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Assistant Research Professor, Political Economy Research Institute and Department of Economics, University of Massachusetts Amherst;

Research Associate, UCL Institute for Innovation and Public Purpose; Lecturer in Economics, Department of Economics, SOAS University of London

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Research Fellow in Green Transition Financing, UCL Institute for Innovation and Public Purpose

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Director, and Professor in the Economics of Innovation and Public Value, UCL Institute for Innovation and Public Purpose

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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 lowcarbon assets is now a key condition for successfully mitigating climate change [PCC, 2018; McCollum et al 2018; Bertram et al, 2021) and dampening potentially destabilising feedback on the economy from stranded higher bon assets fan der Ploeg & Rezai2020; Battiston, Monasterolo, Riahi & vaRuijven, 2021; Semieniuk, Campiglio, Mercure, Volz & Edward 2021). However, scaling up the deployment of capitalensive low carbon technologies, sch as the supply of renewable energy, has become one of the central challenges for accelerating the lowcarbon transition, and mobilisation of the right mix of investors has proved difficult [EA, 2020; Polzin, Sanders & Serebriakov 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 westor 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 allagher, Gruble Kuhl, Nemet & Wilsor 2012). We construct a

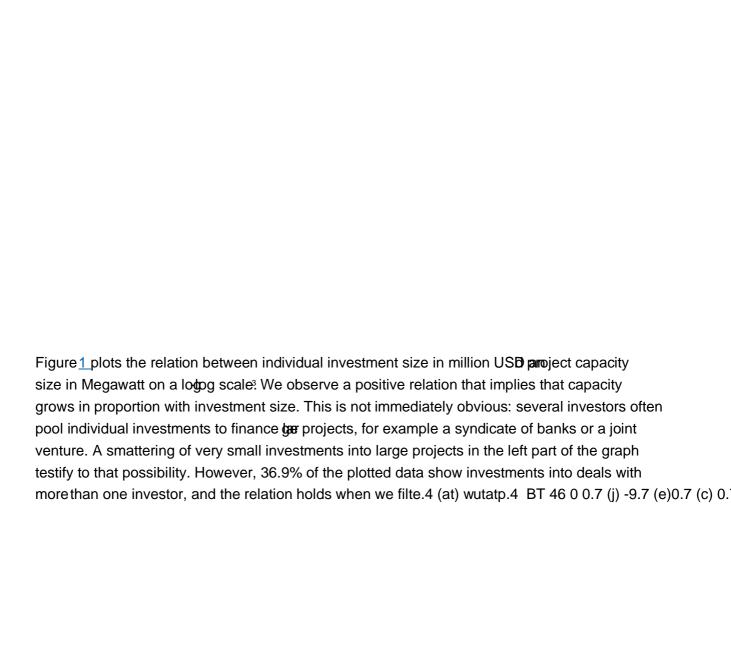


Figure 1: Correlation between capaity and individual investment size (lotog scale); sample of

investments only with observed total project cost. Data sources discussed below.

of	covariates	and the	intercept o	f our re	egression	model	across	different	clusters	in the	ò <b>1∕at</b> ea.

because it comprises a higher	share of lifetime	costs than for c	ompeting fossil e	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  $\hat{O}$ soft $\hat{O}$ hænder(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 propolionately, if at all, with project sizeleuhoff, 2005). Kavlak, McNerney and Trancik(2018) find that for solar modules, since 2004caleeconomies in manufacturing have outweighedlearning by doing and R&D as a factor in reducingsts, andElia, 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 for the Medlock2017). 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 dearthunding for bringing lab research into product developmen 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 applica disciplination 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 relid on systemic approaches to understanding the innovation ecosystem [Mazzucato2016]). Some of this literature focuses on historical analysis that details the role of government institutions ipromoting and financing innovation [feeman, 1995; Perez, 2002; Mazzucato2018]). Conceptually, the role of government agencies in such processes is justified by the pathdependent 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 paradigmazucato & Semieniuk

assessment of their (	effects on mobilising	finance in the rene	ewable energy secto	r is significant

unreported deal values inequal parts to participants Qorrocher & Cappa 2020; Mazzucato & Semieniuk 2018). We designed an imputation procedure that cliffs 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 AppendiA.

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.



## ! Model extensions

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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 relieon our collected mandate indicator as a source of exogenous
variation. We can write 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 y across groups.

Table 3 also shows that the year trend term is positive and implies exponential growth in investors of 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 waithoverall 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. Ourstimated 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 matracetive to the financier and so other things equal may induce large investments. We donot 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 smallegetargaps. 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 sizeneaning that typically highscale projects are the ones that are able

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.

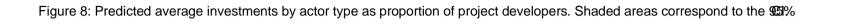
Second, offshore wind is the technology that presents the highest growth rate in average investment across the sample. The estimated random effect coefficient is 0.07, which isnibites in conjunction with our fixed effect average investment in offshore wind doubled every 6.3 years across the sample length. The other technologies that present higher than average growth rates are onshore wind and CSP. However, wide standard errores/pnt 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 clusters. Figure 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, offshoresbore and solar PV exhibit cyclical variation in estimated intercept random effects across the technology ar 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 recoeffey 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 tintistinal investors by analysing technologyyear random effect estimates. Figure shows our technologyyear 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: Technologyyear random effect parameter estimates for bank indicator and 95% CI. Plotted values display the cumulative effect bydding 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 acrossrador 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 iffshore wind over time, we can conclude that



The inclusion of interaction ter

individualinvestment size of private actors by 0.04%. The interactbetween 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 themmercialisation 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 ampleuspply 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 publicing estments in

Howell, S. T. (2017). Financing innovation: Evidence from R&D grantsericanEconomic Review107

- Steffen, B. (2020). Estimating the cost of capital for renewable energy projectsergyEconomics 88, 104783. doi: 10.1016/j.eneco.2020.104783
- Strauss, I. & Yang, J. (2020) orporate secular stagnation: Empirical evidence on the advanced economy investment slowdown (Working Paper No. 2019). INET Oxford Working paper.
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- van der Ploeg, F. & Rezai, A. (2020). The risk of policy tipping and stranded carbon absets al of Envonmental Economics and Managemento. Retrieved from <a href="https://doi.org/10.1016/j.jeem.2019.102258">https://doi.org/10.1016/j.jeem.2019.102258</a> doi: 10.1016/j.jeem.2019.102258
- Wall, R., Grafakos, S., Gianoli, A. & Stavropoulos, S. (20/19)ch 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).

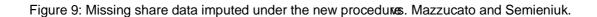
Given the above and the categories of missing data explained in the previous section, we designed an imputation strategy that allows us to utilise the informatioesent in the observed sample. We will describe the strategy in two stages. First, we describe how we treated the dataset in order to also exploit the information contained in the partially observed data. Second, we discuss the modelling strategy used to entire the 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 allow ated shares can be assigned to any of the investors disclosed in the project / zucato & 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

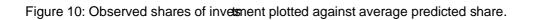
in the vertical dimension. For deals for which we have not enough information about the investors, the procedure defaults to Mazzucato and SemieniukÕs imputation. This results in points located along the 45-degree line. What our results seem to suggest, is that some portion of the participation of investors in multiple deals was overestimated, or underestimated by Mazzucato and SemieniukÕs imputation.



To check the robustness of our new procedure we also attempt to reproduce the observed shares in the dataset. Figurd oplots the average predicted share and the observed shares of investmen 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.

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<sup>&</sup>lt;sup>10</sup> This information can only be gained by information from outside the BNEF dataset and can to a small extent be supplied where INSPIRATIA has superiparticipation data.



## 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 paramete%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 numbering as a parameter vector, we can express the precision in a group conditional on project characteristics:

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

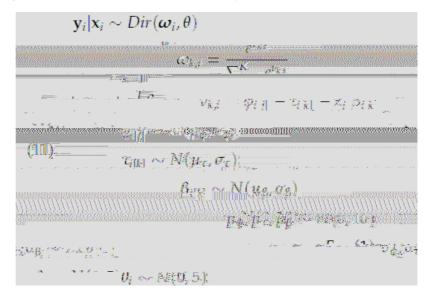
From the above, the target density function and likelihood function are

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

$$I = \prod_{i=1}^n f(\mathbf{y}_i|\boldsymbol{g}_{i}, \boldsymbol{\omega}_i) \underbrace{\mathbf{y}_{i} \cdot \mathbf{y}_{i} \cdot \mathbf{y}_{i}}_{i=1} \underbrace{\mathbf{y}_{i} \cdot \mathbf{y}_{i} \cdot \mathbf{y}_{i} \cdot \mathbf{y}_{i}}_{i=1} \tag{10}$$

## 9.1! Estimation

To approximate the likelihood 0) 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 the turn sampler algorithm 1 Development Team 2019). The full form of the Bayesian multilevel model that we implement is:



In our mode  $\phi_{i[j]}$  and are intercept coefficients that distinguish between investors buying equity or issuing debto the project, and whether the investor is a private or public entity respectively, and are slope coefficient associated to project characteristics that vary based on the investor type. Finally are all hyperparameters that describe the processes that generate the group variation that we are interested in. We assign hyperparameters to fully specify the posterior distribution that we are interested in approximating.

We attempted to fit the model using various permutations of explanatory variables idataset. We settled on the following considering computation time and how well observed shares were able to be reproduced by the model. First, we used <a href="Mezzucatoand Semieniuk">Mezzucatoand Semieniuk</a>(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 Os

ucl.ac.uk/iipp @IIPP\_UCL

UCL Institute for Innovation and Public Purpose 11 Montague Street, London, WC1B 5BP

General enquiries: iipp-research@ucl.ac.uk Tel: +44 (0)20 3108 6961