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About the Institute for Innovation and Public Purpose

The UCL Institute for Innovation and Public Purpose (IIPP) aims to develop a new framework for creating, nurturing and evaluating public value in order to achieve economic growth that is more innovation-led, inclusive and sustainable.

We intend this framework to inform the debate about the direction of economic growth and the use of mission-oriented policies to confront social and technological problems. Our work will feed into innovation and industrial policy, financial reform, institutional change, and sustainable development.

A key pillar of IIPP's research is its understanding of markets as outcomes of the interactions between different actors. In this context, public policy should not be seen as simply fixing market failures but also as actively shaping and co-creating markets. Re-focusing and designing public organisations around mission-led, public purpose aims will help tackle the grand challenges facing the 21st century.

IIPP is housed in The Bartlett, a leading global Faculty of the Built Environment at University College London (UCL), with its radical thinking about space, design and sustainability.

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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 ÔupstreamÕ research and development financing (Kerr & Nanda, 2015; B. H. Hall, 2002). We examine whether investor heterogeneity is also relevant for the ÔdownstreamÕ 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 literature more generally, focuses on the upstream phase of innovation. We study how the quality of finance may impact renewable energy innovation a -0.7 ( ) -T] TJ ET Q q 0.24 0 0 0.24 12 627.92 cm BTal

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 larger 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 filte.4 (at) wutatp.4 BT 46 0 0.7 (j) -9.7 (e)0.7 (c) 0.

of covariates and the intercept of our regression model across different clusters in the data. We because it comprises a higher share of lifetime costs than for competing fossil energy generation, This includes savings thanks to the bulk purchase of certain inputs and spreading the fixed cost of machines. It also includes the important ÔsoftÕ 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«

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 Ôvalley of deathÕ 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 EnergyÕs SBIR grants double their chance of subsequent venture funding compared with rejected applicants; Goldstein et al. (2020) find US Department of EnergyÕs ARPA-

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,

assessment of their effects on mobilising finance in the renewable energy sector is significant
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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.

BNEFÕs 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

Table 1: Investment size by technology summary statistics

	Mean	SD	Min.	First qu.	Median	Third qu.	Max.	Obs.

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

! Model extensions

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:

where T_i is our treatment, z_i

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 investorsÕ 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 donÕt 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

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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.

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

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.

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

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

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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)

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 investments in

Howell, S. T. (2017). Financing innovation: Evidence from R&D grants. American Economic Review, 107

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van der Ploeg, F. & Rezai, A. (2020). The risk of policy tipping and stranded carbon assets. *Journal of Environmental Economics and Management*, *100*. Retrieved from https://doi.org/10.1016/j.jeem.2019.102258 doi: 10.1016/ j.jeem.2019.102258

Wall, R., Grafakos, S., Gianoli, A. & Stavropoulos, S. (2019). Which policy instruments attract foreign direct investments

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!

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

in the vertical dimension. For deals for which we have not enough information about the investors, the procedure defaults to Mazzucato and SemieniukÕs 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 SemieniukÕs 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 distribu

The precision parameter θ can also be modeled as a function of project characteristics. We define a function $h(x_i)$ 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:

$$\theta_i = e^{x_i^T \gamma_i} \tag{8}$$

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

$$f(y_i | \omega_i, \theta_i) \tag{9}$$

$$L = \prod_{i=1}^{n} f(y_i | \omega_i, \theta_i) \quad [illegible] \tag{10}$$

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-turn sampler algorithm (Stan Development Team, 2019). The full form of the Bayesian multilevel model that we implement is:

$$y_i | x_i \sim Dir(\omega_i, \theta)$$

$$\omega_{k,i} = \frac{e^{\nu_{k,i}}}{\sum^{K} e^{\nu_{k,i}}}$$

$$\nu_{k,i} = \varphi_{i[j]} - [illegible] \tag{11}$$

$$\tau_{i[k]} \sim N(\mu_{\tau}, \sigma_{\tau})$$

$$\beta_{i[j]} \sim N(\mu_{\beta}, \sigma_{\beta})$$

[illegible]

$$\theta_i \sim N(0, 5)$$

In our model $\varphi_{i[j]}$ and [redacted] 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 $\beta_{i[j]}$ are slope coefficient associated to project characteristics that vary based on the investor type. Finally [redacted] 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 investorÕs

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