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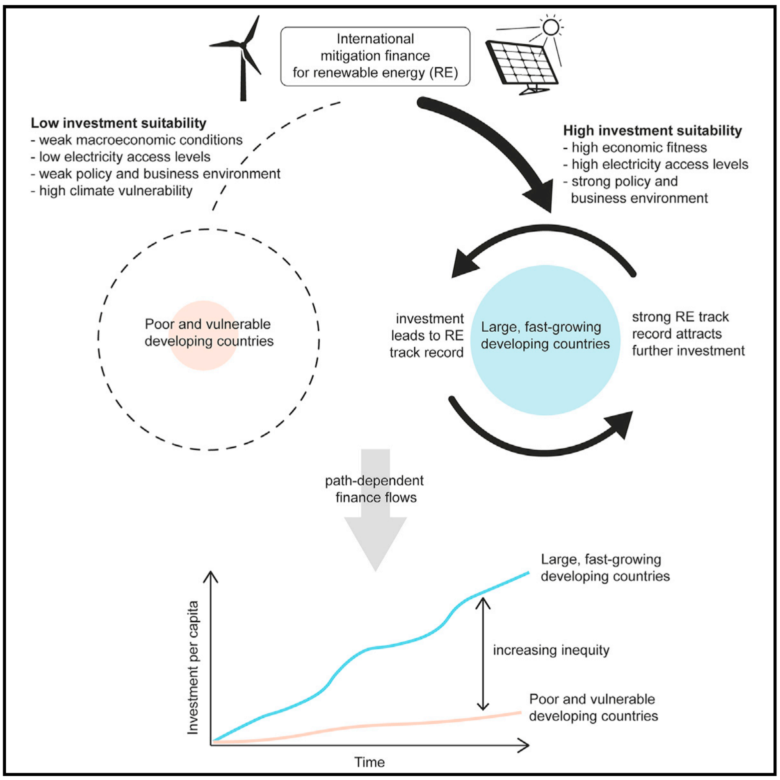
Investment suitability and path dependency perpetuate inequity in international mitigation finance toward developing countries

Graphical abstract



Highlights

- Wind and solar finance is not distributed equitably across developing countries
- International wind and solar finance flows are path dependent
- Countries perceived as high risk are excluded from private finance flows
- Public finance has supported domestic climate action since the Paris Agreement

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In brief

Massive investment in renewable energy to fund countries' energy transitions is required to meet Paris Agreement targets, including provision of finance by developed countries to developing countries. However, finance is not reaching poor and vulnerable countries perceived as high risk by international investors. Our study shows that breaking path-dependent investment cycles that exclude poor and vulnerable countries should be a priority for governments and policymakers in order to align climate finance flows with developing countries' needs.

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Investment suitability and path dependency perpetuate inequity in international mitigation finance toward developing countries

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SCIENCE FOR SOCIETY The Paris Agreement target of limiting global warming to 1.5°C above pre-industrial levels requires massive investment in renewable energy (RE) to fund countries' energy transitions. Equity demands that such finance be provided by developed countries to developing countries, given their respective capabilities and responsibilities for historical emissions. At present, the provision of RE finance is not equitable; finance is not reaching poor and vulnerable countries perceived as high risk by international investors. With each passing year, the consequences of this inequity increase; low RE investment keeps such countries stuck in under-development, high-emissions pathways while leaving climate change unchecked. Our study shows that breaking path-dependent investment cycles that exclude poor and vulnerable countries should be a priority for governments and policymakers at the forthcoming COP28, where the Paris alignment of global financial systems will be paramount to discussions.

SUMMARY

Developed country pledges to provide finance to developing countries for their mitigation actions sit at the heart of international climate cooperation. Currently, climate finance largely flows to big and fast-growing developing countries while low-income and vulnerable countries are underserved. Here, using wind and solar project data, we highlight inequities in the distribution of international investments in mitigation across developing countries and explore the factors that influence public and private investment flows. Results show that public actors are influenced by domestic climate policies since the Paris Agreement, while private finance flows are shaped by investment suitability conditions, which restricts access to both types of finance in the poorest countries. Further, public and private flows are strongly shaped by path dependency, generating an "investment lock-in" that perpetuates distributional inequities. Future international commitments to direct climate finance should address distributional issues to meet countries' needs and the goals of the Paris Agreement.

INTRODUCTION

Financial transfers by developed countries to support climate action in developing countries are an important element of international climate cooperation. Defined long-term targets were first established as part of the Copenhagen Accord in 2009 to advance meaningful mitigation actions.[1] Lately, the Paris Agreement recognized the importance of these flows for developing countries in meeting their nationally determined contributions (NDCs) and defined their scope to encompass the strategies, needs, and priorities of developing countries across both mitigation and adaptation efforts.[2] Within the present structure, climate finance—meaning finance to reduce greenhouse gas (GHG) emissions and/or enhance resilience to the impacts of climate variability and projected climate change[3]—is expected to be delivered using a multitude of international mechanisms and United Nations Framework Convention on Climate Change (UNFCCC) entities, multilateral and bilateral funds, and other public and private finance channels and instruments. However, this has meant that the current system of delivering finance to developing countries is fragmented, decentralized, and presents barriers to developing countries in accessing capital.[4]

Notwithstanding the epistemic ambiguity of what climate finance means and what activities should be considered within the scope of these flows,[5] additional issues surround their governance. These include differences between institutions in accounting climate flows channeled from a range of instruments such as grants, loans, and export credits; doubts over the climate centrality of projects as opposed to the climate co-benefits; lack of understanding of the actors involved in channeling funds and their objectives; and the additionality of finance directed for mitigation and adaptation actions.[6,7] Such disagreements on the quantity and quality of finance makes it difficult to assess whether the current structure of climate finance can meet the purposes of the Paris Agreement and provide adequate, predictable, and equitable finance for developing countries.[4,8]

Moreover, present commitments within international climate agreements cover only a small portion of the actual investment needed in developing countries for mitigation action.[9–11] Resources for such efforts must be scaled up and this is especially true for wind and solar energy technologies that are at the core of the energy transition and sustainable development pathways[12] and currently attract over 50% of international mitigation finance.[13] In developing countries, renewable energy (RE) deployment contributes to mitigation efforts while increasing energy security and progressing sustainable development goals.[14,15] With their growing economies and the potential for future increases in energy demand, it is important that investments in these countries are in sustainable energy rather than high-carbon fossil fuel technologies. This represents a major challenge in developing countries where financial flows must increase by over seven times by 2030 to meet net-zero targets (excluding China), with significant variations among regions.[16]

Meeting this challenge will require unlocking investments from the financial sector.[17,18] Indeed, although almost two-thirds of public climate finance from developed to developing countries is currently directed to mitigation activities,[12] a significant proportion of future finance needs are expected to be delivered by the private sector. Recent analysis presented at the 26th Conference of the Parties (COP26) estimates that up to 70% of global mitigation financing required during the 2020s across the world can be provided by private capital given supportive public policy and public investment.[19] Private finance hence represents a large pool of resources and there is limited possibility of controlling its direction purely through institutional mechanisms at the international level.[7,20]

While the scale of the investment challenge is readily apparent, there is also significant distributional variations in climate finance flows across countries, both with respect to geography and income level. Public finance estimates by the Organization for Economic Co-operation and Development (OECD)[21] show that the largest share of public finance is channeled to the Asian region (43%), with South Asia receiving the largest allocation (18%), and the African region receives a quarter of public funding with East, North, and West Africa capturing the largest allocations (approximately 5% each). With respect to income levels, lower middle-income countries (LMICs) receive the highest share of public funding followed by upper middle-income countries (UMICs), while low-income countries (LICs) receive the least. Private finance similarly has inherent variations. While a significant data gap exists regarding the sources, destination, and purposes of private climate finance,[10] even in terms of future potential, it is expected that certain regions will fare better than others in attracting investments.[19]

In brief, climate finance largely flows to fast-growing developing countries, while LICs, who are the most vulnerable to climate change impacts and the least able to access sufficient finance, remain underserved.[22] Such distributive aspects of climate finance are poorly understood and not accounted for in current finance frameworks.[23] Analysis by the International Renewable Energy Agency (IRENA),[12] for instance, shows that international public finance support for clean energy and RE needs in developing countries is not sufficient to meet the goals of Sustainable Development Goal (SDG) 7, and least-developed countries (LDCs) in particular need enhanced support. Given that 70% of financing needs for the energy transition will be needed in developing countries,[22] it is crucial that finance is distributed more equitably than at present. Additionally, given the importance of private finance in reaching climate goals, it is crucial that developing countries identify how best to attract these funds at the pace needed.[20]

Here, we investigate the differences between developing countries that underly distributional inequity in international mitigation finance by analyzing investments in wind and solar energy, since a large proportion (70%) of the mitigation needs expressed by developing countries relate to the energy sector[10] and these are the two crucial technologies for the low-carbon transition. Using network analysis, we explore the factors that differentially influence public and private actors in their choice of countries for investment and examine how investor priorities have shifted following the Paris Agreement, which signaled increased ambitions of the international finance community to align financial flows with developing countries' needs and priorities. Our results show that public actors are influenced by domestic climate policies since the Paris Agreement, while private finance flows are shaped by investment suitability conditions, which restricts access to both types of finance in the poorest countries. Further, public and private flows are strongly shaped by path dependency, generating an "investment lock-in" that perpetuates distributional inequities. Future international commitments to direct climate finance must address these distributional issues to meet countries' needs and the goals of the Paris Agreement.

RESULTS

Investments are distributed unequally across countries

Using the Bloomberg New Energy Finance (BNEF) database, we construct a project-level dataset of wind and solar investments made between 2010 and 2019 in which finance flowed across borders into a developing country. We focus on this time frame as international investments prior to the Copenhagen Accord of 2009 were negligible, totaling less than 0.5 GW (Fig. S1). BNEF provides financial transaction values for only a small percentage of projects; we therefore used project capacity as a proxy for finance flows. Project capacity is not intended as an accurate substitute for investment value (imputing investment costs from project capacity would deserve its own analysis given cost trends and the heterogeneity in financing conditions across countries[23]) but is fit for our purpose of assessing the distribution of finance across countries and income groups and large-scale

Table 1. Capacity additions from public and private sources across income groups pre and post Paris

	Pre Paris (2010–2015)			Post Paris (2016–2019)		
	Added capacity (GW)	Added capacity per million population (MW)	Countries (count)	Added capacity (GW)	Added capacity per million population (MW)	Countries (count)
Public						
UMI	1.71	70	14	4.09	234	17
LMI	2.27	151	18	4.98	212	22
LI	0.22	6	7	0.63	29	13
Total	4.20	–	39	9.7	–	52
Private						
UMI	3.06	92	19	7.49	237	20
LMI	2.22	59	21	4.32	101	21
LI	0.01	0.5	4	0.29	13	11
Total	5.29	–	44	12.1	–	52

Table summarizes total wind and solar capacity additions from public and private international actors made in a pre-Paris (2010–2016) and post-Paris (2016–2019) period. The 76 developing countries are grouped based on income levels using the World Bank classification: upper middle income (UMI), lower middle income (LMI), and low income (LI). Data source: BNEF.

changes in investment volumes over time. Our analysis covers 1,156 projects comprising 31 GW of renewable capacity in 76 countries using international public and private finance. China and India are excluded from our dataset as these two economic giants (together accounting for over 80% of added solar and wind capacity in the last decade[24]) would dominate investment trends across the developing world. For example, between 2017 and 2018, investment in RE capacity dropped by 24% in the developing world, largely due to investment in China and India falling by 36%, while investments in other developing countries in fact rose by 22% to record levels.[25] China's and India's rapid economic growth, large populations, and the unique size and maturity of their renewables markets mean that investment decisions in these two countries may be driven by a distinct set of factors that do not explain the distribution of finance across the rest of the developing world, to which we restrict the scope of this analysis.

Although the coverage of wind and solar projects is not exhaustive, BNEF is considered the most comprehensive database for renewable assets, particularly in its coverage of developing countries.[26] Aggregating data across the countries in our sample, BNEF reports more total capacity than the International Energy Agency (IEA),[27] because the database includes projects that are under construction/planning and decommissioned. We have included such projects in our dataset since they represent committed finance, which is the focus of our study. Analysis of missing data at country level suggests our dataset is unbiased and representative of international investment activity. Further, comparing the most recent figures for public climate finance flows and their distribution across income groups (similar figures for private finance are not yet available)[21] finds good agreement with our data (see section "data description" for further details).

In terms of overall investment, the period following the Paris Agreement saw a doubling in wind and solar capacity additions using international finance, growing from 9.5 GW in the pre-Paris era (2010–2015) to 21.8 GW in the post-Paris era (2016–2019) (Table 1). Private finance was the major source of investment across both periods, delivering 56% of capacity additions pre-Paris and post-Paris. However, the distribution of capacity additions across income groups is highly unequal. In the pre-Paris era, LICs received 12 times less capacity per capita than UMICs and 25 times less than LMICs from public sources. In the post-Paris era, the LIC share of capacity additions from public finance improves only marginally, in spite of the fact that new funding channels were opened into eight low-income African nations (Mali, Uganda, Burundi, Mozambique, Niger, Eritrea, Madagascar, and Gambia). Capacity additions from the private sector are distributed even more unequally than the public sector. In the pre-Paris period, LICs received 184 times less capacity *per capita* than UMICs and 118 times less than LMICs. However, the post-Paris share of private capacity additions to LICs increases markedly from 0.2% to 2.4% of the total, and, on a *per capita* basis, LICs receive eight times less and 18 times less than LMICs and UMICs, respectively (Table 1). In both periods, private finance shows a stronger preference for UMICs over LMICs compared to public finance. Our data highlight the disproportionately large share of capacity additions made in middle-income countries and the struggle faced by LICs to access wind and solar finance.[21]

Public and private flows of capacity additions show a high degree of correlation, suggesting a common set of investment drivers (Figure S2). Egypt, Mexico, Jordan, Pakistan, and South Africa are the top recipients of both public and private finance, while both types of finance are lacking in the poorest countries of Sub-Saharan Africa (Figure 1). Cumulative capacity additions by country over time show that the rate of addition is uneven and, in some countries, appears to rise sharply in the period following the Paris Agreement (Figure 1). To further explore commonalities and differences in the drivers of public and private investment and the effect of the Paris Agreement on such drivers, we develop a dynamic network model of public and private investments and explore mechanisms of network evolution.

The model is based on discrete choice analysis (see section "discrete choice analysis"), such that the probability of investment by a public or private actor is dependent on a country-specific feature (see section "feature model"). We collate a set of features (Table S1) that have been demonstrated to capture key characteristics of an enabling environment for low-carbon

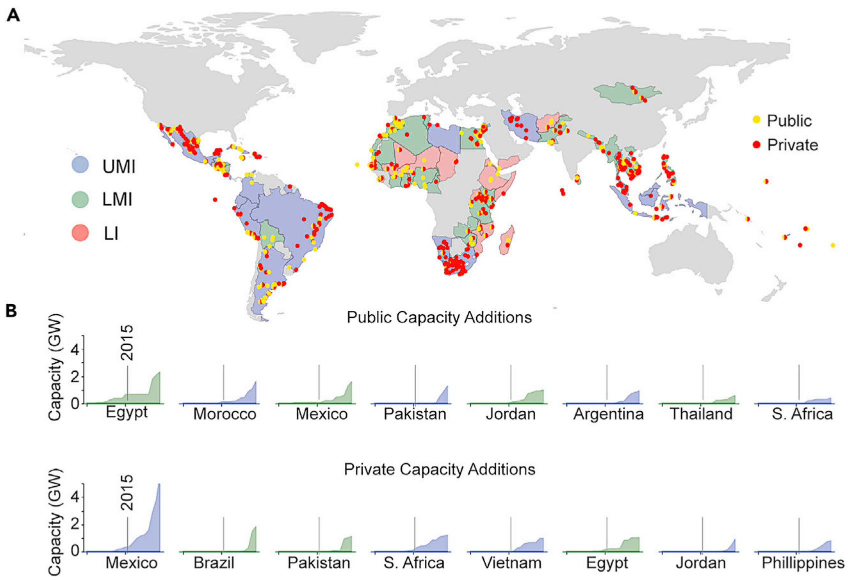

Figure 1. Distribution of public and private international investments across the developing world and over time

(A) Map shows 76 countries included in the analysis color-coded according to their income group; upper middle-income (UMI), lower middle-income (LMI), and low income (LI). The locations of project investments made between 2010 and 2019 are shown as circles color coded according to whether the funding came from public sources (yellow), private sources (red), or both (half-yellow, half-red).

(B) Charts show cumulative wind and solar capacity additions per country between 2010 and 2019 in the top eight recipients of public and private investment. Data source: BNEF.

investment and compare their influence on public and private investment activity pre and post Paris. Four of these features define the investment suitability of countries for RE,[28–32] namely macroeconomic, policy, business conditions, and electricity infrastructure. Macroeconomic conditions are captured by the economic fitness index,[33] which measures a countries economic diversity and correlates well with gross domestic product (GDP). We find economic fitness has stronger explanatory power for our data than GDP, possibly because economic diversity and the ability to produce complex technical products is more relevant to renewables investment. Policy conditions are captured by the World Bank's Regulatory Indicators for Sustainable Energy[34] (RISE) index, which summarizes country policies and regulations in the energy sector (we use only the RE indicators for the RISE score). Business conditions are captured by the ease of doing business[35] index, which measures the favorability of the business environment for new enterprise, and the level of electricity infrastructure is captured as the percentage of the population with access to electricity.[36] A fifth feature is constructed directly from the BNEF data and measures the level of installed wind and solar capacity in a country, capturing its track record in renewables deployment. Endogenous learning processes within low-carbon markets have been shown to shape transition pathways through a "technological lock-in,"[37] but the effect of such endogeneity on the distribution of investments across countries has not yet been examined. With the capacity feature, we test for the presence of path dependency and an "investment lock-in." We also tested a variation of this feature scaled by country size and find it has less explanatory power for our data, pointing to the importance of absolute, rather than per capita, levels of installed capacity for emerging renewables markets. Our set of features thus captures general characteristics of renewables markets, and we find that the key results are technology agnostic (Table S2). Standardization of all feature variables ensures coefficient estimates are comparable across features and statistical analysis indicates an acceptable level of multicollinearity between variables (see section "feature model").

Climate-vulnerable developing countries scoring low on these features face an additional "climate-investment trap,"[23,38] whereby the public costs of mitigation can negatively affect financing conditions. To explore this dynamic, we add a climate vulnerability index[39] to our feature set, which measures countries' exposure to biophysical impacts of climate change, economic sensitivity to climate hazards, and capacity to adapt.

Investment suitability drives private finance flows

We find that the distribution of private finance across the developing world is shaped by four features characterizing a country's suitability for investment. Countries with better macroeconomic, business, renewables policy, and electricity access conditions are more likely to attract private investment both pre and post Paris, highlighting these features as key determinants of a low-risk investment environment for wind and solar energy in developing countries (Table 2). To understand how these features shape the distribution of private investments across income groups, we calculated average feature scores per income group and showed that LICs score lowest on each investment suitability feature and UMICs score highest (Figure 2). Disparities in investment suitability across income groups thus correlate with the observed inequalities in the distribution of private finance (Table 1; Figure 1).

Macroeconomic conditions are a strong determinant of private investments both pre and post Paris, highlighting the importance of local financing conditions for renewable assets with high upfront capital costs and long-term revenue streams.[31] The business environment decreases in relative importance in the post-Paris period, suggesting that the maturation of wind and solar industries in this time may have lowered previously significant administrative barriers, which can be costly and time consuming.[32] This is a potentially important change for developing countries, pointing to a more important role for the renewables policy environment,[28] which can be improved in the short-term through stronger climate targets, financial incentives, and regulatory support. However, while UMICs and LMICs have seen their average RISE scores jump following the Paris Agreement (Figure 2), LIC scores have failed to improve, implying they have not prioritized renewables over other development imperatives. Moreover, low electricity access levels in LICs appear as a barrier to accessing private finance in our results, highlighting the

Table 2. The drivers of public and private sector investment and the effect of the Paris Agreement

	Public		Private			
	θ	$\Delta\theta$	θ	$\Delta\theta$	ρ	N
Economic fitness	1.34* (0.02)	−0.37* (0.02)	1.68* (0.01)	−0.28* (0.02)	0.67	1145
Electricity access	0.75* (0.02)	−0.15 (0.02)	1.19* (0.03)	−0.29* (0.03)	0.38	1153
Renewables policy	0.4* (0.02)	0.25* (0.02)	1.19* (0.02)	−0.24* (0.02)	0.5	1123
Climate vulnerability	−0.7* (0.02)	0.05 (0.02)	−0.7* (0.02)	0.33* (0.03)	0.44	1153
Ease of doing business	0.85* (0.02)	−0.3* (0.02)	1.07* (0.02)	−0.3* (0.02)	0.51	1148
Renewables capacity level	1.15* (0.01)	−0.07* (0.02)	1.31* (0.01)	−0.01 (0.02)	0.78	1156

Results of the feature model tested on six country-specific features: economic fitness, electricity access (percentage of the population with access to electricity), renewables policy (Regulatory Indicators for Sustainable Energy), ease of doing business, climate vulnerability, and renewables capacity level (logarithm of installed MWs). Coefficient estimates (θ) for the period 2010–2019 and the effect of the Paris Agreement ($\Delta\theta$) for the period 2016–2019 are given with standard errors in brackets. A model accuracy score, ρ, gives the Spearman's correlation coefficient between empirical and simulated investment distributions. N is the number of observations per estimation. *Significant at $p < 0.01$.

importance of existing government programs in developing countries to increase energy access under SDG7 goals. However, this also means that countries with large rural populations that struggle to achieve grid-based electrification, which many energy access programs focus on, may be disadvantaged in accessing private capital. In such cases, alternative business models and supportive policies to promote investment in off-grid solutions could be explored.

The climate vulnerability of a country is negatively correlated with each investment suitability feature (Figure S3) and LICs are most vulnerable to climate change impacts (Figure 2). This highlights a dual tragedy for poor and vulnerable countries. First, climate change impacts can generate economic, social, and political externalities that negatively influence sovereign risk and credit ratings and increase the cost of capital.[23,38] Second, and interrelatedly, the low investment suitability of climate-vulnerable countries creates further barriers for international finance, leading to a climate-investment trap[23] of chronically insufficient private funding.

Public finance supports local climate policy action

In contrast to private finance, international public flows are not observed to be as sensitive to the investment suitability features, reflecting the stronger alignment of international public finance with developing country needs (Table 1). Macroeconomic conditions are the strongest determinant of public investment, possibly to ensure the recovery of financing provided. However, in the post-Paris era, economic fitness becomes less influential, suggesting a more mission-oriented role for international public finance[40,41] and a greater emphasis on supporting climate investments in the poorest countries.[42] Further, the renewables policy feature becomes a more significant determinant of public funds in the post-Paris period. This suggests a growing complementarity between international and domestic climate agendas whereby the availability of dedicated public climate finance creates incentives for countries to strengthen renewables policies[43] and public funds are preferentially channeled into countries with strong climate ambitions. Top recipients of public investment, e.g., Egypt, Vietnam, and Jordan, all saw sharp increases in public capacity additions in the post-Paris period (Figure 2), following the introduction of RE targets and strengthened legal and policy frameworks for renewables investment,[34] reflected in increased RISE scores. However, this shift in public investment priorities may indeed handicap the poorest countries, where renewables policies remain weak (Figure 2).

Path dependency is evident in investor decision making

In addition to investment suitability, a highly influential determinant of both public and private finance flows is found to be a country's track record in wind and solar investments, as measured by total wind and solar capacity additions (Table 2). To verify that a track record in renewables investment is an independent determinant of investment decisions and that this result is not significantly influenced by multicollinearity between variables, we also ran a joint estimation of the feature model (see section "feature model"). Under this model specification, renewables capacity level was found to be the most significant determinant of public and private investment decisions (Table S3), validating empirically the presence of path dependency in international investment decisions across countries in the developing world.[44] Such evidence of path dependency in renewables investments points to positive feedback processes happening within renewables sectors,[45] whereby technological and financial learning bring down financing and development costs,[46] signal confidence to the international market, and attract further investments in a virtuous cycle. The international network of public and private finance thus evolves through the strengthening of historical links, rather than the formation of new ones (Figure 3). Such an investment lock-in leads to a highly skewed distribution of finance across countries as well as income groups, with only a small fraction of countries receiving the majority of capacity additions. Between 2010 and 2019, 76% of capacity additions from private sources and 67% of capacity additions from public sources go to the top eight recipient countries (Figure 1).

The investment unsuitability of the poorest countries (Figure 2) is reinforced by the observed path-dependent effects, which embed inequalities in public and private financial flows and impede any systemic shift in funding patterns. This also exacerbates the tension between the role of the public actors as market creators in high-risk countries[40,47] and as prudent financial institutions.[42] Evidence of path dependency corroborates the existence of a climate-investment trap, in which historical inequalities in financing are locked in across countries and income groups

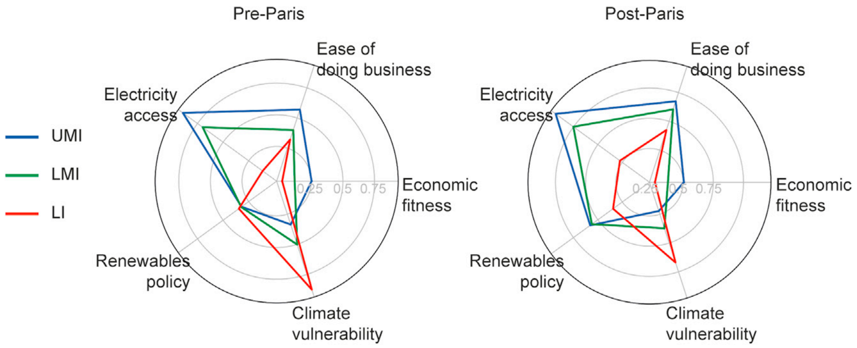

Figure 2. Average investment suitability scores per income group

Charts show average feature scores across income groups (UMI, LMI, and LI) and in two time periods: pre-Paris (2010–2015) and post Paris (2016–2019). Features are standardized to between 0 and 1.

and perpetuate over time due to self-reinforcing mechanisms, with dynamics similar to the poverty trap.[23]

Escaping this investment lock-in particularly for international private finance is essential for developing countries[43] as increasingly public finance is deployed using structures and instruments that induce private capital investment.[48] Hence, we examine the empirical nature of this path dependency to understand the impact of cumulative installed capacity in a given country on the probability of receiving private investment, specifically looking at the most recent post-Paris period. Probabilities are calculated by assigning each country an intrinsic "fitness"[49] that captures the combined effects of investment suitability and path dependence (see section "fitness model"). We observe that, in both wind and solar technologies, the probability of private investment remains low until a significant capacity base is installed. Investment probabilities start increasing rapidly around 1 GW of installed capacity (Figure 4). Path dependency appears to be more dependent on the absolute size of the renewables capacity in a country than the capacity levels per capita (Figure S4 shows a weaker correlation between the relative probability of private investment and the installed capacity per capita), indicating that an investment track record depends on absolute, rather than relative, capacity levels, in line with technological learning processes more generally.[50] Crucially, LICs fall far below this threshold, highlighting the inefficiency of opening finance channels into poorer nations (such as the eight low-income African nations that began receiving public funds post Paris) without the sustained investment that can mobilize private finance at scale.

DISCUSSION

Our analysis describes and analyses the inequitable distribution of international climate finance across developing countries. It highlights what constitutes an effective "enabling environment" for attracting long-term public and private capital[51] and how this has changed over time. Private finance flows are sensitive to the macroeconomic capabilities, business environment, climate policy environment, and electricity infrastructure of a country, while public

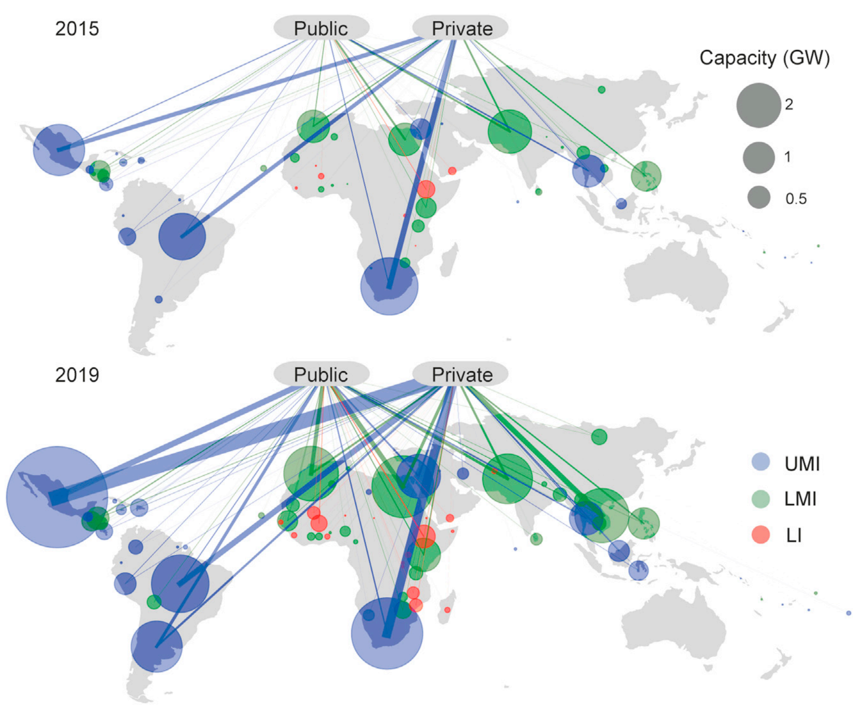

Figure 3. Inequalities in finance across income groups perpetuate over time due to path dependency

Maps depict finance flows to countries from public and private sources in 2015 and 2019. Size of circles represents total wind and solar capacity installed by international public and private sources. Width of links represents installed wind and solar capacity by sector.

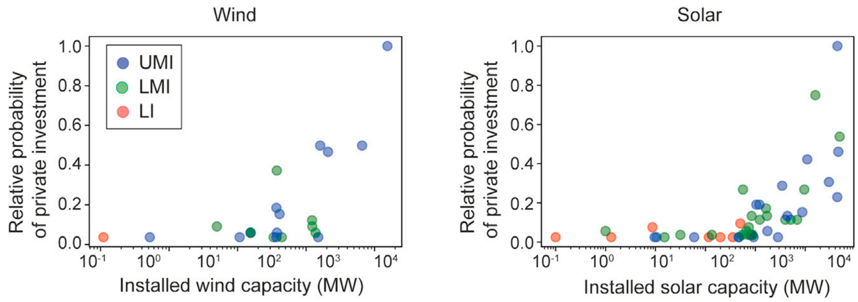

Figure 4. Empirical relationship between relative probability of private investment and installed wind and solar capacity

Plots show the relative probability of private investment for each country in the post-Paris period against installed capacity as of 2019, using IEA statistics. Probabilities are normalized against the country with the highest probability of private investment (wind, Brazil; solar, Mexico).

finance has flowed most strongly into countries with effective climate policies following the Paris Agreement, such as renewables support. We also observe path dependency in investment flows, providing evidence that building a track record of investments is key to mobilizing private finance at scale. Path dependency indicates a form of financial learning[52] that goes beyond technological learning[50] and reflects the maturation of renewables finance markets alongside a growing capacity base. Financial learning can arise when new projects generate investment experience within a renewables market, which allows investors to better assess and mitigate the risk of future projects, thereby lowering financing costs[46] and attracting further investment in a virtuous cycle.

Current international debate on climate finance has focused on the fulfilment of the $100 billion pledge by developed countries, the setting of new long-term financing targets post 2025, and improving the accounting and transparency of finance being channeled to developing countries. Taken together, our results highlight a need to refocus the international climate finance narrative in two key directions. First, distributional issues must be addressed to facilitate a just low-carbon transition,[53] in particular the disparity in funding received by low-income and middle-income countries. In order to mobilize private finance, collaborative governance at the international level should recognize the differential perceptions of the private sector and mitigate weaknesses in the investment suitability of the poorest countries that cannot implement strong supportive packages, to improve the risk-reward balance in more equitable directions. The Sustainable Renewables Risk Mitigation Initiative of the World Bank, for instance, uses a combination of public finance and mitigation instruments to reduce risk for private finance and thereby the cost of capital.[54] Such programs need a more comprehensive remit and dedicated funding. On the other hand, the ethos of the private sector needs to shift in line with Article 2.1(c) of the Paris Agreement.[2] The rules of the game that determine investment suitability should incorporate climate benefits in investment decisions, through economic incentives, regulation, or investor pressure, to lower the cost of capital and improve access for the poorest countries. Second, the presence of path dependency in climate finance flows means that investment decisions by public actors should move beyond project-specific inducements to support more holistic RE roadmaps. Financial and policy mechanisms should target the evolution of the sector and build networks of relationships to initiate path-dependent flows from private sources[55] and unlock developmental co-benefits.[56] UNFCCC financing mechanisms may need to adapt their portfolio allocations to prioritize the growth of renewables industries in underserved countries working alongside domestic public and private finance to break investment lock-ins and create positive loops in investment flows.

During the recent COP climate conferences, developing countries made it clear that further climate commitments and increased cooperation will depend on the delivery of "adequate and reliable finance" to meet current NDC targets.[57] Indeed, many developing-country NDCs are conditional on the provision of international finance.[58] However, the factors underlying the inequities in finance allocations identified in this analysis highlight a structural problem in climate finance delivery that is still not being addressed. A recent funding initiative targeting coal-dependent emerging economies, the Just Energy Transition Partnership (JETP) initiative, has so far only selected large middle-income countries with strong renewables track records as partners (Senegal, Indonesia, India, Vietnam, South Africa).[59] Such partnerships must be made with LICs and countries with undeveloped renewables markets to direct finance commensurate with countries' needs and realize an equitable low-carbon transition.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

The lead contact for this manuscript is Jamie Rickman: jamie.rickman@ucl.ac.uk.

Materials availability

No new materials were generated by this study.

Data and code availability

The analysis results and publicly sourced data are provided with this paper and the supplementary materials. The project-level dataset used to generate the results is proprietary to Bloomberg New Energy Finance (BNEF) and cannot be made publicly available. On obtaining access to the data, the protocols detailed in the section "experimental procedures" can be used to reproduce the results of this study.

All model code used to generate results for this article is archived and freely available at Github: https://github.com/LINKS-ERC/The_Unequal_Distribution_of_Climate_Finance.

Data description

Our data come from the BNEF database, which reports financial transactions on wind and solar assets from 2000 to 2019. Three BNEF datasets for wind and solar assets were used.

1. The projects dataset contains details of wind and solar projects. It provides key project information such as project capacity, financing date and location.
2. The organizations dataset contains details of investors involved in developing and financing wind and solar projects, such as their country of origin and ownership status.
3. The transactions dataset contains details of the transactions, such as the transaction date and type of transaction; e.g., a new build, refinancing, or acquisition transaction.

Table 3. Shares of public finance across income groups

Income group	OECD public finance (% of total)[a]	BNEF public finance (% of total)[b]
LI	12	8
LMI	57	54
UMI	32	38

[a]Source: OECD (2020), Climate Finance Provided and Mobilised by Developed Countries in 2013–2018 (adapted from Figure 2.4).
[b]Source: Bloombery New Energy Finance.

The three datasets were merged and filtered such that each entry in the final dataset pertains to a time-stamped new-build transaction; i.e., a project development.

For projects with no reported capacity, their value was imputed from available data according to the following steps:

1. If the data are available, assign project capacity to be the average capacity of projects in the same country and year and for the same technology type (solar photovoltaic [PV], solar thermal, onshore wind, offshore wind).
2. If there are no data for step 1, assign project capacity to be the average capacity of projects in the same country and for the same technology type.
3. If there are no data for step 2, assign project capacity to be the average capacity of projects for the same technology type.

This step order was chosen to reflect the fact that variability in project size was greatest across technology types, then across countries, then across years.

The dataset comprises a set of heterogeneous investors, including financial actors (e.g., banks and institutional investors) and non-financial actors (e.g., utilities, energy companies and government institutions). A semi-automated approach was used to categorize investors as either public or private using BNEF ownership information. Specifically, the ownership field in the organizations dataset, which labeled investors as, e.g., private or government/public sector. For investors with no ownership information or where BNEF's labeling was not definitive (e.g., the ownership status was subsidiary/division), a Google search was carried out to establish whether the organization was publicly or privately owned, using the rule that the majority stakeholder determined the classification of the organization.

Data preparation

From the BNEF data, we selected projects in which finance flowed across borders into a developing country. The projects included in the dataset could be financed by multiple investors, with at least one investor being international (i.e., located outside of the country where the project was developed). Project information included the date of the transaction, geographical location, and capacity. The dataset was augmented by categorizing each investor as either a public or private, domestic or international actor. To attribute project capacities to each actor involved in a transaction, we use the following protocol adapted from Mazzucato and Semieniuk.[60] If only equity investors are involved, project capacity is attributed equally to each investor. If debt and equity investors are involved, $r \times$ project capacity is assigned equally to each debt investor and $(1 - r) \times$ project capacity is assigned to each equity investor, where r is the average debt share (70%).

To assess the coverage of the BNEF data, we first compared the total reported wind and solar capacity as of 2019 against IEA statistics in the 76 countries included in our analysis. In aggregate, the BNEF data report more wind and solar capacity than the IEA (50 GW of wind and 44 GW of solar capacity is reported by BNEF compared to 36 GW of wind and 34 GW of solar capacity reported by the IEA) because projects are included in the database for which the finance has been committed but the plant is under construction/planning or decommissioned. However, data gaps do exist at country level where BNEF reports less capacity than the IEA in some countries (Figure S5A; Table S4). Such missing observations (unreported projects) would be problematic for our analysis if the probability of missing observations was dependent on the number of observations per country, which would introduce bias. To test for this, we measured the correlation of the missing capacity (capacity reported by the IEA minus capacity reported by BNEF) as a share of the capacity reported by the IEA, against the IEA capacity, for each technology. In the case of wind, we observe no correlation (Figure S5B). Only one country (Bangladesh) has a significant share of missing capacity (66%), but this represents only 1.9 MW, equivalent to a very small number of missing observations/projects. The remaining countries have, on average, 5% missing capacity. We can therefore reasonably assume that observations for wind are missing randomly, and the wind data are representative. In the case of solar, we observe that 13 countries have a high degree of missing capacity (greater than 20%). These countries have low total capacity (<350 MW) and the missing capacity is thus low in absolute terms (50 MW on average). BNEF does not report on installations less than 1 MW,[29] which excludes rooftop installations from the solar dataset, and this can reasonably account for the missing data. Since international finance is not typically used for such small-scale projects, this missing data are not problematic for our analysis. Again, there appears to be no bias in the occurrence of missing data (Figure S5B) and we can reasonably assume that the solar data are representative.

Table 4. Example action log

Source	Source type	Target	Year	Sector
KfW	public	Egypt	2010	Wind
International Finance Corp	public	Thailand	2011	Solar
African Development Bank	public	Morocco	2012	Solar

Synthetic data representing an action log of public investments in wind and solar assets in the pre-Paris period (2010–2015).

We further validate our attribution of capacity additions across income groups using the most recent available estimates of public finance flows to developing countries from the OECD (Table 3). The OECD provides estimates of public finance provided (in the form of equity, grants, and loans) from bilateral and multilateral public sources between 2016 and 2018. We compare the public finance share across income groups with our data from the same period and find good agreement.

Discrete choice analysis

To analyze the drivers and dynamics of public and private finance flows, we construct temporal networks from the investment data where links in the network represent projects. The networks are directed and bipartite, comprising two independent sets of nodes: international investors (source nodes) and the countries in which they invest (target nodes). Multiple investors can be involved in the same project, for example, where project debt is provided by a consortium of banks. In such cases, the multiple investors were treated as a single source node, since we are interested in the distribution of projects across countries and not the particular financing structure of a project. If a project was financed by public and private investors, two separate links in the network are made, one to an investor labeled as private and one to an investor labeled as public. The temporal evolution of the networks can be fully defined through a list of time-stamped network edges or "action log," of which a synthetic example is given in Table 4.

We used a discrete choice framework and the conditional logit to explore network evolution.[61] The action log for the network represents a set of investment choices (i, j, C, t) where each choice is a country j, chosen by investor i from the set C of all countries. The investor is labeled as one of two types: public or private. In the conditional logit model, each type of investor gains an inherent utility, u_{ijt}, by choosing a country $j \in C$ to invest in. The conditional logit model assumes that investors make choices to maximize their utility, U_{ijt}, which is composed of an inherent utility and a random term ε_{ijt} such that $U_{ijt} = u_{ijt} + \varepsilon_{ijt}$. The principle of utility-maximizing behavior states that the probability of an investor choosing a given country to invest in is equal to the probability that the gain in utility, U_{ijt}, exceeds that of all other countries in the choice set. The inherent utility is composed of a set of observed independent variables and the random term represents the unobserved attributes of choices and individuals, similar to the error term in a standard regression model. The probability $P_i(j, C, t)$ of investor i choosing country j from the choice set C at time t is given by

$$P_i(j, C, t) = Pr\,(j = arg\,max_{l \in C}\, U_{ljt}) \quad \text{(Equation 1)}$$

It can be shown that, when the ε_{ijt} follows the standard type I extreme value distribution, the probability of choosing each alternative is proportional to the exponentiated inherent utility[61]:

$$P_i(j, C, t) = \frac{\exp u_{ijt}}{\sum_{l \in C} \exp u_{ilt}} \quad \text{(Equation 2)}$$

We explore two forms of the utility function. First, a utility function based on country-specific feature variables (feature model), which include four features characterizing the investment suitability of a country and a fifth feature capturing its track record in renewables investment. Second, a utility function which assigns each country an intrinsic fitness term, analogous to the fitness model of network evolution[49] (fitness model). Each unique fitness term captures the combined effect of the investment suitability features and the capacity level feature, which may include idiosyncratic interaction terms and non-linearities, as well as other relevant features that were not tested in our study.

Feature model

In the feature model, the utility of country j at time t can be expressed as the product of a feature variable x_{jt} and a coefficient θ_i plus an interaction term, $\Delta\theta_i d_t x_{jt}$, which captures the effect of the Paris Agreement. The dummy variable d_t takes the value 0 if $t \in \{2010, \ldots 2015\}$ and 1 if $t \in \{2016, \ldots 2021\}$.

$$u_{ijt} = \theta_i x_{jt} + \Delta\theta_i d_t x_{jt} \quad \text{(Equation 3)}$$

This model formulation ensures that the coefficients of the feature variables are comparable between temporal regimes and investor types. Importantly, the features can evolve over time and are thus indexed with a timestamp t.

A number of different features, x_{jt}, were tested as measures of a country's utility: macroeconomic conditions, measured by the economic fitness index[33]; renewables policy environment, measured by the RISE index[34]; business environment, measured by the Ease of Doing Business index[35]; electricity access levels, measured by the percentage of the population with access to electricity[36]; climate vulnerability, measured by the ND-GAIN index[38]); and renewables capacity level, the total wind and solar capacity in a country (Table S1).

The renewables capacity level feature was constructed from the BNEF data in the following way: the value in country j and year t was calculated as the logarithm of the installed wind and solar capacity between the year 2000 and t−1. Taking the logarithm of the cumulative installed capacity connects the conditional logit model based on the renewables capacity level feature to the popular preferential attachment model of network growth,[62] which is itself a special case of the conditional logit model where the utility $u_{ij} = \alpha\, log\, d_j$ with d_j being the degree of node j. The capacity level feature thus captures the same "rich-get-richer" phenomenon that preferential attachment describes, in which attachment probability is proportional to a power-law function of node degree. Modeling the wind and solar data together (see Results) and separately (Table S2) gave similar key results. We also investigated an intensive counterpart to the renewables capacity feature to control for country size, in which the logarithm of the installed capacity between 2000 and t−1 was weighted by the size of the population in year t−1. The capacity and capacity per capita feature are strongly correlated (Figure S3) but absolute capacity levels are a stronger predictor of investment than relative capacity levels both in the feature model (Tables 2 and S5) and in the fitness model (Figures 4 and S4). We speculate that absolute capacity is a better predictor of investor decision making than relative capacity because it reflects the size and maturity of the renewables industry in a country and thus the technological, regulatory, and business experience in the sector, which informs the level of risk to an investor.

While GDP is a conventional measure of macroeconomic conditions, we found economic fitness (which is strongly colinear with GDP; Figure S3) to have greater explanatory power for our data. We speculate that this is because it captures the competitiveness of countries through the complexity and diversity of goods they produce, and this is highly relevant to the renewables industry, which requires complex, technical products and services. As a correlate of GDP, economic fitness can be treated as an extensive variable.[63] We also considered its intensive counterpart to control for country size, GDP per capita, and found it had less explanatory power than GDP and economic fitness (Tables 2 and S5). The absolute size of the economy, and, relatedly, its complexity and diversity,[63] thus appears in our analysis as a more relevant driver of investor decision making. Moreover, we do not find that GDP per capita is strongly correlated with the other feature variables explored looking at pairwise correlations (Figure S3) and the variance inflation factor, which indicates acceptable levels of multicollinearity between variables (Table S6), supporting the significance of the other features as independent drivers of investor decision making. However, to control for the moderate correlations between variables and obtain an alternative estimate for the significance of each feature, we also ran a joint estimation of the coefficients, including each feature variable in the model. The joint estimation yields a similar pattern of results (Table S3). In this specification the utility function becomes

$$u_{ijt} = \Theta_i X_{jt}^T + \Delta\Theta_i D_t X_{jt}^T \quad \text{(Equation 4)}$$

where Θ_i is a vector of coefficients $(\theta_i^1, \ldots, \theta_i^p)$, X_{jt} is a vector of feature variables $(x_{jt}^1, \ldots, x_{jt}^p)$, and D_t is a diagonal matrix $diag(d_t)$ of rank p.

The feature set, which has a time resolution of 1 year, contains two types of missing data. First, the climate vulnerability and electricity access features had no data for the year 2019 and, in this case, the value for 2018 was carried forward. Second, some country data were completely missing for certain features. In such cases, the countries with missing feature data were excluded from the respective model, which excluded at most 3% of data (average 0.01% across the six features). The features were standardized to zero mean and unit variance, so that coefficient estimates are comparable across features.

Fitness model

To explore the relationship between the level of installed wind (solar) capacity and the probability of a wind (solar) investment on a country-by-country basis (Figure 4), we also developed a set of models in which a unique time-invariant parameter θ_j was assigned as each country's utility such that $u_{ij} = \theta_j$. Technology-specific investment probabilities for each country can then by computed using

$$P_i(j, C, t) = \frac{\exp \theta_j}{\sum_{l \in C} \exp \theta_l} \quad \text{(Equation 5)}$$

The results presented in Figure 4 can be found in Table S7.

Parameter estimation

We used a maximum likelihood approach to estimate the model parameters. For the feature model, the log likelihood of the choice data $\mathcal{D}$ conditional on θ is given by,

$$L(\theta; \mathcal{D}) = \sum_{(j,C,t) \in \mathcal{D}} \log \frac{\exp \theta\, x_{jt}}{\sum_{(l,C,t) \in \mathcal{D}} \exp \theta\, x_{lt}}. \quad \text{(Equation 6)}$$

This log likelihood function is convex with respect to the parameter θ and can be efficiently maximized using the gradient-based BFGS algorithm.[61]

For estimation of the unique fitness terms in the country fitness models, we make the connection between our discrete choice framework and the fitness model of network growth in which attachment probability is proportional to an inherent node fitness $p_{ij} \sim \lambda_j$ by making the equivalence $\lambda_j = \theta_j$. Following the work of Pham et al.,[64] in which the fitness parameters are drawn from a gamma distribution, we add a regularization term $S = \sum^{(j,C,t) \in D} -\log \Gamma(k) - k \log t + (k-1) \log \theta_j - \frac{1}{t}\theta_j$ to the log likelihood, equivalent to placing a Bayesian gamma prior with shape parameter k and scale parameter t onto the likelihood function. The log likelihood is thus given by

$$L(\theta; \mathcal{D}) = \sum_{(j,C,t) \in \mathcal{D}} \log \frac{\exp \theta\, x_{jt}}{\sum_{(l,C,t) \in \mathcal{D}} \exp \theta\, x_{lt}} + S \quad \text{(Equation 7)}$$

The standard error of parameter estimates is calculated using the bootstrap method.[64]

Model evaluation

To assess the statistical significance of each coefficient, θ_{iT}, in the feature model we used the likelihood-ratio test, comparing the likelihood of the full model against the likelihood of the nested model L_0 with the coefficient under investigation set to 0. The likelihood ratio $\lambda = L_0/L_M$, under some regularity conditions, is asymptotically distributed as[61]

$$-2 \log \lambda \sim \chi_k^2 \quad \text{(Equation 8)}$$

where k is the additional degrees of freedom in the more complex model and p values can be found using this likelihood-ratio chi-squared statistic.

As an additional metric of the explanatory power of each feature variable, we assessed model accuracy, ρ, by simulating network evolution and using Spearman's correlation coefficient to compare the empirical distribution of investments across countries and the average of 40 simulated distributions. A coefficient of 1 thus indicates a given feature perfectly captures the investment activity, while a coefficient of 0 indicates a feature does not perform better than the null model.

SUPPLEMENTAL INFORMATION

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AUTHOR CONTRIBUTIONS

J.R., conceptualization, methodology, analysis, writing – original draft; S.K., conceptualization, writing – original draft; F.L., conceptualization, writing – review & editing; N.A., conceptualization, writing – review & editing, supervision.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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