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# The internal dynamics of fast-growing wind finance markets

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ABSTRACT

Rapidly mobilising finance from a wide variety of sources is crucial for scaling up wind deployment and enabling the clean energy transition. To do so will require an understanding how investors co-invest in wind project finance markets and how internal market dynamics align with rapid growth in deployment. Our analysis of the largest, mature wind markets globally shows that internal market dynamics matter for the pace of growth. We observe a common pathway to fast growth whereby a small set of experienced debt providers, predominantly commercial banks, support a major fraction of all lending activity. These critical investors ascend to prominent positions in the market through a positive feedback process whereby more experienced lenders are more likely to attract new equity partners and this 'financial learning' spurs virtuous cycles of investment. Our results suggest strategic action to boost project finance investments entails leveraging positive feedback dynamics and supporting systemically important lenders.

## 1. Introduction

Mobilizing finance for the clean energy transition is critical for meeting climate targets (Edenhofer et al., 2011; Luderer et al., 2014), but investment in renewable energy (RE) is still far from supplying the required growth in global capacity (McCollum et al., 2018). Annual investment of 2.4 trillion USD is required to keep global temperature rise to below 1.5 °C, which indicates a financing gap of 76% based on recent investment levels (Finance and U.S.C.o., 2014). Wind power is set to be at the heart of the energy transition with the potential to supply three fifths of global electricity by 2050 (IRENA, 2019a), but annual investments must increase two-fold from now until to 2030 and over three-fold for the remaining period (IRENA, 2019b). Scaling-up investments for the clean energy transition will require an understanding of how investors mobilize capital for RE assets.

### 1.1. The current landscape of renewable finance research

Research into RE finance markets has blossomed over the past decade (Elie et al., 2021). Many studies have highlighted the heterogeneous composition of RE finance markets, exploring the behaviours and preferences of different types of investors and their distinct roles in shaping the low-carbon transition (Mazzucato and Semieniuk, 2018; Bergek et al., 2013; Barazza and Strachan, 2020a; Hall et al., 2016; Temmes et al., 2021; Ragosa and Warren, 2019). Underlying this heterogeneity are investor-specific attitudes to risk (Ghosh and Nanda, 2010), and the risks associated with RE investments have thus also been of critical interest (Steggals et al., 2017; Angelopoulos et al., 2017; González and Lacal-Arántegui, 2016). An important stream of literature has focused on the role of policy in shaping and mitigating investment risk (Angelopoulos et al., 2017; González and Lacal-Arántegui, 2016; Bodnar et al., 2018; Pahle and Schweizerhof, 2016; Polzin et al., 2019), assessing key support schemes e.g., feed-in tariffs and contracts for difference for wind assets, against levels of deployment (González and Lacal-Arántegui, 2016; Štreimikienė, 2016). While other studies have examined the interplay between policy design and the heterogeneous risk appetite of investors (Polzin et al., 2019; Dinica, 2006; Wüstenhagen and Menichetti, 2012), exploring how specific types of capital, e.g., institutional capital (Blyth et al., 2015; Polzin et al., 2015), can be mobilized through tailored policy design.

An underlying assumption of this literature is that RE investors will intrinsically supply the capital for deployment growth in response to the right risk/reward incentives and exogeneous market and policy signals (Hall et al., 2017). However, our emerging understanding of RE finance markets as complex, dynamical systems calls attention to the importance of endogenous investor dynamics in the growth of renewables deployment (Hall et al., 2017). In particular, the processes by which investors can influence one another leading to positive feedbacks in investor decision-making, has been little explored. The significance of endogenous processes in RE finance markets has already been demonstrated at

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the sectoral level; learning by RE finance institutions has been shown to dynamically reduce the cost of capital through lowering of investment risk (Egli et al., 2018). In this analysis we push forward the investigation of internal market processes, exploring the investor dynamics which shape RE finance markets and their relation to fast growth in RE deployment.

### 1.2. A complex systems analysis of wind finance markets

This analysis focuses on the investor dynamics that align with fast deployment growth in wind finance markets. We take a complex systems perspective that augments standard economic theory with insights from behavioural and evolutionary economics (Grubb, 2014) in light of two key features of RE finance markets. First, RE investors are heterogeneous with diverse behaviours and preferences (Mazzucato and Semieniuk, 2018; Bergek et al., 2013; Barazza and Strachan, 2020a; Hall et al., 2016). Second, their decision-making is governed by selection pressures, such as learning and competition (Hall et al., 2017; Mercure et al., 2016). Both of these characteristics of RE finance markets give rise to complex dynamics which shape investment flows and drive system evolution. Thus far, agent-based models (ABMs) have been the primary tool to explore the complexity of RE markets (Barazza and Strachan, 2020a; Kraan et al., 2018; Deissenroth et al., 2017; Chappin et al., 2017), and results have highlighted emergent system properties which shape energy transition pathways e.g., path-dependency creating technological lock-ins (Barazza and Strachan, 2020b). In this analysis we take a different approach, using mathematical network analysis to represent wind finance markets as networks of investors connected by their co-investments in wind assets. This approach builds on previous work in the energy transitions space using network theory to explore sustainable business ecosystems (Neumeyer and Santos, 2018), to assess energy flows between economic sectors (Sun and An, 2018), to study international collaborations in emerging low-carbon technologies (Yin et al., 2020) and to explore global patterns of wind technology diffusion (Vega and Mandel, 2018). In comparison to ABMs our approach is parsimonious and offers powerful insights into system dynamics validated by empirical asset-deal level data. While analytic tractability ensures our model is readily interpretable, detailed modelling features are harder to implement in mathematical models (El-Sayed et al., 2012). Our approach is thus complementary to computational methods and our results could serve as building blocks to ABMs with more complex features.

### 1.3. The importance of project finance in wind finance markets

To investigate the internal market dynamics aligned with fast wind deployment we focus on project finance investments which are an increasingly prominent financing structure for RE assets, particularly in mature markets (Steffen, 2018; Ajadi et al., 2020). Two prevalent financing structures exist for capitalizing renewable assets: project finance and corporate finance. In a corporate finance structure, the investment is carried on the balance sheet of the project sponsors. In a project finance structure, the investment is carried off-balance sheet within a separate business entity (e.g., a Special Purpose Vehicle) and lenders rely solely on revenues generated by the specific asset with little or no recourse to the assets of the project sponsors in the case of default. A crucial prerequisite for project finance is, therefore, predictable revenue streams which can be ensured by e.g., long-term power purchase agreements and feed-in tariffs (Steffen, 2018). The past decade has seen a surge in the volumes of project finance supplied to wind markets - it accounted for 82% of offshore wind finance across Europe in 2020 (Brindley et al., 2020). This is a welcome trend given that project financing suits the needs of a diverse range of energy market actors (Steffen, 2018) and can thus facilitate the mobilization of funds from a wide variety of sources. Strategic action to attract new sources of capital and scale-up wind deployment should thus be guided by an understanding of how investors have been providing project finance to the fastest-growing markets.

To conduct a cross-country analysis of project financing in fast-growing wind markets we select the largest, low-risk wind markets globally. We define low-risk markets as those countries with a high level of economic development (classed as high income by the World Bank (World Bank Country and Lending)) and high credit-worthiness (classed as investment-grade by Standard and Poor (Sovereign Risk Indicators)). This selection criteria acknowledges that risk-perception is a strong determinant of investor behaviour (Egli, 2020) and could be a confounding factor in identifying a relationship between internal market dynamics and growth. Investment dynamics in developing markets require additional considerations, as factors such as policy instability, immaturity of financial markets and currency risk make it more difficult to attract finance and investment (Ameli et al., 2021).

### 1.4. Contribution to existing literature

Our analysis thus advances the current understanding of wind finance in several directions. First, it offers a novel theoretical framework for representing complexity in renewable finance markets, complementing existing computational approaches. Second, it provides new empirical evidence on the relationship between internal market dynamics and investment growth in wind markets, which has been limited until now due to the confidentiality of asset-deal level data. Third, it identifies emergent phenomena (e.g., path-dependency through learning processes) and systemically important investors that suggest sensitive intervention points for amplifying growth in wind deployment (Blyth et al., 2015). Our study should therefore be of interest to policy-makers designing strategic action to boost growth in wind deployment; project sponsors, lenders and financial intermediaries involved in project finance for wind assets; as well as energy scholars interested in modelling renewable energy investments.

The structure of the paper is as follows. Section 2 presents the investment data and the methodological approach. Section 3 presents a characterisation of the investor networks, exploring the relationship between network structure, composition, dynamics, and growth in wind deployment. Section 4 presents a model of network evolution which describes the topology of wind project finance investment networks and the underlying investor behaviour. Section 5 concludes with the implications of our results and avenues for further research.

## 2. Materials and methods

### 2.1. Project-level investment data

The analysis is based on a dataset from Bloomberg New Energy Finance which reports financial transactions on wind assets since 2000. The coverage of BNEF's data is highly complete, in some cases reporting more capacity than other trusted sources such as the IEA (Table S1), likely because the BNEF data includes information on wind assets that have secured finance but are not yet operational. Each time stamped project finance transaction on a wind asset involves one or more investors, labelled as either a debt or an equity provider (Fig. 1a). As has been noted (Mazzucato and Semieniuk, 2018), some deals do not report their debt sources and in such cases the unknown creditors are given a unique identifier. Unknown investors represent a small share of the data in the countries analysed (average share of unknown investors is 6%, Table S2). Furthermore, it is likely that unknown investors are smaller firms or private individuals (for whom less information is available) making just one or a few investments, which mitigates against inaccuracies arising from wrongly attributing investments to different investors in the case that they are the same. Further details on data processing can be found in the Supplementary Methods.

Our analysis focuses on low-risk markets, which we characterise as those markets in high income countries, as per the World Bank

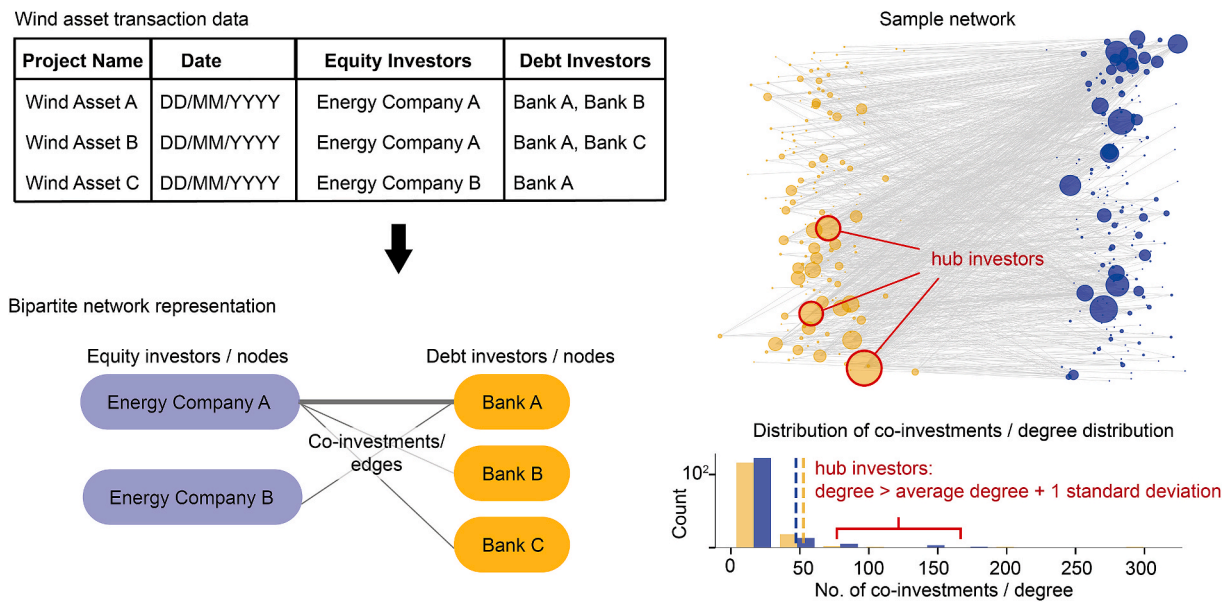


**Fig. 1.** Network representation of asset-deal level data. a) Wind asset-level data is represented as a bipartite network of debt and equity investors connected by co-investments. **b)** Empirical network topologies (top), captured by the distribution of co-investments across investors (bottom) show the presence of investor hubs.

classification (World Bank Country and Lending), and with an investment-grade sovereign rating as defined by Standard and Poor (Sovereign Risk Indicators). We observe that prior to 2010, project finance was a small fraction of total investments in such markets (Fig. S1) and we therefore focus our analysis on the period 2010–2019. We then choose the subset of markets for which installed wind capacity was greater than 1 GW in 2010 (Table 1). This criterion makes our results more generalisable by ensuring the wind markets in our dataset have reached a level of maturity at the start of the analysis, signalled by a significant installed capacity base. Our final dataset consists of 16 countries, including Japan, Australia, United States, Canada and 13 European countries.

### 2.2. Investor heterogeneity

Investor heterogeneity plays an important role in the evolution of renewable finance markets, as different types of investor have distinct preferences, behaviours and attitudes to risk (Mazzucato and Semieniuk, 2018). In project finance investments, a primary division of investors is made between project sponsors (equity investors) and project lenders (debt investors), with the former responsible for raising capital for project development, typically as part of their core business, and the latter expecting returns based solely on the projected revenue of the asset. The distinct roles played by debt and equity investors in wind finance markets is reflected through their differing costs of capital (Steffen, 2020), risk/return requirements (Ghosh and Nanda, 2010), and business types.

Debt and equity investors are themselves heterogeneous sets of actors, which reflects the wide range of economic rationales that exist for using project finance (Steffen, 2018). On the equity side, some project sponsors may choose project finance to mitigate against contamination risk of their existing portfolio (e.g., large incumbent utilities), while smaller actors (e.g., independent power producers) can develop projects beyond what their corporate balance sheet would allow for (Steffen, 2018). On the debt side, project finance can offer attractive risk-adjusted returns for lenders such as banks and institutional investors whose time horizons can be well suited to the lifetime of a wind asset (Kaminker and Stewart, 2012). We thus further classified debt and equity investors into different categories of financial actors according to their business type (energy companies, institutional investors, utilities, commercial banks, public banks, state actors and non-profit investors) to provide more granular information on the investor composition (see Table S3 for definitions). This classification was made using investor information provided by BNEF on business activity and ownership of organisations and, where information was missing, a google search was undertaken.

**Table 1**
Installed wind capacity and average annual market growth rates. Installed capacity statistics are sourced from the International Energy Agency. Average annual capacity growth rates are calculated between 2010 and 2019.

| Country | Installed Capacity 2010 (MW) | Installed Capacity 2019 (MW) | Average annual growth rate (%) |
|---|---|---|---|
| US | 39135 | 103670 | 11.7 |
| Germany | 26903 | 60721 | 9.5 |
| Spain | 20693 | 25583 | 2.4 |
| France | 5912 | 16427 | 12.1 |
| Italy | 5794 | 10679 | 7.2 |
| UK | 5421 | 24095 | 18.3 |
| Canada | 3967 | 13413 | 15 |
| Denmark | 3802 | 6103 | 5.5 |
| Portugal | 3796 | 5223 | 3.7 |
| Japan | 2294 | 3951 | 6.3 |
| Netherlands | 2237 | 4484 | 8.3 |
| Sweden | 2017 | 8681 | 18 |
| Australia | 1864 | 6279 | 14.6 |
| Ireland | 1390 | 4160 | 13 |
| Poland | 1108 | 5837 | 21.9 |
| Austria | 1016 | 3224 | 14 |

### 2.3. Network analysis

Our theoretical framework is based on a conceptualisation of renewable finance markets as networks of investors connected by co-investments in wind assets. Investors are conceived as boundedly-rational agents whose heterogeneous preferences and behaviour are governed by learning and competition which shape network structure (Mercure et al., 2016; Lo, 2005). Many studies of real networks demonstrate the significance of studying the interplay between network structure and dynamics in understanding the evolution of the system as a whole and identifying strategic interventions to affect its future development (Strogatz, 2001; Farmer et al., 2019).

We acknowledge the primary source of investor heterogeneity by

separating equity and debt investors into two independent and disjoint sets of nodes, $U$ and $V$ respectively, to form bipartite networks, $B = \{U, V, E\}$. Edges in the network, $uv$ in $E$, are generated from all the unique pairs of equity and debt investors involved in the financing of a wind asset and represent a co-investment between an equity and a debt investor. Since these interactions are mutual and can be repeated the edges of the network are undirected and weighted (Fig. 1a). The total number of co-investments made by an investor is therefore equal to the weighted degree of their node. We define $w_u$ as the weighted degree of node $u \in U$ and $w_v$ as the weighted degree of node $v \in V$. (See Table S2 for statistics on network size).

### 2.4. Characterising network structure and dynamics

The primary description of a network is given by its degree distribution i.e., the distribution of node degrees (number of co-investments) across all nodes (investors) in the network (Fig. 1b). The precise form of a degree distribution is a signature of network dynamics, revealing how nodes select one another and compete for links (Barabási, 2016). Most real-world networks have degree distributions which are highly right-skewed i.e., most nodes have low degree but a small number of nodes, known as 'hubs', have a high degree (Barabási and Bonabeau, 2003) (Fig. 1b). In bipartite networks hubs are defined separately for the two sets of nodes (debt investors and equity investors); they are nodes with weighted degree greater than one standard deviation above the mean. We define the set of equity investor hubs as $U_H$ where $u \in U_H$ if $w_u > \overline{w}_u + \mathrm{std}(w_u)$ and the set of debt investor hubs $V_H$ where $v \in V_H$ if $w_v > \overline{w}_v + \mathrm{std}(w_v)$. To quantify the right-skew of the degree distributions i.e., the degree to which hubs dominate the network, we use the coefficient of variation (CoV), which is given by the standard deviation of the weighted node degrees divided by the mean,

$$\mathrm{CoV}_{u,v} = \frac{\mathrm{std}\left(w_{u,v}\right)}{\overline{w}_{u,v}} \tag{1}$$

where the subscripts u and v denote the equity and debt parts of the network respectively.

Going beyond the static picture presented by the degree distribution we further define a metric, 'hub activity', to characterize network dynamics. Let $B_t$ denote the network at time $t$ and $m_{uv}(t)$ denote the number of edges between nodes $u$ and $v$ added to$B_{t-\Delta t}$ form $B_t$ , where $\Delta t$ is 1 year. Hub activity, $H^{act}_{[U,V]}(t)$, measures the fraction of new edges $m_{uv}(t)$ attaching to hubs. The subscript $U$ or $V$ denotes the calculation for the equity and debt parts respectively:

$$H^{act}_U(t) = \frac{\sum_{v\in V}\sum_{u\in U_H} m_{uv}(t)}{\sum_{v\in V}\sum_{u\in U} m_{uv}(t)}\ ;\ H^{act}_V(t) = \frac{\sum_{v\in V_H}\sum_{u\in U} m_{uv}(t)}{\sum_{v\in V}\sum_{u\in U} m_{uv}(t)} \tag{2}$$

A high hub activity close to 1 thus indicates that the subset of debt or equity investor hubs undertake the majority of co-investments, whereas a low hub activity close to 0 indicates that investment activity is dispersed across the investors in the network. We use this metric to determine the network dynamics associated with fast growth in wind deployment. Growth in wind deployment was quantified as the average annual percentage increase in installed wind capacity between 2010 and 2019 using statistics from the IEA (Kraan et al., 2018) (Table 1).

### 2.5. Preferential attachment model

The presence of hubs in real, growing networks is often an indication of an edge formation mechanism known as preferential attachment (PA) whereby new nodes prefer to link to more connected nodes due to their visibility or popularity (Barabási, 2016), which over time leads to the formation of highly connected nodes i.e., the hubs. Preferential attachment is thus a positive feedback mechanism through which differences in node degree, capturing differences in investors' experience levels, become amplified over time. The preferential attachment model is a parsimonious and powerful model to describe the growth of networks with right-skewed degree distributions and hub formation. Unlike the fitness model, a popular alternative for describing hub formation which assigns each node an unique 'fitness' (Bianconi and Barabási, 2001), it relies on a single network feature (node degree) to explain network evolution by the common-sense intuition that highly-connected nodes are more likely to form new connections. We also did not include additional features such as transitivity (Newman, 2001) in our model, finding that PA was a significant driver of network growth. However, evidence for PA does not exclude the possibility of additional features and mechanisms playing a role in network growth. For example, our model is unconventional in that it is agnostic to the network evolution that has occurred up to the starting time point (2010), and intrinsic differences in node 'fitness' may be implicit in the structure of the initial network.

In our PA model we focus on the mechanism by which new nodes select existing nodes to connect to. The probability that a new equity node makes a connection with an existing debt node with weighted degree $w_v$ is proportional to an attachment kernel which takes the power-law functional form:

$$A_v(w_v) = {w_v}^{\beta_v} \tag{3}$$

Similarly, the probability that a new debt node makes a connection with an existing equity node with weighted degree $w_u$ is proportional to an attachment kernel which takes the power-law functional form:

$$A_u(w_u) = {w_u}^{\beta_u} \tag{4}$$

The power law exponent $\beta$ thus represents the strength of preferential attachment; the higher the exponent $\beta$ the stronger the preference of new nodes to connect to nodes with high degree. In the following we illustrate parameter estimation and goodness-of-fit assessment for the debt node attachment kernel (Equation (3)), the same procedure can be followed for the equity node attachment kernel (Equation (4)), substituting $u$ and $U$ for $v$ and $V$ and vice versa.

To estimate $\beta_v$ we followed the partial maximum likelihood estimation approach proposed by Inoue et al. (2020) The networks grow from $B_{t-\Delta t}$ to $B_t$ in time-steps of 1 year for $t \in [2010, \ldots, 2019]$. At the onset of time-step $t$, new nodes are added to $B_{t-\Delta t}$ which we denote $U_0(t)$ and $V_0(t)$ for the new equity and debt nodes respectively. This network forms a substrate network for the new edges, which are added independently of one another. We define the set of observed networks $D = \{B_{2010}, \ldots, B_{2019}\}$ and construct the log-likelihood function for the debt node attachment kernel $A_v(w_v)$ as;

$$\mathscr{L}(A_v|D) = \sum_{t=1}^{T}\sum_{u\varepsilon U_0(t)}\sum_{v\varepsilon V(t)} m_{uv}(t)\ \ \log A(w_v(t)\,) - \sum_{t=1}^{T} m_0(t)\ \ \log\left(\sum_{u\varepsilon U_0(t)}\sum_{v\varepsilon V(t)} A(w_v(t)\,)\right) \tag{5}$$

Where $\mathrm{m_{uv}(t)}$ denotes the number of new edges connecting nodes u and v and the total number of new edges connecting new equity nodes to existing debt nodes is denoted $m_0(t) = \sum_{u\varepsilon U_o(t)}\sum_{v\varepsilon V(t)} m_{uv}(t)$. The optimal value of $\beta_v$ was then found by minimizing the negative log-likelihood using the gradient-based BFGS optimization method.

To assess how well the PA model describes the attachment of new equity nodes to debt nodes we use the likelihood-ratio test (Clegg et al., 2016), comparing the likelihood of the PA model $\mathscr{L}_1$ against the likelihood of the null model $\mathscr{L}_0$ with the parameter $\beta_v$ set to 0. The likelihood ratio $\lambda = \mathscr{L}_0/\mathscr{L}_1$, under some regularity conditions, is asymptotically distributed (Overgoor et al., 2019) as,

$$-2\log\lambda\ \sim \chi^2_1 \tag{6}$$

and p-values can be calculated using this likelihood-ratio chi-square statistic.

## 3. Results

### 3.1. Investor hubs are a key structural feature of wind project finance markets

We first characterise the structure of wind project finance markets by looking at the distribution of co-investments between investors in the networks (see Section 2.4). The distributions reveal a distinct network topology that is commonly found in growing social networks (Barabási, 2016); they are highly 'right-skewed' with long tails, showing that most investors make only a few co-investments while a few investors make many co-investments (Fig. 2). In all countries we observe investor hubs in debt and equity markets, defined as the investors in the right-hand side tail of the degree distribution who have total co-investments exceeding the average by one standard deviation.

We observe that while investor hubs are ubiquitous, the extent to which they dominate the networks differs between countries. In real growing networks new links are more often made to the well-connected hubs, due to their visibility or popularity (Barabási and Albert, 1999). We would therefore expect that as the investor networks grow and new equity (debt) investors enter the market, the relative size of the (debt) equity investor hubs should increase. Taking the coefficient of the variation (see section 2.4) of the co-investment distributions to capture the dominance of hubs we indeed observe that the larger the equity (debt) market the greater the dominance of the debt (equity) hubs (Fig. S2). In Denmark, for example, which has a total installed capacity of 6 GW in 2019, the largest debt hub investor has made twice as many co-investments as the average investor. Whereas in the United Kingdom, with a total installed capacity of 24 GW, the largest debt hub investor has made ten times more co-investments than the average. This suggests a common evolutionary pathway for wind project finance markets, whereby hub investors rise to increasingly dominant positions as the networks grow over time.

The domination of energy markets by a few organisations can be driven by large incumbents achieving cost reductions through e.g., economies of scale, better access to finance, or vertical integration of services bringing in multiple revenue streams. On the other hand, smaller local companies can gain a competitive advantage through better knowledge of local political contexts and lower sensitivity to risk (Kruger et al., 2021). We therefore next explore the composition of the investors networks and identify the types of investors occupying the key hub positions.

A diverse range of investors are active in wind project finance markets (Fig. 3), demonstrating the ability of project finance to suit the heterogeneous requirements of different market actors (Steffen, 2018). On the equity side, energy companies are the largest category of project sponsors, including both large incumbents and small independent power producers. Utilities play a smaller role, which may reflect their difficulties in incorporating wind assets (with smaller average capacities than conventional power plants) into existing portfolios (Kelsey and Meckling, 2018). Institutional investors also play a role in equity markets, reflecting the attractive risk-adjusted returns of wind assets for these long-term investors (Kaminker and Stewart, 2012). The equity investor hubs are also a heterogeneous set of actors, and their composition differs between countries reflecting a variety of business and regulatory environments. In France, for example, the Canadian energy company Boralex is the single equity investor hub and has led the French onshore wind market since 2014 through its uniquely integrated business model of development, contracting and operation of projects. By contrast, several municipal utilities appear as equity investor hubs in Germany alongside private companies, reflecting Germany's regional energy market and policy-led energy transition (Wagner et al., 2021).

On the debt side, commercial banks are the largest category of lender in all markets, reflecting the low-risk status of wind assets in these

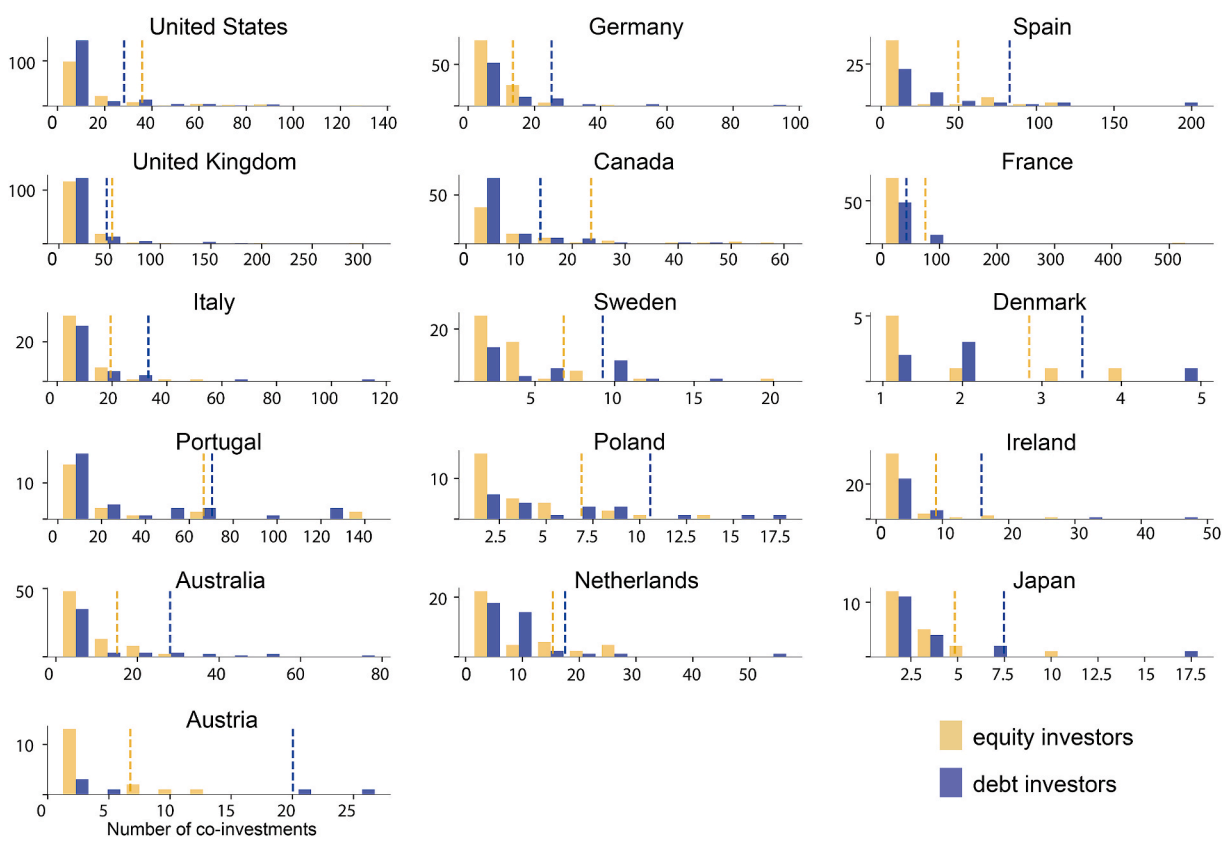


**Fig. 2.** Distribution of co-investments. Histograms show the distribution of co-investments between co-investors in the debt and equity parts of the networks. Dashed lines indicate the average number of co-investments plus one standard deviation; an investor with more co-investments than this threshold is classified as a hub.

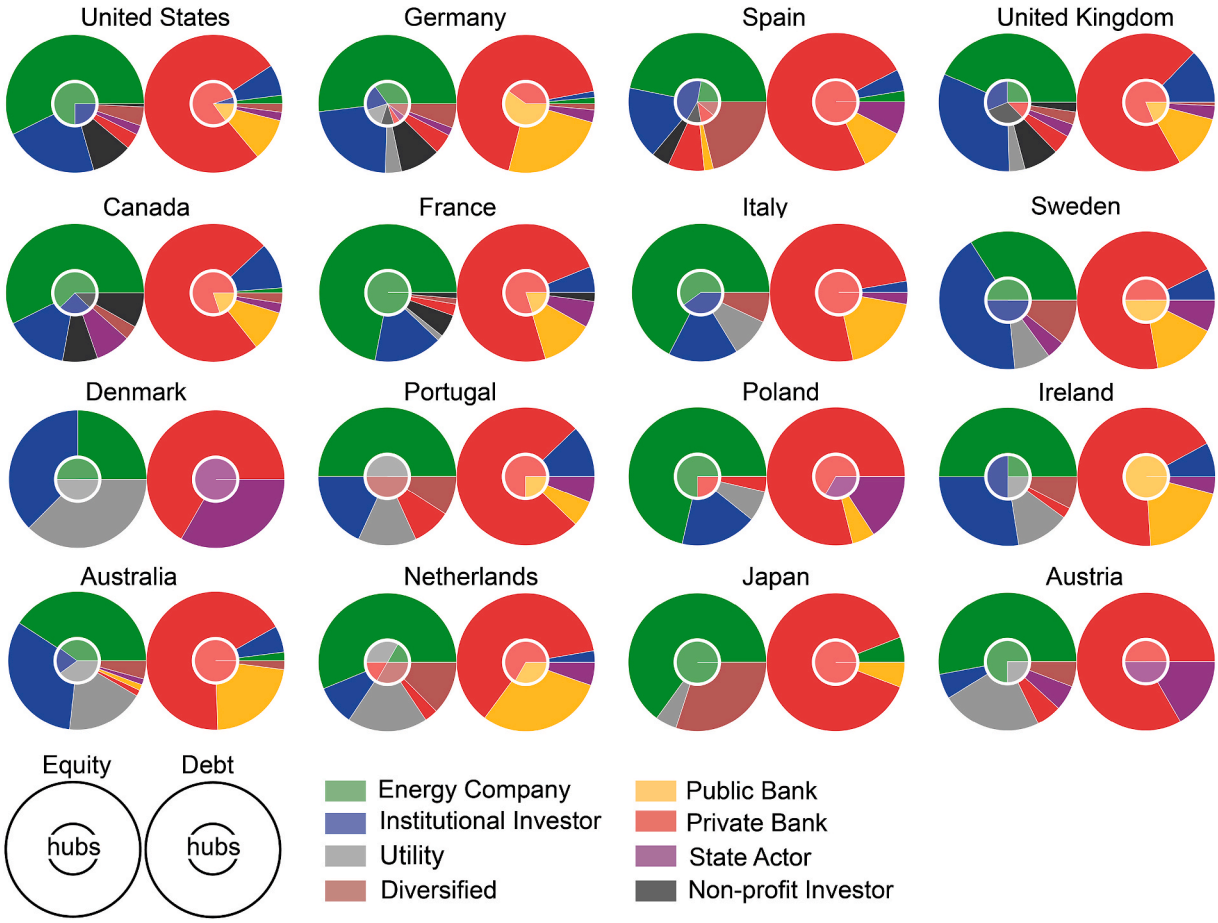


**Fig. 3.** Composition of investor networks. Pie charts show the composition of the equity and debt parts of the investor networks with respect to the business type of investors. Outer pie shows the composition of all investors in the network, inner pie shows the composition of the hubs.

countries (Mazzucato and Semieniuk, 2018), with a smaller role played by public banks (Fig. 3). In many of the largest and most mature markets e.g., US, Spain, UK, Canada, France and Italy (Table S2) commercial banks also occupy the majority of key hub positions. Their strong participation in the sector likely reflects stable policy signals and effective support mechanisms e.g., feed-in tariffs and long-term contracts awarded through auctions in Europe and Canada and production tax credits in the US. By contrast in several of the more nascent markets (Denmark, Poland, Austria, Ireland), public banks and state institutions also occupy the important hub positions. The public/private composition of the debt investor hubs may thus, in some cases, reflect the degree to which a country has transitioned beyond the market creation phase, in which public institutions are expected to be a driving force (Mazzucato and Penna, 2016), towards a privately-led sector. Germany is an interesting counter-example; it is a large and mature market with public banks occupying the majority of hub positions, reflecting the unique framework of national and regional public financing that has supported its energy transition (D'Orazio and Löwenstein, 2020).

### 3.2. *Fast market growth is associated with high levels of debt hub activity*

Having observed investor hubs as a characteristic feature of wind project finance markets, we next investigated the relationship between hub dynamics and market growth. Specifically, we explored how deployment growth, as measured by the average annual increase in installed capacity, is connected to investor hub activity. High hub activity, defined as the percentage of new co-investments undertaken by hub investors over a given period (see Section 2.4), indicates that hub investors dominate the market, financing a large share of all investments, while low hub activity indicates investment activity is shared more evenly between investors.

We observe a strong positive correlation between growth of wind markets and the level of debt hub activity (Fig. 4). In the fastest growing market, Poland, with average annual growth rates of 21.9%, debt hubs are involved in at least 65% of all new co-investments. Commercial banks comprise the majority of the debt hubs in Poland (Fig. 3), and their strong involvement in the market likely reflects strong support for renewables through e.g., renewable energy certificates (Gnatowska and Moryń-Kucharczyk, 2019). The European Bank of Reconstruction and Development is also a prominent debt investor hub in the Polish market, pointing to a key supportive role for multilateral institutions in more nascent wind markets (Table 1). In the slowest growing Spanish market, with an average annual growth rate of just 2.4%, activity is dispersed between debt investors with debt hubs supporting only 17% of investments. The limited involvement of debt hubs, predominantly commercial banks, likely reflects policy uncertainty and heavily reduced government subsidies in Spain leading wind assets to come too risky for the private banking sector (Gabaldón-Estevan et al., 2018).

In contrast, there is no significant correlation between market growth and the activity of equity investor hubs suggesting that equity market dynamics may depend on a wide range of economic, policy and geographic factors that are not represented in our network analysis. For example, policy design can favour distributed generation over utility-scale plants (as has been the case in Denmark and Germany) which could affect size and activity of equity market hubs, while higher resource potential in some countries relative to others may facilitate the growth of large, dominant equity market actors (Kelsey and Meckling, 2018). Understanding the relationship between equity market dynamics

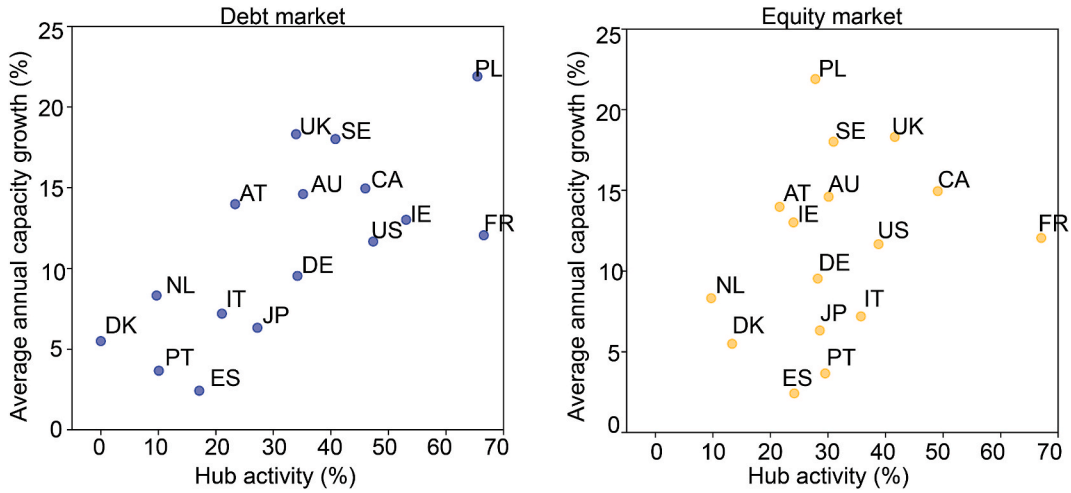


**Fig. 4.** Network dynamics and market growth. Plots show the correlation between hub activity and market growth in the debt and equity parts of the networks. Pearson's correlation coefficient for debt markets; $\rho = 0.7^*$, and equity markets; $\rho = 0.29$. *Significant at $p < 0.01$.

and market growth likely requires a country-specific analysis, which is an interesting avenue for further research.

### 3.3. A preferential attachment model connects fast growth to fast financial learning in debt markets

The distinct debt market dynamics seen in fast-growing markets suggest a key role for debt investor hubs in the project finance ecosystem. We therefore explore the connection between high debt hub activity and fast market growth by developing a quantitative model of network evolution, focusing on the formation of debt hubs. We developed a preferential attachment (PA) model whereby the likelihood of a new equity investor choosing a given debt investor partner increases as a log-linear function of the number of their prior co-investments (Section 2.5, Equation (3)), i.e., experienced lenders are more likely to be chosen by new equity investors. Such a model would explain the observed debt hubs (Fig. 2) and aligns with reports that cite a lack of experience as a barrier to entry in renewables markets (IRENA, 2016).

We found that a PA model well-described 11 out of the 16 countries analysed (Table S4), including the largest and fastest-growing markets (e.g., UK, Australia and Canada who have an average capacity growth greater than ≥15% per year). The five countries for which our model hypothesis was not supported have small network sizes (number of investors) and/or few network links (number of co-investments) suggesting that the size of the data samples may have prohibited robust statistical validation. On the other hand, additional mechanisms of network evolution not included in our model may operate in these countries. Nevertheless, the majority markets demonstrate evidence of preferential attachment which supports the generalisability of this result; debt investors face competition for projects and past lending experience is a major determinant of who will be selected as a project partner.

The process of 'financial learning' (Egli et al., 2018) is an intuitive interpretation of preferential attachment in the context of wind project finance markets. As a debt investor makes more co-investments, they build a track record and accumulate experience and data on past projects. This allows them to make more accurate risk assessments of new projects, reducing their required safety margins on loans. Experienced investors are thus more likely to be chosen by new equity partners since they can offer loans on better terms. The compression of debt margins through financial learning has been identified at a macroscopic level in renewable finance markets (Egli et al., 2018), and here we provide quantitative evidence for financial learning at the scale of the individual investor.

Fig. 5a shows estimates for the model parameter $\beta_v$ which controls the strength of preferential attachment. We observe a trend towards higher beta values in the fastest growing markets, providing a mechanistic explanation for their high debt hub activity; higher values of $\beta_v$ indicate that new equity investors have a stronger preference to invest with debt hubs. Furthermore, a link can be drawn between the strong preferential attachment seen in fast-growing networks (Fig. 5a) and fast rates of financial learning. To illustrate, debt investors in the fast-growing UK market ($\beta_v$ =0.9) will double their likelihood of gaining a new equity partner after doubling their number of co-investments, whereas in the slower-growing Spanish market ($\beta_v$ = 0.4), a debt investor must make six times the number of investments to achieve the same effect (Fig. 5b). Financial learning is likely coupled with exogenous learning processes happening in all parts of the renewables ecosystem (Steffen et al., 2020). Notwithstanding this complexity, we speculate that fast rates of financial learning in debt markets, which bring down the cost of debt finance (Egli et al., 2018), both reflects and engenders confidence in the market. This in turn attracts new equity investors to the market and triggers a virtuous cycle of new investments and capacity additions. The role of debt investor hubs in fast-growing markets thus goes beyond simply providing finance, our results suggest that through the feed-back effects of financial learning, debt investor hubs stimulate network growth.

Finally, we observed that many of the largest debt investor hubs invest in multiple markets, highlighting the globalised nature of the wind project finance ecosystem (Fig. 6). The majority of these international debt investor hubs are commercial banks and the largest and most mature markets (e.g., US, Germany, Spain, UK, Canada, France) are the top destinations for their investments. Interestingly, two of the most active international lenders are Japanese private banks (Sumitomo Mitsui Banking Corp and MUFG bank) who invest more abroad than in their domestic markets, likely due to prolonged low-interest rates in Japan. Their presence has increased competition between lenders in Europe (Brindley et al., 2020), highlighting the important role of foreign private capital in wind project finance markets. The remainder of the international debt investor hubs include one multilateral development institution (the European Bank of Reconstruction and Development) and four German public banks, reflecting Germany's major international role in funding green investment (Griffith-Jones, 2016). These state lenders have more links to the smaller, less mature markets (e.g., Sweden, Ireland, Poland) aligning with our earlier observations of public actors filling financing gaps where commercial lending may be less available (Fig. 3).

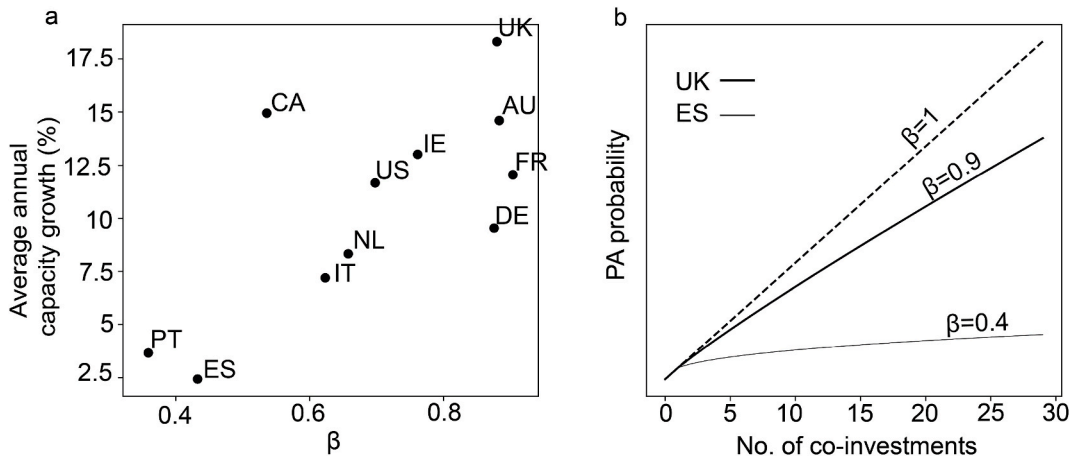


**Fig. 5. A preferential attachment model of network evolution. a)** Maximum likelihood estimates of the preferential attachment exponent shown for countries for which the PA model well explained the empirical data. **b)** PA attachment kernels for two example countries, United Kingdom, and Spain (solid lines), and a linear PA kernel (dotted line).

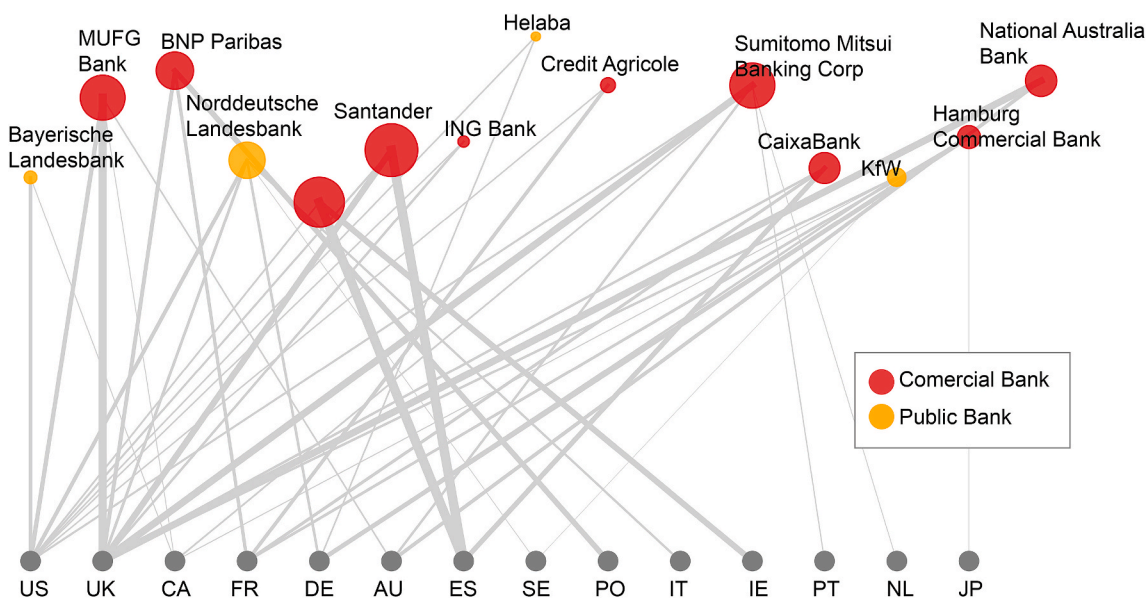


**Fig. 6. International hubs connect multiple markets.** Debt investor hubs (top) are shown connecting multiple markets (bottom). The size of hubs represents the total number of their co-investments and the width of connecting links represents the number of co-investments in each market. Hubs are color-coded according to their investor category.

## 4. Discussion

In this section we first discuss the novelty of our finds and the contribution to existing literature, along with limitations of our analysis and future research needs.

### *4.1. Novelty of the findings in the context of existing literature*

In this study we conducted an analysis of project finance investment dynamics in 16 of the largest low-risk wind markets globally. We find that low-risk wind finance markets share a common evolutionary pathway; a subset of investors rise to prominent positions over time, leading to a characteristic hub structure in which a small subset of experienced investors dominate investment activity. We find that fast growth in wind deployment is associated with highly active debt hubs, predominantly private banks, who perform several critical functions. First, they support investment activity by collectively undertaking over a major portion of new co-investments. Second, they are at the forefront of a financial learning process; as they gain experience their activity increases and equity investors become more willing to partner with them, likely because their experience allows them to better assess and mitigate risk, lowering their cost of debt (Egli et al., 2018). Our results suggest that the activity and presence of debt investor hubs signals confidence to the market and drives down financing costs, which ultimately attracts new projects and boosts growth in deployment.

Our study demonstrates the relevance of a complex systems approach to understanding renewable finance markets. The analytical framework we propose can be used as a tool to study the interactions of heterogeneous actors and their role in market growth, identifying the key actors and their dynamics for strategic policy design. It could also serve as a useful starting point for more realistic models of renewable finance markets for integration into climate mitigation models, which can be strongly influenced by the representation of the finance sector (Mercure et al., 2019; Iyer et al., 2015).

### 4.2. Limitations and future research needs

Our analysis is limited to low-risk markets in developed countries. Given the scale of RE investment needed in developing countries (McCollum et al., 2018) with less mature renewables ecosystems, analysing RE finance markets in such high-risk contexts is a critical avenue for future research. Developing countries have distinct characteristics with respect to their economic, regulatory, and institutional environments (Ameli et al., 2021) which could engender different investor dynamics and pathways to RE deployment growth. Furthermore, given the similar technological and deployment trajectories that solar and wind power have taken, it is pertinent to explore whether our results generalise to solar finance markets, the second key renewable technology for the clean energy transition (IRENA, 2019a).

## 5. Conclusions and policy implications

Our study builds on previous work exploring renewable finance markets from a complex systems perspective (Mazzucato and Semieniuk, 2018; Bergek et al., 2013; Barazza and Strachan, 2020a; Hall et al., 2016; Temmes et al., 2021; Ragosa and Warren, 2019), through which the behaviour of heterogeneous investors is driven by learning and competition, shaping the structure and dynamics of the market (Grubb, 2014). We identify a set of highly active debt investors or 'hubs', the majority of whom are private banks, that play a critical role in wind project finance markets; they support a large share of investments and amplify deployment growth through positive feedbacks associated with financial learning (Egli et al., 2018). Using network analysis of co-investment data to reveal positive feedbacks in wind project finance markets, we provide empirical evidence towards a theoretical understanding of the complexity of renewables ecosystems (Hall et al., 2017). The presence of financial learning in wind project finance markets suggests a sensitive intervention point (Farmer et al., 2019) for public finance institutions; private banks should be encouraged to step into these critical hub positions through the use of risk-mitigating debt instruments e.g., co-lending structures and loan syndication. The effect of financial learning may be particularly pronounced in project finance markets as deals come with significantly higher transaction costs; bills for technical, commercial and legal advisors can sum up to 5–10% of the total project value (Steffen, 2018). Experienced investors can therefore achieve significant cost-reductions by standardizing deal structures and due diligence criteria, while developing tools and in-house expertise for project appraisals. Co-lending and loan syndication, where public banks take the lead role, have the important co-benefit of sharing financial and technical expertise and building the confidence of private lenders (Geddes et al., 2018).

Furthermore, our results underscore the globalised nature of the renewables finance ecosystem through demonstrating the strong international connections between wind project finance markets. While technological knowledge spill-overs are widely recognised as an important accelerant of technology diffusion and deployment (Vega and Mandel, 2018; Grafström, 2018), our results highlight that governments and coalitions should also invest in financial knowledge spill-overs further down the innovation chain, encouraging international investors to propagate their experience between markets, and particularly from mature to less mature renewables ecosystems.

Project finance is set to be an increasingly prominent financing structure for renewable assets and can facilitate the mobilization of capital from a wide variety of sources (Steffen, 2018). Our findings on the internal dynamics of fast-growing wind project finance markets can thus serve policy-makers and energy scholars interested in amplifying growth and encouraging the development of wind finance markets globally.

## CRediT authorship contribution statement

**Jamie Rickman:** Conceptualization, Formal analysis, writing. **Francesca Larosa:** Conceptualization, writing. **Nadia Ameli:** Conceptualization, Supervision, writing.

## Declaration of competing interest

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

## Data availability

The authors do not have permission to share data.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.134129.

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