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HETEROGENEOUS INVESTORS, SCALE ECONOMIES AND THE COMMERCIALISATION OF INNOVATIVE RENEWABLE ENERGY TECHNOLOGIES

Gregor Semieniuk
UCL Institute for Innovation and Public Purpose

Jose Alejandro Coronado
UCL Institute for Innovation and Public Purpose

Mariana Mazzucato
UCL Institute for Innovation and Public Purpose

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Heterogeneous investors, scale economies and the commercialisation of innovative renewable energy technologies

Gregor Semieniuk^ # ±, José Alejandro Coronado# and Mariana Mazzucato#

Abstract

Heterogeneity in the sources of finance matters for innovation outcomes. We study how investor types differ in their investment size and thereby affect renewable energy technology commercialization via scale economies. We build a dataset of 44,417 private and 12,366 public investments into nine renewable energy technologies in 83 countries for the years 2004-2017, overlapping with the commercialisation periods of these technologies. We distinguish various investor types and focus on financial investors. Using a hierarchical model, we show that banks and institutional investors make larger and smaller investments respectively than non-financial project developers, with further heterogeneity across technology year clusters. Public investment has a quantitatively important positive effect on private investment size, which is more pronounced for banks than for institutional investors, including abroad through strong international spill-overs. Our results indicate that commercialization outcomes can be impacted by heterogeneous investor types and that public financing elicits scale economies.

Keywords: renewable energy, financing innovation, energy transition, scale economies, investment decisions, public finance

JEL codes: G11, G20, H54, O33, O38, Q42, Q55

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^ Political Economy Research Institute and Department of Economics, University of Massachusetts Amherst
# Institute of Innovation and Public Purpose, University College London
± Department of Economics, SOAS University of London
Corresponding author: José Alejandro Coronado (jose.arciniegas@ucl.ac.uk)

1. Introduction

Large-scale investment into low-carbon assets is now a key condition for successfully mitigating climate change (IPCC, 2018; McCollum et al., 2018; Bertram et al., 2021) and dampening potentially destabilising feedback on the economy from stranded high-carbon assets (van der Ploeg & Rezai, 2020; Battiston, Monasterolo, Riahi & van Ruijven, 2021; Semieniuk, Campiglio, Mercure, Volz & Edwards, 2021). However, scaling up the deployment of capital-intensive low-carbon technologies, such as the supply of renewable energy, has become one of the central challenges for accelerating the low-carbon transition, and mobilisation of the right mix of investors has proved difficult (IEA, 2020; Polzin, Sanders & Serebriakova, 2021). The literature on financing innovation has long drawn attention to the importance of investor heterogeneity for financing innovation, though the focus has tended to be on 'upstream' research and development financing (Kerr & Nanda, 2015; B. H. Hall, 2002). We examine whether investor heterogeneity is also relevant for the 'downstream' commercialisation phase for renewable energy technologies, and specifically for the generation of scale economies, a key channel for reducing the cost of renewable energy in this phase (Gallagher, Grubler, Kuhl, Nemet & Wilson, 2012). We construct a large and geographically diverse dataset of individual investments into nine renewable energy technologies over 2004-2017, a period overlapping with the commercialization phase of the renewable energy sector. We exploit the fact that these investments are well defined as contributing to asset finance for individuals plants and so individual investment size can be correlated straightforwardly with plant scale. Our results show that the source of finance indeed matters for the size of investments and resulting plant size, with some types of investors systematically investing larger amounts than others, and being more easily mobilised by public co-financing than others.

The sources of finance and their characteristics, such as risk appetite, size, tenor, time to exit, and so on, matter for innovation outcomes. By highlighting the importance of credit to innovation, Schumpeter (1939) was an early catalyser of research in this field. Subsequently, theorising about externalities and incomplete markets has explained the advantageous qualities of public sources of finance for R&D (Arrow, 1962b) and of venture capital for the financing of start-ups (Gompers & Lerner, 2001), and also the impact of business and longer-period cycles on the quality of finance (Perez, 2002). Recent studies refine these results, showing the impact on innovation outcomes of, for example, bank credit (Nanda & Nicholas, 2014; Mann, 2018; Cole & Sokolyk, 2018; Robb & Robinson, 2014), the size of individual venture capital funding tranches (Nanda & Rhodes-Kropf, 2017), or early government funding for radical innovations (Mazzucato, 2018).[1]

With the urgency of climate change mitigation, energy innovation has once again moved into focus (Chan, Goldstein, Bin-Nun, Anadon & Narayanamurti, 2017). Due to the urgency, understanding any impact of heterogeneous quality of finance on outcomes — such as the pace at which low-carbon technologies catch up with their fossil fuel-driven competitors — is of particular concern. Research documents that heterogeneity does matter (Goldstein, Doblinger, Baker & Anadón, 2020; Howell, 2017), but most of this analysis, as with the innovation finance

[1] Frequent literature reviews summarise the research on financing innovation (B. H. Hall, 2002; B. H. Hall & Lerner, 2010; Kerr & Nanda, 2015; Padilla-Ospina, Medina-Va´squez & Rivera-Godoy, 2018; Lerner & Nanda, 2020)

literature more generally, focuses on the upstream phase of innovation. We study how the quality of finance may impact renewable energy innovation at the downstream commercialisation phase.

The impact of finance on commercialisation is particularly relevant for technologies with high upfront investment needs, with which the energy sector is replete (Granoff, Hogarth & Miller, 2016). Here, a demonstration project's cost can exceed a billion USD (Lester, 2014). Within the energy sector, the overnight capital cost for renewable energy technologies makes up a higher share of the cost structure than for fossil-powered competitors; the 'fuel (for example the wind) is free, so they are even more capital-intensive than their fossil competition (Kim & Park, 2016). Ghosh and Nanda (2010) refer to such deployment of at-scale investments as sitting in the hard to finance space of innovation. Nemet, Zipperer and Kraus (2018) document a high average public finance share of 46% in investments into 646 'first of a kind' and 'nth of a kind' demonstration projects in various capital-intensive sectors since 1946, further indicating that the quality of finance may also matter at the commercialisation stage.

One channel by which types of investors can impact innovation outcomes is by their potentially heterogeneous choice of investment size. Investment size matters due to scale economies, one of the key channels by which commercialisation helps reduce cost and bring technologies to market. The importance of scale economies in electricity generation (not just the transmission and distribution network) is a well studied area in industrial economics, though typically at the firm level (Nerlove, 1963; Christensen & Greene, 1976; Hartley & Kyle, 1989; Bernstein & Parmeter, 2019). Our data allows us to study the effect of investment on scale at the plant level.

Our constructed dataset covers 44,417 individual private investments in 83 countries over the period 2004-2017, as well as 12,366 public investments. These investments are gathered from the Bloomberg New Energy Finance (BNEF) asset finance database that associates investments into new build renewable energy projects with sources of finance. We substantially clean and correct this data, expanding on Mazzucato and Semieniuk (2018), and we further augment it with a Bayesian missing data analysis for project-level financing shares. The investments cover nine renewable energy technologies, with 86% of all investments financing solar PV and onshore wind power plants. In addition, we collect a complete set of annual country-specific policy indicators from various sources, where feed-in tariffs are additionally technology-specific and auctions are deal-specific.[2]

[2] The only study to our knowledge using an earlier version of the BNEF data for quantitative analysis at the individual investment level is Cárdenas Rodríguez, Haščič, Johnstone, Silva and Ferey (2015). Their dataset ends in 2011, comprising only a few thousand investments and missing the entire post-crisis development in the sector.

Figure 1: Correlation between capacity and individual investment size (log-log scale); sample of investments only with observed total project cost. Data sources discussed below.

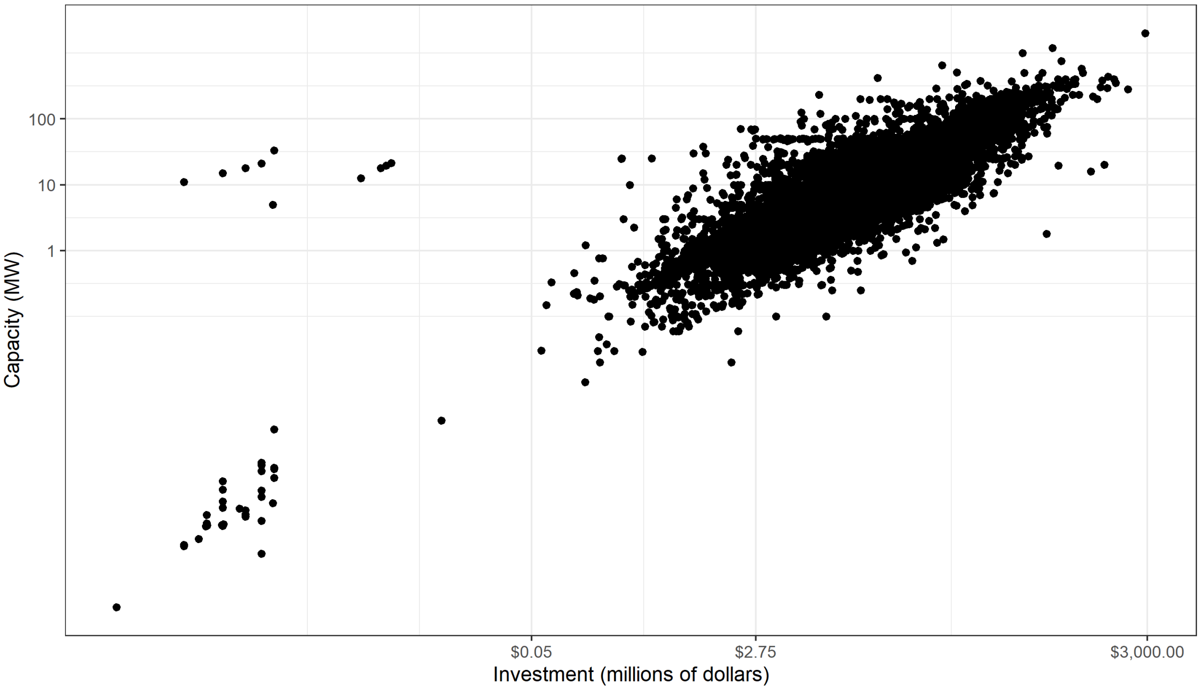


Figure 1 plots the relation between individual investment size in million USD and project capacity size in Megawatt on a log-log scale.[3] We observe a positive relation that implies that capacity grows in proportion with investment size. This is not immediately obvious: several investors often pool individual investments to finance large projects, for example a syndicate of banks or a joint venture. A smattering of very small investments into large projects in the left part of the graph testify to that possibility. However, 36.9% of the plotted data show investments into deals with more than one investor, and the relation holds when we filter out projects with single investors. Given the importance of scale economies, the relationship we observe in Figure 1 motivates our study of how sources of finance are correlated with investment size or, in other words, whether heterogeneous investors influence the achievement of scale economies.

We investigate two specific questions arising from the literature. First, there has been a longer-standing effort to mobilise institutional investors awesome financial resources for investment into renewable energy (Croce, Stewart & Yermo, 2011; Kaminker & Stewart, 2012). The rationale is to boost constrained resources of strategic private investors, notably project developers and utilities, and reduce the need for public investments (Polzin et al., 2021). Therefore, we ask whether the focus on institutional investors is effective from the point of view of generating scale economies and thereby accelerating commercialisation. We also contrast this investor type with banks, the class of financial actor that is typically considered risk-averse, which would suggest small investment sizes (Campiglio, 2016; B. H. Hall & Lerner, 2010). We find that, on average, banks make investments that are 39% bigger than the average investment by project developers. In contrast, institutional investors perform, on average, smaller investments than project developers

[3] For projects with multiple investors, we distribute total capacity across investors using the ratio of total investment in the project to total project capacity.

(3% smaller). The investment size of both banks and institutional investors tends to be sensitive to different technologies. Bank investment size in onshore wind and PV is above average in relation to other technologies, while bank investment into small hydro is below average. In contrast, institutional investors make smaller investments in onshore wind and PV.

To investigate if these investment patterns are conditional on risk, we look at the evolution of investment size across the sample by technology and time. We find that average investment size increases exponentially over time, and that investment size grows between 4% and 5% annually. This pattern varies significantly across technologies, but with investment size into solar PV plants remaining stable throughout the sample. At the same time the proportional difference between the investment size of project developers, banks and institutional investors into onshore and PV falls in selected years at the end of the sample period. That is, in these two technologies, we observe a convergence of investment size across sources of finance. This is not the case for offshore wind, where we observe divergence in investment for banks. These different patterns are consistent with lower risk and completed commercialisation (onshore wind and, in the latter part of our sample, PV) reducing the heterogeneity in sources of finance and their impact on innovation outcomes. In sum, the sources for investment clearly matter for the investment size and the generation of scale economies in innovation.

Second, the benefits of (co-)financing by state-owned actors are a matter of debate. Although governments have the resources to direct massive investments into low-carbon sectors, standard economic theory cautions that this could distort markets and crowd out potential private sources of finance. With recent discussions of COVID-19 stimulus packages and their multiplier effects, this debate has only become more salient (Hepburn, O'Callaghan, Stern, Stiglitz & Zenghelis, 2020). However, studies trying to empirically shed light on this problem in the renewable energy sector look at aggregate mobilisation of private resources, not the size of individual investments (Polzin, Migendt, Täube & von Flotow, 2015; Ang, Rottgers & Burli, 2017; Corrocher & Cappa, 2020; Deleidi, Mazzucato & Semieniuk, 2020). We study how public sources of finance influence scale economies by looking at their relation to the investment size of other actors.

Due to scale economies, crowding out would imply smaller investment sizes since publicly funded projects would take a higher market share. We find evidence of the opposite. The aggregate amount of public finance in the renewable energy sector normalised by the economy's total electricity output is positively correlated with investment sizes. Our results show that a 1% increase in overall public finance normalised by the economy's total electricity output increases *individual* private investor's average investment size by 0.05%, with the estimate falling to 0.04% when we correct for endogeneity. This relation is stable between institutional investors and banks, and matters quantitatively because it affects every private investment in the country on average. We also study this relation at the global scale by considering how investment size into different technologies changes in relation to changes in global public finance flows. A a global scale, the effect of public finance flows on investments into technologies is conditional on the source of finance. Institutional investor investment size is negatively correlated with global public finance flows, while bank investment size is positively correlated.

To carry out our study we implement a Bayesian hierarchical (mixed effects) model in order to identify different investment patterns across data clusters. Our model allows us to vary the effects of covariates and the intercept of our regression model across different clusters in the data. We use this to distinguish differences in investment size of different sources of finance across different technologies and over time. This allows us to identify changes in investment size associated with different risk contexts, either due to the particular technology that is financed or due to the development of such technology over time. We also instrument our public investment data with clean energy investment mandates and control for potential endogeneity in a two-stage least-squares regression.

In section 2 we review the financing of renewable energy supply; the role of commercialisation in innovation; and existing evidence on the impact of finance on commercialisation in the low-carbon sector. In section 3 we describe the data and in section 4 the model. Section 5 reports the results, while section 6 discusses them. The last section draws implications from our study for scaling up the financing of capital-intensive commercialisation investments in the low-carbon transition and for further research.

2. Financing renewable energy deployment

2.1 Financing needs in renewable energy

Economic Transitioning the energy sector to a low-carbon future requires tremendous investments into reorienting the supply mix from one mainly based on fossil fuels towards one dominated by renewable energies, possibly supplemented with fossil fuels whose emissions are offset by carbon capture and storage or sequestration. The International Energy Agency projects that globally $370 billion dollars need to be invested annually into renewable energy power supply only between 2020-2030 to support the stated policies of countries. For a reasonable chance to avoid more than a 2C average temperature increase (the IEAs Sustainable Development Scenario) this figure rises to $589 billion annually if climate change mitigation is pursued. In order to reach net zero by 2050, compatible with the Paris Agreements aim to keep global warming well below 2C, the required investment is larger still (IEA, 2020). Many of these investments are into costly, indivisible units of infrastructure character. Although some technologies, such as solar PV, can be split up into small projects and thus are granular (Wilson et al., 2020), the most cost-efficient variant due to economies of scale is to also deploy 'utility-scale' (greater than 1MW capacity) power plants in PV (Steffen, 2020). For instance, in 2020, Lazard (2020) reports utility-scale fixed-tilt solar PV had a $42/MWh levelised cost of energy (LCOE), whereas the corresponding residential (rooftop) solar PV LCOE was $150/MWh. Sun-tracking utility-scale PV even lowered the LCOE to $31/MWh.[4]

A favourite financial vehicle to finance these lumpy assets at scale is non-recourse project finance, typically highly leveraged to lower the weighted average cost of capital, whereby the renewable energy plant is its own legal entity and liability is limited to the assets this special purpose vehicle owns (Steffen, 2018). The upfront investment cost is of particular importance,

[4] Higher residential prices do not preclude system-wide cost advantages from a mix of utility and residential generation.

because it comprises a higher share of lifetime costs than for competing fossil energy generation, which requires costly fuels. The upshot is that scale economies in upfront fixed costs are especially significant.

Governments have been developing instruments to accelerate renewable energy investments for at least the last three decades and the average of $310 billion invested annually only into renewable power supply (as opposed to, for example, biofuels) over 2015-2019 is a result of those efforts. For our study, it is important to note that most historical investments were made during a time of market formation for renewable technologies where these were being commercialised. Incentivising investors to direct their funds into renewable energy generation technology required discrete government regulation, subsidies or other support policies to be able to compete with the incumbent: fossil fuels. The 2005 United States Renewable Fuel Standard, which mandates mixing 10% ethanol into domestic gasoline, is an example of such a regulation. The 2000 German feed-in tariff, which sets a fixed above-market price and combines it with an offtake guarantee for renewable electricity, is an example of a subsidy. Recent estimates suggest that unsubsidised utility-scale solar PV and onshore wind are now often competitive even with fully depreciated fossil fuel-generated electricity (Lazard, 2020), and some investors now see solar PV investments on par with purchasing a commodity (Egli, 2020). However, this favourable picture does not hold for the period of our database: 2004-2017. The cost of producing electricity from solar PV fell 86% from 2000 to 2014 and for onshore wind it fell 35% over the same period (Trancik, 2015). Therefore, the deployment of these technologies by and large falls into the commercialisation phase of the innovation landscape and the question of the impact of finance on innovation outcomes applies (Gallagher et al., 2012; Sagar & van der Zwaan, 2006).

2.2 The commercialisation phase in renewable energy

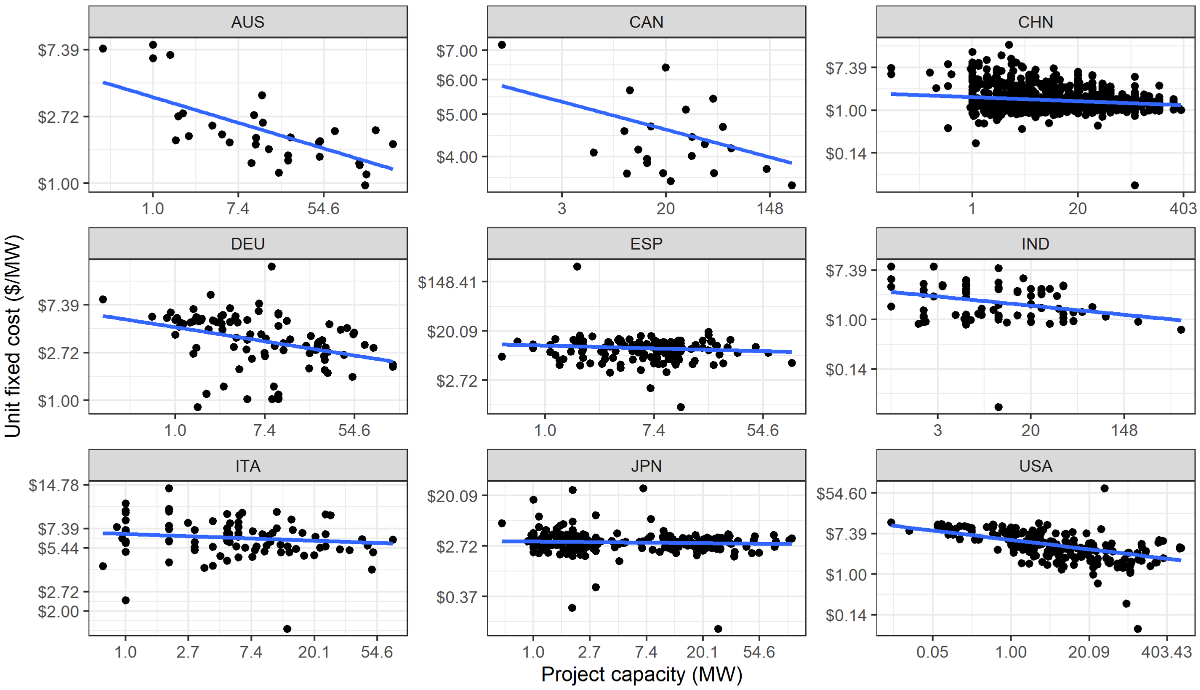
The commercialisation phase in renewable energy plays an important role in the overall innovation process. Commercialisation refers to a situation where a fully developed product is demonstrated at scale, and then deployed with a view to making it commercially viable and economically rational to adopt. It is an important component of innovation, as learning by doing and scale economies are powerful drivers of cost reductions, and via feedback effects also affect earlier phases of innovation (Arrow, 1962a; Lundvall, 1992; Freeman, 1995). This is when markets are formed for newly developed products here, renewable energy power plants such as wind farms, solar parks or biomass plants. Learning by doing and scale economies that drive the cost reduction during commercialisation are interlinked (Dasgupta & Stiglitz, 1988), yet distinguishing them conceptually is useful. Learning by doing in other words, by building first and then subsequent power plants of a certain type can improve processes and product, and thereby lead to lower costs and faster onset of widespread diffusion (Sagar & van der Zwaan, 2006). These learning-by-doing effects operate at the industry level, where early deployment generates experience and lowers costs for later investments, but can also lead to redesign of and changes to the product. In other words, feedback effects influence more upstream phases of the innovation landscape (Gallagher et al., 2012).

Scale economies instead lead to cost reductions at the plant level (Wilson, 2012). The larger plant size allows spreading fixed costs over a larger set of units, thereby lowering total average costs.

This includes savings thanks to the bulk purchase of certain inputs and spreading the fixed cost of machines. It also includes the important 'soft' overhead (or transaction) costs in energy projects that are incurred for securing permits and setting up the financing arrangements, where risk management tools, and export credit guarantees or other concessionary benefits are costly, but vary less than proportionately, if at all, with project size (Neuhoff, 2005). Kavlak, McNerney and Trancik (2018) find that for solar modules, since 2001 scale economies in manufacturing have outweighed learning by doing and R&D as a factor in reducing costs, and Elia, Taylor, O´ Gallachóir and Rogan (2020) find that for wind manufacturing combined scale and learning by doing effects were more important during 2005-2017 than R&D for cost reductions.

We are unaware of comparable quantitative evidence for the cost reduction attributable to scale economies at the project level; however, Barbose and Darghouth (2019) document a decline over time in the 'soft cost' of installation of about 50% for large non-residential US solar PV, which could at least partly be associated with scale effects. Our own data allows investigating the correlation of project size with per unit overnight capital cost, measured in USD/Megawatt. Figure 2 shows a negative correlation between project size in Megawatt of plant capacity and the unit fixed cost in million USD/MW for solar PV projects in a set of large countries. Hence scale economies are observed at the plant level even without controlling for a time trend. Such scale economies are to be expected in renewable energy plants (Wilson, 2012; Gallagher et al., 2012), and the evidence here confirms their importance in reducing cost and hence accelerating the pace at which they can be deployed.

Figure 2: Correlation between solar PV project capacity in Megawatt and per unit overnight capital cost in million USD (log-log scale); sample of investments only with observed total project cost. Data sources discussed below.



While the commercialisation phase is thus central to innovation, it presents its own challenges for financing. Since investments are much lumpier than during development and prototyping, investors with increasing risk aversion may be deterred. The lack of funding for recurring large-scale investments before the product becomes competitive is often referred to as the 'valley of death' to highlight the problem of lack of financing (Hartley & Medlock, 2017). Due to the proliferation of the term, the lack of financing for the commercialisation phase has also been called the second valley of death, to distinguish it from the dearth of funding for bringing lab research into product development (Gallagher et al., 2012). Mazzucato (2018) stresses the importance of patient public finance to overcome the valley of death since it could last up to 15 years. Therefore, the question of how heterogeneous sources of finance affect commercialisation looms large.

2.3 Evidence on financing affecting energy commercialisation

Existing quantitative research on financing innovation has largely focused on R&D phases of innovation. Howell (2017) finds that winners of the US Department of Energy's SBIR grants double their chance of subsequent venture funding compared with rejected applicants; Goldstein et al. (2020) find US Department of Energy's ARPA-E funded firms were twice as likely to patent as their peers, and were also more likely to innovate in energy storage than companies funded by other grant programmes; and Pless, Hepburn and Farrell (2020) recommend data generation by funding agencies compatible with quasi-experimental studies, like that of Howell (2017), to help estimate the causal effect of public financing of energy innovation. For venture capital, Nanda, Younge and Fleming (2015) document that venture capital-backed renewable project developers tend to register more influential and novel patents than established firms, and that the sharp decline of venture capital finance after 2008 may have impacted the type of innovation undertaken. Meanwhile, Gaddy, Sivaram, Jones and Wayman (2017) and Lerner and Nanda (2020) express doubts about the suitability of shorter-term (ten-year) venture capital funding cycle with energy innovation.

The evidence of the impact of heterogeneous sources of finance on commercialisation rests more on conceptual considerations and case studies (Wüstenhagen & Menichetti, 2012). An early conceptual contribution highlighted six different types of investors, although most focus was on the dichotomy between small own-use investors, such as roof-top solar and utility scale investors, not between different types of finance for utility scale (Langniss, 1996). Some studies have also analysed how venture capital and private equity differ in their investments in asset finance (Ghosh & Nanda, 2010; Criscuolo & Menon, 2015).

Perhaps the most conceptual attention has been applied to how financial investors could help strategic investors increase aggregate investments. Strategic private investors, mainly project developers and utilities, may be too cash-constrained to expand financing project development on balance sheet (S. Hall, Foxon & Bolton, 2017). Therefore, greater participation by financial investors would alleviate that burden. Project finance is a way to increase leverage and debt, and bring on board banks (Steffen, 2018). Institutional investors (the broad class of financial investors that manage and invest the funds of others) have been looked to for the provision of additional equity finance (Polzin et al., 2015, 2021). While evaluations of the success of expanding the scale of investment by means of financial investors exist, it is less understood how these types of finance affect innovation outcomes at the project level.

On the other hand, arguments on how public investment helps scale up investments in innovative sectors of the economy have relied on systemic approaches to understanding the innovation ecosystem (Mazzucato, 2016). Some of this literature focuses on historical analysis that details the role of government institutions in promoting and financing innovation (Freeman, 1995; Perez, 2002; Mazzucato, 2018). Conceptually, the role of government agencies in such processes is justified by the path-dependent character of technological progress. Strong feedback mechanisms reinforce the direction of technological change due to the cumulative nature of learning (Dosi, 1982). Hence innovations that lie beyond the scope of the current technological paradigm require public interventions, given that markets will encourage the development of currently cheaper and/or less risky alternatives within the technological paradigm (Mazzucato, 2016; Mazzucato & Semieniuk, 2017).

A few studies examine quantitatively the interaction of aggregate private and some types of public investment flow or other policy, by drawing on financial microdata from BNEF, as we do, but then aggregating country-year investment flows (Eyraud, Clements & Wane, 2013; Polzin et al., 2015; Ang et al., 2017). None of these studies distinguish between sources of finance in any detail. The studies by Corrocher and Cappa (2020), and Deleidi et al. (2020) distinguish public and private asset finance flows and find that more public financing mobilises more private funds. However, this does not allow for studying different types of private investments. Cárdenas Rodríguez et al. (2015) use project level investment data for 2000-2011, but since they simply measure the effect of public investment on private investment in the same project, they, unsurprisingly, find a negative correlation. Their main focus is on the effects of other policies on the private contribution to a deal, controlling for its size. Wall, Grafakos, Gianoli and Stavropoulos (2019) is an exception in terms of data sources as it uses data on foreign direct investment from the *Financial Times* to find that public investments had a negative effect on the FDI flowing into a country's renewable energy sector. But it is limited in its ability to explore overall financing patterns, as it lacks data on domestic investment flows that may or may not be substituted for by FDI. Perhaps unsurprisingly, in their review, Polzin, Egli, Steffen and Schmidt (2019) find limited evidence for the effect of public financing on private finance, and Bhandary, Gallagher and Zhang (2021) identify this effect as a knowledge gap. Quantitative empirical evidence about the heterogeneity of finance beyond the public/private dichotomy is hardly discussed in any review (Polzin, 2017; Bhandary et al., 2021).

A more differentiated view on the financial sector arises from a focus on development finance institutions, including a new set of green investment banks with a mandate to allocate their entire portfolio of investments in line with a low-carbon transition (OECD, 2015). Case studies of individual development finance institutions have found they accelerate the shift to low-carbon energy alongside providing countercyclical stabilisation investments (Mazzucato, 2021) and perform various due diligence and first-mover roles for individual projects before private investors come on board that same project (Geddes, Schmidt & Steffen, 2018; Marois, 2021). Moreover, the total investment portfolio of state-owned institutional investors is skewed towards more risky technologies within the sector of renewable energy supply, as compared with other sources of finance (Mazzucato & Semieniuk, 2018). However, the overall effect of development finance institutions is shrouded in a debate about whether they crowd out or otherwise hinder aggregate development (Deleidi et al., 2020). Given this heated debate the absence of a quantitative assessment of their effects on mobilising finance in the renewable energy sector is significant (Carreras, 2020).

In our present study, we provide the first quantitative evidence on how a type of finance at a more granular level than the public/private divide correlates with investment size. First, given the attention to increasing the role of financial investors, we examine how both banks and institutional investors correlate with investment size and scale economies. In particular, given that banks are hypothesised by Ghosh and Nanda (2010) not to invest in high-risk investments and that institutional investors have been widely seen as the key source of finance in asset deployment, we hypothesise that banks may be less and institutional investors more apt at large investments and realizing scale economies than the default investor: project developers. However, given that our data covers a sample period in which the risk associated with some technologies goes down, we hypothesise that average investment sizes should converge.

Due to the continued debate about the relationship between public and private, we also examine how the intensity of public financing of renewable energy in a country interacts with private investment size. The intensity is defined as the aggregate public financing in the renewable energy sector divided by electricity consumption to control for country size. As previous studies find that public finance mobilises private finance, we hypothesise that the degree of public finance intensity encourages larger private investment sizes and scale economies. However, we also hypothesise that this correlation varies across time, subject to the business cycle. To keep the analysis tractable given the size of our dataset, we do not distinguish between types of public finance except when we instrument investments with clean investment mandates.

3. Data

Our asset finance data is built from individual asset finance transactions for renewable energy projects.[5] The raw data is from the BNEF asset finance, organisation and project databases. The first traces financing flows for about 90,000 asset finance deal participations in over 60,000 unique deals, allowing equity and debt sources, and whether the deal is for a newly built project or for acquisition or refinancing, to be distinguished. Hence, our data consists of repeated sampling of populations over time divided by multiple cross sections. A deal finances one or more utility-scale renewable energy supply plant, such as a wind farm of at least 1MW generating capacity. For comparison, a middle-income household in the US has a potential for about 11kW generating capacity on average for rooftop solar PV (Sigrin & Mooney, 2018). As such, our database effectively excludes small generators for own use, and includes either strategic investments by private project developers and utilities or those of financial investors, as well as various public financing sources.

While deal values are usually reported or at least estimated by the data provider, the share that each investor in the deal takes on is left unreported in 7.8% of deals. In order to extract as much information from the database as possible, previous research has imputed investment shares to

[5] Renewable energy here comprises wind, solar, geothermal, biomass and waste, small hydro and marine energy.

unreported deal values in equal parts to participants (Corrocher & Cappa, 2020; Mazzucato & Semieniuk, 2018). We designed an imputation procedure that classifies missing data into groups, imputes investment shares using a Dirichlet likelihood, and uses deal and investor characteristics to generate variation across investment shares. The details of our missing data classification scheme can be found in Appendix A.

BNEF's companion organisation database allows identifying the characteristics of the source of finance, which is key for our strategy to distinguish the quality of finance. We use sectoral classification and an 'organisation type' variable, which indicates whether an organisation is state-owned, a private or publicly listed company, or non-profit, to distinguish financial and strategic, as well as public and private, investors. We also use the company headquarters of the investor's parent company to identify the true type of the investor. That is particularly important for renewable energy projects where there is often a 'project company' or special purpose vehicle recorded at the place of the plant into which investors pour their money, but it says little itself about the nature of the companies behind it. In fact, we disassembled 100 joint ventures and special purpose vehicles using internet searches to find the investors behind these front companies. We also identified the nature of 80 'defunct' companies that were either public or private companies when still operational. In general, we make about 7,000 corrections to the company characteristics data using internet searches to correctly attribute investors and hence financing flows to groups of investors. To illustrate the prevalence of these corrections, note that any company that has any stock market listing at all is simply recorded as a 'quoted company'. To verify whether it is a privately or state-controlled company, we check whether the government owns more than 50% of the shares, in which case we classify it as state-owned in line with common practice (Prag, Röttgers & Scherrer, 2018). Lastly, the project database permits attributing capacity to most financing deals in the dataset, including when more than one plant is financed by the same deal.

After imputation we calculate individual private investment size, distinguishing year, technology and source of finance. We focus on new-build investment deals. Our final dataset contains 44,417 observations that span yearly investments in the period 2004-2017 across 83 different economies. This includes the 37 members of the OECD and 40 of these countries are classified as low or middle-income by the World Bank's classification scheme. Table 1 presents summary statistics for private investment size by technology.

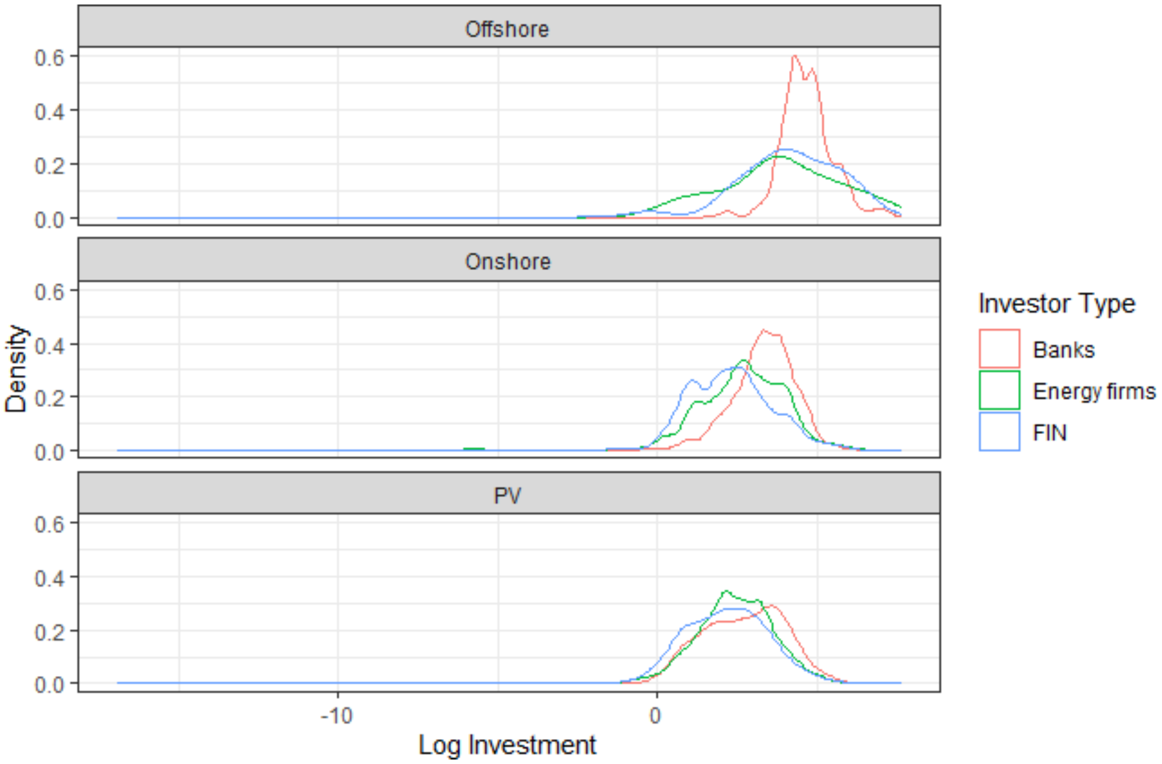
Table 1: Investment size by technology summary statistics

	Mean	SD	Min.	First qu.	Median	Third qu.	Max.	Obs.
Total	30.48	63.18	< 0.0001	4.96	13.44	33.28	3392	44417
Solar PV	22.17	42.28	< 0.0001	4.08	10	24.22	1500	19806
Onshore wind	34.27	60.43	< 0.0001	5.95	15.81	42	2902	16504
Offshore wind	229.1	366.2	0.002	42.3	107.8	264.9	3392	273
Biofuels	45.42	69.36	0.0002	7.1	20.54	55.47	829.28	1914
Biomass and waste	34.83	58.46	< 0.0001	6	16.97	43.98	1050	3371
CSP	90.34	144.5	0.0004	27.83	48.28	100	2126	387
Geothermal	46.9	65.1	0.001	7.57	29.94	54.9	465.03	242
Marine	4.83	5.14	0.04	1.75	3.39	5.45	26.32	59
Small hydro	19.27	20.4	0.0001	6.43	12.6	25.1	198.6	1861
Public investment	48.83	122.94	< 0.0001	10.17	23.69	57.9	5700	12366
Mandated investment	66.02	134.37	0.0002	8.81	25.53	65.88	1767	1023

Values are in millions of USD at market exchange rates. Technology-specific investments exclude investments financed by public sources. Mandated investment refers to all public investments by organisations with a mandate. Public investment and mandated investment summary stats include investments across all technologies.

The investment size distribution is right-skewed with standard deviations close to mean investments across technologies. Average investments tend to be smaller in PV and onshore wind, where most of the observations are concentrated. The largest investments are recorded in offshore wind and concentrating solar power (CSP). Figure 3 shows the density of log investment by selected technologies and investor types. Relative to institutional investors and project developers, banks tend to make larger investments into offshore and onshore wind. Our econometric strategy attempts to explain these differences in investment size across investors and technologies.

Figure 3: Size distribution of log of investments in million USD by selected technologies and investor types.



We complement the investment data with a rich set of policy and economic indicators to control for the different policy and macroeconomic environments in which investments occurs (see table 2 for a summary). As policy indicators, we track administrative feed-in tariffs, as well as revenue support via competitive auctions. The latter has not been included in any of the studies we reviewed in section 2 that apply econometric methods to study investment flows. Both variables are continuous, and we significantly extend the OECD's feed-in tariff database that only holds complete data for about 40 countries by collecting data from various databases and government documents for the remaining 40 countries. We also measure renewable energy obligations and tax credits using indicators. All of these variables characterise policies that are directed at improving the risk-return profile of projects in that country (or are project-specific for auctions) and so de-risk large investments.

Moreover, we use a set of more indirect policy and macroeconomic controls. First, we construct a comprehensive dataset with country renewable electricity targets. The targets data includes the yearly entries per country that register the initial year the target was set in place, the year the target is to be achieved, whether the target is on the proportion of renewables on energy production or consumption, and the target proportion of renewables. We use these to build a yearly gap-to-target variable that consists of the ratio of the difference between the current participation of renewables and the targeted share, and the difference between the target year and the observation year.[6] Hence, the variable takes negative values when countries are below

[6] Our target gap variable g_{jt} for country *j* in year *t* is defined as $g_{jt} = \frac{s_{jt}-T}{TY-t}$, where s_{jt} is the share of renewables in electricity production, *T is the targeted share of renewables in electricity production, and TY is the target year for T.*

their target, with the magnitude being weighted by how close countries are to the target year. For years in which there is no target we include an indicator variable and set the gap to 0. We further account for country characteristics by incorporating GDP growth rate, the interest rate and the carbon price, as well as the World Bank's Regulatory Indicators for Sustainable Energy (RISE), an index between 0 and 100 that summarises country policies and regulations in the energy sector. We only use renewable energy indicators for the RISE score.

Finally, we also register public organisations mandated to develop or invest into renewable energy. There are three types of public organisation that can be mandated to make renewable energy investments. The first is under direct control of a government which has an explicit, typically quantifiable renewable energy or climate change target (for example, a ministry under central government or a department under a municipality). The second is a state-owned enterprise or department with an explicit mandate to invest in renewable energy or to meet or contribute towards climate change targets (either through legislation, articles of association or similar). The third is a state-owned company without an explicit mandate, but with high levels of government influence in the management of the company (strong government presence on, or selection of, the board or evidence of the body carrying out regular government work, such as implementing subsidy schemes or similar) and a clear and explicit renewable energy and/or climate change targets and strategy by the owning government. This evaluation was carried out with internet searches, organisation by organisation.

Table 2: Explanatory variables summary

	Data type	Units	Source	Mean	SD
FiT	continuous	US dollars/kWh	OECD & own search	0.01	0.19
Average auction price	continuous	US dollars/kWh	BNEF	1.09	10.05
Renewable energy obligation	dichotomous	N/A	REN21	0.18	0.38
Tax credit	dichotomous	N/A	REN21	0.42	0.49
Mandate	dichotomous	N/A	own search	0.3	0.46
Carbon price	continuous	US dollars/tCO2	World Bank	7.1	13.42
RISE score	continuous	proportion	World Bank	49.82	18.49
GDP growth rate	continuous	rate	IMF	3.26	3.53
Interest rate	continuous	rate	IMF	24.17	6.37
Target gap	continuous	rate	own search & REN21	-0.0005	0.04

Explanatory variables summary table. Dichotomous variables take the value of 1 when the policy is active in the country.

Our data is characterised by repeated observations of a population that can be divided into multiple groups. For instance, we can group observations by years, technologies and countries to attempt to identify how the relevant outcome variable of interest varies across them. A useful method for analysing data structures in which outcomes are hypothesised to depend on group membership is hierarchical models. These are models in which the value of the outcome variable of interest depends on group membership. The following section describes in detail the way we implement hierarchical models to identify differences in investment patterns across investor types.

4. Econometric model

In this section we describe in detail the econometric model we implemented to test our hypotheses. We implement a hierarchical (mixed effects) model to estimate our investment regression. The model allows for investments to vary across different grouping schemes. That is, we are able to group investments by different characteristics; the methodology allows us to estimate parameter variation across the different groups.

Hierarchical or multi-level models are regression models in which observations are grouped and the variation of the outcome variable of interest depends on group membership (Gelman & Hill, 2007). Such models have been used in economics in studies where researchers attempt to distinguish genuine variation across groups when estimating fixed effects in the presence of sampling errors and variation in sample size across clusters (Meager, 2019; Strauss & Yang, 2020). Hierarchical models allow for group coefficient variation, but at the same time treat these subsections of the data as part of a larger population group. By doing so, this approach allows the data to determine the degree of group variation for each variable. This means that estimated random effects are a compromise between no pooling and complete pooling estimators (Gelman & Hill, 2007). Additionally, the total mean squared error for all parameters is lower when estimating them jointly relative to standard procedures that estimate parameters separately (James & Stein, 1992).

Our data can be grouped across years, technologies and countries. We opt to focus on year and technology groups to identify differences in investor size across different risk profiles that are associated with the degree of maturity of technologies. Additionally, we introduce country controls to capture country-specific variation. Two more issues motivate our use of hierarchical models. First, we expect our imputation procedure to introduce additional variation in investment size. Hence, estimated fixed effects for our technology and year clusters could reflect variation from our imputation. Furthermore, technology fixed effect estimators are misleading since they treat technologies as though they are completely different to each other. This could be a problem since there is reason to think that differences in costs across technologies (and hence investment) vary due to unobserved characteristics in our data. As an example, consider an investor deciding to invest in a solar PV plant located in a region with high solar exposure. Such a scenario could lead to the investor reassessing the risk profile of solar PV due to the lower LCOE, inducing them to invest higher amounts. Hierarchical models allow us to take into account such situations by estimating random effect components that are a compromise between complete pooling and non-pooled estimators. Our model is specified as follows:

$$
\begin{aligned}
y_i &\sim \mathrm{N}(X_i^1\beta^1 + X_i^2\beta^2_{j[i]} + X_i^3\beta^3_{k[i]}, \sigma_y^2), \text{ for } i = 1, \dots, n \\
\beta^2_j &\sim \mathrm{MVN}(0, \Sigma^2), \text{ for } j = 1, \dots, J \\
\beta^3_k &\sim \mathrm{MVN}(0, \Sigma^3), \text{ for } k = 1, \dots, K
\end{aligned}
\tag{1}
$$

where y_i is normally distributed with variance parameter σ_y^2. The mean of the normally distributed outcome variable depends on three covariates matrices. X^1 is a $N \times 16$ matrix of fixed effects regression predictors and β^1 is the corresponding fixed effects vector. The matrices X^2 and X^3 are the technology-year (J = 126) and technology (K = 9) random effects predictors. The vectors $\beta^2_{j[i]}$ and $\beta^3_{k[i]}$ measure the additional effect of a unit change in any of our technology-year and technology covariates respectively when i is a member of j and k (random effects). Additionally β^2_j and β^3_k follow a multivariate normal distribution centred around 0, and correlation matrices Σ_2 and Σ_3. We do this since we use β^1 to model fixed effects of covariates that we allow to vary across our clusters.[7] We further expand on the variance-covariance structure of the model and the choice of priors in Appendix C.

Our outcome variable of interest is the log of the investment size of individual investors. However, as in Cárdenas Rodríguez et al. (2015), we also report results using an inverse hyperbolic sine transformation (IHS), since investment data is skewed when using the log transformation. We scale our investment data to USD instead of millions of USD to implement the IHS transformation (Bellemare & Wichman, 2020). Initially we estimate a model that includes the variables described in Table 2 (excluding mandates) and indicator variables that distinguish between types of finance. We distinguish banks, institutional investors, private utilities and other investors, with project developers being the default actor type.[8] We use our country-specific variables from Table 2 to control for country differences in order to focus on technology and year random effects, and we limit our regression to actor types in order to identify differences in types of finance and how those differences evolve across years and technologies. We take project developers as the reference category for all our categorical variables, so investments by types of finance are always compared to the baseline average investment of project developers.

We also introduce a time trend term t_{jk} to capture changes in average investment over time. This is necessary due to the possibility of simultaneous but unrelated trends in y_i and technology-year predictors (Fairbrother, 2014). Hence, X^1 consists of a set of ten country specific predictors (including an indicator when the country has a target), an intercept, a time trend term and four investor type binary variables, totalling 16 estimated fixed effects. We allow variation across technology-years and technology for our intercept value, our bank indicator and our institutional investors indicator. Additionally, we estimate technology random effects for our time trend component to capture yearly changes in investment size across technologies. We avoid introducing a year random effect component since our dataset contains no year-level covariates and to avoid potential convergence problems (Schmidt-Catran & Fairbrother, 2016). In summary, our model includes fixed and random effects for our intercept (the average investment of project developers), our bank indicator, our institutional investors indicator and our time trend component, totalling 414 jointly estimated random effects components.

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[7] Alternatively we could exclude predictors in X^1 that are already present in either X^2 or X^3 and include location parameter vectors M^2 and M^3 in the multivariate normal likelihood that describes the variation of our technology-year and technology predictors. In that setting the estimated vector of means is equivalent to the estimated fixed effect vector (Gelman & Hill, 2007).

[8] These others comprise non-profits, other non-financial firms and investments with unclassified financing sources, which were grouped after ascertaining that their coefficients had overlapping confidence intervals.

4.1 Model extensions

The advantage of hierarchical models is that they allow for a richer set of relationships to be explored. We discuss two extensions of (1) that allow us to explore the relation between public finance flows and average investment size. First, we consider the introduction of group level predictors in (1) to estimate their effect on our outcome variable. For example, we could be interested in the relationship between technology level characteristics (such as policies targeted to specific technologies) and outcomes measured at the level of individual investors (average size of investment). This can be easily done by specifying (1) to include group level predictors. Formally, our model can be rewritten in the following way:

$$\begin{aligned} y_i &\sim \mathrm{N}(X_i^1\beta^1 + X_i^2\beta_{j[i]}^2 + X_i^3\beta_{k[i]}^3, \sigma_y^2), \text{ for } i = 1, \ldots, n \\ \beta_j^2 &\sim \mathrm{MVN}(U_j^2 G^2, \Sigma^2), \text{ for } j = 1, \ldots, J \\ \beta_k^3 &\sim \mathrm{MVN}(U_k^3 G^3, \Sigma^3), \text{ for } k = 1, \ldots, K \end{aligned} \tag{2}$$

where U^2 is a matrix of technology-year predictors, U^3 is a matrix of technology predictors, G^2 a matrix of technology-year coefficients and G^3 a matrix of technology coefficients. The values that these variables take are constant across observations within the same group. The elements in matrices G^2 and G^3 can be understood as interaction terms, measuring the longitudinal and cross-sectional relation between the random predictors, and our technology-year and technology level covariates. This can be easily seen if we write (2) as a set of linear regressions.

$$\begin{aligned} y_i &= \sum_{s=0}^{16} \beta_s^1 x_{si}^1 + \sum_{r=0}^{3} \beta_{jr[i]}^2 x_{ri}^2 + \sum_{q=0}^{4} \beta_{kq[i]}^3 x_{qi}^3 + \epsilon_i \\ \beta_{jr}^2 &= \gamma_{r1}^2 u_{j1}^2 + \gamma_{r2}^2 u_{j2}^2 + \cdots + \eta_{jr}, \text{ for } r = 1, \ldots, 3 \\ \beta_{kq}^3 &= \gamma_{q1}^3 u_{k1}^3 + \gamma_{q2}^3 u_{k2}^3 + \cdots + \eta_{kq}, \text{ for } q = 1, \ldots, 4 \end{aligned} \tag{3}$$

Notice that our equations for group level parameters do not include an intercept due to fixed effects already captured by the elements of β^1. By writing the random effects parameters in terms of the elements of U^2, U^3, G^2 and G^3 we easily note that, for example, the parameter γ_{q1}^3 captures the interaction between a technology predictor u_1^3 and the random component x_q^3.

This allows us, for instance, to measure the additional effect on a bank's (random predictor) average investment size due to changes in average public investment flows per technology (technology level covariate). Notice that including the intercept in X^2 and X^3 allows us to estimate fixed effects for our group level variables. Technology-year covariates are decomposed into a technology mean variable and a mean centred technology-year covariate in order to distinguish between longitudinal and cross-sectional relations (Fairbrother, 2013, 2014). Variables can be included at any of the three levels of our model. They differ in that variables included at the technology-year and technology level are constant for members within a group.

Second, we consider the possibility of relying on an instrumental variable strategy to correct for possible endogeneity problems between our outcome variable and predictors of interest. Specifically, this strategy relies on our collected mandate indicator as a source of exogenous variation. We can write (1) to include an instrument component to estimate treatment effects the following way:

$$\begin{aligned}
\begin{pmatrix} y_i \\ T_i \end{pmatrix} &\sim \mathrm{N}\left(\begin{pmatrix} X_i^1\beta^1 + X_i^2\beta^2_{j[i]} + X_i^3\beta^3_{k[i]} + \beta^T T_i \\ \rho + \delta z_i \end{pmatrix}, \Sigma^1\right), \text{ for } i = 1, \ldots, n \\
\beta^2_j &\sim \mathrm{MVN}(0, \Sigma^2), \text{ for } j = 1, \ldots, J \\
\beta^3_k &\sim \mathrm{MVN}(0, \Sigma^3), \text{ for } k = 1, \ldots, K
\end{aligned} \tag{4}$$

where T_i is our treatment, z_i our instrument, and β^T the effect of the treatment on our outcome variable. Model (3) can be extended to a scenario in which treatments vary across clusters. This would be the case if treatments were assigned individually and our outcome of interest was clustered. However, since the relevant treatment we are interested in (aggregate public finance flows) are assigned to the group, we avoid varying any parameter characterising the distribution of T_i (Gelman & Hill, 2007). In what follows we present the results of our implementation of all of these three models. We carry out our estimation using Stan.

5. Results

Fixed effects estimates are reported in Table 3. Results are stable across both transformations. Banks tend to invest larger amounts relative to project developers. Our fixed effect estimates suggest that banks perform investments whose size is on average 39% higher than that of the average project developer, according to our IHS results.[9] In contrast, institutional investors invest amounts below average. Their investments are on average 3% lower than those of the average project developer. However, the standard error associated to this estimate is quite high. Therefore, we are not able to conclude, as we hypothesised, that banks' investment size is smaller, nor that institutional investors' investment size is larger than investments by developers on average. We also identify variations in investment size across other actors. On average, private utilities perform investments 60% larger than the average energy firm. Our fixed effect estimates for the remaining actors suggest that they tend to make smaller investments relative to project developers (20% smaller relative to project developers).

Despite the large standard errors for our institutional investors fixed effects, we do not interpret the coefficient as a lack of distinct institutional investor behavior. The model allows us to analyse variation across technology and time clusters. Since each individual cluster has its own estimated

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[9] As noted by Bellemare and Wichman (2020), we can approximate the standard semi-elasticities using the hyperbolic sine transformation by taking the exponential of both sides of the regression equation and noting that exp $\tilde{y} = y + \sqrt{y^2+1} \approx 2y$ for large y, where $y = \sinh \tilde{y}$.

coefficient for institutional investors, we are not able to rule out any relation without analysing the random effect estimates. The same can be said for other covariates that vary across groups.

Table 3 also shows that the year trend term is positive and implies exponential growth in investors' average investment size. Our estimated effect of just above 0.04 implies an annual growth rate of around 4%. This relation is not stable across technology groups as we will see when we consider technology variation. The fixed effect estimate for the RISE policy environment score covariate is negative. This implies that investors located in countries with an overall better environment for investments into renewable energies tend to make smaller individual investments on average. Presumably, the more favourable policy conditions in such countries also ensure profitability also in smaller scale projects. Our estimated GDP growth rate effects are negatively related to average investment size, which we take as further evidence for the above. We observe a positive relation with the rate of interest. Higher interest rates make debt financing for renewables more attractive to the financier and so other things equal may induce large investments. We don't distinguish between debt and equity investment in our regression model since banks already account for the overwhelming majority of debt finance in the data.

Our more directly relevant policy variables all have the expected sign. Our estimated target gap coefficients are negative. This implies that average investment in countries with a higher target gap are proportionally bigger relative to countries with smaller target gaps. This is consistent with the pattern of smaller scale projects being more common in the data in the latter years, when the target gap is smaller. We also find a positive relation between the average auction price of a project and investment size, meaning that typically high-scale projects are the ones that are able to secure renewable energy auctions. Finally, the level of FiT, and the presence of renewable energy obligations and tax credits, have positive estimated effects. But the FiT credible interval is too wide to be certain of any effect. The FiT is the only variable of the three that varies continuously and one possible explanation is that while a FiT helps scale investments, a change in its level may not.

Table 3: Regression coefficient estimates

	Log transform					IHS transform				
	Estimate	SD	L CI	U CI	$\hat{R}$	Estimate	SD	L CI	U CI	$\hat{R}$
Intercept	15.97	0.35	15.29	16.62	1.01	16.67	0.33	15.97	17.26	1.01
Banks	0.34	0.15	0.04	0.65	1.01	0.33	0.15	0.03	0.63	1.00
Institutional investors	-0.02	0.12	-0.25	0.23	1.00	-0.03	0.11	-0.23	0.19	1.00
Private utilities	0.47	0.02	0.43	0.51	1.00	0.47	0.02	0.43	0.52	1.00
Other investors	-0.22	0.02	-0.26	-0.19	1.00	-0.22	0.02	-0.26	-0.19	1.00
Year	0.05	0.02	0.01	0.09	1.00	0.04	0.02	-0.001	0.09	1.00
RISE	-0.01	0.001	-0.01	-0.01	1.00	-0.01	0.001	-0.01	-0.01	1.00
Carbon price	-0.01	0.00	-0.01	0.00	1.00	-0.01	0.00	-0.01	0.00	1.00
Rate of interest	0.02	0.001	0.02	0.02	1.00	0.02	0.001	0.02	0.02	1.00
GDP growth rate	-0.02	0.004	-0.03	-0.01	1.00	-0.02	0.004	-0.03	-0.01	1.00
FiT	0.01	0.18	-0.31	0.38	1.00	0.03	0.19	-0.33	0.42	1.00
Target gap	-4.06	0.33	-4.66	-3.41	1.00	-4.04	0.32	-4.65	-3.39	1.00
No target i.d.	0.09	0.02	0.06	0.13	1.00	0.09	0.02	0.06	0.13	1.00
Average auction price	0.005	0.001	0.003	0.01	1.00	0.005	0.001	0.003	0.01	1.00
Renewable energy obligation	0.31	0.02	0.27	0.36	1.00	0.31	0.02	0.27	0.36	1.00
Tax credit	0.21	0.02	0.17	0.25	1.00	0.21	0.02	0.18	0.25	1.01
Technology-year random effects SD										
Intercept	0.50	0.03	0.45	0.56	1.00	0.50	0.03	0.44	0.56	1.00
Banks	0.42	0.05	0.34	0.51	1.00	0.42	0.04	0.34	0.52	1.00
Institutional investors	0.45	0.04	0.37	0.54	1.00	0.44	0.04	0.37	0.53	1.00
Technology random effects SD										
Intercept	0.92	0.14	0.68	1.24	1.00	0.94	0.16	0.67	1.28	1.00
Banks	0.60	0.11	0.43	0.87	1.00	0.60	0.11	0.43	0.85	1.00
Institutional investors	0.48	0.12	0.28	0.77	1.00	0.45	0.10	0.28	0.68	1.00
Year	0.22	0.05	0.14	0.33	1.00	0.23	0.05	0.14	0.33	1.00
σ_y	1.18	0.002	1.18	1.18	1.00	1.18	0.002	1.18	1.18	1.00

LCI and UCI show lower and upper bound of 95% credible interval (CI). The CI represents the region in the posterior distribution in which a parameter value falls with a specific probability (95%). $\hat{R}$ is the potential scale reduction factor. We follow the convention of $\hat{R} > 1.01$ to identify non-converging Markov chains. Result variation between the two models is marginal.

5.1 Random effects and variation in investment size

To begin discussing our estimated differences in investor size across groups we first focus our attention on the estimated standard deviation of the random effects. The last rows of Table 3 show estimated standard errors of our intercept and slope random effects at each level of the model. Notice that random effects present more variation at the technology level than at the technology-year level. This implies that the time-varying component in our dataset is mainly captured by our time trend term.

Figure 4 shows random effect estimates at the technology level added to our estimated fixed effects for our IHS transformed model. Estimated random effects for intercept, banks and institutional investors' investment dummies have large standard errors relative to the point estimate size and often intersect with the fixed effect estimate. There are some notable exceptions.

First, our intercept random effect for marine technology is of -1.59, implying that average investment in marine is 20% of average investments across the sample. Additionally, the estimated intercept random effect for offshore wind is 0.98, which means that average investment into offshore is 2.7 times bigger in relation to other technologies.

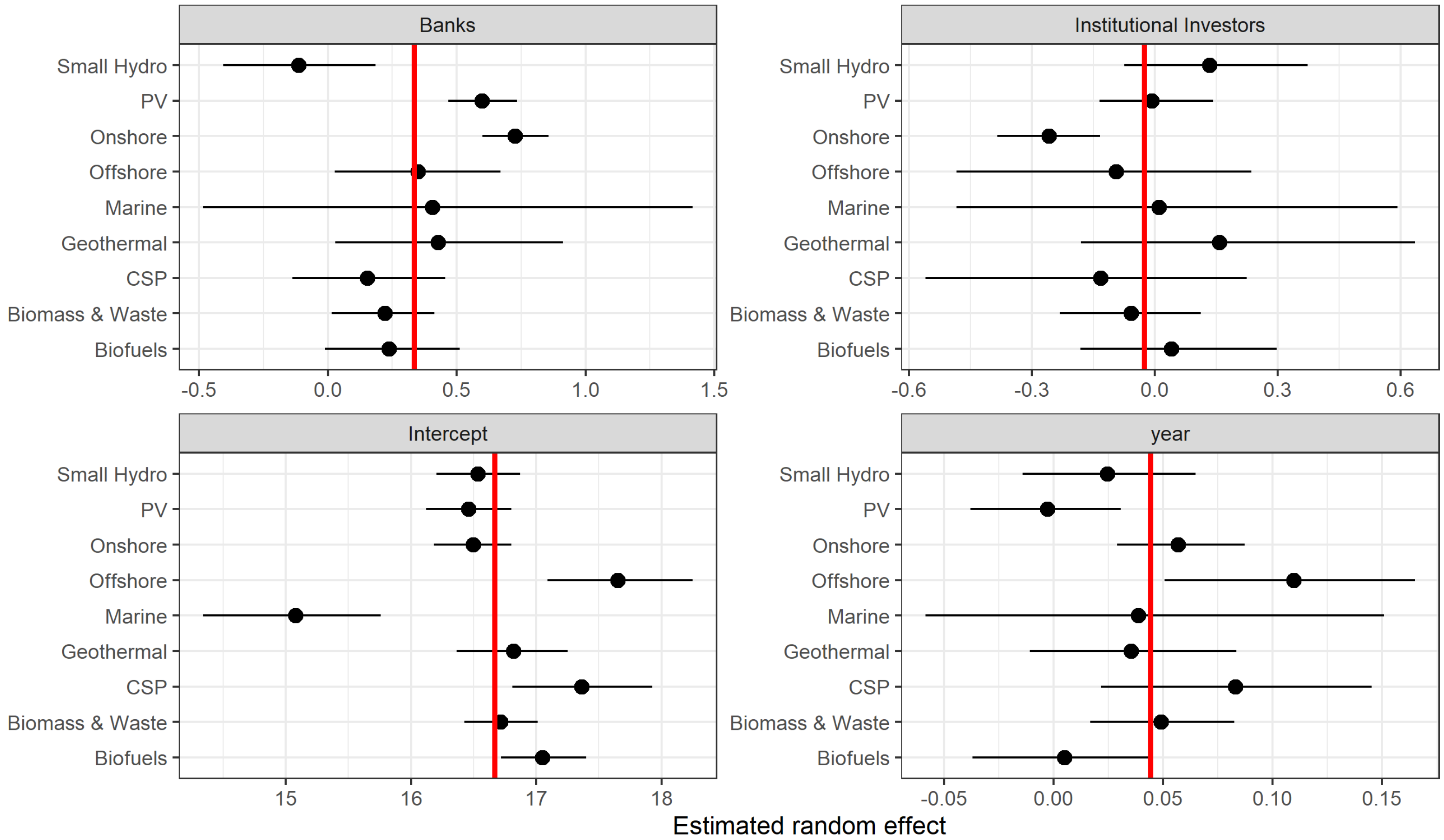
Second, bank average investments relative to project developers in small hydro are smaller. This can be seen from adding the fixed effect estimate for our bank dummy (0.33) and the random effect estimate for banks investing into small hydro (-0.45). Combine this small sum with an extremely small random effect for the intercept when taking into account investments into small hydro and relatively high confidence intervals to conclude that there is too much uncertainty to say that bank investment in small hydro is on average higher than that of project developers. Additionally, we observe bank average investment in PV and onshore being above average investments by banks in other technologies. The cumulative effect for average investment size by banks implies that investment is 2.1 times (onshore) and 1.82 times (PV) of project developers. We are not able to conclude the same for other technologies due to the high confidence intervals of our estimated bank random effects. Hence, with the exception of small hydro, banks invest on average larger amounts than project developers, with the proportional difference increasing further with PV and onshore wind.

Third, institutional investor average investment is higher than project developers in small hydro when taking into account random effects. Nevertheless, given the overall small role small hydro plays in renewable energy and the high estimated random effects errors, we still cannot confirm our hypothesis of relatively large institutional investor investment sizes. On the other hand, estimated random effects for onshore wind show a tendency of institutional investors to under-invest relative to project developers (23% less for onshore relative to project developers).

Results for our year trend term random effects present estimates of differing exponential growth trends across technologies. Two changes in trend are important to highlight. First, Solar PV has an estimated trend random effect of -0.05, which in conjunction with our estimated fixed effect implies that we can't conclude that average investment in Solar PV has grown over the sample. This is indicative of the dramatic reduction in Solar PV LCOE that presumably allowed projects to scale up without much change in upfront investment. Similarly, we find evidence that suggests that biofuels have not experienced increases in upfront investment across the sample years.

Second, offshore wind is the technology that presents the highest growth rate in average investment across the sample. The estimated random effect coefficient is 0.07, which implies that in conjunction with our fixed effect average investment in offshore wind doubled every 6.3 years across the sample length. The other technologies that present higher than average growth rates are onshore wind and CSP. However, wide standard errors prevent us from drawing conclusions with high certainty about the growth patterns of these technologies.

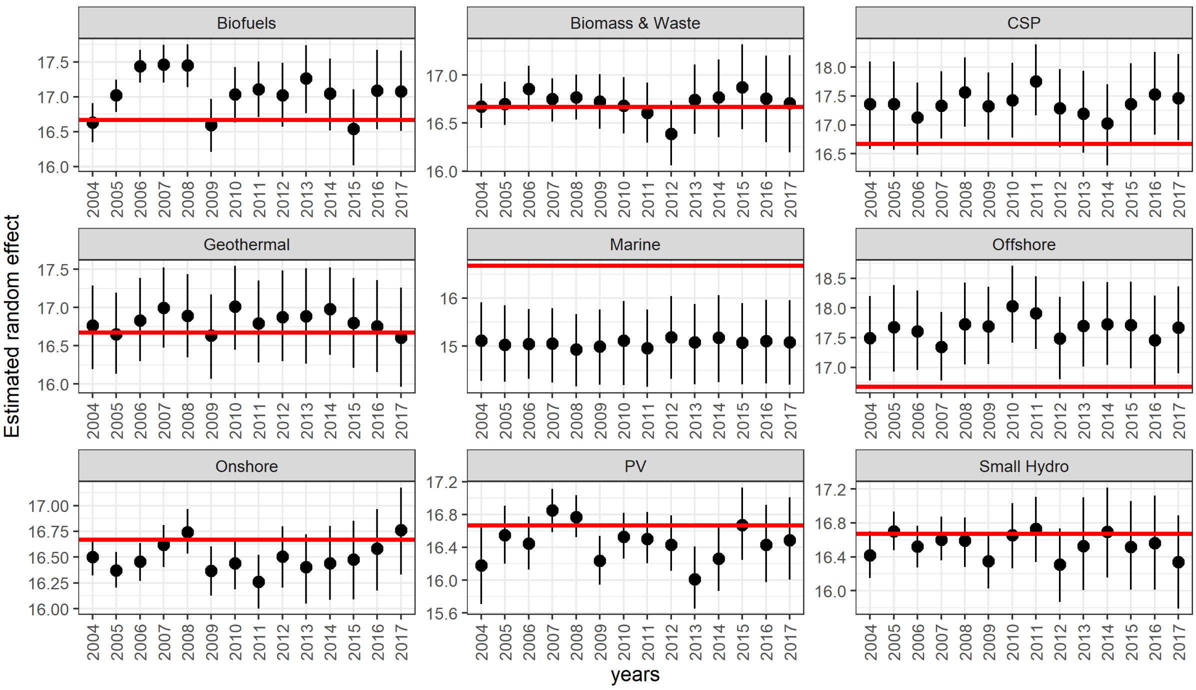
Figure 4: Technology effect parameter estimates and 95% CI. The estimated effect is calculated by adding the corresponding fixed and random effects. The red line crosses the fixed effect value.



We can further investigate these changes in size by considering variation across technology-year clusters. Figure 5 shows how estimated intercept random effects vary across technologies and years. These results show that baseline investment values mainly remained stable. However, we observe further variation in investment size that the model identifies with shifts in the parameters in particular years. Biofuels, CSP, offshore, onshore and solar PV exhibit cyclical variation in estimated intercept random effects across the technology-year clusters. The degree of variation across the years between the technologies differs, but in most (with the exception being offshore wind) we observe a drop in estimated investment size after the 2008 crisis, a small recovery after 2011, a second fall of investment size (mainly in biofuels and solar PV) and a recovery after 2015.

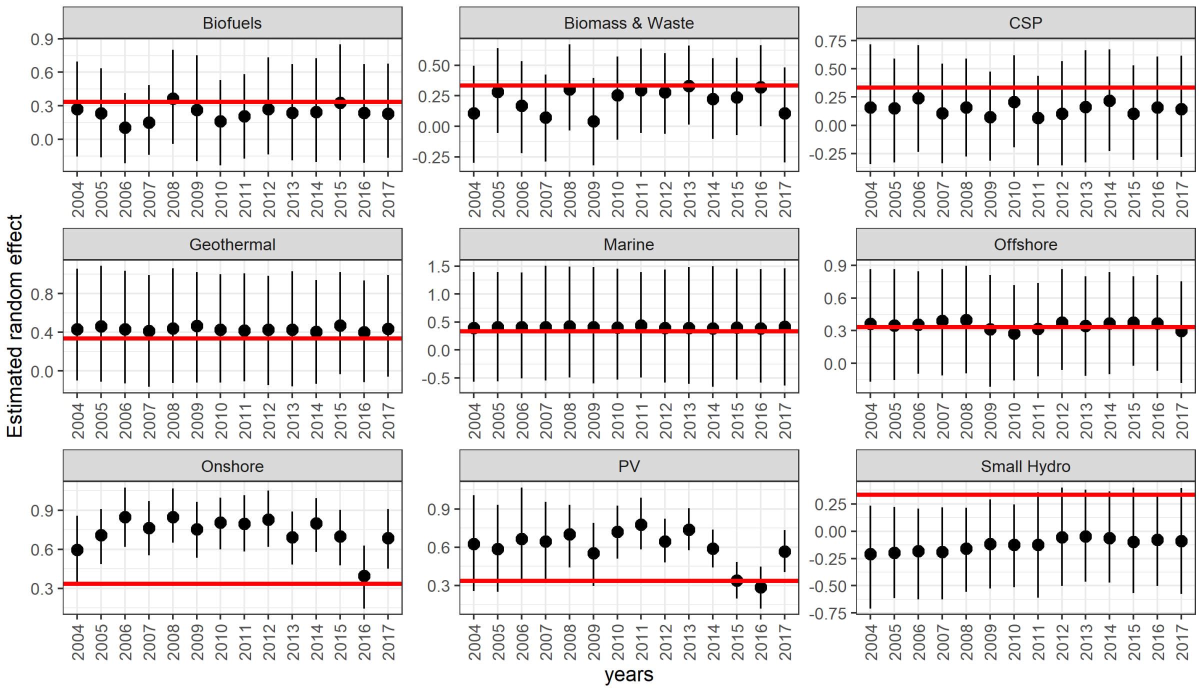
Similarly, we can investigate the investment trends of banks and institutional investors by analysing technology-year random effect estimates. Figure 6 shows our technology-year random effect coefficients for our banks indicator. Random effect coefficient estimates show stable patterns to changes in bank investment size. These estimates are negative in the latter years of the sample for solar PV and onshore wind. For the former, years 2015 and 2016 show a scenario in which the difference between project developers and banks in terms of size of investment was smaller when considering investments into PV. The random effects estimates for both years imply that bank investment into PV in 2015 and 2016 was 39% higher than that of project developers. This is in contrast with the rest of the years in which average investment into PV was 82% higher, as we reported when discussing the technology random effect estimates for PV. Given that the average investment size in PV remained stable in the latter years of the sample, as shown by our random effect estimate in Figure 5, this implies that in the latter years of the dataset we can observe convergence between banks and project developers in average investment size into solar PV. This is similarly seen in onshore average investment size, with the caveat that average investment size into onshore wind technologies was increasing over time, as described by our random effect trend term (Figure 4).

Figure 5: Technology-year random effect parameter estimates for intercept and 95% CI. Plotted values display the cumulative effect by adding fixed and random effects. The red horizontal line corresponds to the pooled estimate.



Institutional investors' investment size into PV and onshore also show a declining trend in the later years of the dataset, albeit with less stable behaviour in contrast to bank random effects. Figure 7 shows our estimated coefficients across technologies and years. First, we observe multiple instances of changes in investment size in onshore and PV. In contrast to banks, average investments into onshore wind and PV show cyclical shifts across the sample. For onshore this means that in specific years (2013 and 2017) average investment size is not dramatically different to that of project developers. However, we do observe sharp drops in average investment size for onshore throughout the sample as well. For instance, investment by institutional investors in 2011 and 2015 was 58% smaller than average project developers in those same years. In contrast, PV random effect estimates show a declining trend from 2010, with a sharp recovery in 2017. We observe that institutional investors' investment fell in relation to project developers' investment. Average investment into PV went from being 34% higher than project developers' investment in 2010 to being 33% smaller in 2016.

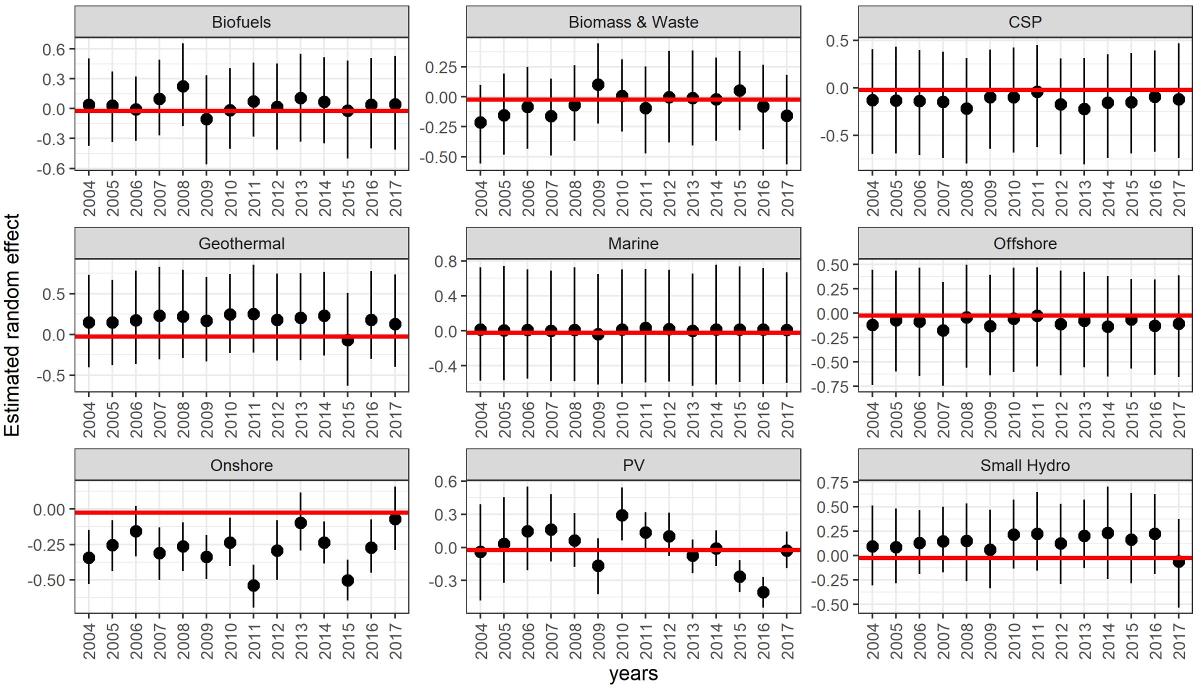
Figure 6: Technology-year random effect parameter estimates for bank indicator and 95% CI. Plotted values display the cumulative effect by adding fixed and random effects. The red horizontal line corresponds to the pooled estimate.



What does this mean for changes in the scale of investment across these sets of technologies across different sources of finance? By comparing these trends with the variation of our intercept value we can arrive at several conclusions. First, average investment size has been growing in onshore and offshore wind over time. This is consistent with the observed patterns of increases in median capacity for onshore and offshore wind across our dataset. Second, average investment size in solar PV has remained stable over time, falling prominently after 2014, despite median capacity also showing an increasing trend, as in onshore and offshore wind. Third, the gap between average bank investment, project developers and institutional investors has fallen in PV and in onshore wind. This development is due to the fall in average investment by commercial banks and the cyclical variation of investment size in onshore and PV; we observe convergence in these sets of technologies of average investments by banks and developers as we hypothesised. Finally, small hydro is an interesting case, the only technology in which commercial banks invest smaller amounts relative to project developers. This relation is stable across time.

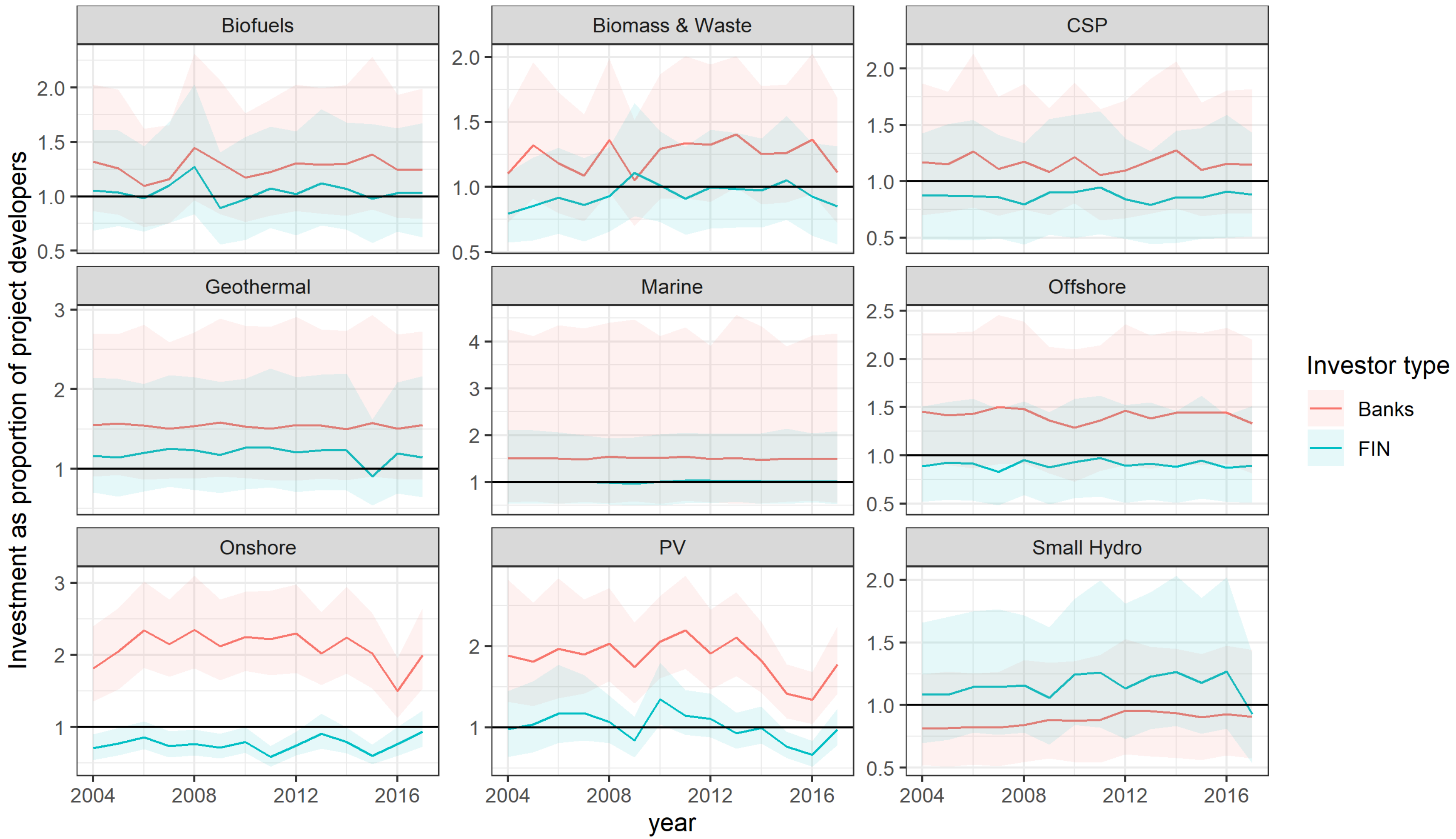
We can show the patterns of investment size in banks and the differences in institutional investors by adding the different fixed and random effects. We can construct predictions of average investment size per technology, year, and actor type. This is shown in Figure 8 as a proportion of project developers' investment. Notice that in general, investment size patterns are relatively stable across technologies. That is, the proportional difference between average investment between sources of finance varies little over time. This difference widens or falls when we observe sharp increases or decreases in average investment size for particular years. Examples of these temporal effects can be found in solar PV and onshore wind. Here we observe that in the latter years of the sample the proportional difference between investors falls. This implies that in the latter years of the sample there is less differences in investment size across actors for solar PV and onshore wind. Offshore wind is another technology that is worth mentioning since we found higher rates of exponential growth in investment sizes relative to other technologies. Since we observe no shifts in investment differences in offshore wind over time, we can conclude that investment size across actors diverges in absolute levels, due to the growth trend in investment in offshore wind.

Figure 7: Technology-year random effect parameter estimates for institutional investors indicator and 95% CI. Plotted values display the cumulative effect by adding fixed and random effects. The red horizontal line corresponds to the pooled estimate.



We are also interested in understanding what causes the variations identified above. We explore this by trying to estimate group level parameters for public finance flows. Formally, our model only changes by the introduction of public finance covariates at the technology-year level and the investment level. This allows us to identify fixed effects values for public investment flows and capture how this effect varies across technology-year groups. Our dataset also contains information on investments carried out by public institutions, which allows us to compute aggregate public investment flows. We are interested in assessing to what extent observed variations in actor size are explained by public finance, since we hypothesise that public investment can potentially induce changes in private investment in the context of innovative economic sectors. In the next section we present results on a version of our model that introduces the public investment covariate.

Figure 8: Predicted average investments by actor type as proportion of project developers. Shaded areas correspond to the 95% CI.



5.2 Public investment and private investment size

We now shift our focus to the identification of variation in response to public finance by investor type across the different cross-sections. To do so, we include several public investment covariates. Formally, our regression now contains fixed effects for public investment at the three levels of our model (individual investor, technology-year and technology). We construct a public investment covariate by totalling investments financed by publicly owned sources for each country-year-technology group in our dataset. We then normalise this variable by the annual electricity output in the country to control for the electricity market size. We rely on the IHS transformation to identify the proportional relation between average investments and aggregate public finance flows. Second, we include a mean centred average public investment per technology-year and an average public investment per technology across all years. The latter two covariates sum public investments across countries and attempt to distinguish longitudinal and cross-sectional effects of public finance into technologies, examining global effects of public investment on innovation from international spillovers. Therefore, they are not normalised by electricity output.

To evaluate how public investment can potentially describe some observed patterns captured by the random effects components of the model, we estimate three specifications that include interaction terms between our group level variables and our random effects components. First, a model with an interaction term between our time trend and our technology-level global average public investment variable (Model 2), known as a growth curve. We incorporate a growth curve term to measure the effect of stable cross-sectional characteristics (technological differences stable over time) on the yearly change of the outcome variable y_i (Fairbrother, 2014). Second, a model that introduces interactions between our banks and institutional investors' dummies and the global public investment variable by technology (Model 3). Third, a model that includes an interaction between our country specific level public investment normalised by electricity output and our banks and institutional investors' dummies (Model 4). Results of these three models relative to the initial specification from the previous section (Model 1) are presented in Table 4.

Table 4 shows our estimated fixed effect values (we omit reporting fixed effects for our control variables since the differences between models are marginal). First, we identify a positive relation between average investment and aggregate public finance flows. A 1% increase in aggregate public investment per TWh of electricity increases average baseline *individual* investment size of private actors by 0.05%. This is consistent across all the specifications that we estimate. This result is quantitatively important since the increase in public investment positively affects private investment size in *all* projects, on average. It gives strong support to our second hypothesis that more intense public investment correlates with scale economies realised by private investors. In contrast, we are not able to identify meaningful variation in investment size across technologies over time due to increases in public investment. This can be concluded from our estimated results of the effect of the average yearly deviation (L. public). Finally, we find evidence that suggests the presence of persistent spillover effects across countries for technologies with heavy public financing. A 1% increase in global aggregate public flows per technology increases average investment size by 0.42%. This strong correlation can be explained by the persistent increases in public financing in the renewable energy sector as reported by Mazzucato and Semieniuk (2018).

The inclusion of interaction terms in Models 2 and 3 suggests that the effects vary temporally and across investor types. The growth curve coefficient estimate shows a negative relation between cross-sectional differences in global public finance flows and time in Model 2. This implies that the elasticity of investment size with respect to global public financial support for the technology diminishes over time. The interaction terms in Model 3 have opposite effects, with higher levels of average public investment globally positively correlated with average investment size for banks and negatively correlated for institutional investors. This suggests that global public support has different effects depending on the source of finance present. Differences in local public finance flows (per country) in Model 4 show that banks are positively correlated (albeit somewhat weakly) with them, while they have no meaningful effect on institutional investors.

To conclude, for commercial banks, changes in global public finance flow and local public investment intensity have positive effects on investment size. In contrast, institutional investors' average investment reacts to changes in average global public finance into technologies, but not to domestic aggregate public investment intensity. Interestingly, we observe a negative relation between institutional investors average investment size and average global public finance, which we believe may be driven by small hydro, a mature technology (Polzin et al., 2021), where institutional investors make larger investments (Figure 8) but overall public investment is low.

As Cárdenas Rodríguez et al. (2015) point out, there are potential endogeneity concerns between private investments and public policies. Both private investors and governments might be mobilised by environmental concerns to promote green investments. The same argument applies for average private investment size and our public finance flows covariates. To check potential bias in the previous models' estimator, we further augment our results by implementing an instrumental variable approach that relies on our public organisations mandate variable. We use our mandate indicators to calculate flows of mandated public finance and use them to predict our aggregate public finance flows, introducing the country-specific controls that we included in our previous regressions. Mandates provide a source of exogenous variation because they do not by themselves induce larger private investment sizes. However, we expect a mandate to correlate positively with the total investment by public investors. We take a further step to rule out correlation between instrument and outcome variable. State banks and other public financial organisations could fulfill their mandates through the extension of credit to commercial banks (Marois, 2021). This implies that our instrument could be correlated with private bank investment. This investment consists of around 10.5% of our data. Since we have no data to identify credit lines to commercial banks, we only implement the two-stage least squares regression on a subsample of our data that excludes commercial bank investment. This prevents us from estimating random effects associated with our commercial bank dummy.

In order to implement the procedure, we first predict (IHS) aggregate public investment flows using a fixed effects estimator to account for the high presence of zero observations in the panel. We use (IHS) mandated investment flows and our other country specific covariates. Results are shown in the final column of Table 4. The results show that our estimated effect for aggregate public investment flows is still positive although the estimated effect is reduced to 0.04. That is, a 1% increase in aggregate public investment per TWh of electricity increases the average baseline *individual* investment size of private actors by 0.04%. The interaction between institutional investors and aggregate public finance flows remains insignificant.

Table 4: Regression coefficient estimates all models.

	Model 1	Model 2	Model 3	Model 4	2SLS
Intercept	16.73	7.49	10.34	7.83	16.7
	(0.24)	(1.81)	(2.55)	(1.72)	(0.23)
Banks	0.34	0.32	0.03	0.08	
	(0.12)	(0.1)	(0.19)	(0.2)	
Institutional Investors	-0.05	-0.05	-0.17	-0.18	-0.18
	(0.08)	(0.07)	(0.7)	(0.15)	(0.15)
Year	0.04	0.17	0.05	0.05	0.05
	(0.02)	(0.2)	(0.02)	(0.02)	(0.02)
A. public ($/TWh)		0.05	0.05	0.05	0.04
		(0.003)	(0.003)	(0.003)	(0.004)
L. public ($)		0.00	0.00	0.00	
		(0.00)	(0.00)	(0.00)	
G. public ($)		0.42	0.28	0.41	
		(0.09)	(0.12)	(0.08)	
		-0.005			
G. public × trend ($)		(0.01)			
			0.1		
G. public × banks ($)			(0.04)		
			-0.1		
G. public × I.I. ($)			(0.03.)		
				0.02	
A. public × banks ($/TWh)				(0.01)	
				0.008	0.008
A. public × I.I. ($/TWh)				(0.009)	(0.009)
					0.08
A. mandated public ($/TWh)					(0.01)
Policy controls	Yes	Yes	Yes	Yes	Yes

Numbers in parentheses indicate standard errors. All public investment covariates are transformed using the IHS function. A. public corresponds to the aggregate flows of public finance for deployment of projects of a technology within a country-year normalised by the country's electricity output; G. public corresponds to the non-normalised average of aggregate public flows across countries and years, in other words, a global average public finance flow per technology; L. public corresponds to the deviation between the global average and the yearly average across countries per technology; I.I. stands for institutional investors. We also report the relation between mandated investments and public investment from the 2SLS.

6. Discussion

The results show the heterogeneity in sources of finance in renewable energy deployment. First, during commercialisation, institutional investors are associated with rather fewer scale economies than most other investors. This result aligns with previous discussions that attest to the difficulties for institutional investors of rebalancing their portfolios towards low-carbon sectors (Silver, 2017; Ameli, Drummond, Bisaro, Grubb & Chenet, 2020). Here we see that, while the idea to 'de-risk' investments is one potential way to incentivise these investors to allocate their funds anyway (Steckel & Jakob, 2018), another is to look closely at which investors are most appropriate to a specific phase of the innovation landscape and who can improve the risk-return trade-off by financing at larger scale. For instance, banks and private utilities make on average 39% and 60% larger investments respectively in our sample, and banks' relative investment sizes into onshore wind and solar PV are even larger. Thus, our first hypothesis based on existing literature needs to be inverted: banks tend to be effective at generating scale economies, but institutional investors do not.

In line with recent research that highlights the importance of credit for R&D, we find that banks are far from the risk-averse latecomers that they are sometimes portrayed as in schematic depictions of innovation 'chains'. We find quite consistently that banks make large investments across technologies and risk levels, strongly driving scale economies. Since 80% of bank investments in our dataset are via debt, this suggests that project finance, with its high leverage, is effective at eliciting scale economies. The strong results are even more remarkable, because large projects are often financed by a syndicate of banks, suggesting that the true scale effects, especially in large offshore and CSP developments, are even higher, as every participating bank scales up its credit. On the other hand, the small equity shares may lower some project developers' investments, even though they are instrumental in arranging the project. Yet, since the vast majority of investments do not report debt, and since leveraged projects tend to be large in absolute size, any effect on the intercept coefficient is likely to be small.

Banks also show a higher public investment intensity elasticity of their investment size relative to other financial actors. Two channels may contribute. First, banks are often in consortia along with development finance institutions. When the latter participate and improve financing conditions (Geddes et al., 2018), banks may particularly benefit and be willing to release larger investment tranches. Second, banks often also receive concessional credit lines from development finance institutions that in turn enable them to extend credit to renewable energy projects at favourable rates (Marois, 2021). While we cannot establish this channel due to a lack of publicly available data, this could explain the strong elasticity, to the extent that development finance institutions typically operate both with direct project investment and credit lines at the same time.

Our results about the effect of public investment intensity are the first to our knowledge that attempt to link the influence of an active public sector on project-level private investment. By combining microlevel private investments with an aggregate public investment, we find a remarkably positive elasticity, suggesting that public finance not only acts on mobilising more private finance at the extensive margin, as previous studies have found, but also on increasing investment size at the intensive margin, unlocking scale economies. This result also holds for technologies with higher absolute levels of public investment at the global level over all years. This evidence suggests an additional, international scale-economy spillover from public support of renewables. All of this suggests that the presence of public investments, which is sometimes critiqued from a 'crowding out' perspective, has on average beneficial effects on the rate of commercialisation of renewable energy technologies.

We confirm that the effect of public investments is not driven by endogeneity thanks to our instrumental variable setup. Our instrument, a mandate to invest in renewable energy, which introduces exogenous variation into our analysis, also sheds light on the distribution of public finance across governmental actors. From our data, 44% of mandated public investment flows across the whole sample are from state banks. Hence, in light of our findings, state banks mandated to promote the deployment of renewable energy projects have played a disproportionately large role in eliciting scale economies between 2004 and 2017. Previous research has pointed towards the importance of public financial institutions in the process of market creation for innovative economic sectors, particularly due to its ability to invest heavily in economic sectors with longer time frames in mind (Mazzucato & Penna, 2016; Geddes et al., 2018; Mazzucato, 2021). Further research exploring the quantitative effects of state bank behaviour is needed.

7. Conclusion

Financing costly upfront investments has emerged as an important bottleneck in a fast transition to a low-carbon economy. Here we have drawn on the financing of innovation literature to examine the impact of heterogeneous sources of finance on innovation outcomes in the commercialisation phase of renewable energy technologies. Noting existing academic and policy discussions, we have hypothesised that institutional investors are making larger investments and banks are making smaller investments, rendering the former more effective and the latter less effective at realising scale economies. We have also hypothesised that more public investments into the sector (not necessarily the same deal) help private investors scale up their investment size. We analyse a rich asset finance dataset for renewable energy supply over 2004-17 in a hierarchical model setup to study bank and institutional investor behavior across time and technologies. Contrary to our first hypothesis, in the dataset banks, along with private utilities, make on average larger investments and so these two actors are most effective at generating scale economies. On the contrary, institutional investors make smaller investments on average. Our second hypothesis is confirmed. Every 10% of additional public finance normalised by electricity consumption correlates with 0.5% larger private investment size, thereby acting as a determinant of scale economies, and we confirm this effect with an instrumental variable analysis. This is true on average both for banks and institutional investors, although there is considerable variation across technology-year clusters. Our results thus confirm that different financing sources created heterogeneous outcomes during renewable energy commercialisation.

These insights are highly relevant to the debate about the transition to a low-carbon economy. With ever tighter deadlines to achieve ever more ambitious carbon emission reductions, notably in the energy sector, every opportunity to realise scale economies is welcome. Our results suggest that there may be value in targeting efforts at mobilising those sources of finance which are more effective at generating scale economies and accelerate the commercialisation of technologies. In our data, utilities and banks have on average been more effective at that, thanks to their propensity to make large investments. While much debate has focused on bringing in institutional investors due to their ample supply of funds, our results suggest that this debate might be well complemented with a discussion about how utility and bank investments could be incentivised to make more investments at the stage of technology commercialisation, due to their apparent appropriateness to invest at this juncture. Our results also show that public co-investments in renewable generation are a determinant of larger private investments, including via international spillovers, and can therefore help private investors realise scale economies. Institutional investors are now getting on board the increasingly fully formed market for renewable energy supply, for example via green bonds. However, our results may also be relevant for mobilising finance for scale economies forming markets in other capital-intensive, low-carbon technologies that are not yet as advanced as renewable energy supply. This is an area where additional research could advance the understanding of the extent to which results for the energy sector have external validity in other sectors.

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8. Appendix A

In this appendix we elaborate on how we prepared the dataset in order to impute investment proportions for missing entries at the deal level. We categorise the types of missing values that we encountered in two dimensions. The first dimension categorises missing data by how much of the share information is missing at the deal level. We distinguish between 'partially observed' and 'unobserved deals'. Deals that are partially observed are deals that disclose part of the investor shares, but some proportion of the investment is unavailable. Deals that are unobserved disclose no information about the proportions of the total investment associated with each investor. A partially observed project will be a project that contains information about the source of, for example, 60% of the investment in the project. On the other hand, an unobserved project would tell us the sources of finance, but won't provide information as to how the investment is distributed among its sources.

The second dimension categorises data based on missing information about individual investors' shares. We distinguish between deals with investors whose participation in the project is not disclosed and deals in which all investors are assigned a share of total investment. Even if all investors have a disclosed participation, the project can still be partially observed since the proportions might not add to unity. Table 5 summarises our categories and presents examples of the type of missing data that we encountered.

Table 5: Data anomaly categorisation

	Individual investor missing data	No individual missing data
Completely observed	Shares add to 100%, but some investors have no participation.	These observations are completely observed.
Partially observed	Shares add to less than 100%. Some investors have no participation.	Shares add to less than 100%
Unobserved	Investors have no participation	N/A

There are three types of anomaly in the data that we did not categorise: deals which have disclosed investors that have 0% participation; deals which have only one investor without any disclosed participation; and deals whose investor participation sums to more than 100%. For the first anomaly, we decided to treat deals with investors that have 0% participation as if the share of that particular investor was missing. For the second anomaly, we it considered appropriate to attribute 100% of the participation to the only source of investment listed. Finally, for the third anomaly, we decided to normalise the shares so that they add up to 100%. We describe below the imputation procedure and analyse the robustness of our results.

There are three mechanisms that generate missing observations: missing completely at random (MCAR); missing at random (MAR); and missing not at random (MNAR). If the mechanism causing the missing data depends neither on the observed data nor on the unobserved data, it is categorised as MCAR. The advantage of MCAR is that it allows for the omission of the unobserved data points (the incomplete dataset is representative). If the omission mechanism depends on the observed data, it is categorised as MAR. Under MAR, missing observations can be predicted using the relationship identified with the observed information. Finally, when the mechanism depends on the omitted data points, it is categorised as MNAR. Our imputation procedure assumes that the pattern of missing observations depends on the observed data points (MAR).

Given the above and the categories of missing data explained in the previous section, we designed an imputation strategy that allows us to utilise the information present in the observed sample. We will describe the strategy in two stages. First, we describe how we treated the dataset in order to also exploit the information contained in the partially observed data. Second, we discuss the modelling strategy used to predict missing values.

8.1 Data treatment

In our data categorisation, we identified a set of data anomalies that both contain information useful for the imputation procedure and require some imputation. Two types of missing data have this characteristic: deals that are partially observed and have missing individual data; and deals that are partially observed and do not have missing individual data. In both of these cases, some proportion of the investment is not distributed among the investors. They differ in that in the latter all investors have some assigned ownership of the portion of investment allocated between investors, while the former contains investors without any disclosed ownership (N/A entries). This category of partially observed data is of note as we are interested in imputing the remaining non-allocated proportion while at the same time using the information already contained in it to perform the imputation. In order to do the above we will need to treat partially observed data in the following way.

For data points that are partially observed, and don't have missing individual data, we create a new entry in the dataset (a new project) with the same number of investors and the same project-associated characteristics (geographical location, gearing, technology and so on). This new data entry differs from the original one in that there is no assignation of share of investment to any source of finance. The original data entry is then normalised so that shares of each investor add to 100%. This is done in order to use the original data entry as a completely observed data point and use the new entry to predict the remaining non-allocated share. Once the imputation is performed the final distribution is calculated as a weighted average between the original distribution and the imputed distribution. The weights of the final distribution are assigned based on the proportion of investment that is not allocated. For instance, if a particular project is partially observed and the sum of the shares allocated to each investor is equal to 60% (the non-allocated investment shares corresponding to 40%), the weights assigned to the original distribution and the predicted distribution in the imputation are 0.6 and 0.4 respectively.

The procedure for data points that are partially observed and have missing individual data is quite similar to the one described above. We also create an auxiliary observation to perform the prediction, with the final imputation being a weighted average between the original distribution and the predicted one. However, given that the original data entry has unobserved entries and that we would like to utilise the original distribution as a completely observed data point, we assign a small random proportion to the unobserved investors (we sample from a uniform distribution bounded between $1 \times 10{-}^{9}$ and $1 \times 10{-}^{5}$). Hence, the only difference between the treatment of the partially observed entries centres around how to create a completely observed data point. Both treatments explained for partially observed data entries assume that the non-allocated shares can be assigned to any of the investors disclosed in the project (Mazzucato & Semieniuk, 2018). Following the two treatments we are able to distinguish between entries in our dataset that can be used as information to be fed into our estimation procedure, and entries used to predict the unobserved shares.

8.2 Modeling strategy

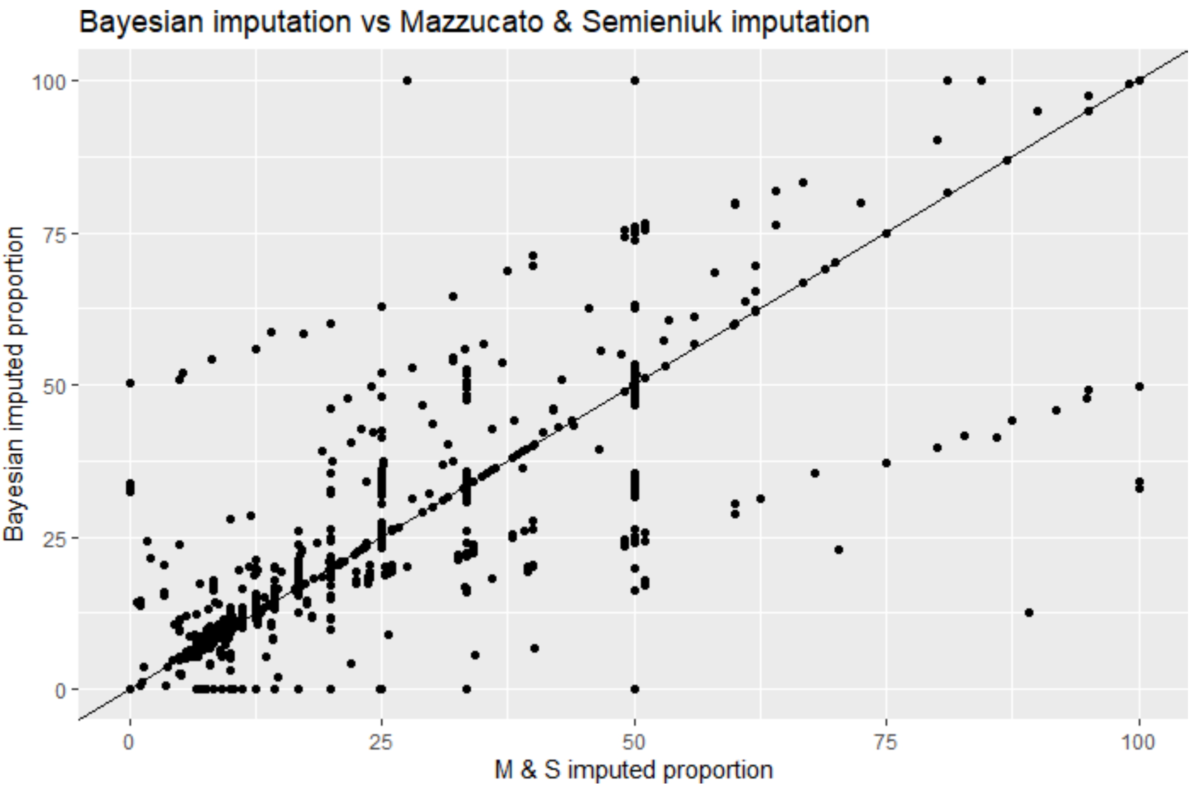
To identify the relevant information in our dataset that can be used to predict the unobserved shares, we can exploit the structure of the dataset itself. The dataset contains information about individual investors in the project (for instance, whether the investor is a public or private entity) and information about the project itself (technology, geographical location, gearing ratio). Due to this, the dataset can be said to have a hierarchical structure; we are able to identify characteristics that generate variation at multiple levels. For instance, we are able to identify characteristics that generate variation across groups of projects, for example technology, geographical location and gearing ratio, among others. At the same time, we are able to identify characteristics that generate variation within deals (across investors).

We expect these different types of variations to be correlated and so the appropriate strategy to approach the imputation procedure is to model the variation using a multi-level model. Multi-level models are suitable in these scenarios, because they are a compromise between sampling from a complete pooled dataset and an unpooled dataset (Gelman & Hill, 2007). With a completely pooled dataset we imply that the data is sampled from the same model, therefore omitting variation other than variance. In a scenario where we analyse unpooled data, the opposite is claimed. Each entry is modeled independently from each other, implying that the variation in the data is too large to combine. Multi-level models strike a compromise by viewing individual parameters associated with the observations as a sample of a population distribution of parameters. That is, the variation across entries depends on the variation of parameters that are sampled from a common distribution. For example, in the context of our dataset, variation in the distribution of investment between deals could depend on the type of technology used in the project. In order to compare deals with different technologies the variation generated by different technologies is modeled from the same distribution.

Another relevant aspect that informs our choice of model is the structure of the outcome variable in the dataset. The outcome variable that we are interested in imputing is a distribution. This implies that for each project we are interested in predicting a multivariate outcome that consists of proportions that add to unity. Hence, the appropriate model to use in this setting is a Dirichlet distribution. We elaborate on the technical details of the imputation procedure in Appendix A.

The outcome of the procedure is summarised in Figure 9. As can be readily seen, the earlier imputation by Mazzucato and Semieniuk in the case of unobserved data results in a mechanical assignment of 50%/50% for two investors, 33.3%/33.33%/33.3% for three investors, and so on, that underestimates the true variation in participation shares. The new procedure implemented here generates greater variation. This can be seen in Figure 9 by noticing the increased variation in the vertical dimension. For deals for which we have not enough information about the investors, the procedure defaults to Mazzucato and Semieniuk's imputation. This results in points located along the 45-degree line. What our results seem to suggest, is that some portion of the participation of investors in multiple deals was overestimated, or underestimated by Mazzucato and Semieniuk's imputation.

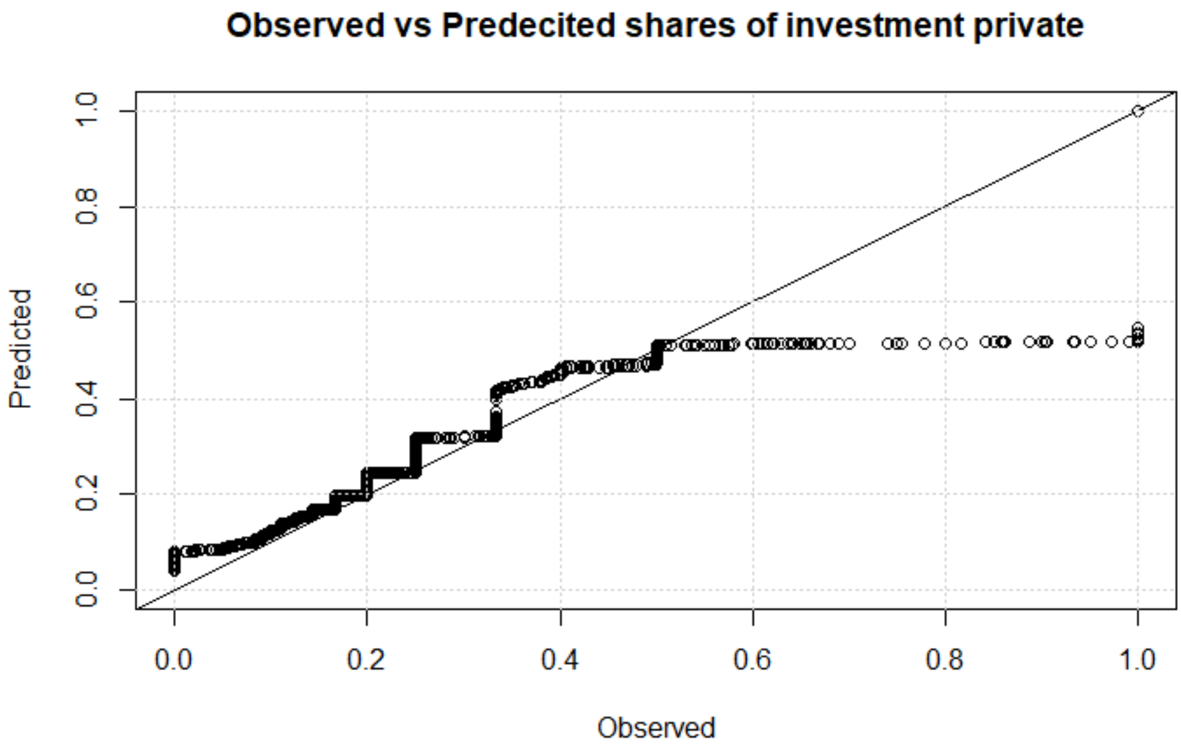
Figure 9: Missing share data imputed under the new procedure vs. Mazzucato and Semieniuk.

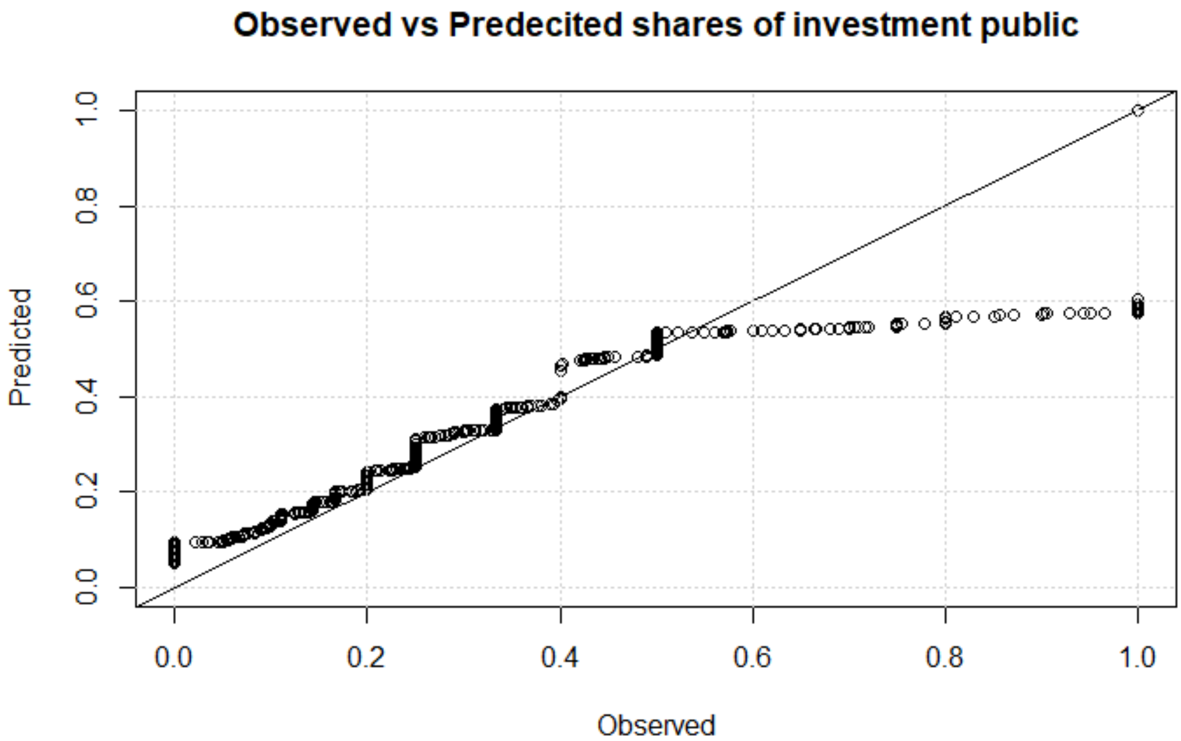


To check the robustness of our new procedure we also attempt to reproduce the observed shares in the dataset. Figure 10 plots the average predicted share and the observed shares of investment by public and private actors. So far, the procedure performs adequately when predicting participation of actors in deals below 50%. However, more information is required in order to be able to predict higher shares.[10]

[10] This information can only be gained by information from outside the BNEF dataset and can to a small extent be supplied where INSPIRATIA has superior participation data.

Figure 10: Observed shares of investment plotted against average predicted share.





9. Appendix B

This appendix elaborates on the technical details of the missing data imputation using a hierarchical model with the outcome variable (the shares contributed by each investor) Dirichlet distributed. The Dirichlet distribution is a multivariate analog of the beta distribution. Each draw of the Dirichlet distribution is a vector of proportion whose sums add to unity. A vector of proportions that follows a Dirichlet distribution is:

$$f(\mathbf{y}|\boldsymbol{\alpha}) = \frac{1}{B(\boldsymbol{\alpha})}\prod_{i=1}^{K} y_i^{\alpha_i - 1}$$

Where, $\mathbf{y} = (y_1, \ldots, y_K)$, and $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_K)$. With $y_i \in (0, 1)\ \forall i = 1, \ldots, K$, and $\sum_{i=1}^{K} y_i = 1$. Here, $\boldsymbol{\alpha} > 0$ is a shape parameter vector, and $B(\boldsymbol{\alpha})$ is the multinomial beta function. The summation $\sum_{i=1}^{k} \alpha_i = \alpha_0$ is a precision parameter (the higher its value the higher the density around the expected value). We can define the expected value of a component as:

$$E(y_i) = \frac{\alpha_i}{\alpha_0}$$

Our procedure models each distribution as sampled from a Dirichlet distribution, with the corresponding concentration parameter associated to each investor as a function of the characteristics associated to such investor $\alpha_i = g(\mathbf{x}_i)\alpha_0$. Here, $\mathbf{x}_i$ is a vector of observed characteristics that we use as predictors, while g is a function that maps the individual component characteristics to their expected value. For the purposes of our modeling we rely on the following parametrisation:

$$\mathbf{y}_i|\mathbf{x}_i \sim Dir(\boldsymbol{\omega}_i, \theta) \tag{5}$$

Here, $\theta_i = \alpha_{0,i}$ and $\boldsymbol{\omega}_i = (\omega_{1,i} \ldots \omega_{K,i})$, with $\omega_{k,i} = E(y_{k,i}|\mathbf{x}_i)$. We can define linear predictors using both component-wise coefficients and project-wise coefficients. Component coefficients are characteristics associated exclusively with the investor in a project, while project coefficients are associated with project characteristics. A linear predictor $\nu_{k,i}$ for investor k in project i can be defined in terms of the vector of observed characteristics. We can partition the vector into two vectors, one containing investor characteristics and another one containing project characteristics. We denote both of these vectors as $\mathbf{z}_{k,i}$ and x_i respectively. A linear predictor $\nu_{k,i}$ can be written as:

$$\nu_{k,i} = \mathbf{z}_{k,i}^T \beta_{k,i} + \mathbf{x}_i^T \zeta_i \tag{6}$$

Here, $\beta_{k,i}$ and ζ_i are component-wise and project-wise coefficients. Since every $\omega_{k,i} \in (0, 1)$ we take the exponential and normalise the linear predictors in each project:

$$\omega_{k,i} = \frac{e^{\nu_{k,i}}}{\sum_{k=1}^{K} e^{\nu_{k,i}}} \tag{7}$$

The precision parameter θ can also be modeled as a function of project characteristics. We define a function $h(\mathbf{x}_i)$ that maps project characteristics to a positive real valued number. Defining γ as a parameter vector, we can express the precision in a group conditional on project characteristics:

$$\theta_i = e^{\mathbf{x}_i^T \gamma_i} \tag{8}$$

From the above, the target density function and likelihood function are:

$$f(\mathbf{y}_i | \boldsymbol{\omega}_i, \theta_i) \tag{9}$$

$$L = \prod_{i=1}^{n} f(\mathbf{y}_i | \boldsymbol{\omega}_i, \theta_i) \tag{10}$$

9.1 Estimation

To approximate the likelihood (10) we implement an inference algorithm through R Stan. Two variations of Markov chain Monte Carlo algorithms are used by Stan, the Hamiltonian Monte Carlo algorithm and its adaptive variant the no-U-turn sampler algorithm (Stan Development Team, 2019). The full form of the Bayesian multilevel model that we implement is:

$$\begin{aligned} \mathbf{y}_i | \mathbf{x}_i &\sim Dir(\boldsymbol{\omega}_i, \theta) \\ \omega_{k,i} &= \frac{e^{\nu_{k,i}}}{\sum_{k=1}^{K} e^{\nu_{k,i}}} \\ \nu_{k,i} &= \phi_{i[j]} + \tau_{i[k]} + \mathbf{x}_i^T \beta_{i[k]} \\ \phi_{i[j]} &\sim N(\mu_\phi, \sigma_\phi) \\ \tau_{i[k]} &\sim N(\mu_\tau, \sigma_\tau) \\ \beta_{i[k]} &\sim N(\mu_\beta, \sigma_\beta) \\ \mu_\phi, \mu_\tau, \mu_\beta &\sim N(0, 10) \\ \sigma_\phi, \sigma_\tau, \sigma_\beta &\sim Exp(1) \\ \theta_i &\sim N(0, 5) \end{aligned} \tag{11}$$

In our model $\phi_{i[j]}$ and $\tau_{i[k]}$ are intercept coefficients that distinguish between investors buying equity or issuing debt to the project, and whether the investor is a private or public entity respectively, and $\beta_{i[k]}$ are slope coefficient associated to project characteristics that vary based on the investor type. Finally, $\mu_\phi, \mu_\tau, \mu_\beta, \sigma_\phi, \sigma_\tau$ are all hyper-parameters that describe the processes that generate the group variation that we are interested in. We assign hyper-priors to fully specify the posterior distribution that we are interested in approximating.

We attempted to fit the model using various permutations of explanatory variables in our dataset. We settled on the following considering computation time and how well observed shares were able to be reproduced by the model. First, we used the Mazzucato and Semieniuk (2018) risk measure as it incorporates country and technology wise information. Presumably, institutional considerations and the technical aspects of each project are incorporated into each investor's perception of risk. In order to identify the relative effect caused by a higher participation of public finance we calculated the ratio of public investors to total investors in each project and used it as an explanatory variable. Finally, we relied on the gearing ratio to control for each project's financial leverage.

10. Appendix C

In this appendix we describe the variance-covariance structure of correlation matrices $\Sigma 2$ and $\Sigma 3$ and provide a full list of our selected prior probability distributions for model (1). A covariance matrix Σ can be decomposed into $D(\tau)\Omega D(\tau)$, where Ω is a correlation matrix, τ a vector of coefficient scales and $D(.)$ a diagonal matrix. We can recover elements from the covariance matrix Σ from this mapping.

The decomposition requires including priors for τ and Ω. Gelman and Hill (2007) suggests an inverse Wishart distribution as a prior correlation for Ω. Recently the most common choice for prior is an LKJ distribution, motivated partially by the fact that the posterior distributions for the variance and correlation when using an inverse Wishart prior can be biased (Alvarez, Niemi & Simpson, 2014). The LKJ distribution is defined by $\mathrm{LKJCorr}(\Omega/\eta) \propto \det(\Omega)^{\eta-1}$. The parameter η determines the degree of correlation, with $\eta > 1$ concentrating the density around the unit matrix (less correlation), and $\eta < 1$ favouring more correlation. When $\eta = 1$ the result is a uniform distribution on the space of correlation matrices which is non-informative. Our full list of priors is:

$$\begin{aligned} \beta^1 &\sim N(0,10) \\ \gamma^2, \gamma^3 &\sim N(0,5) \\ \sigma_y &\sim \mathrm{Cauchy}(0,10) \\ \tau^2, \tau^3 &\sim \mathrm{Cauchy}(0,2) \\ \Omega^2, \Omega^3 &\sim \mathrm{LKJCorr}(5) \end{aligned} \tag{12}$$