The Hidden Structure Of Energy Efficiency Finance

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Abstract
The broader financial system plays a key role in channeling capitals towards energy efficiency technologies to meet the climate goals. In this study, we analyse the market for energy efficiency finance as a complex system, where interactions of heterogeneous investors give rise to large scale investment trends. By analysing the investment system as an evolving network of inter-linked investors, this study identifies the key actors that have directed investment flows in energy efficiency technologies, patterns of investors' interactions in terms of co-investments and the evolution of the investment landscape. These elements are critical to deploy instruments of public finance and policy effectively to accelerate the energy efficiency technologies deployment.

Keywords: Climate Finance, Energy Efficiency Investment, Networks

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Introduction

The landmark Paris Agreement calls for vast and rapid investment into low-carbon and energy efficient technologies (WEI 2020, UNFCCC 2015). Investments in energy efficiency (EE) are particularly crucial to reduce the energy demand for a growing world economy and are listed as core measures for sustainable recovery plans (IEA 2020); EE is indeed the most cost effective way to reduce emissions, while improving energy security and competitiveness (IEA 2019). Estimates from IEA suggest that unlocking the full potential of efficiency, would imply global investments to double by 2025, and double again between 2025 and 2040 (IEA 2018, 2019). However, EE investment levels have remained largely unchanged since 2014 and are insufficient to meet the climate goals (WEI 2020).

A number of well-known and recognised market barriers led to under investment in these technologies. Financing constraints linked to the high-upfront cost of such interventions (Ameli and Brandt 2015a,b, Schleich and Gruber 2008), along with information asymmetry concerning different aspects of energy products (Myers 2020, Carroll, Aravena and Denny 2016, Howarth and Sanstad 1995), are major barriers to investing in energy efficiency. For instance, consumers with financing constraints and with poor access to capital are less likely to take up EE improvements (Schleich et al. 2019); and very few consumers actually know the costs and benefits of different energy solutions, how much energy they use/consume or what rates of return to expect from energy efficiency measures (Davis and Metcalf 2016, Allcott 2013). Another explanation for underinvestment in EE is linked to heuristic decision-making where consumers often use 'rules-of-thumb' or tend to simplify complex assessments by using 'heuristic' estimates (Kahneman and Tversky, 1979; Shogren and Taylor 2008; Tietenberg 2009). Such behavioural aspects in addition with different consumer profiles can have strong influence on the uptake of EE investment (Blasch et al. 2017, Trotta 2018, Pelenur and Cruickshank 2012, Gillingham et al. 2009).

More recently, a few studies have started to investigate low-carbon investment patterns from a financial perspective. Some scholars have explored how financing conditions and their dynamics affect the competitiveness of low-carbon assets (Steffen 2020, Egli et al. 2018, Krupa and Harvey 2017, Angelopoulos et al. 2016). While others have focused on the characteristics of financial actors involved in the related investments highlighting the importance of different types of investors in shaping the low-carbon transition (Mazzucato and Semieniuk 2018, Hall et al. 2016, Bergek et al 2013). This nascent research stream has so far, however, overlooked the role of the financial system to foster EE technology deployment as well as the structures that drive it.

The broader financial system, meaning the set of actors comprising it, plays a key role in channeling capital towards EE technologies. Indeed, the interactions and dynamics of its heterogeneous actors, who have diverse investment preferences and operate in different markets, collectively shape the development of individual EE technologies and the actual investment flows towards them. However, such investors' interconnections remain unexplored in climate policy analyses, which usually take the existing structure of financial systems as given.

This study aims to fill this gap by analysing the evolution of energy efficiency (EE) finance market - referring to capital flows directed towards energy efficiency interventions with direct greenhouse gas mitigation benefits (Buchner et al. 2019) - from a network perspective (Schweitzer et al. 2009, May et al. 2008). We study the EE finance market as a complex system, where the financial actors and the set of connections between them comprise the network, to capture investors' systemic importance and their dynamics when investing in a portfolio of EE technologies. The network evolves as result of the dynamic behaviour of these heterogeneous financial actors, which leads to the emergence of specific outcomes/trends (Hall et al. 2017, Arthur 2015, Mitchell 2009, Lo 2005).

Many examples of real networks show the significance of network evolution and dynamics to understand the development of a given system as a whole to tailor specific solutions to manage it (Strogatz 2001, Hopcroft et al. 2004, Kossinets and Watts 2006, Boccaletti et al. 2006, Gross and Sayama 2009). Indeed, there are important system attributes which cannot be fully accounted for without considering the interplay between structural and dynamical characteristics of the system. For instance, regime shifts in financial markets like recession and expansion phases depend both on structure (e.g. connectivity) and dynamics (e.g. volatility, correlation patterns and processes of self-organisation) of the system. By understanding these evolutionary processes, the changes of behavior and dynamics taking place, it would thus be possible to affect the future development of the system (Farmer et al. 2012, Farmer et al. 2019). Key features of this analysis are thus to determine the key actors leading investment flows towards EE technologies, patterns of investors' interactions in terms of co-investments and the evolution of the investment landscape.

This analysis advances the nascent literature exploring the role of the financial sector in the global transition to a low-carbon economy. To the best of our knowledge, it is the first attempt to account for complexity thinking and systemic perspective to study the market for energy efficiency finance. Moreover, this study looks at a portfolio of EE technologies rather than a single one as the diversity of such technologies is a further element of complexity to the understanding of EE adoption. Finally, our analysis provides new empirical evidence on energy efficiency investment by exploiting a novel dataset, namely the Bloomberg New Energy Finance (BNEF), which reports detailed financial data at project level across several EE technologies.

The remainder of this paper is organized as follows. Section 2 presents the network approach employed in this analysis. Section 3 describes the data and the global landscape of energy efficiency investment. Section 4 shows the evolution and growth of the energy efficiency network over time, while section 5 elaborates some policy implications and concludes.

Methodology

The complex system of energy efficiency investments is analysed by exploring the interconnections between investors and projects. These interconnections are defined at multiple levels of aggregation to understand the unique structure and dynamics of the system such as by aggregating projects by the technology employed, homogeneous investors into investor categories, and investors and projects on the basis of their country of origin. We represent investors and projects as two different sets of nodes in a 'bipartite network', namely a network where nodes belong to two mutually exclusive sets and only connections between two nodes in different sets are allowed (Holme et al 2003). Bipartite networks are usually compressed by one-mode projection into one set category (actors or projects) and related projected networks show connections to common nodes in the bipartite network. We focus on the projected network of investors, where investors supporting energy efficiency projects are visualised as nodes and their dependencies due to co-investments in the same projects are represented as links (supplementary materials).

We then employ the General Temporal (GT) model to analyse the network dynamics and growth over time (Pham et al. 2016). This model incorporates the preferential attachment (PA) and fitness mechanisms to study the growth of the network. With PA, wherein nodes acquire new links based on the strength of their existing connections, we account for the tendency of a particular technology to attract further investment as a result of existing investments ('rich get richer') (Barabási and Albert 1999, Krapivsky et al., 2000). While with the fitness model, wherein nodes acquire new links based on their intrinsic qualities, we capture the inherent attractiveness of a technology to investors ('fit get richer') (Caldarelli et al. 2002). The objective is to estimate the strength of these two processes in driving networks' evolution (Ke et al. 2015; Wang et al. 2013).

In the GT model the probability of a node to acquire a link at a particular time is proportional to the attachment function of its degree at the time and to its time-invariant intrinsic fitness. Formally, the probability that a node n_i with degree $k_i(t) = k$ at time t acquires new links at time-step t is proportional to $A_k \times f_i$ as formalised in the following equation:

$$\pi(t) \propto A_k \times f_i$$

where, A_k is the generic attachment function and f_i is the node fitness.

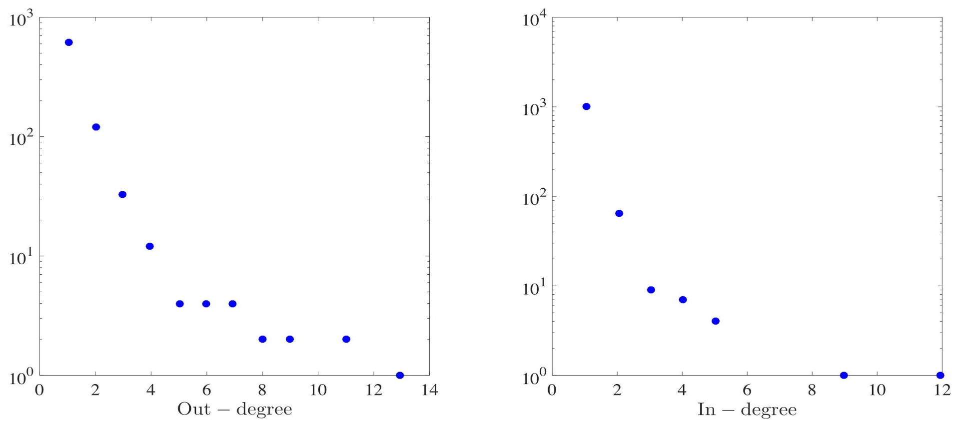
To empirically estimate the PA function and node fitnesses from observed network data, the model does not impose constraints on the functional form of the PA function, nor does it assume a specific fitness distribution (Pham et al., 2015). Joint estimation of the PA function and node fitness allows us to better estimate the influence of each mechanism since it takes into account the impact of the other and can indicate the relative strength of each. It also provides a better understanding of the evolutionary mechanisms behind network growth, than those obtained from models estimating A_k and f_i in isolation. The method adopts a Bayesian approach and formulates the estimation problem as the maximization of the log-likelihood function of the GT model. The method optimises the objective function using a Minorize-Maximization algorithm to obtain the estimates for A_k and f_i.

The Energy Efficiency Landscape

Our analysis covers worldwide energy efficiency investments from 2000 to 2017 in six broad EE technology families detailed in 17 sub-technologies using project-level investment data from BNEF (Tab 1 and supplementary materials Fig M.1 and M.2). Energy efficiency investors have been categorised into 14 groups based on the nature of their business to understand their common patterns of investment (supplementary materials). The investor-project investment network comprises I = 802 unique investors, P = 1103 projects and $\sum A_{ip}$ = 1238 investments.

Figure 2 shows the out-degree distribution for the investors (number of different projects an investor has funded) and the in-degree distribution for projects (number of investors a project has received funding from). Both sides of the network are characterized by a prevalence of specialized nodes, indeed 77% of investors financed only one project, and, symmetrically, 92% of projects have received funding from one investor only, while a small minority of projects / investors are involved in more than one financial transaction.

Fig 2: Degree Distribution Showing Out-degree Distribution For Investors And The In-degree Distribution For Projects



The leading investors in the system are the utility companies (both state and investor-owned ones) which are involved in almost 60% of the projects, followed by original equipment manufacturers (OEM)/services companies and the public sector (i.e. government). Digital energy interventions have received most investments comprising around 65% of the total transactions, with leading technologies, smart metering and smart grids, accounting for roughly 45% of the total; energy storage projects (grid-scale and distributed storage) reached 19% of total investments, while fuel cells accounted for 10%. Other technologies attracted on average less than 2% of total investment.

Table 1: Investor Type Investing In Energy Efficiency Technologies (2000-2017)

Investor type	Digital Energy	Efficiency: Built Environment	Efficiency: Industry	Efficiency: Supply Side	Energy Storage	Fuel Cells	Total	Total (%)
State-Owned Utility	294	6	1	9	46	12	**368**	**29.40**
Investor-Owned Utility	271		1	6	63	26	**367**	**29.40**
OEM/Services Company	48	2	2	2	68	25	**147**	**11.80**
Government	75	23		2	15	15	**130**	**10.40**
Energy Cooperative	67				6		**73**	**5.80**
Research Organisation/ University	31	2		1	19	8	**61**	**4.90**
Institutional Investors	15	3	3	2	5	6	**34**	**2.70**
Construction/ Real Estate	5				6	4	**15**	**1.20**
Diversified*	18		7		6	24	**55**	**4.40**
Total	**824**	**36**	**14**	**22**	**234**	**120**	**1,250**	
Total (%)	**65.90**	**2.90**	**1.10**	**1.80**	**18.70**	**9.60**		

Source: Authors' calculations based on Bloomberg New Energy Finance (BNEF) dataset.

*Diversified includes chemicals, steel, food, retail, eCommerce, defence and aerospace and other sectors.

Looking at the geographical distribution, top countries in terms of active projects are the United States, Canada, Australia and some European countries, like France, Germany, Italy and the United Kingdom (Fig 3a). We observe that most projects are financed by investors based in the same country (roughly 93%); this applies to all major countries, e.g. the US, UK, China, Canada, Japan, whose investors are all financing projects in their respective countries. This trend seems to suggest that investors' home bias applies to energy efficiency investment. Previous research has explained investors' preference for domestic assets as result of their better access to information (Coval and Moskowitz 1999, 2001), familiarity with the local policy settings and regulatory context, as well as with associated home-risks (Baltzer et al. 2015, Bailey et al. 2008). Only 7% of total transactions relate to energy efficiency cross border flows reflecting investment opportunities in specific markets and geographical proximity (Fig 3b). The US and the UK have been the biggest recipients of cross-border energy efficiency investments whereas Germany, the US and Canada have been the biggest originators of cross-border investment. The most significant financial flows originate from Canada and Germany targeting investments in the UK and the US, and Austria and the US respectively.

Figure 3a: Energy Efficiency Investments Worldwide (transactions 2000-2017)

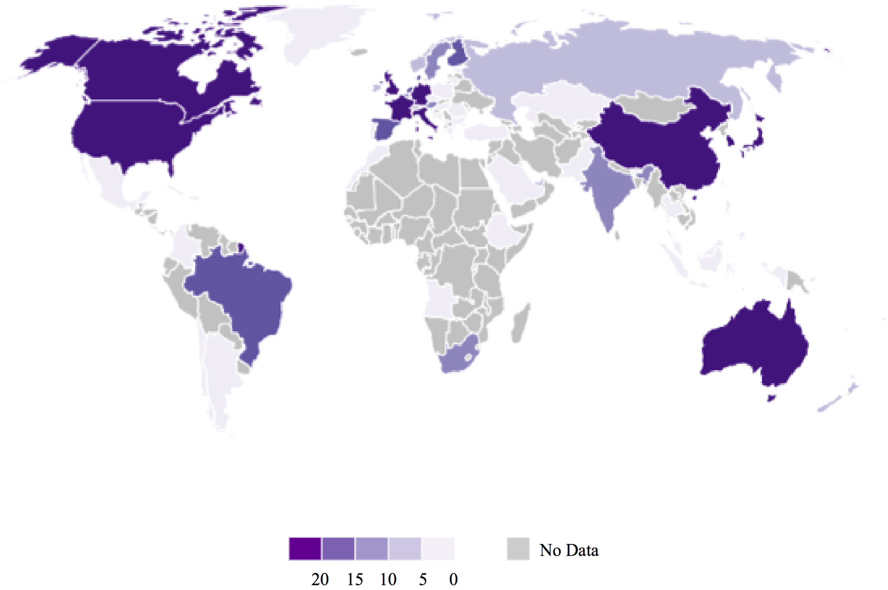
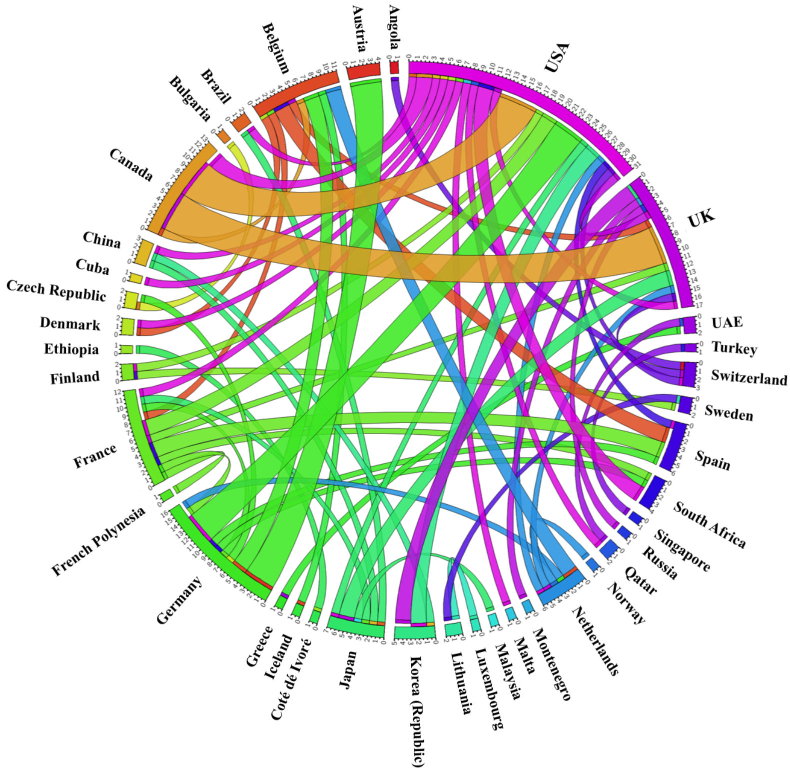


Figure 3b: Cross Border Flows Of Energy Efficiency Investments

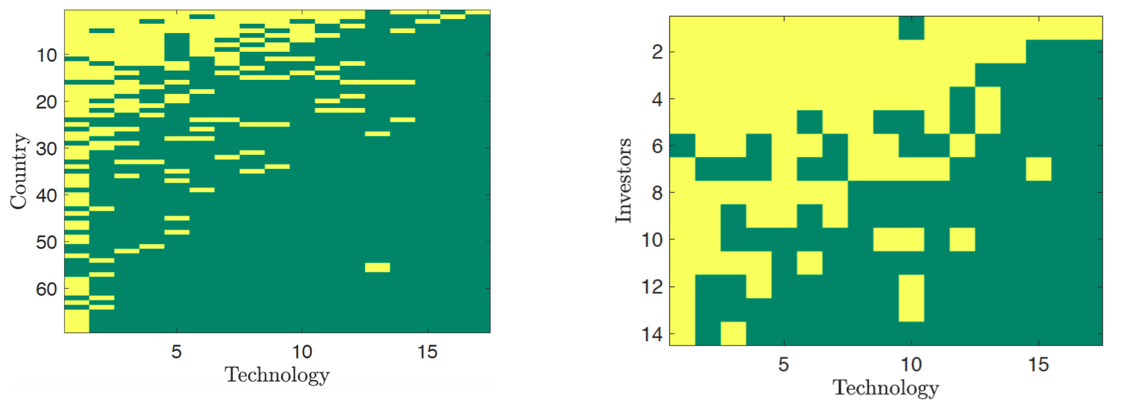


Note: Each country is assigned a unique colour. The colour of each chord indicates the country of origin of the investment flows while the thickness indicates the size. The scale in the diagram indicates the number of investment transactions reported by BNEF and it might not be an exhaustive depticion of current EE investments.

Having looked at the broader energy efficiency investment landscape, we investigate whether certain countries have a well-defined investment profile and different investors have marked investment preferences. In both cases, the related networks reveal the emergence of a nested structure suggesting the presence of few generalists and specialists (Fig 4 and supplementary materials). At the country level, few countries invest across a wide portfolio of technologies, such as the US, UK, and China, and, symmetrically, several technologies, such as smart metering and smart grid, receive investments from a multitude of countries. This is accompanied by the presence of specialist countries, which invested in only one or two technologies, and of specific technologies which have received funding only from a few countries, like Japan for grid-scale storage and South Korea for stationary fuel cell technologies. Such relationships suggest most countries are specialising in different technologies as a result of their strategic investment choice on key technology for their country (noting that 93% investments are domestic). Similarly, on the investor side, few investor categories, such as governments and utilities, invested across a spectrum of technologies (i.e. smart grid, smart metering, smart T&D), while some preferred a few key technologies, like OEM/services companies that invested mainly in storage-related projects.

Figure 4: Nested structure of the Country-Technology and Investor-Technology Networks

Nested structure of the country-technology network *Nested structure of the investor-technology network*



The colours in the maps do not account for link weights, and only show whether a link is present (yellow) or absent (green) between two nodes. Both adjacency matrices show the presence of a few "generalist" countries/investors with investments in most technologies, and a few "specialist" ones investing in very few technologies. These are arranged in a nested structure, e.g. specialists typically invest in technology subsets in which more generalist nodes invest as well.

Regarding the structure of the system, it is a relatively sparse network, where some investor and project nodes form pairs or small groups of connected nodes otherwise disconnected with the rest of the network (Fig 5a). They indicate that individual investors are not active enough in terms of co-investing, refinancing or acquisition of projects in the secondary market to form a highly interconnected and active financial system. The analysis of existing links connecting different investors to common project nodes provides an indication of common investment patterns (Fig 5b). In particular, utilities and governments have been the most prolific in investing in common projects. The public sector has played a key role in providing capital for projects by supporting investments from other investors, as it was involved in 73% of all co-investments, and thus stimulating a crowding-in investment processes. The finding confirms investment trends also observed in renewable technologies, where the involvement of public investors triggered more private capitals (Deleidi et al 2020, Owen et al 2018, Mazzucato and Semieniuk 2018).

Figure 5a: Aggregated Network Of Financial Actors (2000-2017)

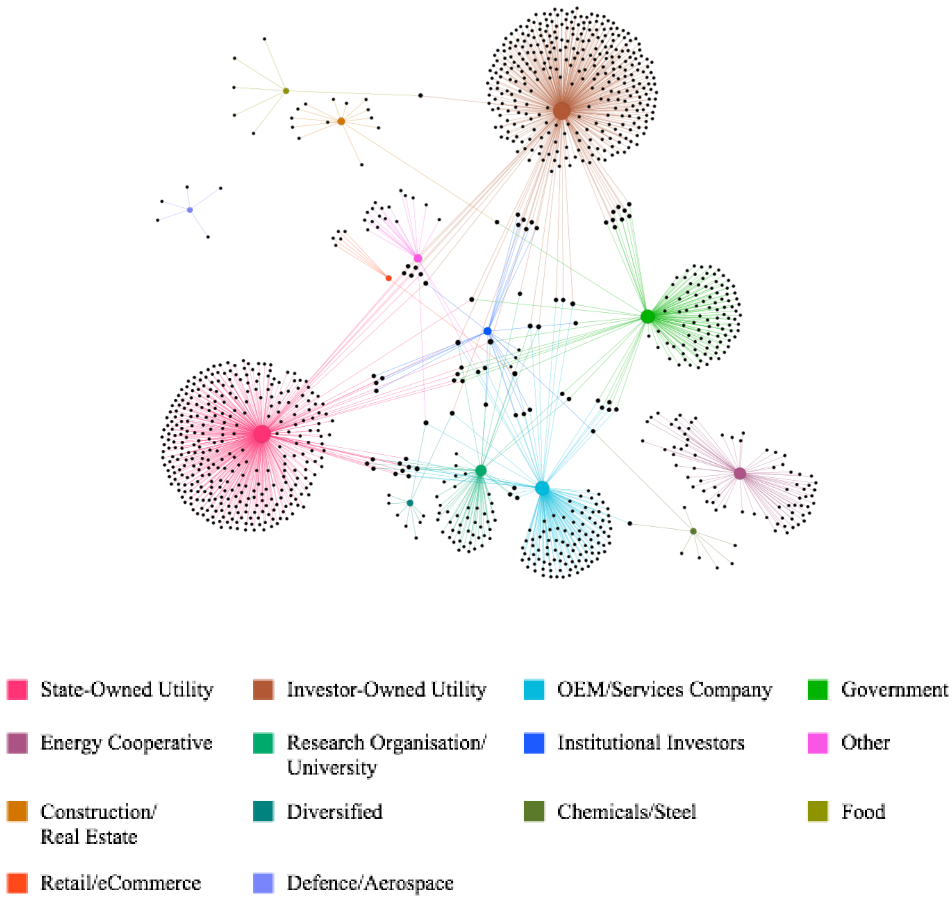
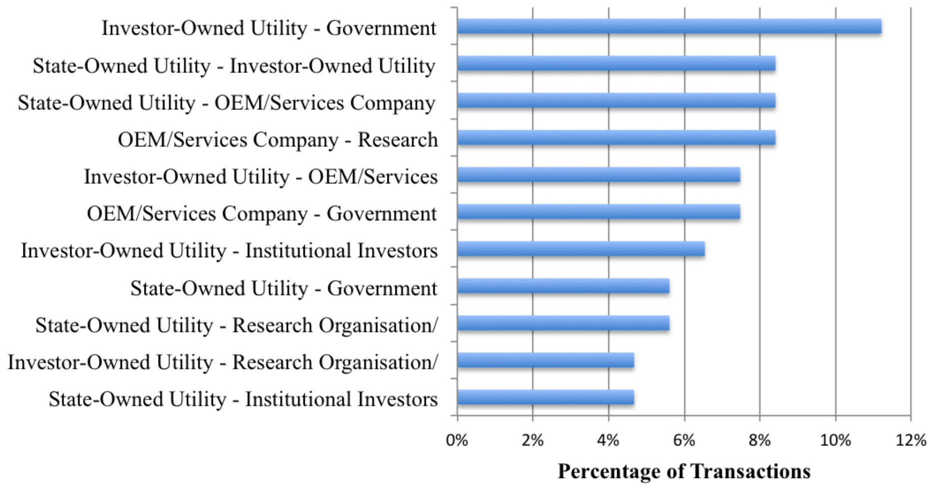


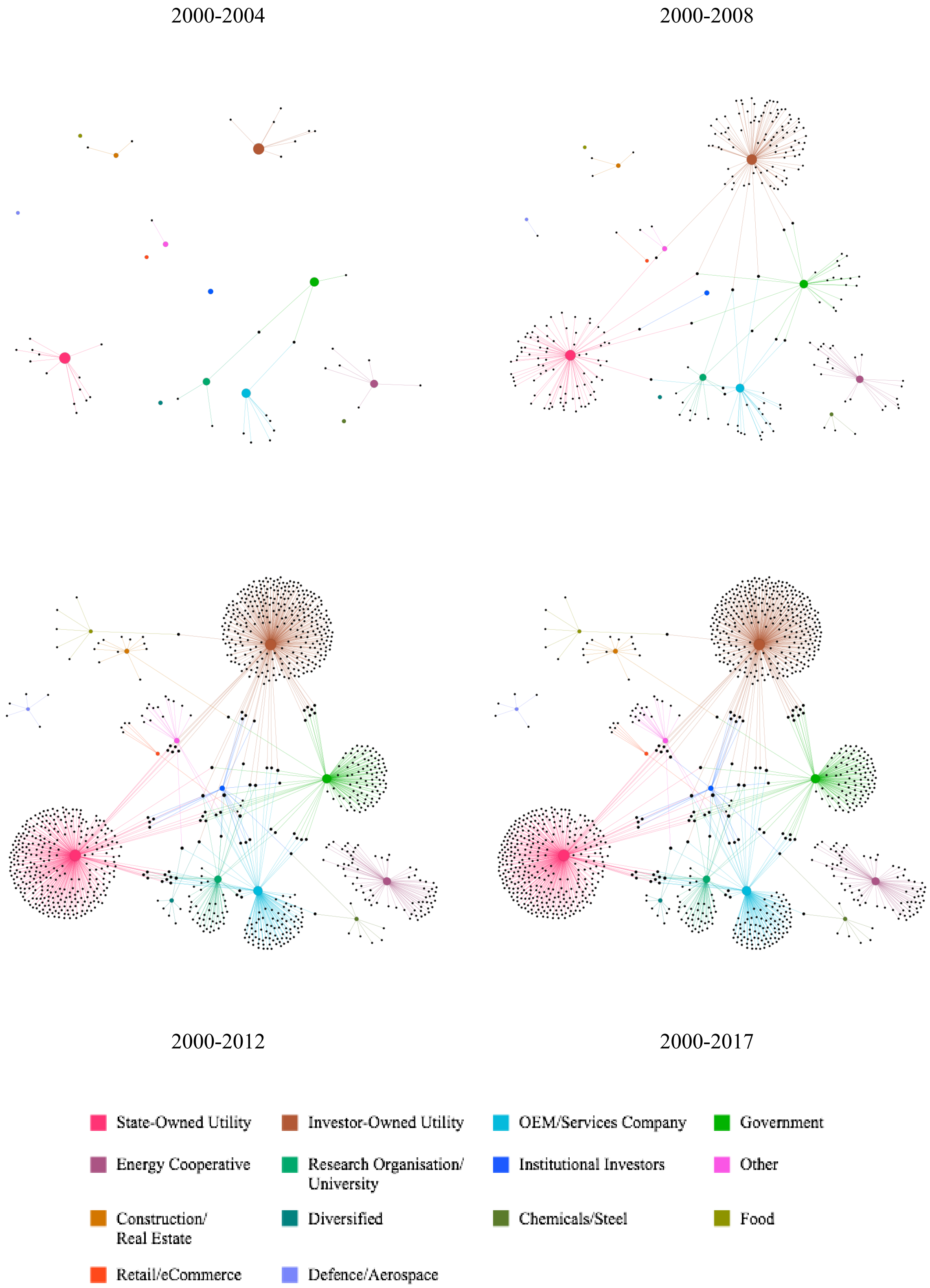
Figure 5b: Co-Investment Patterns (2000-2017)



Evolution, dynamics and growth of the energy efficiency network

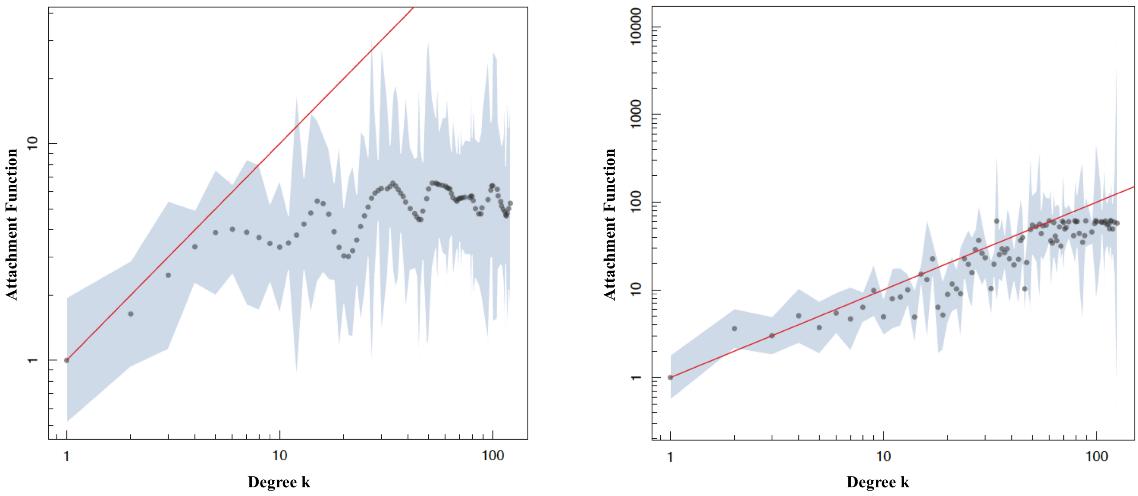
The network evolution over almost the last 20 years is analysed by looking at snapshots of bipartite networks over time (Fig 6). The aim is to discern what types of actors and relationships have been most critical in shaping the evolution of investment patterns at particular points in time. The first phase (2000-2004) indicates a period of early growth with low investment levels and limited connectivity. Utilities are the key investors along with the public sector (government, state-owned utilities and research organisations). The second phase (2005-2008) sees a higher investment level and improved connectivity in the network. Utilities continue to dominate the investment landscape by being involved in 68% of total investment transactions, but they are also supported by OEM/services companies, government and energy cooperatives (25% combined share). The increased investments in this phase indicates a growing confidence in energy efficiency technologies (especially digital energy) and financial collaborations amongst investors. The third phase (2009-2012) represents the highest growth phase with high levels of investment and greater connectivity. Utilities continue to be the major investor participating in 58% of transactions, but also robust support is being offered by OEM/services companies and government, which see their involvement grow to 12% and 11% of investment transactions respectively. This high growth phase is indicative of maturing technologies with all investors looking to substantially boost their deployment and displaying high levels of connectivity through co-investments, refinancing and acquisition transactions. In particular, digital energy projects are the most attractive technology for investors, together with energy storage which experienced over six times jump in the number of investment transactions. The fourth phase (2013-2017) is characterized by a slow-down in the growth of the sector. The share of utilities in the overall investment transactions reduces to 48% as well as governments and OEM/Service companies, comprising 25% of the transactions. The connectivity of the network however grows to its highest level. The increased connectivity in the network is mainly led by a mature phase of key digital energy technologies with increased confidence among investors. However, efficiency investment growth has weakened in this last phase as policy support showed signs of slowing down (WEI 2018).

Figure 6: Aggregated Network Of Investors And Its Evolution Over Time (2000-2017)



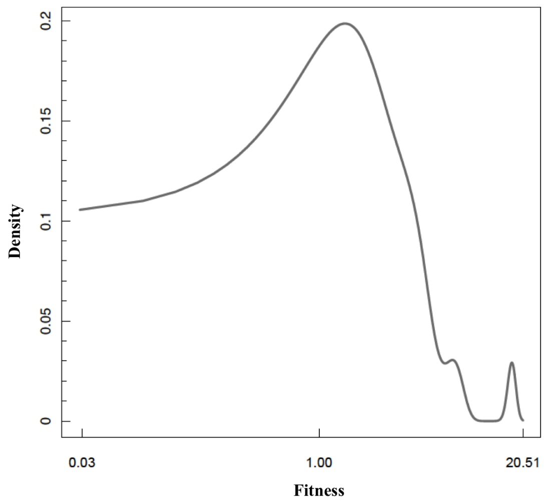
We then analyse the growth of the energy efficiency investment network to identify processes driving the formation of new links in the system and leading to the actual investment landscape. Following Pham et al. (2016)'s approach, we measure the respective influences of the preferential attachment and the fitness models. The estimated attachment function in case of joint estimation with fitness and the PA-only case is shown in Fig 7.

Figure 7: PA Function in isolation (Right), PA Function with fitness (Left)



(α = 0.035, when fitted to $A_k = k^{\alpha}$) (α = 0.798, when fitted to $A_k = k^{\alpha}$)

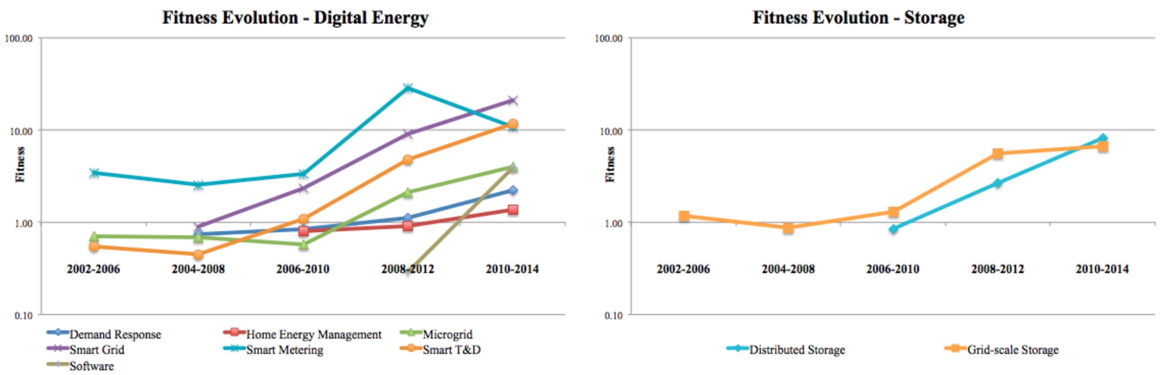
Figure 8: Distribution of nodes' fitness



The increasing function of the estimated A_k suggests the existence of the 'rich get richer' effect (corresponding to an increasing A_k on average), however when the fitness influence is considered, the PA mechanism results appear over-estimated. The joint estimation of PA and technology fitness indicates an increasing attachment function initially, highlighting that technologies with existing investments tend to attract further investment, but only up to a point (Fig 7). As the links of the technologies grow, the attachment function levels out, and technologies' fitness explain the further investments received by each technology. This suggests that the 'rich get richer' mechanism becomes weaker when the 'fit get richer' effect is considered, showing that to some extent technology's ability to attract new investment is explained by its fitness.

There are few technologies with very high fitness (significantly greater than 1) that correspond to higher levels of investment (Figures 8 and 9, supplementary materials Table M.4). Overall higher node fitness is characterised by greater link accumulation resulting in higher investments. Smart metering, smart grid and grid-scale storage have the highest fitness values, which explain the significant investments made in these technologies. Despite having just two investments before 2008 (first in 2003), the high fitness value of smart grid technologies has seen it acquire significant investments since that time. In contrast, despite having investments since 2000, grid-scale storage has attracted less investments due to its lower fitness compared to smart grid. Software and home energy management have attracted some investments even though being later technologies (first investments in 2009) due to their moderate fitness values. Transmission efficiency has experienced low investments since its emergence in 2004, which correlates with a low fitness value. The case of waste heat recovery is similar.

Figure 9: Digital Energy And Storage Technologies' Fitness Evolution Overtime



These investment patterns reflect mainly public spending and regulations support (i.e. energy standard and mandates) in specific EE technologies, which led to economies of scale and technological improvements increasing investors' confidence in such sectors (BNEF 2017 and 2018a). For instance, modernization of the grid with spending on digital technologies, supported by regulatory frameworks in countries such as China and the United States, has been a key driver for investment in electrical network's replacement and upgrades (BNEF 2017 and 2018b, WEI 2018). In particular, China is leading the deployment of smart grids thanks to its unique market structure characterised by state ownership of the transmission and distribution sector, and the central role played by the government in policy setting. Investment patterns also reflect technologies' fitness evolution over time. All technologies under digital energy (e.g. smart metering, smart grid, smart T&D) together with storage interventions (i.e. grid-scale storage and distributed storage) showed the highest fitness values and became increasingly attractive to investors over time, having initial fitness values around 1 in 2002 and reaching fitness values of 10 in 2014 (Fig 9).

Conclusions and Policy Implications

Analysing the market for energy efficiency finance as a complex evolving system of inter-linked investors, highlights the key actors who have directed the investment flows, patterns of interactions in terms of co-investment and their dynamics over time. Overall, we can observe that the EE markets are relatively nascent for many technologies compared to their potential for further development, likely due to the lack of clear business models for investment or instruments to monetise the efficiency gains. As a result the number of investor interactions have been relatively limited as shown by the sparse nature of the investor networks, although they have improved in recent years with maturing technologies and increased deployment.

This study suggests that utility companies, both state and investor-owned, are the most active and influential actors in the system. They have displayed a strong preference for digital energy and energy storage projects thereby playing a key role in the development of these markets. Indeed, for utilities, operational savings, efficiency and maintenance expenditure such as reduced meter reading, outage management, and customer service, are the most immediate value drivers for investing, and have potentially driven their behaviour in the system (BNEF 2018b). Given utilities' critical role in the system, policies and regulations should boost their engagement in the energy efficiency market. For instance, regulations surrounding the use-of-system tariffs along with efficiency mandates, and simplified market structures, can establish a long-term return proposition for investing in EE. As an example, in the US, regulation is supporting utilities' business models to evolve towards greater exposure to network investments based on regulated and contracted pricing (WEI 2018).

Government investment through state institutions has also played a key role in the deployment of EE technologies. While their involvement has been across the broad spectrum of EE technologies, their contribution is most notable for technologies centred on efficiencies in the built environment. Lacking a clear business model to spur external investment as compared to digital energy or storage technologies, public finance has been key to their adoption. However, to rapidly increase the deployment of these technologies, both regulation, such as stronger green building mandates, and market creation is necessary to attract investments from private actors.

Analysis of existing co-investment patterns amongst different actors, shows that utilities have been the biggest attractors of investments while Governments, OEM/Services companies and Research Organisations have been key providers of co-investments. This trend underlines the importance of the public sector as a hub in the investment chain, especially compared to the limited role played by other private financial institutions including banks. It is also indicative of the nascent state of the EE markets with technology-centric investment patterns. In this case, policies favoring co-relationships between different investors can help to stimulate crowding-in investment processes and further the deployment of EE technologies. In a recent study, Geddes et al (2018) showed that state investment banks are crucial to catalyse private investment, as they enable the financial sector to create trust and track record for low-carbon assets.

Finally, our analysis shows how the energy efficiency investment system grew over time suggesting that technologies' existing investments and their inherent attractiveness to investors determine the investment in the sector. The case of digital energy technologies, particularly smart grids, smart metering and smart transmission & distribution, demonstrates how the combination of public spending, regulations support and technology improvement led to an increasing market confidence in this technology - especially in countries like the US and China, making it the most attractive one to investors. The same is true for storage technologies where the growth of renewables, technology improvement and strong policy support have provided a robust business model to accelerate their deployment.
Some EE technologies, such as waste heat recovery and transmission efficiency, have experienced low investments since their emergence and are not currently attracting investors' choices due to technical developments still required for improving their performance. Other key energy efficiency technologies, like demand response and lighting, despite their potential and relative technology maturity, have not attracted much investment over time. In these cases, development of new business models and policy support could target critical technologies that are currently displaying low fitness values to improve their attractiveness to investors.

Broadly speaking, an improvement in the economics of EE technologies through technological change, regulatory mandates, market demand or policy incentives, can improve their inherent fitness and potential role in the evolving EE landscape. Policy design to promote upcoming innovative energy efficiency technologies can also target specific investors based on the role played in promoting similar technologies and increasing their adoption in the system. Such policies may then target utilities, OEM/services companies and research organisations/universities for energy storage technologies or utilities and energy cooperatives for digital energy or chemical/steel companies for industrial energy efficiency. Governments may also consider direct investments in promising technologies where historically their investments have induced co-investments, such as technologies for built environment efficiency, fuel cells and digital energy.

Understanding the evolutionary processes in the energy efficiency sector is thus needed to inform policy-makers and to boost the future development of such markets. Using the case of energy efficiency investments and methods of network science, this study shows the merit of analysing the complex interplay of heterogeneous investors in different technologies over time, to mobilise EE finance. Influencing key actors, leveraging existing interconnections between them, deploying instruments of public finance and policy to accelerate the growth of energy efficiency investment, can lead to nonlinear deployment of key technologies and guide the evolution of the low-carbon system to achieve climate objectives.

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Acknowledgements
This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 802891). NA also acknowledges support from the Complex Built Environment Systems (CBES) Platform Grant (grant number EP/P022405/1). GL acknowledges support from an EPSRC Early Career Fellowship (grant number EP/N006062/1).

Author contributions
NA coordinated the research and the design of the study, with inputs from all authors. NA wrote the article with support from GL and SK on specific sections. SK and GL performed the data analysis. All authors reviewed the article.

Competing interests
The authors declare that they have no competing interests.

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Supplementary materials

Data Description

The analysis is based on Bloomberg New Energy Finance (BNEF) dataset, which tracks data on low-carbon investments worldwide since 2000. In particular, the data used for the analysis consists of three BNEF datasets:

1. the Projects dataset containing details of energy efficiency projects. It provides key project information such as project value, commissioning and completion date, financing date, current owner, project developer and location. The energy efficiency technologies analysed are summarised below in Table M.1a,b:

Table M.1a: Energy Efficiency technologies

Category	Description
Digital energy	It covers applications of information and communication technology to improving efficiency and intelligence of the transportation and usage of energy. Smart metering, smart grid, demand response, self-healing grids, virtual power plants and home building automation are some examples.
Efficiency: built environment	It covers technologies reducing the use of energy in homes, retail and commercial buildings. Such technologies include advanced insulation, building components, HVAC (heating, ventilation, and air conditioning), lighting and intelligent systems for managing power consumption, as well as the tools and services that allow companies to design and implement energy-smart buildings.
Efficiency industry	It includes technologies used to streamline and save resources in industrial processes. Examples are process control and monitoring, sensors and software, and waste-heat recovery.
Efficiency: supply side	It covers technologies resulting in a step-change improvement in the efficiency of generation and transmission systems. Examples include: motor or generator design, technologies improving transmission efficiency in high-voltage-direct-current (HVDC), high-voltage-alternating-current (HVAC) and high-temperature-superconductors (HTS), as well as software, sensor and control technologies.
Energy storage	It covers technologies such as batteries, flywheels and ultracapacitors, which can store and release energy in the form of electricity.
Fuel cell	It covers fuel cells and their various applications. Fuel cells are electrochemical cells that convert chemical energy from fuel such as hydrogen into electricity. They can be used in consumer, transportation or stationary applications.

Table M.1b: Breakdown of energy efficiency technologies in sub-technologies

Technology	Sub-Technology
Digital Energy	Demand Response
Digital Energy	Home Energy Management
Digital Energy	Microgrid
Digital Energy	Smart Grid
Digital Energy	Smart Metering
Digital Energy	Smart Transmission & Distribution (T&D)
Digital Energy	Software
Efficiency: Built Environment	BMS & EE Electronics
Efficiency: Built Environment	Building Services
Efficiency: Built Environment	Lighting
Efficiency: Built Environment	Materials
Efficiency: Industry	Waste Heat Recovery
Efficiency: Supply Side	Transmission Efficiency
Energy Storage	Distributed Storage
Energy Storage	Energy Storage for Transportation
Energy Storage	Grid-scale Storage
Fuel Cells	Stationary Fuel Cell

2. the Organisations dataset containing details of companies and organisations involved in developing and financing energy efficiency projects, and it provides information such as the business description and country;

3. the Transactions dataset containing details of project finance transactions such as the transaction date, transaction type, financing type, equity providers and debt providers.

The final data used to build the networks and perform the related analyses is constructed by merging the transactions, organisations and projects datasets pertaining to the energy efficiency technologies for the period 2001-2017. A thorough validation exercise was conducted on the extracted datasets to ensure consistency among them and where necessary the data was augmented with information contained in textual description fields for projects, organisations and transactions. Public information such as organisation websites, public announcements and news reports were used to improve consistency of data where possible. Based on these validation and augmentation processes, a consistent Projects, Transactions, Organisations mapping was obtained.

To generate insights about financial actors, the investor organisations were classified into actor categories to best represent the actors investing in energy efficiency projects. Each organisation was assigned a category based on its stated business description available from BNEF and based on information from the public domain through corporate websites and government registries. This process resulted in 14 actor categories as reported in table M.2.

Table M.2: Investor category

Category	Description
State-owned Utility	Utility company engaged in the production, transmission or distribution of energy in which the majority stake (greater than 50%) is held by the Government either directly or through one of its institutions
Investor-owned Utility	Utility company engaged in the production, transmission or distribution of energy in which the majority stake (greater than 50%) is held by private individuals or corporations
OEM/Services Company	Manufacturers of equipment used in the energy sector and companies providing technical/non-technical services to energy companies
Government	Federal/State/City governments and their institutions
Energy Cooperative	Utility company established as a cooperative association and whose primary goal is to provide services to its members
Research Organisation/ University	Organisations whose primary purpose is conduct fundamental research, innovate and develop technologies, and disseminate knowledge
Institutional Investors	Companies whose primary business is to collect money from its investors and acquire assets seeking monetary return
Construction/ Real Estate	Companies involved in constructing buildings and infrastructure, and developing real estate projects
Chemicals/ Steel	Companies that produce industrial chemicals and steel-based products
Food	Companies involved in producing, processing, warehousing and distributing food products
Retail/ e-Commerce	Companies involved in supplying consumer goods and services through physical and internet-based presence
Defence/ Aerospace	Companies involved in producing and selling military technology/ weapons/ civilian and military aircrafts
Diversified	Companies operating in multiple and possibly unrelated businesses across regions
Others/ Unknown	Organisations that can not be classified in the above categories or whose nature of business could not be determined on the basis of the information in the public domain

Methodology

The energy efficiency network

In an investor network perspective, we represent both investors and projects as nodes in an $I \times P$ bipartite network - a network where nodes belong to two mutually exclusive sets with no connections between nodes of the same set (Fig M.1 and M.2). This network is described by an adjacency matrix A such that $A_{ip} = 1$ if investor i has contributed to financing project p, and $A_{ip} = 0$ otherwise. The out-degree distribution for the investors (i.e., number of different projects an investor has funded) is calculated as $k_i^{out} = \sum_{p=1}^{P} A_{ip}$, and the in-degree distribution for projects (i.e., number of investors a project has received funding from) is calculated as $k_p^{in} = \sum_{i=1}^{I} A_{ip}$.

The weight of the connections in the resulting bipartite networks of aggregate nodes represent the sum of out-degree/in-degree of constituent investor/project nodes.

The statistical significance of repeated interactions between nodes is assessed by using the approach suggested by Tumminello et al. (2011). For the sake of clarity, we use the country-technology network as an example. Let W be the $C \times T$ weighted adjacency matrix of such network, where the entry W_{ct} represents the number of times country c has funded projects in technology t. Let us also define the *out-strength* $\sigma_c^{out} = \sum_{t=1}^{T} W_{ct}$, which represents the total number of investments made by country c, whereas the *in-strength* $\sigma_t^{in} = \sum_{c=1}^{C} W_{ct}$ represents the total number of investments received by technology t. We assume that we are interested in assessing the statistical significance of a specific entry W_{ct} against a null hypothesis of random interaction, i.e. a scenario in which each country distributes its σ_c^{out} investments at random across the available T projects. Under this null hypothesis, we can associate a p-value to entry W_{ct} by computing $p(W_{ct}) = \sum_{x=W_{ct}}^{min[\sigma_c^{out}, \sigma_t^{in}]} H(x \mid N, \sigma_c^{out}, \sigma_t^{in})$, where N is the total weight in matrix W, and

$$H(x|N, \sigma_c^{\mathrm{out}}, \sigma_c^{\mathrm{in}}) = \frac{\binom{\sigma_c^{\mathrm{out}}}{x}\binom{N-\sigma_c^{\mathrm{out}}}{\sigma_c^{\mathrm{in}}-x}}{\binom{N}{\sigma_c^{\mathrm{in}}}}$$

computes the probability of random interactions generating a link of weight x between two nodes with the out-strength σ_c^{out} and in-strength σ_t^{in}, respectively. Statistically validated relationships correspond to links that are significant at a certain univariate significance level (1% in our case) corrected with the False Discovery Rate criterion for multiple hypothesis testing.

This methodology can also be straightforwardly generalized to test the statistical significance of co-occurrences, namely, situations where pairs of nodes in one of the two layers of a bipartite network share large numbers of neighbors. Let us suppose we are interested in testing the co-occurrence $n_{cd} = \sum_{t=1}^{T} \Theta(W_{ct})\,\Theta(W_{dt})$ of two nodes c and d with out-degrees $k_c^{out} = \sum_{t=1}^{T} \Theta(W_{ct})$ and $k_d^{out} = \sum_{t=1}^{T} \Theta(W_{dt})$, respectively, where Θ denotes the indicator function such that $\Theta(y) = 1$when $y \geq 0$and $\Theta(y) = 0$otherwise. Then, a p-value associated to the probability of observing a co-occurrence equal to or higher than n_{cd} under random interactions can be computed as $p(n_{cd}) = \sum_{x=n_{cd}}^{min[k_c^{out}, k_d^{out}]} H(x \mid T, k_c^{out}, k_d^{out})$. When assessing the statistical significance of co-occurrences on the other layer of a bipartite network, this formula straightforwardly generalizes to $p(n_{tz}) = \sum_{x=n_{tz}}^{min[k_t^{in}, k_z^{in}]} H(x \mid C, k_t^{in}, k_z^{in})$.

When applying this procedure repeatedly in the same network to test all interactions or all co-occurrences, a multiple hypothesis testing correction must be applied in order to avoid false positives. Following Tumminello et al. (2011), we adopted the very conservative Bonferroni correction.

Figure M.1: Weighted Country-Technology Network Of Investments

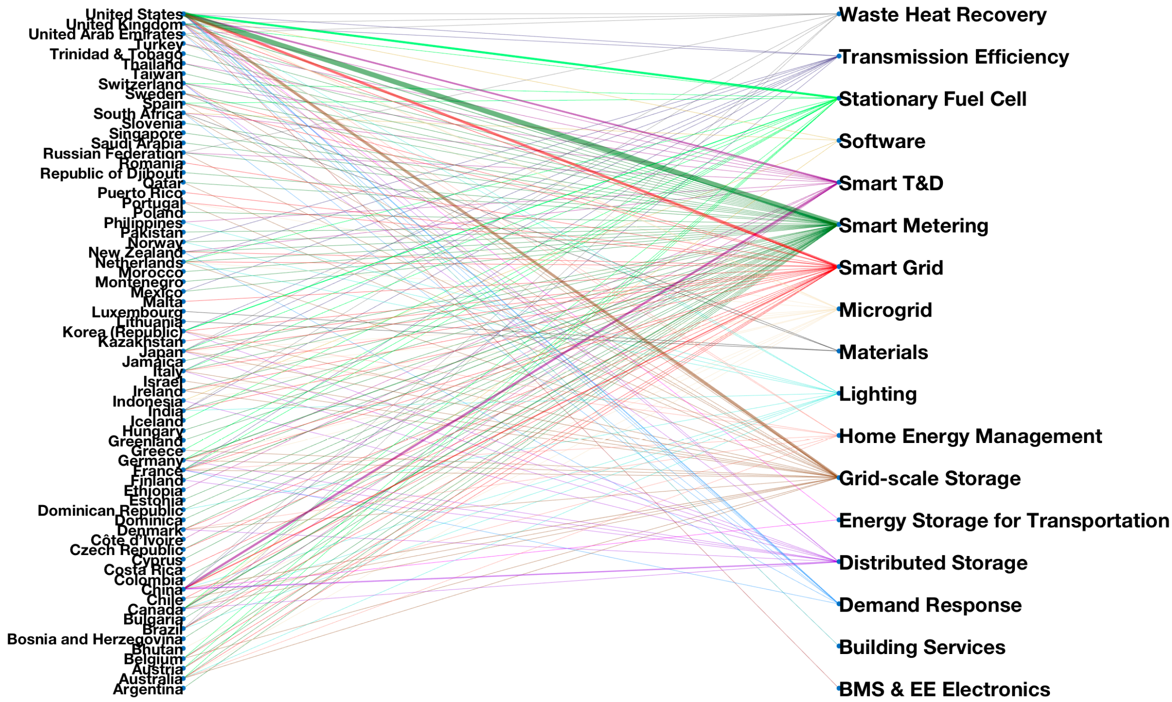
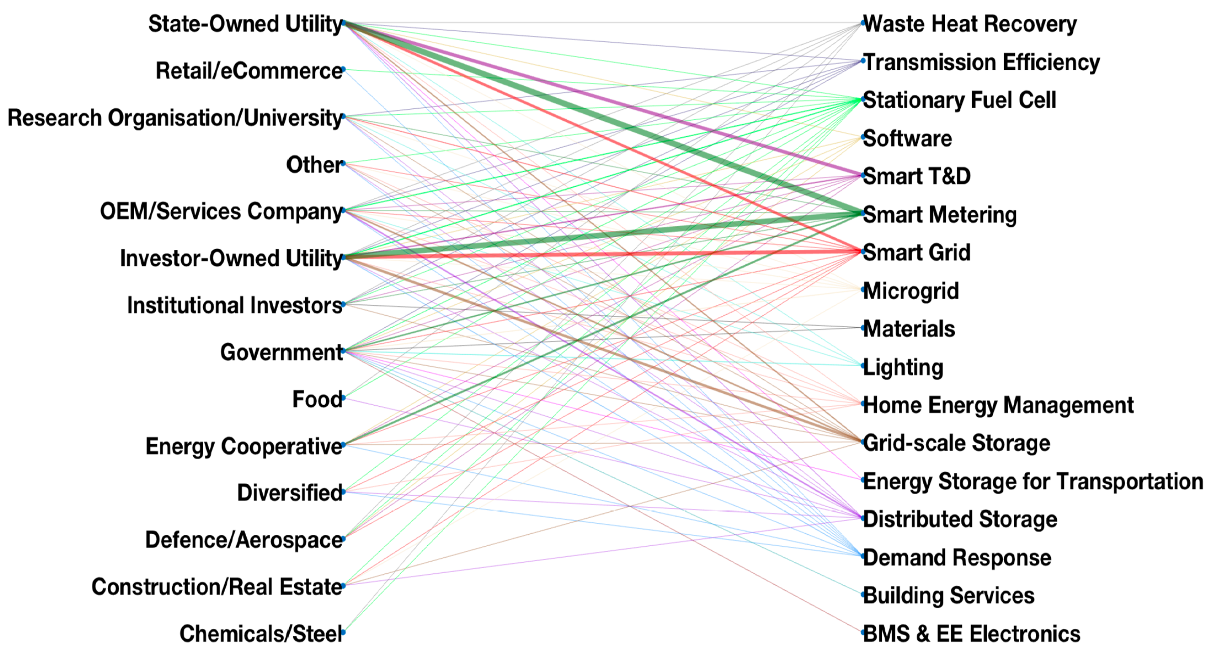


Figure M.2: Weighted Investor-Technology Network Of Investments



Investors’ preferences and countries’ specialisation

We investigate countries’ specialisation and investors’ preferences by applying the link validation method Tumminello et al. (2011) to assess whether some countries and investor categories have marked preferences for investment in a certain technology. We detected 11 statistically significant relationships in the country-technology network and 13 validated relationships in the investor-technology network (Tab M.3).

Table M.3: Statistically validated relationships

Countries	Technologies
China	Smart Transmission & Distribution
South Korea	Stationary Fuel Cell
China	Distributed Storage
Finland	Smart Metering
Netherlands	Microgrid
Lithuania	Materials
France	Home Energy Management
United States	Demand Response
India	Lighting
Canada	Smart Metering
Canada	Software

Investors	Technologies
State-Owned Utility	Smart Transmission & Distribution
OEM/Services Company	Distributed Storage
Government	Lighting
Energy Cooperative	Smart Metering
Chemicals / Steel	Waste Heat Recovery
Retail / eCommerce	Stationary Fuel Cell
OEM/Services Company	Grid-scale Storage
Investor-Owned Utility	Smart Grid
Institutional Investors	Materials
Research Organisation / University	Microgrid
Government	Microgrid
State-Owned Utility	Smart Metering
Food	Stationary Fuel Cell

Such relationships complement the picture presented in the main text, as it can be seen, most of the generalist countries (i.e. US, China, Canada) invest preferentially in one, or at most two, specific technologies whilst maintaining a broader technology portfolio. Furthermore, most countries are specialising in different technologies as a result of their strategic investment choice on key technology for their country (noting that 93% investments are domestic). For instance, China is specialised in smart T&D and distributed storage, and no other country has a distinguished preference for investments in these technologies. In the investor-technology network, different categories of investors tend to preferentially finance projects in one (or at most two) technology with little overlap. In particular, utilities have a marked preference for digital energy technologies, with state-owned ones preferentially financing smart T&D and smart metering projects, and privately-owned ones preferentially financing smart grid projects. Also, OEM and services companies have a marked preference for storage-related projects. This technology selection may reflect the nature of investors' business.

Finally, we applied a variant of the above procedure to test the co-occurrence of investments, meaning whether pairs of countries/investors co-invest in large numbers of technologies or whether pairs of technologies receive large numbers of investments from the same country/investor. This analysis detected four statistically significant pairs of technologies, which are: distributed storage and grid-scale storage, distributed storage and home energy management, grid-scale storage and stationary fuel cell, home energy management and stationary fuel cells. These technology pairs received investments from exceedingly similar groups of investors. For instance, grid-scale storage and stationary fuel cells, which is the most significant pair, have received investments from 24 and 16 countries respectively, with 14 countries investing in both.

Table M.4: Technologies' Fitness And Its Evolution Overtime

Sub technologies	Number of Connections	Overall Fitness*	Fitness evolution				
			2002-2006	2004-2008	2006-2010	2008-2012	2010-2014
Smart Metering	352	17.35	3.42	2.56	3.36	28.56	10.71
Smart Grid	206	7.36	-	0.90	2.37	9.05	21.06
Grid-scale Storage	159	4.57	1.19	0.87	1.30	5.59	6.65
Smart T&D	120	3.94	0.55	0.45	1.10	4.81	11.66
Stationary Fuel Cell	120	3.75	0.95	1.27	1.15	3.72	7.70
Distributed Storage	72	2.62	-	-	0.85	2.65	8.14
Microgrid	68	2.47	0.71	0.69	0.57	2.10	4.04
Home Energy Management	26	1.46	-	-	0.79	0.91	1.38
Software	15	1.45	-	-	-	0.29	3.91
Demand Response	37	1.32	-	0.73	0.84	1.13	2.25
Lighting	29	1.10	-	0.63	0.62	0.79	1.53
Transmission Efficiency	22	0.83	0.86	1.07	0.26	0.33	0.73
Waste Heat Recovery	14	0.56	-	-	0.68	0.36	0.00
Materials	5	-					
Energy Storage Transportation	3	-					
BMS & EE Electronics	1	-					
Building Services	1	-					

* The fitness estimation utilises data from 2000-2014. The period of 2015-2017 is left out due to sparse data.

Data availability

The data supporting the findings of this study are available from Bloomberg terminals (Bloomberg New Energy Finance database and Bloomberg data), but restrictions apply to the availability of these data, which were used under licence for the current study, and are not publicly available.

Computer code

The written source code is available on GitHub
https://github.com/nadiaameli/ee-investment-network