U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Location-dependent Public-private Interaction in Catalyzing Solar Technology Commercialization

Robust Investor Ecosystem and Independent Technology Validator Are Needed in the Same Location to Accelerate Technology Commercialization

Disclaimer

Authors

The authors of this report are:

Emanuele Francesco Pecora, U.S. Department of Energy, Solar Energy Technologies Office, 1000 Independence Avenue SW, Washington DC 20585 & ORAU, 100 ORAU Way, Oak Ridge, TN 37830

Jonathan P. Trinastic, U.S. Department of Energy, Solar Energy Technologies Office, 1000 Independence Avenue SW, Washington DC 20585 & American Association for the Advancement of Science, 1200 New York Ave NW, Washington, DC 20005

Acknowledgments

The authors wish to thank Garrett Nilsen and Victor Kane, who designed and managed most of the funding opportunities analyzed in this paper, for their insight on these programs, their comments and feedback on the data collection and analysis, and on the final manuscript; Kyle Fricker, Marie Mapes, and Lenny Tinker for their comments and feedback on the data collection and analysis and on the final manuscript; Casey Canfield, Jack Hoskins, Robert Margolis, and Dave Rench-McCauley for the useful discussions on the methodology of the data analysis.

The authors thank ORAU through the U.S. Department of Energy Oak Ridge Institute for Science and Education for the financial support.

Executive Summary

We analyze the solar startup landscape in the United States and investigate the role of public funding and other factors in the success of small businesses. Three solar entrepreneurial hubs - Silicon Valley, Los Angeles / San Diego, Boston - contain significantly more solar venture capital activity than the rest of the country. Through statistical modeling, we find that public funding for companies in these hubs has an outsized impact on their success in finding future investment, even after controlling for company and environmental factors. A regression discontinuity analysis establishes a causal link between public Federal funding and the success of a small business in soliciting private follow-on investment. Public funding can have a powerful role in sustaining private investment in a company, but its impact largely depends on the local investment space in which the company exists.

Table of Contents

1 Introduction

The United States has a robust ecosystem of private investors (angels, venture capitalists, impact investors, corporations, pension funds, etc.) that allows rapid technology development and enables disruptive changes [1–3]. However, clean energy technologies (cleantech) and solar technologies, specifically, are not currently the main focus of these investors, both in terms of number of finalized deals and amount of money invested [4–7]. After a burst of private investments between 2006 and 2011 that resulted in significant losses, funding for cleantech experienced a substantial contraction [8–11], which was subsequently met to a smaller extent by public research and development (R&D) investments. In addition to the clear societal benefits offered by clean energy technologies, supporting successful technology transfer mechanisms and enabling accelerated transition of new technologies from laboratories to market have consistently been two important goals of the U.S. Government [12–14]. In fact, the U.S. has actively invested in R&D projects led by small businesses, primarily through the Small Business Innovation Research (SBIR) and Small Businesses Technology Transfer Research programs [15,16] since 1982. These programs support entrepreneurs across a wide range of technology areas, with a particular emphasis on defense and health-related applications. Furthermore, individual Federal agencies support small businesses through funding programs for specific technologies. As an example, during the last couple of decades, the Solar Energy Technologies Office (SETO) established within the Office of Energy Efficiency and Renewable Energy (EERE) of the U.S. Department of Energy (DOE) has consistently funded small businesses via different programs spanning multiple initiatives (including the Solar America Initiative and the SunShot Initiative). See section 8.1.2 for a more detailed list of these funding opportunities.

The impact of public funding programs has been investigated by several research groups (mostly with a focus on their influence on downstream R&D, publication, and patenting) both in the U.S. [17–20] - with a specific interest on the SBIR program [21–24] - and in other countries [25,26]. However, these studies take into consideration programs designed to cover broad industry and technology spaces with the risk to confound the impact of general policies and programs with industry-specific trends and features. Intrinsic differences between business sectors might obfuscate trends and lead to conclusions that are too general to be relevant. We have an unique opportunity to analyze the public intervention on a defined space (the solar industry) over more than 10 years (2007-2018), while the solar industry grew from having negligible value to significant global deployment [27–29]. We focus on a specific metric - follow-on funding – as a measure of public funding impact and its interaction with private investment. It should also be noted that the SETO programs represented in this study have a cost share requirement (a minimum of 20% for low tier projects, and a minimum of 50% for higher tier / demonstration projects)[1]. As a secondary effect, this requirement generally increases the quality of the applications, or at least the ability to generate follow-on investment: the applicants need to

[1] Cost share is generally defined as the portion of the total project costs not reimbursed by DOE; those costs must be paid by the awardee based on the requirements in 10 CFR 600, EPAct 2005, and Energy Act 2020.

validate their idea and secure some form of seed funding before accepting their SETO award. Although our analysis focuses on a specific program impacting the solar industry, we believe that the results, driven by a rigorous statistical methodology, can provide useful insights into other sectors and beyond the United States.

In this paper, we first analyze the solar startup landscape in the United States and show the typical behavior for a small business developing new solar hardware or software technologies. In particular, we identify three solar entrepreneurial hubs in the country: the greater San Francisco/San Jose/Oakland metropolitan areas - referred to as Silicon Valley, the Greater Boston area, and the metropolitan areas of Los Angeles/San Diego. We develop a general linear model to find key predictors of future equity deals, and conduct a regression discontinuity analysis to establish a causality link between these predictors and the success of a small business in soliciting private follow-on investment. In this paper, "follow-on investment" is defined as any private investment in the small business finalized from the calendar year following the application to SETO. Therefore, any private investment raised to meet the cost share requirement for the award is not included in our analysis. We then explore similarities and differences in the impact of Federal funding based on the type of follow-on funding (equity, debt, or grants). Public funding can have a powerful role in sustaining further private investment in a company. However, the size of this role largely depends on the local investment space in which the company exists. The results of this study illuminate the public-private interactions that may guide investment in solar technology, and provide important feedback for how future public funding programs could be designed to maximize their ability to help companies gather private investment.

2 U.S. solar startup landscape

Despite the significant compound annual growth rate of solar installations around the globe, the overall size of the solar industry is still small compared to other technology sectors, and the number of small businesses[2] generating new technologies is quite low. We used Pitchbook [30] - a specialized firm focused on research and data analysis on companies, deals, funds, investors, and service providers across the entire private investment lifecycle including venture capital, private equity, and M&A transactions - to collect the number of equity deals completed in the solar space between 2000 and 2017 in the U.S. (Fig. 1(A), solid yellow). Although not an exhaustive list, the results represent a good approximation of the size and activity of solar startups. In fact, equity deals represent the majority of all transactions in the solar space, as shown in Fig. S1. Details of the query, data collection methodology, and definitions adopted in our dataset are discussed in sections 8.1.1 and 8.1.2. The solar space became attractive to investors in 2007; only less than a dozen deals were completed every year prior. At the peak

[2] We adopted the definition of small business utilized by the U.S. Small Business Administration (SBA). See section 8.1.2 for additional information.

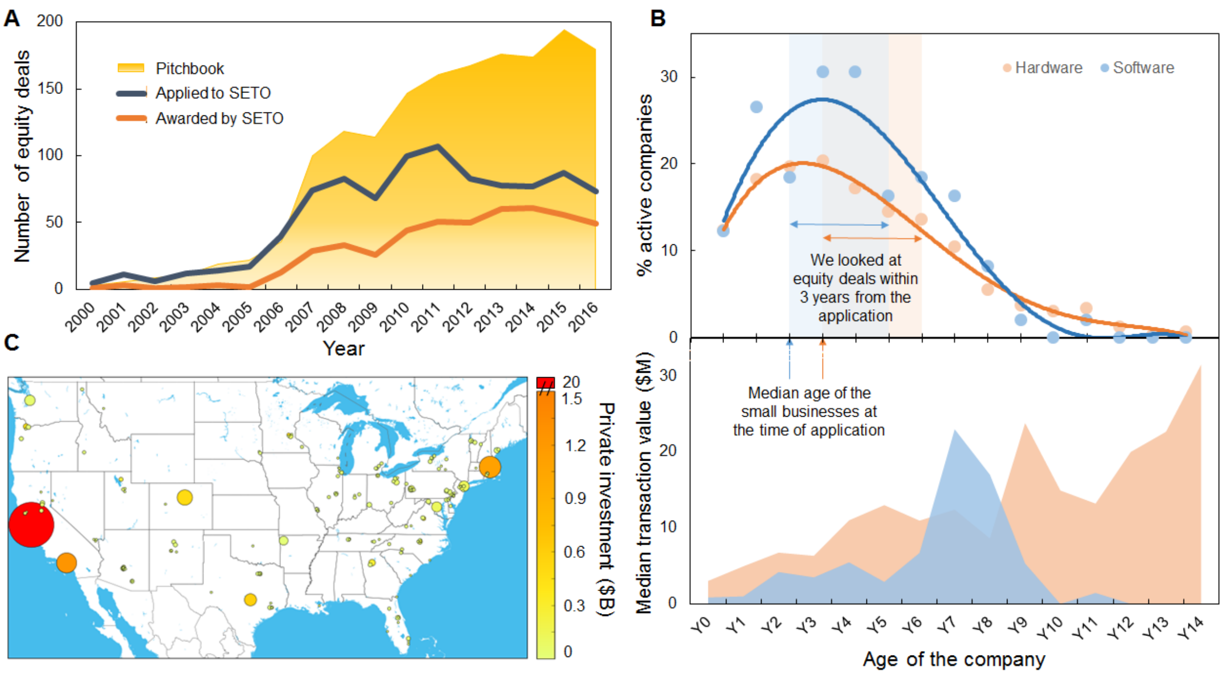

Figure 1. Analysis of the landscape of U.S. solar small businesses and typical evolution of solar hardware and software companies. (A) Number of solar equity deals in the U.S. recorded by Pitchbook over the years (solid yellow). Number of equity deals finalized by companies that have applied to SETO funding and were either funded or not funded (blue line). Number of equity deals finalized by companies funded by SETO (orange line). The first of the programs investigated herein was announced in 2007. The blue line overlaps with the yellow region before that. We interpret this as evidence that almost all domestic active solar companies applied to these early funding programs, showing the great need for Federal support for solar R&D activities. (B) Top: percentage of hardware and software solar companies that finalized an equity raise at any point of their life. The overlay boxes show the median age of the companies at the time of the application, and highlight the time window (3 years from the application) we considered for this study. Bottom: median transaction value for hardware and software solar companies as a function of their age. (C) Geographic distribution of number of active solar companies (represented by size of the circle) and amount of private equity investments (represented by fill color of the circle). Data are collected from Pitchbook and include transactions between 2000 and 2017

(2015), about 200 transactions were recorded per year. To put this in a broader context, a similar search for the cleantech sector in the same timeframe (2000-2017) returns an average of more than 400 transactions per year, with more than 800 transactions per year recorded every year in the last 5 years. In Fig. 1(A), we also plot the number of equity deals completed by companies that applied for SETO funding (blue line) as well as by only companies awarded by SETO (orange line). Deals finalized at any time in the company's history, before and after their application for funding are recorded. Equity deals made by companies who applied to SETO funding programs represent roughly half of all equity deals recorded for U.S. solar companies in this timeframe, giving a sense of the extent of these programs in the space. Using the dataset we collected from different sources tracking all the companies SETO interacted with over the years, we are able to reconstruct the average funding history of a solar startup. Fig. 1(B), shows the percent of active companies (top panel) and the median transaction value (bottom panel) as a function of the age of the company. Y0 is the incorporation year. We show data for hardware and software companies independently to account for the different funding requirements for the two classes of technologies. The peak of activity for both classes occurs three to four years after the companies have been incorporated. The number of active companies decreases as they age. This could be related to three reasons: 1) the company stops raising private funds because an exit (e.g., acquisition, merger, or initial public offering) was completed; 2) it no longer needs venture capital (e.g., it is making significant revenue); or 3) the company went out of business.

The bottom panel of Fig. 1(B) shows that hardware and software companies have very different trajectories. Software companies require less capital at the beginning and then ramp their fundraising efforts either to scale their product and make revenue or to increase their valuation right before an exit. On average, an exit happens 7-8 years after incorporation. In contrast, hardware companies require more funds to continue their product development. The median transaction value increases each year, up to a \$30M average transaction value 14 years after incorporation (although very few companies remain in business that long: this number is an average of few data points). Our database does not include companies older than 14 years, so it is possible that this trend continues over an even longer timeframe. It is also important to note that the Federal support to these companies is a small fraction of the amount of money needed to fully develop a new technology and bring it into the market; the average DOE award amount is lower than \$1M. However, our analyses suggest the impact of SETO funding can be significant if other conditions are met. This is also indicative of the mismatch between the needs of technology development in the solar space, especially hardware products, and how the venture capital system is structured in the United States. In fact, venture investments are designed to pursue a quick (3-5 years) exit with very high return on investment (in the range of 10-100x). The timeframe and the amount of capital needed by solar companies is not compatible with this traditional venture structure [5,31,32].

Private investment in solar technologies occurs in a geographically asymmetric manner. In this paper, we introduce the definition of a “solar hub” to identify the geographic locations in the US where there is a significant solar startup ecosystem. We followed a data-driven approach to identify hubs using Pitchbook data on the zip code location of all the solar companies who raised at least one equity deal in the time frame between 2000 and 2017. Fig. 1(C) summarizes our findings. The circle size indicates the number of active solar companies in a specific region[3], and the shade indicates the amount of private equity investment in the region. Three areas (solar hubs) clearly jump out for both the number of companies and total private investment: Silicon Valley, Los Angeles / San Diego, and Boston. These are the only three areas with more than 50 active solar companies raising more than \$1B in private equity investment. The activity or the amount of investment in every other area in the US is significantly lower. Solar hubs account for 55% of the active solar small businesses and for more than 80% of the solar equity investments

[3] We looked at the number of companies rather than the number of deals to capture the presence of an ecosystem (having few companies in a location closing multiple deals does not constitute a hub).

in the US (with Silicon Valley being a clear outlier). In this paper, we compare the impact of Federal funding inside and outside of these three solar hubs.

3 Impact of public funding

In order to evaluate the connection between Federal funding and follow-on private investments, we examined equity deals closed within three years from a company's application to SETO. This analysis assumes that a follow-on event within this time window is closely related to the SETO award. On the other hand, if an application was not selected for an award, one can reasonably assume that the technology readiness level and company maturity did not change significantly between the moment when they applied for Federal funding and the three following years.

The average number of equity deals closed as a function of the company's application ranking[4] demonstrates a generally linear relationship, as companies ranked highly by the SETO review process tend to close 2-3 times as many deals as those ranked near the bottom of a given application pool (Figure 2). SETO's review and selection process appears to be in alignment with the independent assessment made by private investors. Note that SETO publishes only the list of funded companies in alphabetical order and that application scores, rankings, and non-funded applicant names are considered procurement-sensitive information, so investors cannot make investment decisions based on this ranking data. It should also be noted that investor's funding decisions are completely independent from the SETO assessment of the applications, despite anecdotal evidence that public announcement of SETO selections improved one or more companies' chances of securing a future funding round. The approximately linear ranking-equity relationship indicates that SETO and private investors identified a similar quality of innovative technology and business prospects in this company pool. Of particular interest, a visual jump in the number of closed deals does not exist across the SETO funding line, as both unfunded and funded companies similar in ranking average about one closed equity deal within three years after applying to SETO (see Figure 2 close to the dashed vertical line). Public funding from SETO by itself does not appear to increase the probability of receiving follow-on funding for the average company. However, the following sections will demonstrate through statistical models that second-order interactions between SETO funding and other factors can have a significant role in modulating the impact of Federal funding for solar companies.

[4] See Figure S2 for more info on the ranking methodology.

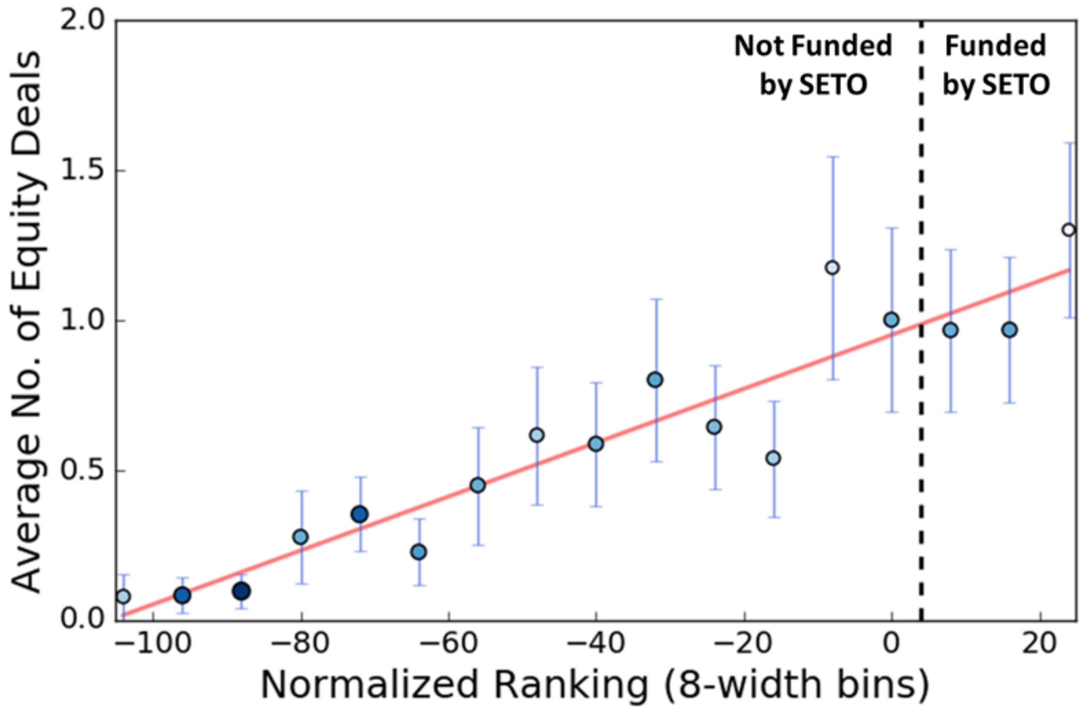

Figure 2. Average number of equity deals for solar companies that applied to SETO programs as a function of the normalized DOE ranking. Each data point represents the average of eight consecutive positions in the ranking. The red line represents a linear fit to the ranking-equity deal relationship. The shade of each dot is related to the number of applications in each bin (darker color indicating more applications). The difference is due to the different number of applications in each funding opportunity. The funding threshold (dashed line) divides funded and not funded applications

4 Predicting future equity deals: the role of hubs

To better understand the impact of Federal funding on the ability of companies to procure private investments, we constructed a general linear model to predict the number of equity deals secured by all first-time SETO applicants. In addition to SETO funding as a predictor, other environmental factors and company attributes were included as covariates, such as company age, previous equity/debt/grant financing, and whether the company's primary technology involved hardware or software (see section 8.1.3 for details about the methodology and model). To account for the role of a company's geographic location, we included a binary "solar hub" variable indicating whether the company was located in Silicon Valley, Los Angeles/San Diego, or Boston (see discussion above for more details), as well as the median income of its ZIP Code. The application year served as a proxy for the specific market conditions or other environmental factors that could affect the solar investment space over time. Interaction terms were included in the model based on a priori hypotheses and exploratory analyses of relationships between predictors. After including all these potential interaction terms, statistically non-significant ones were removed from the final model discussed below. Although the included potential predictors are not exhaustive, our list includes those variables that are commonly used in the literature to analyze the success of a startup.

Although Federal funding is often assumed to incentivize private follow-on funding, model results indicate that being funded by SETO alone is not a statistically significant predictor of the number of equity deals received (Fig. 3(A)). The deal multiplier is defined as the predicted, multiplicative increase in the number of equity deals for a unit increase in a given predictor. Receiving funding from SETO provides a deal multiplier that is statistically indistinguishable from 1, indicating that this public funding alone does not help or hurt a company's investment chances. The same conclusion can be made for a company's location: being in a solar hub does not have a significant impact on the success of a startup. Despite the lack of independent effects, a strong synergy between SETO funding and geographic location dramatically boosts the likelihood of future investments. A small business funded by SETO and located in a solar hub makes 1.5-4.5 times the number of equity deals than a company funded by SETO but outside a hub or a company not funded by SETO, controlling for all other factors in the model (Fig. 3(A), SETO/Hub interaction variable). Across the sample, SETO-funded companies in a solar hub received 1.5 equity deals over the three years after the award, roughly three times as many as companies not funded by SETO or funded but outside a hub (Fig. 3(B)).

These results can be interpreted in different ways. In general, it appears that public funding may be more effective at incentivizing private equity follow-on funding where there is a larger investor ecosystem in place. Despite an increasingly globalized economy, these results suggest that locality could still play an important role in investors being aware of new startups [33]. Another interpretation could be that hubs have so many more start-up candidates in the ecosystem that investors in these areas need a signal to sort through the noise of a large number of nascent technologies. This latter interpretation could indicate the need for a third-party, independent technology validator (SETO playing this role here) to give investors confidence in a new technology or startup. Other factors could play a role as well, such as solar hubs nurturing a more diverse set of high-risk, high-reward ideas. Other researchers and analysts have observed preliminary evidence supporting a similar trend in different contexts [10,34]. Moreover, our findings are consistent with the concept of clusters of innovations, defined as "global economic hot spots where new technologies germinate at an astounding rate and where pools of capital, expertise, and talent foster the development of new industries and new ways of doing business" [35–39]. However, relatively few, if any, studies have shown how public funding can interact with these innovation clusters and provide synergistic value in a statistically rigorous manner, controlling for important factors such as previous equity raised and company age. To our knowledge, these are the first statistical results to show how a Federal intervention in the clean energy space can be particularly effective when applied to an already-established ecosystem.

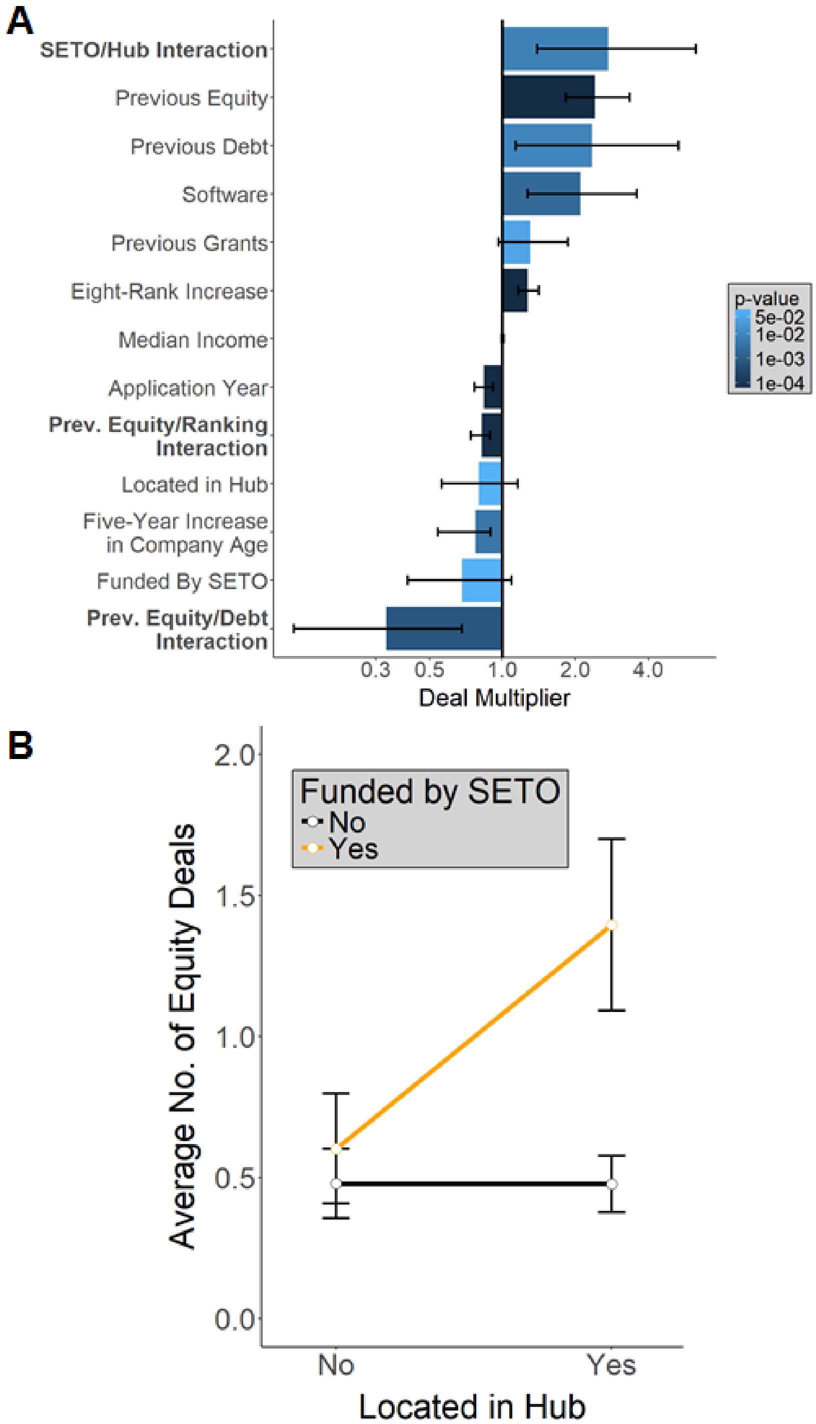

Figure 3. Results of the general linear model. (A) Impact of different variables on the probability of securing an equity deal, expressed as deal multiplier associated to each predictor. Deal multiplier is defined as the multiplicative increase in the number of equity deals predicted by the model for a unit increase in the predictor of interest. Error bars represent the 95% bootstrapped confidence interval (converged using roughly 10,000 samples). The shade of the fill color represents the statistical significance associated to each variable (p-value). As an example, a p-value of 0.05 means that there is 1 in 20 (1/0.05) chance that the associated effect is a false positive and not significantly different from 1. (B) Average number of equity deals for companies located or not located in a solar hub, and funded or not funded by SETO

Regarding other aspects of the model, securing previous private investments (both in the form of equity deals or debt financing) increases the probability of a company obtaining more private funding (Fig. 3(A)). This result corroborates analyses by other researchers and analysts [4–6] indicating that the venture capital structure in the U.S. relies too heavily on other investor decisions, rather than a technical and/or economic due diligence. This is especially true in the cleantech sector, which is relatively new and lacks consolidated industry knowledge, despite being often sensationalized in the media. It should also be noted that the interaction of the two variables (a company having secured both equity raises and debt financing) leads to a diminished ability to raise even more future deals (deal multiplier of 0.3, see Prev. Equity/Debt Interaction predictor in Fig. 3(A)). This finding confirms industry expectation that, if a company has already raised equity funds and debt, it is in a very late stage of technology development, possibly generating revenue, and is less likely to require further equity investment. Although this finding may be intuitive, the result indicates that we are capturing relevant industry trends and helps to validate the relevance of the model as a whole.

Furthermore, based on our analysis, securing private investments for new hardware and manufacturing technologies is much harder than for software. In fact, software companies are able to secure on average twice the number of equity deals compared to manufacturing companies. This is consistent with the general trends discussed previously (Fig. 1(B)) and with the traditional venture capital model [7]. Investors are looking for high probability of very high returns within less than three years. Companies developing software products are most likely to satisfy the needs of such investors.

Our analysis also shows that successful solar startups have the right idea at the right time. The SETO award year is a strongly significant predictor of equity deals, with a deal multiplier around 0.8, indicating that a company applying in 2015 would receive about a third of the deals compared to a company in 2010. The total number of equity deals has risen since 2007 (Fig. 1(A)), however our analysis of the industry landscape suggests that those deals involve just a few companies, making it more and more difficult for a new company to raise money and secure its first deal. The total amount of money invested by venture capitalists has decreased substantially over the years, increasing the competition for funding. Our data suggests that private investors prefer repeated funding rounds to the same entities at the expense of new entrants (like the companies included in this study). Higher-order polynomials fitted to this trend were insignificant, suggesting that the availability of equity deals have linearly decreased over time since the beginning of the SETO small-business programs studied here.

Other predictors we looked at include the impact of previous grants (very weak statistical significance), the increase in the DOE ranking (very strong effect, consistent with the data shown in Fig. 2), the median income in the ZIP Code of the company location (no impact), and the age of the company (older companies are less likely to secure equity funds).

5 Regression discontinuity analysis

The general linear model using the entire sample of SETO applicants elucidated the impact of different predictors on the success of a startup in raising private funds, highlighting the importance of SETO funding for companies inside a solar hub to receive follow-on investments. However, this model cannot establish causality between predictors and the number of equity deals due to the "third-variable" problem, in which a hypothetical unobserved variable correlates highly with an included predictor and muddies any causal explanation. To understand a causal link between SETO funding and follow-on equity funding, we next discuss a regression discontinuity analysis using a subset of our dataset. For this analysis, applications around the funding cutoff line (Fig. 2) are included in a simpler regression model in an effort to compare companies with characteristics approximately randomized across the funding line, such that the only difference between funded and unfunded companies is their receipt of the SETO award (see sections 8.1.4 and 8.1.5 for more information about our model and the quantitative method we used to determine the size of this subset). The Regression Discontinuity Design (RDD) allows us to make conclusions about causality if the following assumptions are met: 1) the intervention (SETO funding) occurs after ranking; 2) the funding cutoff line is arbitrary enough that company characteristics near the cutoff are randomized; and 3) any predictor not randomly distributed is controlled for in the model. We believe the DOE selection process and our model largely meets these criteria with a couple caveats (see section 8.1.4 for details about review/selection process). The results of supplementary analyses provided in sections 8.1.5 and 8.2 provide strong evidence that our RDD results can be interpreted as a causal argument for the role of public SETO funding in facilitating subsequent private support for companies in solar hubs.

Since the RDD model relies on a smaller subset of data near the funding line, a smaller number of predictors are included in the model to maximize statistical power. Necessary predictors include the SETO funding intervention, the application ranking, solar hub location, interactions between these variables, as well as any covariates not randomly distributed across the funding cutoff. It was found that both previous equity deals and award year were not randomly distributed, as companies not in a hub and just below the funding line both hold significantly more equity deals, and applied in earlier years compared to the rest of the dataset (Figs. S3 and S4). In addition to these variables, we have also included the hardware/software binary variable and company age in the model because they demonstrated significant effects in the general model using the entire sample size.

The RDD model results are very consistent with those found in the model using the entire dataset (shown in section 4 of this paper). Once again, neither SETO funding or geographic location alone have a significant impact, however their interaction provides a strongly significant effect, providing a fourfold increase in the number of equity deals compared to companies not in a hub and/or not funded by SETO (95% CI: 2-16) (Fig. 4). These results are a strong case for a causal role in SETO funding leading to greater private investment for solar companies after the award because we have controlled for the two variables not randomized across the funding line. The

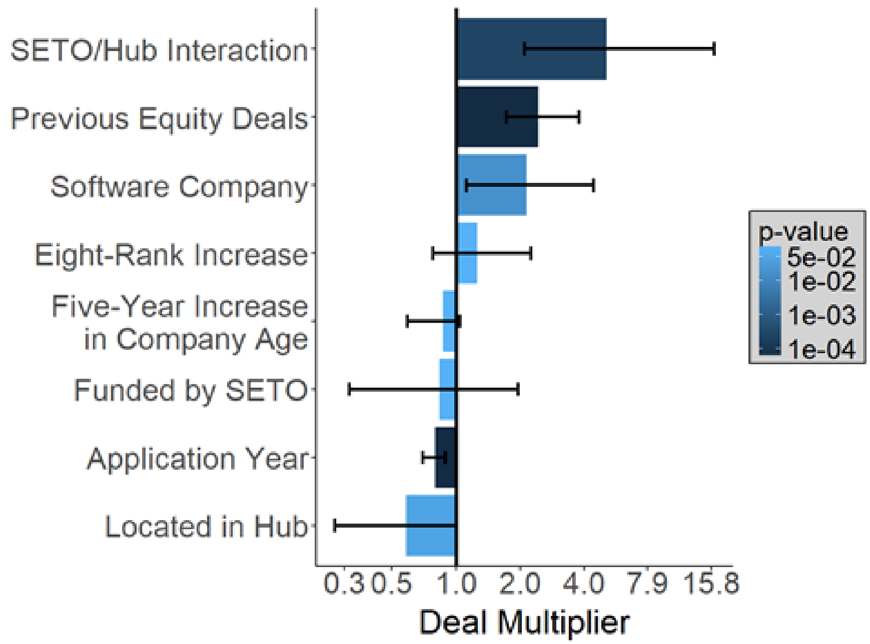

Figure 4. Impact of different variables on the probability of securing an equity deal as calculated with the regression discontinuity analysis, expressed as deal multiplier associated to each predictor. The shade of the fill color represents the p-value for each predictor

causality argument would only be disconfirmed if another variable not included in the model were found to vary exactly with the SETO funding intervention. We believe we have analyzed and included most of the company attributes associated with startup success, and look forward to any future work that would suggest other important variables to include. Also similar to the larger model, both more previous equity deals and being a software company increases a company's predicted number of equity deals received, and applying in later years reduces the predicted number of deals. Results are extremely similar across various bandwidth values in the RDD (Table S2), indicating the results are not sensitive to or dependent upon the choice of bandwidth and number of companies included.

A closer look at the average number of deals for companies just below and above the funding cutoff line can further our understanding of the impact of SETO funding. Without breaking down companies by their geographic location, no discontinuity in the number of equity deals exists at the cutoff (Fig. 5(A)). However, when examining only companies in a solar hub, a clear discontinuous jump occurs, with companies just above the funding line receiving three times as many deals as those below (Fig. 5(B)). In contrast, the reverse trend is seen for companies not in a hub, with those just below the funding line showing a widely variable but larger number of equity deals compared to those above (Fig. 5(C)).

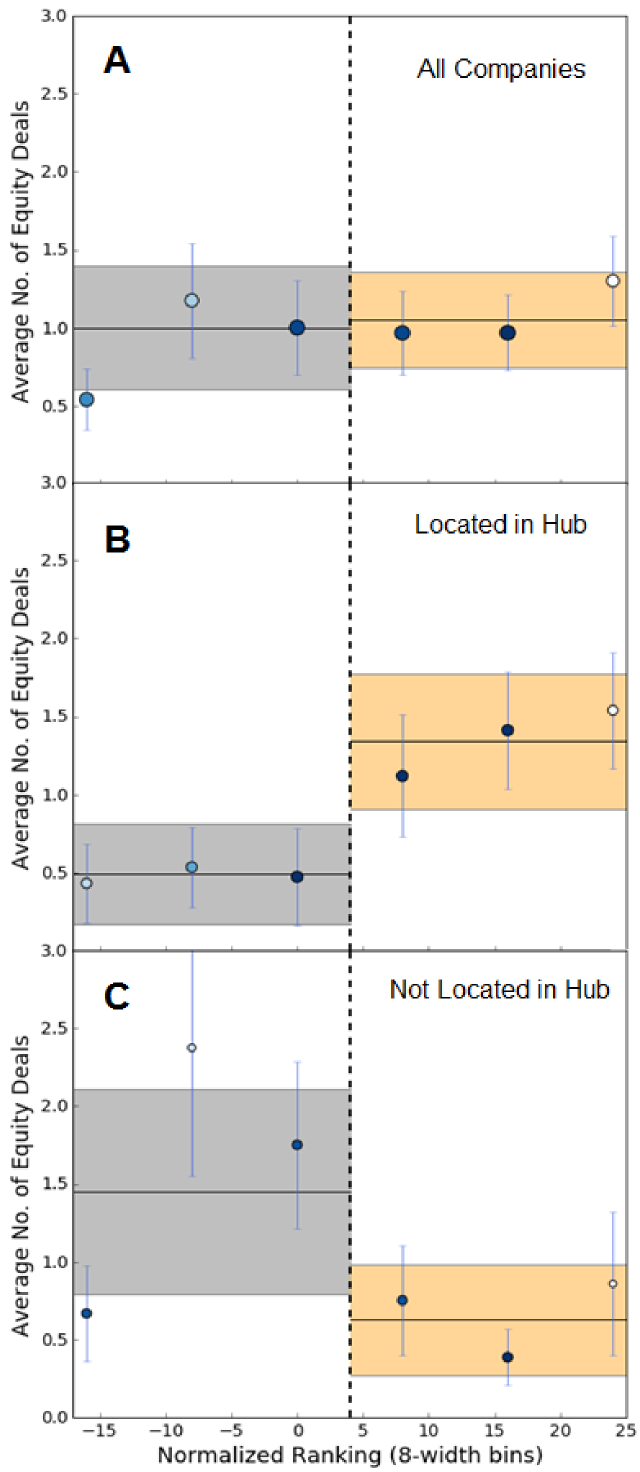

Figure 5. Synergistic Effect of SETO Funding and hub ecosystem as shown by the regression discontinuity analysis. Average number of equity deals for companies right above and below the funding line for the entire dataset of companies (A), only the companies located in a solar hub (B), and only the companies not located in a hub (C). Horizontal lines and the shaded areas represent respectively the average and standard deviation values between the data points shown in the plots

This comparison at first suggests that SETO funding is hurting companies not in a solar hub. However, it is important to consider the covariates not randomly distributed around the cutoff to explain the phenomenon. As discussed above, both previous equity funding and application year are strong predictors of future equity deals, and both demonstrate significantly different distributions for companies not in hubs and not funded by SETO (Figs. S3 and S4). In our sample, since unfunded companies not in a hub applied with about twice as many previous deals as the rest of the samples (and applied about 1.5-2 years earlier) these attributes led to a much higher number of deals for these companies, even though they were not funded by SETO.

The analysis above demonstrates the clear need to check that all company attributes are randomized around the cutoff for an RDD design and to include those not randomized in the model. After accounting for both previous equity and application year, the interaction between SETO funding and company location is strongly significant, confirming results from the general linear model and emphasizing the important role that public funding plays in solar hub locations.

6 Key predictors of other investment types

In the previous analyses, we have taken into consideration only equity deals under the assumption that equity investment is a required initial step in the overall successful path of bringing new technologies to market. We now test this hypothesis to verify if the same predictors have any effect on other types of private or public investment. Following our classification of investment types (see Table S1 for our complete definition), we now perform two additional general linear models with the entire sample to predict the number of debt financing deals (Fig. 6(B)) as the number of public or private grants received (Fig. 6(C)). We are still limiting our analysis to the first three years after the time of the application to be able to infer a link between the application for Federal funding and the investment action by the private sector. Fig. 6 provides a direct comparison between the calculated values for the deal multipliers in the case of equity deals (panel A, repeated from Fig. 3 to allow an easier comparison), debt (panel B), and grants (panel C).

Government funding is not linked to debt financing in any case, directly or through the interaction with another variable. This is a clear reflection of the traditional nature of these Federal programs, consistently aimed at supporting early-stage research and technology development as opposed to scaling-up companies or products. Having had previous debt financing events or previous equity rounds are the strongest predictors of future debt financing. Software companies seem to still have some advantage over hardware companies in raising debt. All the other predictors do not have a strong impact. This is also a reflection of the different nature of due diligence made by banks and financiers before approving debt financing, aimed at verifying the ability to generate sufficient cash flow to repay the loan rather than on the technology itself.

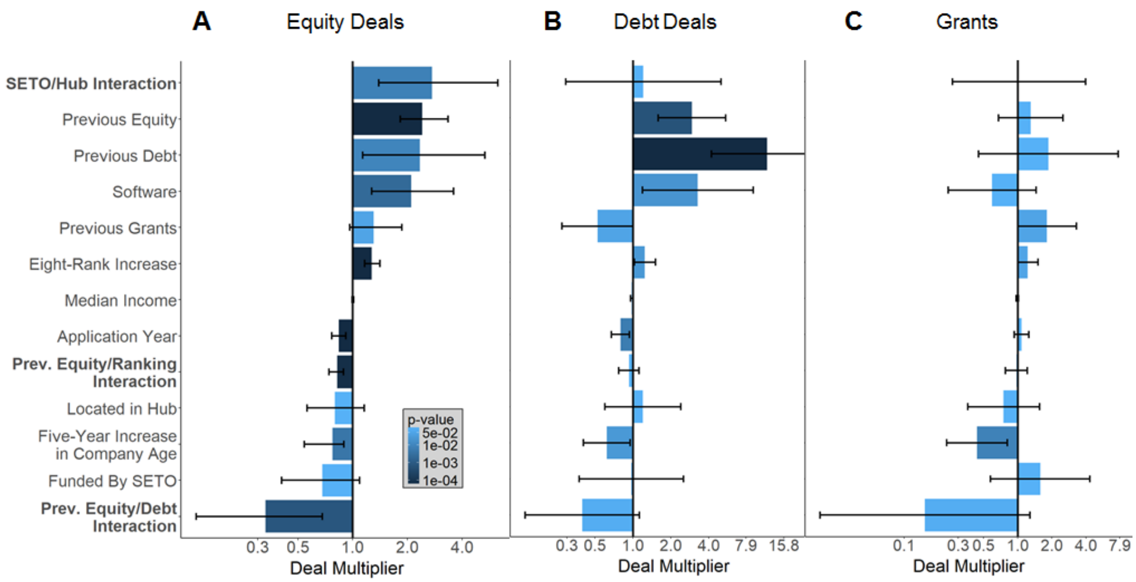

Figure 6. Impact of different variables on the probability of securing an equity deal (A), raising debt (B), or winning a public (Federal or state) grant expressed as deal multiplier associated to each predictor. The shade of the fill color represents the p-value for each predictor. The entire dataset has been used for this analysis; the general linear model has been applied

SETO funding does not appreciably increase the number of public or private grants from other sources. Furthermore, the model as a whole is a poor predictor of receiving grants, as company age is the only statistically significant predictor. One of the stated goals of the funding opportunities examined in this study was to assist independent small businesses which can fully support themselves after the Federal financial assistance, continue to grow, and successfully bring a new technology into the market. These opportunities were not intended for creating a product, organization, service, or other entity or item which requires continued government support to operate. Our findings can be considered an ex-post validation of the success in meeting this goal.

7 Conclusions

In conclusion, we analyzed a large dataset of companies operating in the solar space in the United States in the last 10 years. By adopting rigorous statistical methodologies, we identified predictors of the number of deals made by solar small businesses and assessed the impact of Federal funding on the technology transfer to the private space. SETO funding has a strong association with future equity deals for companies located in solar hubs and a limited impact on companies receiving future grants or debt deals.

8 Supplementary information

8.1 Materials and methods

8.1.1 Pitchbook query

Results shown in Fig. 1 are based on data exported from PitchBook [30] using the query available at this link: https://my.pitchbook.com/?pcc=147826-00. We queried the PitchBook database using "solar" as only keyword. We filtered the results to include only companies with office location in the United States, and having completed a Venture Capital raise (All VC Stages, All Round Numbers, All Series). At the time of completion of this work, this query resulted in 753 unique companies, 2,165 unique deals, 1,574 unique investors.

8.1.2 Database

We collected data about any type of funding event related to 584 solar small businesses that applied to the following funding opportunities run by SETO or previous iterations of the same DOE program since 2007: Pre-Incubator, Incubator 1, Incubator 2, Incubator 3, Incubator 4, Incubator 5, Incubator 6, Incubator 7, Incubator 8, Incubator 9, SunPath 1, SunPath 2, SunPath 3, SolarMat 1, SolarMat 2, SolarMat 3, SolarMat 4, SolarMat 5, Technology to Market 1, Technology to Market 2, Technology to Market 3 [40,41]. We used the small business definition adopted by the U.S. Small Business Administration (SBA) [42]. This information was self-reported by the applicant at the time of the application. Companies could apply more than once; the final list of 584 companies was obtained starting from 962 distinct applications. Of these companies, 129 were awarded, for a total of 174 different awards. The total DOE investment on these awards across the different programs amounts to $240.68M.

Data on funding events were collected from three different data sources: Pitchbook [30], a specialized firm focused on research and data analysis on companies, deals, funds, investors and service providers across the entire private investment lifecycle including venture capital, private equity and M&A transactions; Crunchbase operated by TechCrunch [43], a crowd-sourced database of the startup ecosystem, consisting of investors, incubators, startups, key people, funds, funding rounds and events; Bloomberg New Energy Finance [44], a data company focused on energy investment and carbon markets research, tracking investment trends and deal flow. For each transaction, we recorded year of the event, company name, amount, and funding type (see Table S1 for the classification we adopted). We tracked 2219 funding events (1080 entries from Pitchbook, 607 entries from CrunchBase, 532 entries from Bloomberg New Energy Finance). We manually removed duplicates; in case of discrepancies between two or more data sources, we selected the higher amount reported. The final database has 1418 unique funding events.

We collected all data associated a company through its entire history, including transactions occurred before and after the application to DOE.

8.1.3 Negative binomial regression model

The primary dependent variable (DV) for our analyses, the number of equity deals in the three years after application to SETO, can be well-represented using a negative binomial (NB) distribution (see Fig S5). A goodness-of-fit test demonstrated that the NB distribution ($\chi^2 = 6.27$, $p = 0.1$) provides a much better fit for this variable than a Poisson distribution ($\chi^2 = 651.98$, $p < 0.0001$), indicating that the distribution of equity deals is overdispersed.

Based on this information, negative binomial regressions were performed for all statistical models discussed in this paper, using a general linear model (GLM) package in R with a log link that automatically calculate the dispersion parameter based on the data. This link family provides familiar interpretation of regression coefficients such that their exponentiated values provide the multiplicative increase in the DV for a unit increase in the independent variable (IV), holding all other IVs constant.

Three separate models were performed for each type of follow-on funding: equity, grants, and debt. The following equation modeled the expected number of deals for a single company:

$$E[y_i|\boldsymbol{x}] = \boldsymbol{e}^{\beta_0+\beta_T x_T+\beta_R x_R+\beta_{R2} x_R^2+\beta_H x_H+\beta_E \log x_E+\beta_D \log x_D+\beta_G x_G+\beta_S x_S+\beta_I x_I+\beta_Y x_Y+\beta_A x_A+\beta_{TR} x_T x_R+\beta_{TH} x_T x_H+\beta_{YS} x_Y x_S+\beta_{RE} x_R \log x_E+\beta_{ED} \log x_E \log x_D}$$

where $E[y_i|\boldsymbol{x}]$ is the expected value of the DV given a set of predictor values, all β's are regression parameters, and $y_i = y_e$ is the number of equity deals, $y_i = y_g$ is the number of grant deals, and $y_i = y_d$ represents the number of debt deals for the three separate models conducted. Across all cases, the independent variables are as follows:

- x_T is the binary 'treatment' variable indicating whether a given applicant was funded by SETO (1) or not (0).
- x_R is the normalized selection ranking variable centered around the funded/not-funded cutoff.
- x_H is the binary variable indicating whether a company applicant is located in a designated solar hub region (1) or not (0).
- x_E is the count of number previous equity deals by a company prior to its SETO application.
- x_D is the count of number previous debt deals by a company prior to its SETO application.
- x_G is the count of number previous grant deals by a company prior to its SETO application.
- x_S is the binary variable indicating whether a company applicant produces a software (1) or hardware (0) product.

- x_I is the median income of the zip code in which the company applicant is incorporated.
- x_Y is the year of the company's SETO application.
- x_A is the age of the company at the time of its SETO application.

All variable relationships were visually inspected to determine the potential for 1) nonlinear relationships between an IV and the DV, and 2) interactions between IVs. Based on these inspections, a log-transform of previous equity (x_E) and previous debt (x_D) data were performed due to a plateau in the number of future deals predicted as the number of previous deals becomes large. In addition, interaction terms in the equation above were included based on their visual inspection and confirmed statistical significance when entered into the model. Interactions included the model based on visual inspection of their relationship, but not significant in the model, were removed for clarity to minimize the overall number of explanatory variables.

In all models, the β_{R2} and β_{TR} terms are nonsignificant and therefore removed from final model results for the sake of clarity. Their inclusion or exclusion does not dramatically change the significance or effect size of any other variables. Adjusted R^2 values are reported for all model results as a preliminary way to prevent overfitting by solely adding additional predictors.

Regarding sample size, G-Power [45,46] was employed to determine a minimum number of samples required to estimate a medium effect size ($f^2 = 0.15$) for the R^2 increase when including both the SETO funding and funding-hub interaction variables to the model, with a Type 1 error rate of 0.05 and power of 0.95. The power analysis suggests a minimum of 107 samples, indicating our sample size of 584 companies is sufficient.

8.1.4 Regression discontinuity analysis assumption testing

A formal regression discontinuity (RD) analysis requires that: 1) the intervention (SETO funding) occurs after ranking; 2) the funding cutoff line is arbitrary enough that most company characteristics near the cutoff are randomized; and 3) covariates are continuous across the cutoff and any predictor not randomly distributed is controlled for in the model. The first requirement is met by the review process, as funding is provided to applicants only after a ranking has been finalized. The second requirement is largely met by the DOE review and selection process. As stated in the funding opportunity announcements, the Selection Official may consider the technical merit, the Federal Consensus Board's recommendations, program policy factors, and the amount of funds available in arriving at selections for this FOA, all of which result in a final selection ranking. In fact, DOE officials and even external independent reviewers (subject-matter experts) are aware of the expected number and average size of the awards during the review and selection process. Program policy factors include but are not limited to the degree to which the application exhibits technological or programmatic diversity when compared to the existing DOE project portfolio; the degree to which the application optimizes the use of available funding to achieve programmatic objectives; the degree to which the application is likely to lead to increased employment and manufacturing in the United States or provide other economic benefit to U.S. taxpayers; the degree to which the final group of selected applications represent a desired geographic distribution; the degree to which the proposed project avoids duplication/overlap with other publicly or privately funded work. All covariates selected for the model also demonstrate continuity across the cutoff, satisfying the third RDD requirement (Figure S3). Two covariates demonstrate substantially different means on each side of the cutoff, as shown in Figures S4 and S5, due to strongly linear slope near the cutoff.

It is possible that the use of program policy factors could alter the expected random distribution of applicants immediately above and below the cutoff line if the same type of companies were consistently chosen across all funding opportunities based on the factors described above. This possibility seems unlikely, however, because of these details about the review process, we describe several statistical tests described below that build the case that we account for covariates showing relationships with ranking around the cutoff, and that these variables by themselves cannot predict a discontinuity in predict number of follow-on deals at the funding cutoff line. We believe the results of these supplementary analyses provide strong evidence that our RDD results indicate a causal argument for the role of public SETO funding in companies receiving subsequent private support.

McCrary [47] suggested a statistical analysis to test the continuity of the running variable (in this case, SETO ranking) in RDD analyses. If manipulation either by companies or by reviewers were commonplace, it is assumed that one would see an accumulation in the density function of the ranking variable on either side of the cutoff. Figure S7 plots the probability density function of the SETO ranking variable on each side of the funding cutoff ($x = 0$). Visually, no jump in the density can be seen at the cutoff, and the McCrary test confirms that there is no significant discontinuity ($z = 0.17042$, $p = 0.8647$, bin-width of 2.572 and bandwidth of 24.818).

Although this is a promising result to indicate no manipulation around the cutoff, the McCrary analysis does not technically apply to cases when the running variable is not strictly continuous as is the case here with a discrete ranking variable. Therefore, additional tests are required to determine the extent to which, if any, covariates are not randomized around the funding cutoff. First, we perform a logistic regression with logit link to predict SETO funding (x_T) using all other predictors in the model, using a ranking bandwidth of +/- 20 above and below the cutoff (135 companies, results do not change for other bandwidths). This test can indicate whether funded and not-funded companies have been sorted based on any of the covariates that could provide a confounding effect with SETO funding to create a regression discontinuity. Across all predictors, only company age (x_A, $e^{\beta} = 0.91$, $p = 0.04$) and the software/hardware binary variable (x_S, $e^{\beta} = 3.22$, $p = 0.02$), suggesting that older companies were only slightly less likely to receive funding, and software companies were significantly more likely to receive SETO funding, on average, across all funding programs. In fact, software technologies have been a specific focus of some of the funding opportunities examined here. SETO has been one of the very few offices providing Federal funding to companies developing software technologies, and the number of applications in the software space sometimes was higher than applications for hardware technologies. Based on these results, we include both age and software/hardware variables in the final RDD model (described below) to control for these covariates. Note that there could always exist other variables confounded with the funding variable when the strict RDD assumptions are not met, however we believe we have accounted for most potential covariates that would play a significant role.

A final method to assess whether a jump at the cutoff is due to the treatment variable or other covariates is to visually compare predictions between 1) the full model with covariates and treatment variable and 2) a model only including covariates. Figure S8 compares each of these models, splitting apart predictions for companies located in a hub (left pane) and not in a hub (right pane) to account for the SETO-Hub interaction discussed in the main text. Covariates included in these models are x_R, x_H, x_Y, x_A, x_E, and x_S, along with significant interactions. As is clearly seen in the left pane, for those companies in a hub, the model with covariates only (red line) predicts a continuous increase in the number of deals predicted across the funding line. In strong contrast, the full model including x_T demonstrates a sharp discontinuity across the cutoff line, nearly tripling the predicted number of deals if funded by SETO. For those companies not located in a hub, a discontinuity in the opposite direction is seen in both models, largely explained by the larger number of companies with previous equity funding directly below the cutoff line as described in the main text.

Taken together, although the DOE selection process does not formally meet every assumption required for a causal interpretation, the RD results discussed in the text suggest a causal role of SETO funding helping companies to gather private support in solar hub regions.

8.1.5 Regression discontinuity analysis final design

After considering results of the above analyses to test assumptions and determine important covariates, the final RD model employed the following model:

$$E[y_i|\boldsymbol{x}] = e^{\beta_0+\beta_T x_T+\beta_R x_R+\beta_{R2} x_R^2+\beta_H x_H+\beta_E \log x_E+\beta_S x_S+\beta_Y x_Y+\beta_A x_A+\beta_{TR} x_T x_R+\beta_{TH} x_T x_H}$$

where $E[y_i|\boldsymbol{x}]$ is the expected value of the DV given a set of predictor values, all β's are regression parameters, and $y_i = y_e$ is the number of equity deals, $y_i = y_g$ is the number of grant deals, and $y_i = y_d$ represents the number of debt deals for the three separate models conducted. Across all cases, the independent variables have the same definitions as for the full regression model discussed in the section above. The x_R^2 variable was not significant in any RD model, indicating a fairly linear relationship between the number of deals and DOE selection ranking, and therefore it has been removed from most results for simplicity.

The primary methodological question regarding RD designs is the choice of bandwidth. We have implemented a cross-validation method originally discussed in Imbens [48] to determine an optimal bandwidth, however we have replicated statistical models across multiple bandwidths above and below the optimal choice to confirm the robustness of the findings. Figure S9 plots the mean squared error (MSE) of the RD model above for increasing choice of bandwidth. Clearly, three plateau regions are seen in which the MSE is roughly the same. Based on these results, RD models were conducted using bandwidths of 15, 20, and 30 to confirm the robustness of the results. Results are largely insensitive to bandwidth, with the SETO funding-hub interaction strongly significant across all choices (see Table S2). The only significant trend with respect to bandwidth is the increasing effect size and statistical significance of software companies having a higher probability of receiving equity deals. Results from the model using the bandwidth of 20 are reported in the main text.

8.2 Supplementary figures

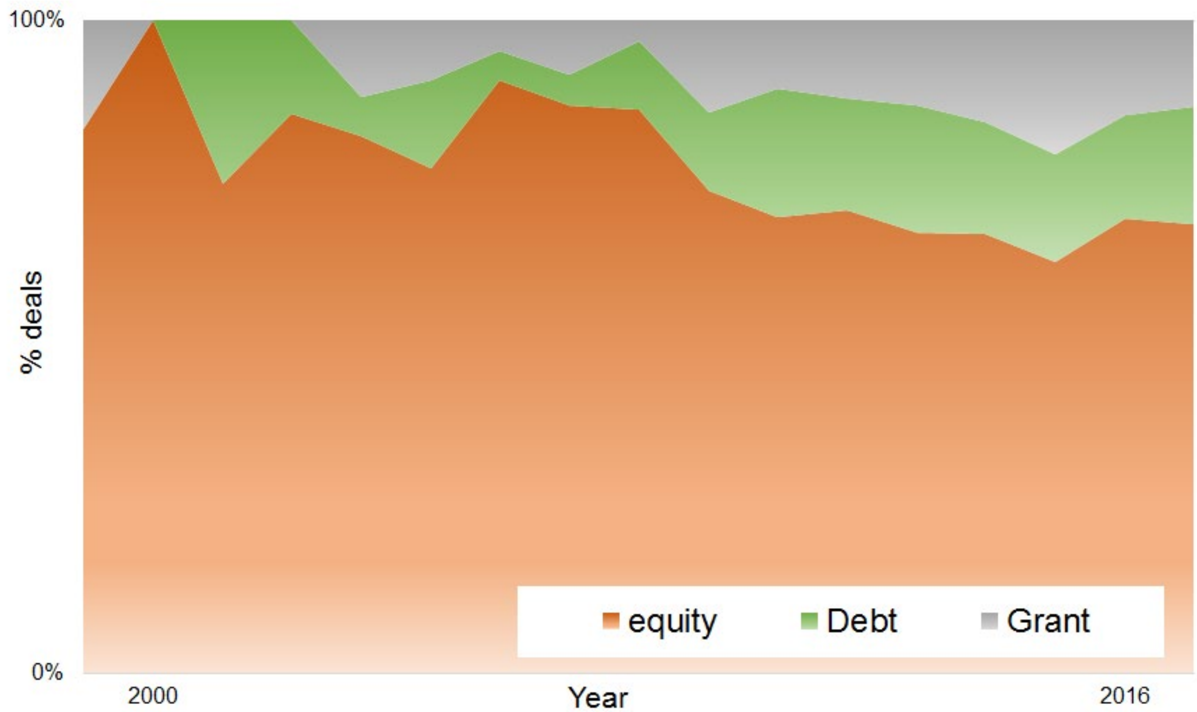

Figure S1. Percentage of equity, debt, and grant deals for each year between 2000 and 2016 made by solar companies that interacted with SETO. The majority of transactions at any point in time are equity deals

Ranking	FOA 1	FOA 2
10	A	A
9	B	
8	C	
7	D	B
6	E	
5	F	
4	G	C
3	H	
2	I	
1	J	D
0	K	
-1	L	
-2	M	E
-3	N	
-4	O	
-5	P	F
-6	Q	
-7	R	
-8	S	G
-9	T	
-10	U	
-11	V	H
-12	W	
-13	X	
-14	Y	I

Figure S2. Schematic representation of the normalization procedure we adopted to establish the ranking position within funding opportunities with a different number of applications and awards. First, we assigned position 1 in the ranking to the lowest scoring funded application, and position 0 to the highest scoring not-funded application. Then, the funding opportunity with the highest number of funded applications will dictate the highest possible position in this ranking; the funding opportunity with the highest number of not funded applications dictates the lowest possible position in the ranking. Applications ranking for each funding opportunity was then determined through a linear interpolation process between the highest and the lowest possible positions. Numbers in the figure are just an example and do not represent the actual number of total applications in our dataset

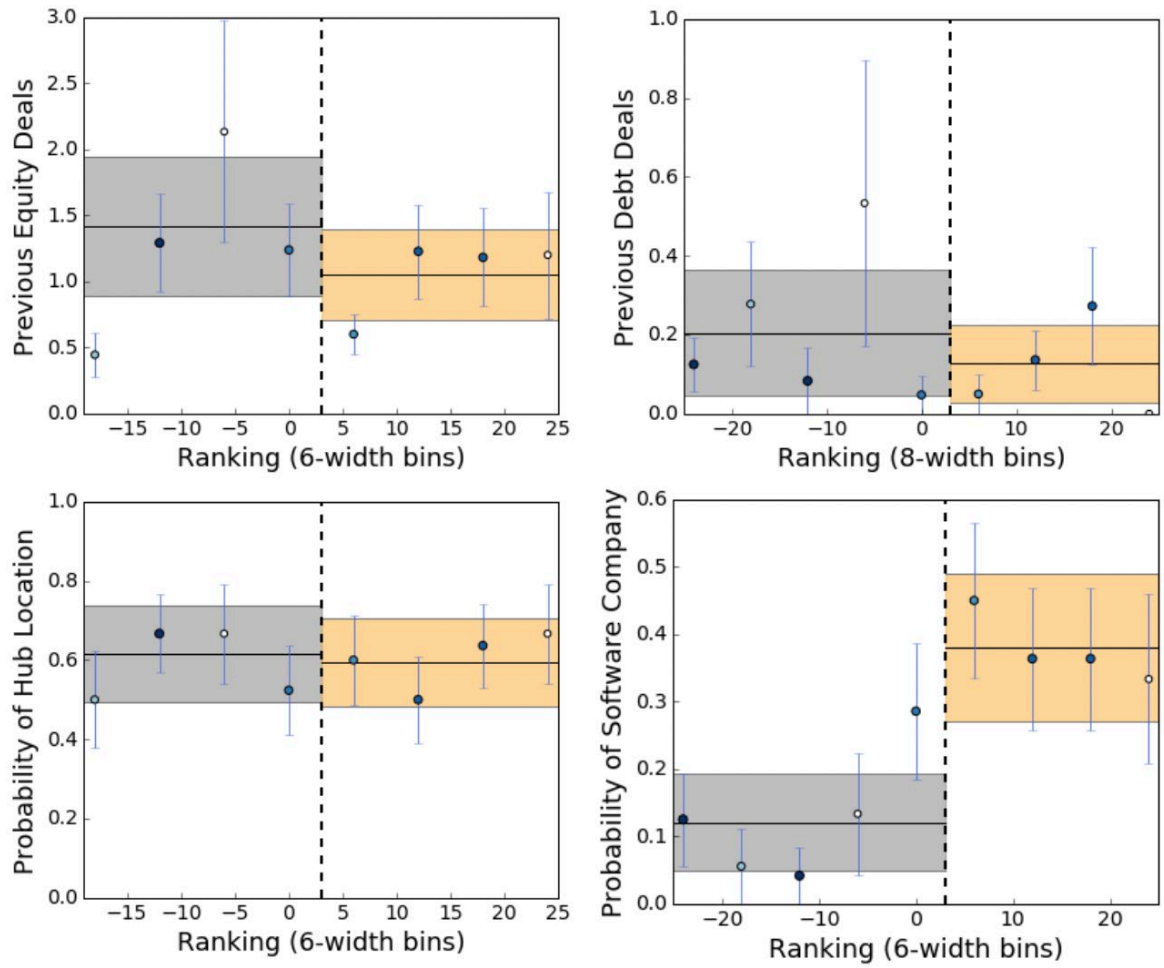

Figure S3. A sample of relationships between application ranking and covariates using 6-width binning. The dotted vertical line in each graph indicates the funding cutoff. In each graph, application ranking is plotted along the x-axis and the covariate of interest is plotted along the y-axis. Although nonzero-slopes exist across the funding cutoff line that create different means on each side, all relationships are generally continuous. Those variables with significant relationships with application ranking near the cutoff (e.g., Previous Equity Deals, Software Company) are included as covariates in the RDD model

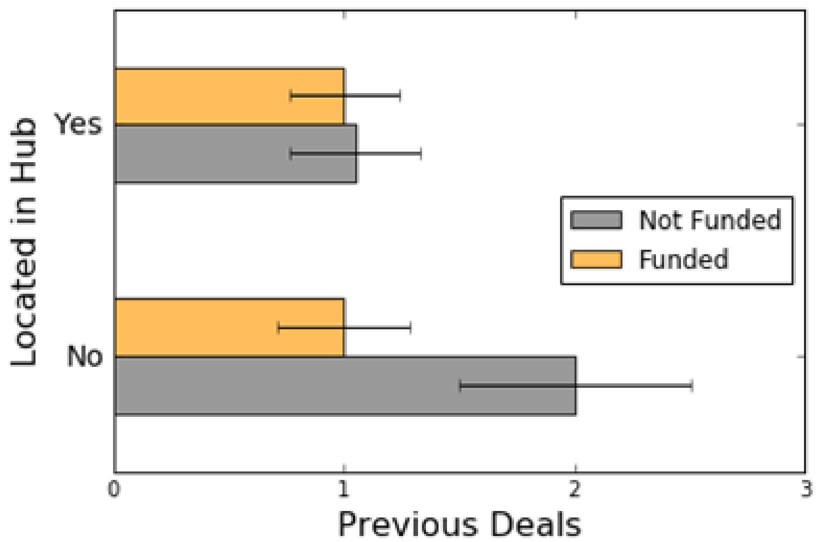

Figure S4. Number of previous equity deals for companies located and not located in a solar hub, comparing funded and not funded applications. Companies not funded by SETO and not in a hub have disproportionately more previous equity deals than average. This reflects the nature of the SETO programs, focusing on new ventures with limited history, but also the nature of the companies outside the solar hubs

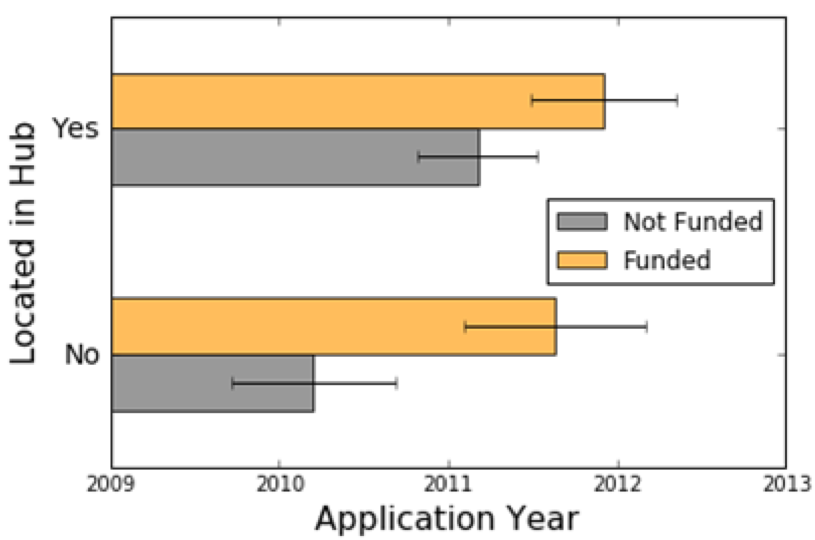

Figure S5. Average application year of companies located and not located in a solar hub, comparing funded and not funded applications. Our dataset has a disproportionate number of applications that were not funded by SETO and were not in a hub in the earlier rounds of the program

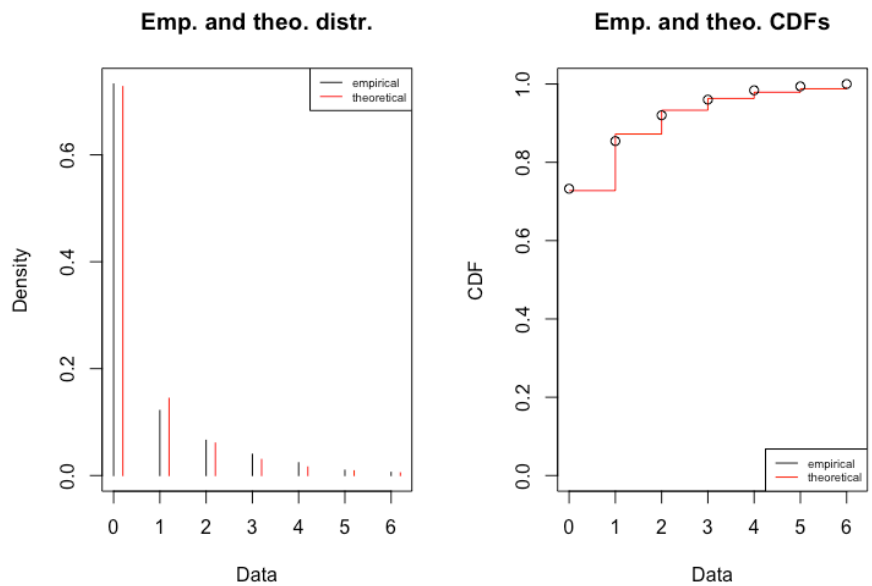

Figure S6. The comparison of the theoretical negative binomial distribution (red line) to the actual distribution of the number of equity deals used as the primary dependent variable in this analysis. The left pane shows the theoretical versus actual probability density function and the right pane demonstrates a similar comparison of the cumulative density functions

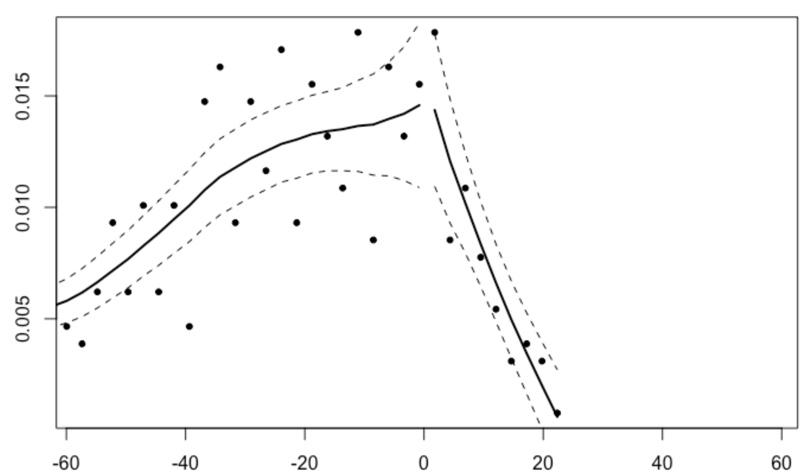

Figure S7. Density as a function of the SETO ranking variable along the x-axis. Black circles represent mean density given a bin width of 2.572. Solid black line indicates the best fit of a density function independently on each side of the cutoff

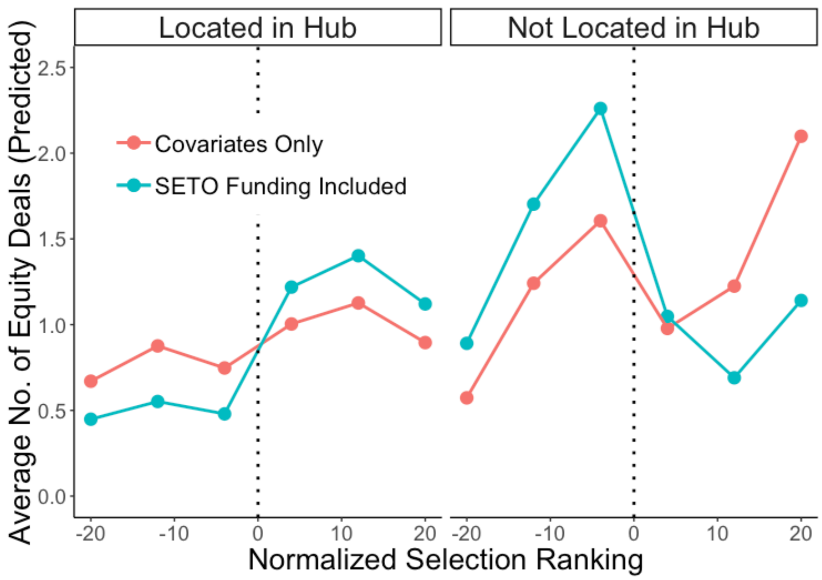

Figure S8. Predict average number of equity deals as a function of SETO selection rankings for the full covariates plus treatment model (blue line) compared to the covariates-only model (red line). The left pane illustrates predicted number of deals for companies in a hub, whereas the right pane visualizes the predict deals for companies not located in a hub. The left pane demonstrates the clear discontinuous jump in predicted number of deals at the funding line for those companies in a solar hub region

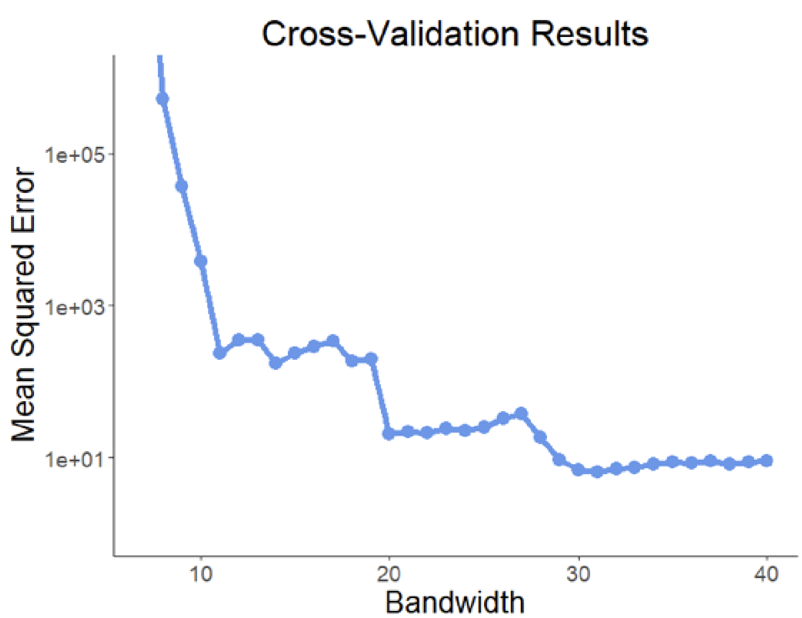

Figure S9. Predict average number of equity deals as a function of SETO selection rankings for the full covariates plus treatment model (blue line) compared to the covariates-only model (red line). The left pane illustrates predicted number of deals for companies in a hub, whereas the right pane visualizes the predict deals for companies not located in a hub. The left pane demonstrates the clear discontinuous jump in predicted number of deals at the funding line for those companies in a solar hub region

8.3 Supplementary tables

Table S1. Classification of the different funding types adopted in this paper. We grouped different funding types into 4 groups, depending on the level of perceived risk associated the typical investor and on the typical expected return at the time of the transaction

Equity	Exit	Debt	Grants
Angel / Seed	Merger & Acquisition	Public debt	Incubator
Private Equity	IPO	Private debt	Accelerator
Series A			Private grant
Series B			Public grant
Series C			Product crowdfunding
Series D			
Series E			
Series F			
Series G			
Series unknown			
Series Early Stage			
Series Late Stage			
Bridge			
Convertible Note			

Table S2. Beta weights (β), standard errors, (SE), and probability values (p-values) associated with predictors in the regression discontinuity analysis predicting equity deals for various choices of bandwidth (15, 20, and 30). A normalized ranking variable was used for all analyses. Bolded results are significant at the *p* < 0.01 level

	Bandwidth								
	15			20			30		
Predictors	β	SE	*p*	β	SE	*p*	β	SE	*p*
Funding (x_T)	0.07	0.49	0.88	-.19	0.42	0.65	-0.26	0.38	0.50
Hub (x_H)	-0.64	0.33	0.06	-0.55	0.27	0.04	-0.24	0.23	0.29
Ranking (x_R)	-0.01	0.03	0.89	0.01	0.02	0.74	0.01	0.01	0.56
Funding: Hub Interaction	**1.52**	**0.54**	**0.004**	**1.65**	**0.44**	**<0.001**	**1.21**	**0.40**	**0.002**
Funding: Ranking Interaction	0.01	0.06	0.91	0.02	0.04	0.57	0.02	0.03	0.51
Award Year (x_Y)	**-0.20**	**0.06**	**0.001**	**-0.23**	**0.05**	**<0.001**	**-0.24**	**0.05**	**<0.001**
Age (x_A)	-0.03	0.03	0.24	-0.03	0.02	0.16	-0.03	0.02	0.12
Log of Previous Equity (x_E)	**0.89**	**0.20**	**<0.001**	**0.88**	**0.17**	**<0.001**	**0.88**	**0.15**	**<0.001**
Hardware / Software (x_T)	0.61	0.38	0.11	0.80	0.33	0.02	**1.12**	**0.29**	**<0.001**

References

[1] Gompers Paul And, *The Venture Capital Revolution*, J. Econ. Perspect. **15**, 145 (2001).

[2] W. D. Bygrave and J. A. Timmons, *Venture Capital at the Crossroads* (Harvard Business Press, 1992).

[3] M. Kenney, How Venture Capital Became a Component of the U.S. National System of Innovation, SSRN Electronic Journal (2011).

[4] Singer, Peter L and Bonvillian, William B, *"Innovation Orchards": Helping Tech Start-Ups Scale*, Information Technology & Innovation Foundation: Washington, DC, USA (2017).

[5] B. E. Gaddy, V. Sivaram, T. B. Jones, and L. Wayman, *Venture Capital and Cleantech: The Wrong Model for Energy Innovation*, SSRN Electronic Journal (2016).

[6] G. Silverberg, *Innovating in a New Market: Challenges for Cleantech*, Harvard University, The Graduate School of Arts and Sciences, Cambridge (2015).

[7] D. Rotman, *Can Energy Startups Be Saved?*, Technol. Rev. **116**, 83 (2012).

[8] S. Ghosh and R. Nanda, *Venture Capital Investment in the Clean Energy Sector*, SSRN Electronic Journal (2010).

[9] A. Marcus, J. Malen, and S. Ellis, The Promise and Pitfalls of Venture Capital as an Asset Class for Clean Energy Investment, Organ. Environ. **26**, 31 (2013).

[10] Saha Devashree And, Cleantech Venture Capital: Continued Declines and Narrow Geography Limit Prospects, Brookings Institution Report (2017).

[11] J. Eilperin, *Why the Clean Tech Boom Went Bust*, https://www.wired.com/2012/01/ff_solyndra/.

[12] B. Bozeman, Technology Transfer and Public Policy: A Review of Research and Theory, Res. Policy **29**, 627 (2000).

[13] OMB, *FY19 Research & Development Budget Priorities*, https://www.whitehouse.gov/sites/whitehouse.gov/files/ostp/fy2019-administration-research-development-budget-priorities.pdf.

[14] *Technology Transfer of Federally Funded R&D*, https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/pcast-03-techtransfer.pdf.

[15] *SBIR.Gov*, https://www.sbir.gov/.

[16] Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) Homepage | U.S. DOE Office of Science (SC), https://science.energy.gov/sbir.

[17] I. Busom ∗ and ∗ I. B., *An Empirical Evaluation of The Effects of R&D Subsidies*, Economics of Innovation and New Technology **9**, 111 (2000).

[18] P. David, B. Hall, and A. Toole, Is Public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence, 1999.

[19] D. Guellec and B. van P. de la Potterie, *The Impact of Public R&d Expenditure on Business R&d* (2000).

[20] S. T. Howell, Financing Constraints as Barriers to Innovation: Evidence from R&D Grants to Energy Startups, SSRN Electronic Journal (2015).

[21] J. Lerner, The Government as Venture Capitalist: The Long-Run Impact of the SBIR Program, SSRN Electronic Journal (1996).

[22] S. J. Wallsten, The Effects of Government-Industry R&D Programs on Private R&D: The Case of the Small Business Innovation Research Program, Rand J. Econ. **31**, 82 (2000).

[23] D. B. Audretsch, A. N. Link, and J. T. Scott, *Public/Private Technology Partnerships: Evaluating SBIR-Supported Research*, Public Support of Innovation in Entrepreneurial Firms.

[24] S. T. Howell, *Financing Innovation: Evidence from R&D Grants*, Am. Econ. Rev. **107**, 1136 (2017).

[25] D. Czarnitzki and G. Licht, Additionality of Public R&D Grants in a Transition Economy: The Case of Eastern Germany, SSRN Electronic Journal (2005).

[26] H. Inoue and E. Yamaguchi, *Evaluation of the Small Business Innovation Research Program in Japan*, SAGE Open **7**, 215824401769079 (2017).

[27] E. J. OShaughnessy, The Evolving Market Structure of the U.S. Residential Solar PV Installation Industry, 2000-2016, 2018.

[28] R. Fu, D. Feldman, R. Margolis, M. Woodhouse, and K. Ardani, U.S. Solar Photovoltaic System Cost Benchmark: Q1 2017, 2017.

[29] U.S. Energy Information Administration (EIA) - Total Energy Monthly Data, https://www.eia.gov/totalenergy/data/monthly/.

[30] *Pitchbook*, https://www.pitchbook.com.

[31] C. H. Rubina Singh, How Innovative Startups Can Flourish In A Changing Cleantech Landscape, No. https://www.cse.fraunhofer.org/hubfs/How%20Innovative%20Startups%20Flourish%20in%20a%20Changing%20Cleantech%20Landscape%2008152017.pdf, 2017.

[32] M. Migendt, Emergence of Cleantech as an Investment Category – Media Attention and Venture Capital Investment, in Accelerating Green Innovation (Springer Fachmedien Wiesbaden, Wiesbaden, 2017), pp. 9–29.

[33] L. Fleming and K. Frenken, The Evolution of Inventor Networks in the Silicon Valley and Boston Regions, Adv. Complex Syst. **10**, 53 (2007).

[34] J. A. Lerner, *Boulevard of Broken Dreams* (Princeton University Press, Princeton, NJ, 2012).

[35] M. E. Porter, *The Competitive Advantage of Nations*, in *Rugman Reviews* (Macmillan Education UK, London, 2009), pp. 209–216.

[36] J. S. Engel, Global Clusters of Innovation: Lessons from Silicon Valley, Calif. Manage. Rev. **57**, 36 (2015).

[37] M. E. Porter, *Clusters and the New Economics of Competition*, Harv. Bus. Rev. **76**, 77 (1998).

[38] M. Delgado, M. E. Porter, and S. Stern, *Clusters and Entrepreneurship*, J. Econ. Geogr. **10**, 495 (2010).

[39] B. Van Looy, K. Debackere, and P. Andries, Policies to Stimulate Regional Innovation Capabilities via University-Industry Collaboration: An Analysis and an Assessment, R D Manag. **33**, 209 (2003).

[40] Financial Opportunities: Funding Opportunity Exchange, https://eere-exchange.energy.gov.

[41] C. E. Jennings, R. M. Margolis, and J. E. Bartlett, Historical Analysis of Investment in Solar Energy Technologies (2000-2007).

[42] *Small Business Administration*, https://www.sba.gov/blogs/how-and-why-determine-if-your-business-small.

[43] *Crunchbase*, https://www.crunchbase.com/.

[44] *Bloomberg New Energy Finance*, https://about.bnef.com/.

[45] F. Faul, E. Erdfelder, A.-G. Lang, and A. Buchner, G*Power 3: A Flexible Statistical Power Analysis Program for the Social, Behavioral, and Biomedical Sciences, Behav. Res. Methods **39**, 175 (2007).

[46] Universität Düsseldorf, *G*Power*, http://www.gpower.hhu.de.

[47] J. McCrary, Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test, J. Econom. **142**, 698 (2008).

[48] G. W. Imbens and T. Lemieux, *Regression Discontinuity Designs: A Guide to Practice*, J. Econom. **142**, 615 (2008).

U.S. DEPARTMENT OF
ENERGY

Office of
ENERGY EFFICIENCY &
RENEWABLE ENERGY

For more information, visit:
energy.gov/eere/solar

DOE/EE-2569 • March 2022