicly owned banks are likely to invest more than other banks, especially once the technology is not new, although those with higher experience with the technology (Tech >10, Bank >10) are seen to gain higher market share. This is also possibly because many government-led renewable energy targets were formulated after the year 2015 (Paris Agreement), a period represented mostly by "Tech > 10" in our regression models.

The share of deals or capacity with government actors exhibits a negatively significant influence when the technology and banks are new. It also exhibits a negatively significant influence on the deal share of banks that have been around in the technology for a long time ((tech >10, bank >10) and on the capacity share of banks that are new when the technology is not (tech >10, bank <10). Last, share of deals or capacity with past borrowers, a measure of relationships with borrowers, now exhibits a positive and significant impact on deal share when banks and technology are new and on deal and capacity share when banks are new, but technology is not. Hence, finding a borrower and lending to it indeed plays an important role during the early stages of a technology. It loses its significance once many other borrowers enter the market and become potential avenues of profit for banks.

5. Discussion of results

The examination of the three strategies reveals that banks apply a mix of strategies to gain confidence in a technology asset through the technology's maturity or lifecycle. The strategies also vary with a bank's experience with the technology. However, each strategy has its own specific use case with respect to lending on project-financed assets.

The strategy of *brownfield lending* is unique to project-financed assets. The strategy assumes that risks in the post-construction or operator phase are more important to understand than other risks since the lent amount is to be repaid during operations. Our results partially support this assumption. Higher brownfield lending is positively linked to the higher greenfield capacity share in the static results and higher greenfield capacity share in the early years of technology opening in the dynamic results. This conforms with the unique case of the three technologies that have increased in their transaction size with technology maturity. Thus, brownfield lending for higher-capacity assets or numerous assets of higher cumulative capacity prepares lenders to lend for larger greenfield assets that increase in size with time.

However, brownfield lending does not prepare banks to lend on a larger number of assets in our data, as the greenfield deal share does not have a significant effect. This result is corroborated by the finding that brownfield lending is also not an indicator of bank participation. It only has an effect once a bank decides to participate. This behavior is particularly pronounced in the case of banks that enter early when a technology is new. In this case they also benefit in terms of deal share in addition to capacity share. Thus, in this period of high uncertainty, the information gained about the performance of the technology through any number and capacity of brownfield assets is useful in gathering confidence in riskier greenfield assets. The strategy also works for early bank entrants after the technology is mature. However, the use is to expand market dominance rather than learn about the technology's risks. On the other hand, banks that enter after the technology is mature benefit less from brownfield lending (only regarding increasing greenfield capacity share), as there is already a large asset size achieved in individual transactions by the time the technology matures.

The strategy of *syndication,* unlike brownfield lending, is common in bank lending more broadly. Syndication is practiced to reduce investment risks and exchange information between lenders (Casamatta & Haritchabalet, 2007; Dennis & Mullineaux, 2000; Meuleman et al., 2009). It is also practiced by inexperienced banks to enter a new area of lending on the backs of experienced lenders. In theory, syndication is expected to transmit information about the new technology so that banks can enter and lend more in the future. However, in our analysis, syndication has a negative effect on the likelihood of participating, but once banks decide to participate, syndication has a positive impact on future greenfield market share measured by capacity share, as seen in the static analysis. The impact on deal share is found to be insignificant. The results indicate that banks syndicate on larger capacity assets where the participating banks can benefit from reduced risk. The result is congruent with what we already know from private equity syndication literature (Ivashina & Scharfstein, 2010).

In the dynamic analysis, the influence of syndication is like brownfield lending. It is significant and positive for both deal and capacity share when the technology is new. Furthermore, early entrant banks gain in terms of greenfield deal share and capacity share. However, they do not benefit if they continue to syndicate once the technology is mature. Furthermore, banks that enter late gain in capacity share. The implication of these findings is that early entrant banks enjoy increased capacity by syndicating when they must gather information on technology risks to reduce information asymmetry between lenders and borrowers (Berger & Dick, 2007). Banks who enter the technology late use syndication on large asset lending to claw market share away from incumbents.

The strategies of *information diffusion and sourcing* are practiced to make a bank known in the lending network and to source information on the technology risks and lending opportunities from potential borrowers, respectively. The diffusion of information to other banks increases participation, although the result reflects participation from information diffusion in later years once the banking network has adequately evolved. In contrast, sourcing information from borrowers has no effect on bank participation. Both information diffusion and sourcing aid in increasing market share measured by deal share or capacity share once banks decide to participate in the static analysis. However, the two information strategies differ fundamentally in their timing. Information diffusion to other banks is positive and significant in the later years of the technology. This includes the 15-year period in Table 6 and the two models in Table 7 when the time since technology opening is greater than 10 years. This is a corollary of the strength of the bank network and the number of banks there are in any given year. On the other hand, information sourcing from borrowers is positive and significant in the early years of the technology when there are few banks in the network, and banks must rely on borrowers to develop an understanding of technology risks.

6. Conclusion

Our research departs from prior studies, taking a static perspective and distinguishes between the strategies applied by banks to gain market share in project-financed new technology lending. It finds that in the absence of strong bank networks in a technology's early years, brownfield lending, syndication, and information sourcing from borrowers are viable strategies to increase market share. Over time, as bank networks are formed, which strategies are deployed depends on how long a bank has been in the technology. If the bank was an early entrant and remained a lender once a technology is mature, brownfield lending and information diffusion are viable strategies. The two strategies work to shore up the reputation of the bank, to the detriment of imparting information on technological risks. If a bank is a late entrant, then information diffusion is useful for accessing a larger number of opportunities, but brownfield lending, syndication, and information diffusion are useful for increasing capacity share. As a result, those who enter late must significantly risk more capital and be well connected in the banking system to gain a position in the new technology.

The main contribution of this work is that we identify the extent to which early entrants rely on borrowers rather than on lenders when lending networks are weak. In such situations, they syndicate to reduce their risks. This finding expands on existing works that analyze bank behavior under established banking conditions (Alperovych et al., 2022;

Ivashina & Scharfstein, 2010). Hence, the result underscores the need for bank managers to develop early borrower relationships, especially in emerging technologies where indirect introduction to borrowers via private equity or venture capital may not be possible (Ivashina & Kovner, 2011; Kerr & Nanda, 2015b). In such a case, policies could be implemented to create strong networks between borrowers (i.e., the technology innovators) and banks, albeit with aims at improving information disclosure by borrowers to increase information disclosure (Chava et al., 2017; Hoffmann et al., 2019; Saidi & Žaldokas, 2021). A swift exchange of information when bank networks are underdeveloped is necessary to accelerate lending for a technology.

Our further contributions stem from the controls that we examine in studying the three strategies. First, banks owned by governments are found to lend more (higher market share as measured by deal share and capacity share) than private banks, particularly once the technology is mature. This suggests that policymakers can use government- or state-owned banks to promote social policy through technologies reliant on external credit. However, their ability to enforce this policy agenda must be researched to avoid compromising banks' commercial interests (Steffen et al., 2022) or crowding out private lending. Second, banks with a higher share of deals or capacity with government actors do not extend their banking activities to gain market share or lend more to technology assets. The government actors in our analysis include state investment banks and government agencies that are driven to crowd in lending on technology assets (Geddes et al., 2020; Mazzucato & Semieniuk, 2017; Waidelich & Steffen, 2024). The underwhelming magnitude of our results suggests that government actors are either selecting the wrong banks or are deliberately targeting first-time or niche banks with a lower risk appetite to induce technological learning and risk taking among those unlikely to do so without government support.

Finally, our study also opens avenues for future research. Future analysis can incorporate balance sheet information of banks and privately held companies. Poor reporting of this information currently forces us to rely on endogenous proxy variables to interpret controls such as borrower reputation. As a result, we are also limited in our ability to explain what motivates banks to participate, especially in the early years, because of the inconclusive results of the logit models. We are also limited by the potential of endogeneity in information centralities since they rely on construction of a networks that might themselves stem from past successes of a bank.

Furthermore, with higher reporting, future analyses can also incorporate the role of equipment suppliers and other actors not investing in the assets but crucial for constructing and operating the assets. Such analysis may provide further nuance on bank decision making, especially with respect to lending for physical infrastructure assets. Finally, future work could also examine bank behavior in local context and compare the behavior to the global patterns while incorporating deals that may have been terminated to overcome survivorship bias or analyze the behavior or large globally connected banks that benefit from larger networks than smaller banks. Research in this direction is needed to address the idiosyncratic behavior of many banks that lend only a few times to technology projects.

CRediT authorship contribution statement

Bjarne Steffen: Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Anurag Gumber:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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Declaration of Competing Interest

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jclimf.2025.100073.

Data availability

The empirical results of this work are based on data procured from third-party data service providers, namely Bloomberg Finance L.P. Authors are not authorized to share data. The code to replicate the results is provided at this link: https://data.mendeley.com/datasets/df5zf9jhgs/2.

References

Ahmed, J. U.-d (2010). Priority sector lending by commercial banks in India: A case of barak valley. *Asian Journal of Finance Accounting, 2*(1), 92–110.

Alperovych, Y., Divakaruni, A., & Manigart, S. (2022). Lending when relationships are scarce: The role of information spread via bank networks. *Journal of Corporate Finance, 73*, Article 102181. https://doi.org/10.1016/j.jcorpfin.2022.102181

Amore, M. D., Schneider, C., & Žaldokas, A. (2013). Credit supply and corporate innovation. *Journal of Financial Economics, 109*(3), 835–855. https://doi.org/10.1016/j.jfineco.2013.04.006

Amuakwa-Mensah, F., & Näsström, E. (2022). Role of banking sector performance in renewable energy consumption. *Applied Energy, 306*, Article 118023. https://doi.org/10.1016/j.apenergy.2021.118023

Anderson, P., & Tushman, M. L. (2018). Technological discontinuities and dominant designs: A cyclical model of technological change. *In Organizational innovation* (pp. 373–402). Routledge.

Andersson, J., Perez Vico, E., Hammar, L., & Sandén, B. A. (2017). The critical role of informed political direction for advancing technology: The case of Swedish marine energy. *Energy Policy, 101*, 52–64. https://doi.org/10.1016/j.enpol.2016.11.032

Banerjee, A., Chandrasekhar, A. G., Duflo, E., & Jackson, M. O. (2013). The diffusion of microfinance. *Science, 341*(6144), Article 1236498. https://doi.org/10.1126/science.1236498

Banerjee, A., Chandrasekhar, A. G., Duflo, E., & Jackson, M. O. (2019). Using gossips to spread information: Theory and evidence from two randomized controlled trials. *The Review of Economic Studies, 86*(6), 2453–2490.

Benfratello, L., Schiantarelli, F., & Sembenelli, A. (2008). Banks and innovation: Microeconometric evidence on Italian firms. *Journal of Financial Economics, 90*(2), 197–217. https://doi.org/10.1016/j.jfineco.2008.01.001

Bento, N., & Fontes, M. (2015). Spatial diffusion and the formation of a technological innovation system in the receiving country: The case of wind energy in Portugal. *Environmental Innovation and Societal Transitions, 15*, 158–179. https://doi.org/10.1016/j.eist.2014.10.003

Bento, N., & Fontes, M. (2019). Emergence of floating offshore wind energy: Technology and industry. *Renewable and Sustainable Energy Reviews, 99*, 66–82. https://doi.org/10.1016/j.rser.2018.09.035

Bergek, A., Hekkert, M., Jacobsson, S., Markard, J., Sandén, B., & Truffer, B. (2015). Technological innovation systems in contexts: Conceptualizing contextual structures and interaction dynamics. *Environmental Innovation and Societal Transitions, 16*, 51–64. https://doi.org/10.1016/j.eist.2015.07.003

Bergek, A., Jacobsson, S., Carlsson, B., Lindmark, S., & Rickne, A. (2008). Analyzing the functional dynamics of technological innovation systems: A scheme of analysis. *Research Policy, 37*(3), 407–429. https://doi.org/10.1016/j.respol.2007.12.003

Berger, A. N., & Dick, A. A. (2007). Entry into banking markets and the Early-Mover advantage. *Journal of Money, Credit and Banking, 39*(4), 775–807. https://doi.org/10.1111/j.1538-4616.2007.00046.x

Bharath, S., Dahiya, S., Saunders, A., & Srinivasan, A. (2007). So what do I get? The bank's view of lending relationships. *Journal of Financial Economics, 85*(2), 368–419. https://doi.org/10.1016/j.jfineco.2005.08.003

BloombergNEF. (2024a). *Organizations Data*. ⟨https://www.bnef.com/data-and-tools⟩.

BloombergNEF. (2024b). *Renewable Assets*. ⟨https://www.bnef.com/data-and-tools⟩.

Bofondi, M., & Gobbi, G. (2006). Informational barriers to entry into credit markets. *Review of Finance, 10*(1), 39–67. https://doi.org/10.1007/s10679-006-6978-2
Bolton, P., & Kacperczyk, M. (2023). Global pricing of Carbon-Transition risk. *The Journal of Finance, 78*(6), 3677–3754. https://doi.org/10.1111/jofi.13272
Boot, A. W. A. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation, 9*(1), 7–25. https://doi.org/10.1006/jfin.2000.0282
Böttcher, J. (2020). *Green banking: Realizing renewable energy projects*. De Gruyter Oldenbourg. https://doi.org/10.1515/9783110607888
Bruche, M., Malherbe, F., & Meisenzahl, R. R. (2020). Pipeline risk in leveraged loan syndication. *The Review of Financial Studies, 33*(12), 5660–5705. https://doi.org/10.1093/rfs/hhaa029
Casamatta, C., & Haritchabalet, C. (2007). Experience, screening and syndication in venture capital investments. *Journal of Financial Intermediation, 16*(3), 368–398. https://doi.org/10.1016/j.jfi.2007.03.003
Chava, S., Nanda, V., & Xiao, S. C. (2017). Lending to innovative firms. *The Review of Corporate Finance Studies, 6*(2), 234–289. https://doi.org/10.1093/rcfs/cfx016
Crawford, G. S., Pavanini, N., & Schivardi, F. (2018). Asymmetric information and imperfect competition in lending markets. *American Economic Review, 108*(7), 1659–1701.
Curtin, J., McInerney, C., Ó Gallachóir, B., Hickey, C., Deane, P., & Deeney, P. (2019). Quantifying stranding risk for fossil fuel assets and implications for renewable energy investment: A review of the literature. *Renewable and Sustainable Energy Reviews, 116*, Article 109402. https://doi.org/10.1016/j.rser.2019.109402
Degl'Innocenti, M., Frigerio, M., & Zhou, S. (2022). Development banks and the syndicate structure: Evidence from a world sample. *Journal of Empirical Finance, 66*, 99–120. https://doi.org/10.1016/j.jempfin.2022.01.002
Degryse, H., & Van Cayseele, P. (2000). Relationship lending within a Bank-Based system: Evidence from european small business data. *Journal of Financial Intermediation, 9*(1), 90–109. https://doi.org/10.1006/jfin.1999.0278
Deleidi, M., Mazzucato, M., & Semieniuk, G. (2020). Neither crowding in nor out: Public direct investment mobilising private investment into renewable electricity projects. *Energy Policy, 140*, Article 111195. https://doi.org/10.1016/j.enpol.2019.111195
Dell'Ariccia, G., & Marquez, R. (2004). Information and bank credit allocation. *Journal of Financial Economics, 72*(1), 185–214. https://doi.org/10.1016/S0304-405X(03)00210-1
Dennis, S. A., & Mullineaux, D. J. (2000). Syndicated loans. *Journal of Financial Intermediation, 9*(4), 404–426. https://doi.org/10.1006/jfin.2000.0298
Đukan, M., Gumber, A., Egli, F., & Steffen, B. (2023). The role of policies in reducing the cost of capital for offshore wind. *iScience, 26*(6), Article 106945. https://doi.org/10.1016/j.isci.2023.106945
Edler, J., & Georghiou, L. (2007). Public procurement and innovation—Resurrecting the demand side. *Research Policy, 36*(7), 949–963. https://doi.org/10.1016/j.respol.2007.03.003
Edler, J., & Yeow, J. (2016). Connecting demand and supply: The role of intermediation in public procurement of innovation. *Research Policy, 45*(2), 414–426. https://doi.org/10.1016/j.respol.2015.10.010
Egli, F., Steffen, B., & Schmidt, T. (2018). A dynamic analysis of financing conditions for renewable energy technologies. *Nature Energy, 3*(12), 1084–1092. https://doi.org/10.1038/s41560-018-0277-y
Engelberg, J., Gao, P., & Parsons, C. A. (2012). Friends with money. *Journal of Financial Economics, 103*(1), 169–188.
Geddes, A., Schmid, N., Schmidt, T. S., & Steffen, B. (2020). The politics of climate finance: Consensus and partisanship in designing Green state investment banks in the United Kingdom and Australia. *Energy Research Social Science, 69*, Article 101583. https://doi.org/10.1016/j.erss.2020.101583
Geddes, A., & Schmidt, T. S. (2020). Integrating finance into the multi-level perspective: Technology niche-finance regime interactions and financial policy interventions. *Research Policy, 49*(6), Article 103985. https://doi.org/10.1016/j.respol.2020.103985
Geddes, A., Schmidt, T. S., & Steffen, B. (2018). The multiple roles of state investment banks in low-carbon energy finance: An analysis of Australia, the UK and Germany. *Energy Policy, 115*, 158–170. https://doi.org/10.1016/j.enpol.2018.01.009
Geroski, P. A. (2000). Models of technology diffusion. *Research Policy, 29*(4), 603–625. https://doi.org/10.1016/S0048-7333(99)00092-X
Greig, C., Keto, D., Hobart, S., Finch, B., & Winkler, R. (2023). Speeding up risk capital allocation to deliver net-zero ambitions. *Joule, 7*(2), 239–243.
Grosvenor Clive & Stokes (2019). *Internal Report to InfraCo Africa*. ⟨https://www.pidg.org/wp-content/uploads/2019/07/Head-of-Business-Development-Profile.pdf⟩.
Gumber, A., Egli, F., & Steffen, B. (2024). *Technology innovation and financial development: Measuring the financial maturity of renewable energy technologies*. Available at SSRN 5068405.
Gumber, A., Zana, R., & Steffen, B. (2024). A global analysis of renewable energy project commissioning timelines. *Applied Energy, 358*, Article 122563. https://doi.org/10.1016/j.apenergy.2023.122563
Gurara, D., Presbitero, A., & Sarmiento, M. (2020). Borrowing costs and the role of multilateral development banks: Evidence from cross-border syndicated bank lending. *Journal of International Money and Finance, 100*, Article 102090. https://doi.org/10.1016/j.jimonfin.2019.102090
Hellmann, T., Lindsey, L., & Puri, M. (2007). Building relationships early: Banks in venture capital. *The Review of Financial Studies, 21*(2), 513–541. https://doi.org/10.1093/rfs/hhm080
Hoffmann, A. O. I., & Kleimeier, S. (2021). Financial disclosure readability and innovative firms' cost of debt. *International Review of Finance, 21*(2), 699–713. https://doi.org/10.1111/irfi.12292
Hoffmann, A. O. I., Kleimeier, S., Mimiroglu, N., & Pennings, J. M. E. (2019). The American inventors protection act: A natural experiment on innovation disclosure and the cost of debt. *International Review of Finance, 19*(3), 641–651. https://doi.org/10.1111/irfi.12174
Hombert, J., & Matray, A. (2016). The real effects of lending relationships on innovative firms and inventor mobility. *The Review of Financial Studies, 30*(7), 2413–2445. https://doi.org/10.1093/rfs/hhw069
Höwer, D. (2016). The role of bank relationships when firms are financially distressed. *Journal of Banking Finance, 65*, 59–75. https://doi.org/10.1016/j.jbankfin.2016.01.002
Hsu, P.-H., Tian, X., & Xu, Y. (2014). Financial development and innovation: Cross-country evidence. *Journal of Financial Economics, 112*(1), 116–135. https://doi.org/10.1016/j.jfineco.2013.12.002
Ivashina, V. (2009). Asymmetric information effects on loan spreads. *Journal of Financial Economics, 92*(2), 300–319. https://doi.org/10.1016/j.jfineco.2008.06.003
Ivashina, V., & Kovner, A. (2011). The private equity advantage: Leveraged buyout firms and relationship banking. *The Review of Financial Studies, 24*(7), 2462–2498. https://doi.org/10.1093/rfs/hhr024
Ivashina, V., & Scharfstein, D. (2010). Loan syndication and credit cycles. *American Economic Review, 100*(2), 57–61. https://doi.org/10.1257/aer.100.2.57
Kanger, L. (2021). Rethinking the Multi-level perspective for energy transitions: From regime life-cycle to explanatory typology of transition pathways. *Energy Research Social Science, 71*, Article 101829. https://doi.org/10.1016/j.erss.2020.101829
Kerr, W. R., & Nanda, R. (2015a). Financing innovation. *Annual Review of Financial Economics, 7*(1), 445–462. https://doi.org/10.1146/annurev-financial-111914-041825
Kerr, W. R., & Nanda, R. (2015b). Financing innovation. *Annual Review of Financial Economics, 7*(7, 2015), 445–462. https://doi.org/10.1146/annurev-financial-111914-041825
Klaaßen, L., & Steffen, B. (2023). Meta-analysis on necessary investment shifts to reach net zero pathways in Europe. *Nature Climate Change*. https://doi.org/10.1038/s41558-022-01549-5
Kumar. J, C. R., & Majid, M. A. (2020). Renewable energy for sustainable development in India: Current status, future prospects, challenges, employment, and investment opportunities. *Energy, Sustainability and Society, 10*(1), 2. https://doi.org/10.1186/s13705-019-0232-1
Larosa, F., Rickman, J., & Ameli, N. (2022). Finding the right partners? Examining inequalities in the global investment landscape of hydropower. *Global Environmental Change, 74*, Article 102518. https://doi.org/10.1016/j.gloenvcha.2022.102518
Markard, J. (2020). The life cycle of technological innovation systems. *Technological Forecasting and Social Change, 153*, Article 119407. https://doi.org/10.1016/j.techfore.2018.07.045
Massa, M., & Rehman, Z. (2008). Information flows within financial conglomerates: Evidence from the banks–mutual funds relation. *Journal of Financial Economics, 89*(2), 288–306. https://doi.org/10.1016/j.jfineco.2007.10.002
Mazzucato, M., & Semieniuk, G. (2017). Public financing of innovation: New questions. *Oxford Review of Economic Policy, 33*(1), 24–48. https://doi.org/10.1093/oxrep/grw036
Mazzucato, M., & Semieniuk, G. (2018). Financing renewable energy: Who is financing what and why it matters. *Technological Forecasting and Social Change, 127*, 8–22. https://doi.org/10.1016/j.techfore.2017.05.021
McCollum, D. L., Zhou, W., Bertram, C., de Boer, H.-S., Bosetti, V., Busch, S., Després, J., Drouet, L., Emmerling, J., Fay, M., Fricko, O., Fujimori, S., Gidden, M., Harmsen, M., Huppmann, D., Iyer, G., Krey, V., Kriegler, E., Nicolas, C., … Riahi, K. (2018). Energy investment needs for fulfilling the Paris agreement and achieving the sustainable development goals. *Nature Energy, 3*(7), 589–599. https://doi.org/10.1038/s41560-018-0179-z
Meuleman, M., Wright, M., Manigart, S., & Lockett, A. (2009). Private equity syndication: Agency costs, reputation and collaboration. *Journal of Business Finance Accounting, 36*(5-6), 616–644.
Naidoo, C. P. (2020). Relating financial systems to sustainability transitions: Challenges, demands and design features. *Environmental Innovation and Societal Transitions, 36*, 270–290. https://doi.org/10.1016/j.eist.2019.10.004
Nemet, G. F., Zipperer, V., & Kraus, M. (2018). The valley of death, the technology pork barrel, and public support for large demonstration projects. *Energy Policy, 119*, 154–167. https://doi.org/10.1016/j.enpol.2018.04.008
Nykvist, B., & Maltais, A. (2022). Too risky – the role of finance as a driver of sustainability transitions. *Environmental Innovation and Societal Transitions, 42*, 219–231. https://doi.org/10.1016/j.eist.2022.01.001
Papke, L. E., & Wooldridge, J. M. (2008). Panel data methods for fractional response variables with an application to test pass rates. *Journal of Econometrics, 145*(1), 121–133. https://doi.org/10.1016/j.jeconom.2008.05.009
Polzin, F., Egli, F., Steffen, B., & Schmidt, T. S. (2019). How do policies mobilize private finance for renewable energy?—A systematic review with an investor perspective. *Applied Energy, 236*, 1249–1268.
Rajan, R. G., & Zingales, L. (1998). Financial dependence and growth. *The American Economic Review, 88*(3), 559–586.
Ramalho, E. A., Ramalho, J. J., & Henriques, P. D. (2010). Fractional regression models for second stage DEA efficiency analyses. *Journal of Productivity Analysis, 34*, 239–255.
Rickman, J., Larosa, F., & Ameli, N. (2022). The internal dynamics of fast-growing wind finance markets. *Journal of Cleaner Production, 375*, Article 134129. https://doi.org/10.1016/j.jclepro.2022.134129
Saidi, F., & Žaldokas, A. (2021). How does Firms' innovation disclosure affect their banking relationships? *Management Science, 67*(2), 742–768. https://doi.org/10.1287/mnsc.2019.3498
Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The Journal of Finance, 45*(4), 1069–1087.

Steffen, B. (2018). The importance of project finance for renewable energy projects. *Energy Economics, 69*, 280–294. https://doi.org/10.1016/j.eneco.2017.11.006

Steffen, B., Karplus, V., & Schmidt, T. S. (2022). State ownership and technology adoption: The case of electric utilities and renewable energy. *Research Policy, 51*(6), Article 104534. https://doi.org/10.1016/j.respol.2022.104534

Steffen, B., Matsuo, T., Steinemann, D., & Schmidt, T. S. (2018). Opening new markets for clean energy: The role of project developers in the global diffusion of renewable energy technologies. *Business and Politics, 20*(4), 553–587. https://doi.org/10.1017/bap.2018.17

Steffen, B., & Schmidt, T. S. (2019). A quantitative analysis of 10 multilateral development banks' investment in conventional and renewable power-generation technologies from 2006 to 2015. *Nature Energy, 4*(1), 75–82. https://doi.org/10.1038/s41560-018-0280-3

Steffen, B., & Schmidt, T. S. (2021). Strengthen finance in sustainability transitions research. *Environmental Innovation and Societal Transitions, 41*, 77–80. https://doi.org/10.1016/j.eist.2021.10.018

Steffen, B., Schmidt, T. S., & Tautorat, P. (2019). Measuring whether municipal climate networks make a difference: The case of utility-scale solar PV investment in large global cities. *Climate Policy, 19*(7), 908–922. https://doi.org/10.1080/14693062.2019.1599804

Stoneman, P., & Battisti, G. (2010). Chapter 17 - the diffusion of new technology. In B. H. Hall, & N. Rosenberg (Eds.), *Handbook of the Economics of Innovation, 2* pp. 733–760). North-Holland. https://doi.org/10.1016/S0169-7218(10)02001-0.

Sufi, A. (2007). Information asymmetry and financing arrangements: Evidence from syndicated loans. *The Journal of Finance, 62*(2), 629–668.

Taylor, M., & Taylor, A. (2012). The technology life cycle: Conceptualization and managerial implications. *International Journal of Production Economics, 140*(1), 541–553. https://doi.org/10.1016/j.ijpe.2012.07.006

Vermeulen, F., & Barkema, H. (2001). Learning through acquisitions. *Academy of Management Journal, 44*(3), 457–476. https://doi.org/10.5465/3069364

Waidelich, P., & Steffen, B. (2024). Renewable energy financing by state investment banks: Evidence from OECD countries. *Energy Economics, 132*, Article 107455. https://doi.org/10.1016/j.eneco.2024.107455

Wulff, J. N. (2019). Generalized two-part fractional regression with cmp. *The Stata Journal, 19*(2), 375–389. https://doi.org/10.1177/1536867X19854017

Xin, F., Zhang, J., & Zheng, W. (2017). Does credit market impede innovation? Based on the banking structure analysis. *International Review of Economics Finance, 52*, 268–288. https://doi.org/10.1016/j.iref.2017.01.014