Business Plan Competitions and Technology Transfer

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Technical Report
NREL/TP-7A10-55659
September 2012

Contract No. DE-AC36-08GO28308

NATIONAL RENEWABLE ENERGY LABORATORY

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Prepared under Task No. DOGF.2000

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Executive Summary: *Business Plan Competitions and Technology Transfer*

The U.S. Department of Energy (DOE) commissioned this report in order to examine the effectiveness of business plan competitions at helping cleantech startup companies become successful business entities. Success is broadly defined in this report by the company's ability to attract outside investors and to raise funding, both of which we view as a proxy for the company's likelihood to effectively transfer its technology to the market for wide-scale production.

The report's findings may be used to support the value of business plan competitions—particularly the National Renewable Energy Laboratory's (NREL) Industry Growth Forum (IGF), a clean technology business plan competition. This report concludes that companies that present at the IGF on average raise several million more dollars in funding than those that applied and were not selected to present—a key indicator of a company's chances for future success. Another discovery in the report demystifies the assumption that a company's physical location and proximity to a larger pool of investors (such as those based in California and Massachusetts) significantly impact its chances of success.

Key findings of the report include:

INTRODUCTION: Business plan competitions are as important to nascent companies that may be seeking early-stage funding as they are to venture capitalists (VCs) looking for new investment opportunities. For cleantech startup companies, the premier competition for presentations of this ilk is the IGF, which facilitates entrepreneurs' ability to meet with private investors who can help young companies bridge the gap in funding needed to bring their technologies to the market. The IGF also affords DOE and NREL the opportunity to support the application of research and development needs to the market using public sector funds.

1. Clean technologies have a variety of challenges to overcome: they generally take longer to develop and, by and large, cost more than competing fossil fuel-based technologies. In order to drive down costs, large amounts of public funds have been invested in universities, national laboratories, and other institutions. When government-funded research projects show commercial promise, they are often spun-off into startup companies to more efficiently pursue market opportunities, in what is commonly referred to as the technology transfer process.

1.1 Startup companies often lack the capital and management structure to adequately manage the risk of transitioning a prototype technology into a successful product. Therefore, these companies often require funding from private sources, such as angel investors, venture capitalists, or some other form of funding. To secure this kind of funding, a company must convince investors that it can overcome the risk of investment and successfully build a business.

1.2 In recent years, business plan competitions have spread beyond their business school origins and may be affiliated with industry organizations or other entities. The IGF, which is part of a broader commercialization effort by NREL to facilitate technology transfer and support the clean technology industry, is an example of this evolution. The IGF uses clean technology investors and insiders to select the most promising companies, potentially reducing the amount of work that VCs do to find new, quality investments.

1.3 While the number of business plan competitions has exploded in recent years, so far there have been no studies on the effectiveness of these competitions at increasing venture capital funding. This report attempts to develop an econometric model to empirically estimate the "treatment effect" of participating in the IGF.

2. A difference-in-differences (DD) model is used to analyze how effective the IGF is at promoting interactions between investors and clean technology startups. Additionally, a network model was developed to analyze funding syndication in clean technology venture capital, allowing for comparisons between IGF presenters and the rest of the clean technology industry.

2.1 A regression equation was developed to evaluate the potential IGF treatment effect. Taking into account that negotiations between startups and venture capital firms may take many months, analysis was limited to the 2004 – 2009 IGF applicants and presenters. It was felt that not enough time had passed to reasonably evaluate the success of the 2010 and later IGF applicants. Based on descriptive statistics, IGF presenters seem to be more likely to raise funding after the competition. The report seeks to examine whether this can be attributed to an IGF treatment effect or is simply caused by selection bias.

2.2 The DD model was used to analyze how a startup's attributes (e.g., location and participating in another competition, such as the Cleantech Open) impacts the amount of post-IGF venture capital funding that IGF presenters (the treatment group) were able to raise compared with non-presenters, or companies that applied but were not selected to present (the control group).

2.3 An equation is defined in this section to estimate the differences in the ways venture capitalists decide to invest in IGF startups. For example, to minimize risk, some VC firms or individuals may decide to invest jointly in a startup.

3. Results

3.1 The result of the DD model suggests that IGF judges' rankings are a good indicator of a company's future success. For example, a company with a judges' score (S'_{it}) one standard deviation above average is likely to raise \$1.7 million more in funding.

3.2 To test if additional fixed effects might reduce the IGF treatment effect, the report examined whether fixed effects based on location, such as if the startups were based in California, Massachusetts, and New York (given their large venture capital communities) gave them an advantage over startups located in other states. Results suggest that location does not impact the IGF treatment effect a startup experiences; entrepreneurs can create viable clean technology startups anywhere in the U.S. In reality, the perceived success of states such as California or Massachusetts may be due to quantity of startups and not quality.

3.3 Next, the model tested for funding differences between IGF presenters and all other clean technology startups. To illustrate how IGF presenters' venture capital funding networks differed from those of non-presenting clean technology startups, the information was constructed into a graph. On visual inspection of the entire network of clean technology investment, IGF presenters appeared on average to be more highly connected with the venture capital community (i.e., received investment from a large number of VCs) than the average cleantech startup. Some factors as to why this might be true include increased competition for investment, better vetted business plans, or simply that presenting at the IGF reduces information asymmetries, thereby facilitating investment.

4. Conclusions of this report suggest that the IGF has a positive effect for cleantech startups' ability to raise venture capital funding. On average, it was found that IGF presenters are able to attract more investors, as well as raise about $4.4 million more than similar companies that applied but were not selected to present. Even when controls for state-level fixed effects or for startup participation in the Cleantech Open were accounted for, these results were unchanged. This analysis suggests that the IGF seems to be an effective tool for NREL to support clean energy companies and the clean technology industry. However, the IGF is not a definitive indicator when predicting the ability of these companies to achieve long-term success, or to replace fossil fuel-based technologies. These positive results suggest that the IGF is an additional means by which DOE can facilitate the adoption of clean technologies beyond the funding of research and development.

Business Plan Competitions and Technology Transfer

Business Plan Competitions Drive Investment Syndication and the Successful Capitalization of Startup Companies

Christopher M. Worley[1] and Thomas D. Perry IV[2]

Abstract

Business plan competitions are used in many industries to stimulate interactions between startup companies and potential investors, inducing investment in those companies and fueling technology transfer into the marketplace. However, no empirical studies have tested the effectiveness of these competitions at helping companies raise funding and become a successful business entity. We use a difference-in-differences model to estimate the effect of participation in the National Renewable Energy Laboratory's (NREL) Industry Growth Forum (IGF), a clean technology business plan competition. We find that companies that present at the IGF on average raise \$4.4M ($p<0.01$) more than those that applied and were not selected to present. We find no significant effect from company location and proximity to investors, which suggests that the business clusters' effect on a company's success may be limited. Presenting companies exhibit increased investment syndication compared to the rest of the clean technology industry; for example, an IGF presenter with \$9M in funding may have twice the number of investors as typical clean technology startups that raised the same amount of funding but did not present at the IGF. These findings suggest that business competitions can help nascent companies raise financing and help venture capitalists find investment opportunities, and may serve as an effective policy tool to facilitate the growth of clean technology companies, industries, and technology transfer.

Keywords: *clean technology, startup company, venture capital, business plan competition*

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Introduction

Business plan competitions are events where startup companies present their business plans to groups of potential investors. These competitions are equally important for entrepreneurs who may be seeking early-stage capital and for venture capitalists (VCs) looking for new investments. While the website for every business competition touts the success of their participants, it is unclear if business competitions actually foster and support the development of new startup companies.

One such business plan competition is the National Renewable Energy Laboratory's (NREL) Industry Growth Forum (IGF), which was established in 1995 and has been held annually since 2002.[3] As part of broader deployment efforts by the U.S. Department of Energy (DOE) Office of Energy Efficiency and Renewable Energy (EERE) to support the commercialization of low-carbon technologies, the IGF focuses on clean energy startups. By attending the IGF, startup companies hope to raise the funding they need to bring their product to market, and investors (such as venture capitalists) hope to find investments that will earn a significant return. By running and supporting the IGF, the DOE and NREL hope to foster the burgeoning clean technology industry. The market for venture capital funds has been characterized as having information asymmetries, which theory suggests leads to a sub-optimal level of investment (Admati and Pfleiderer, 1994). The IGF seeks to reduce these information asymmetries to increase venture capital funding and drive the transfer of clean technology into the market.

The technological innovation literature often frames the development and adoption of new technologies in terms of market demand "pulling" and scientific research "pushing" technological change (Nemet, 2009). Along these lines, the federal government encourages the development adoption of clean technologies through traditional policy tools like research and development funding, subsidies, or tax credits. While consumers may have positive attitudes toward clean technologies, they ultimately require added incentives to help clean technologies compete on price. So, a wide variety of tax credits and subsidies have been used to encourage the adoption of clean products through "demand pull." For example, wind power producers receive a Production Tax Credit of 2.2 cents/kWh for power generated at all sites that are in operation by the end of 2012.[4] In contrast, public sector funds can be used in research and development for the basic scientific research required to "push" new technologies to market. As an example of this model, the DOE allocated 13% of the FY2009 budget for Basic Energy Sciences.[5] But between these two policy incentives, fledgling technologies often require private funding to bring their technologies to market, and they may find it difficult to raise that funding if their technologies are not fully proven. The IGF attempts to facilitate the interactions of startup companies and private investors to help companies bridge the gap in funding (Murphy and Edwards, 2003). As such, the IGF represents a decidedly different type of public policy instrument as compared to research and development funding or tax credits.

There is a lack of empirical analyses of business plan competitions, so it is unclear whether such competitions are effective at increasing venture capital funding. This paper seeks to estimate the effect of the IGF on venture capital funding, thereby addressing two topics thus far overlooked in the academic literature: the effectiveness of business plan competitions at stimulating funding, and business plan competitions as an alternative policy tool to increase technology development and adoption. We begin with a broad discussion of efforts to develop clean technologies, the role of venture capital and startup

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[3]For more information, visit the IGF website: http://cleanenergyforum.com/

[4]The DOE maintains an online database outlining the federal, state, and local incentives for renewable energy (http://www.dsireusa.org/).

[5] For a broader outline of federal R&D funding see the following report by the Congressional Research Service (John F. Sargent Jr., "Federal Research and Development Funding: FY2011" http://www.fas.org/sgp/crs/misc/R41098.pdf Accessed 5/5/2011).

companies, and the suboptimal level of investment that may occur when there are information asymmetries between startups and investors. Next, we outline our data sources, and discuss the difference-in-differences (DD) model that we use to test the treatment effect for IGF presenters. Then we analyze the role that the IGF plays in modifying venture capital funding syndication networks, which may be a result of decreased information asymmetries. Finally, we discuss the policy implications for technology transfer and conclude by highlighting opportunities for future work.

1 Background

Established in 1977, NREL has focused on the basic and applied scientific research needed to develop clean technologies.[6] This research has unique challenges due to the nature of these technologies and the markets in which they operate. Clean technologies often have long development cycles and must compete with fossil fuel-based technologies that generally have lower costs and for which much of the U.S. economy is optimized. The lower costs of fossil fuel technologies, however, often fail to take into account the multitude of environmental effects from the burning of fossil fuels. So, in the absence of a green tax, clean technologies must make dramatic cost reductions to compete with fossil fuel-based technologies.

To drive down the costs and to overcome technical limitations of clean technologies, large amounts of public funds have been invested in universities, national laboratories, and other institutions (Salmenkaita and Salo, 2002). When government-funded research projects show commercial promise, they are often spun-off into startup companies so that they may more efficiently pursue market opportunities (Carayannis et al., 1998)—the technology transfer process in its most pure form. Similarly, large corporations often invest in clean technology research and development due to perceived opportunities in the energy sector; however, those projects benefit from the company's established business infrastructure. Startup companies often lack the capital and management structure to adequately manage the risk of transitioning a prototype technology into marketable products. As such, startups often require venture capital or some other form of funding (Murphy and Edwards, 2003).

1.1 Venture Capital

Funding during the technology transfer process—from fundamental research to commercial product—comes from different sources in the financial value chain (Figure 1). The very earliest stages of development are often research projects at universities and national laboratories that are largely funded by the government. Capital is required to develop the technology into a workable prototype. When the research shows promise, the university (or government laboratory) may spin off the research project into a startup company. At this point, funding shifts from public sources to private sources, such as angel investors and venture capitalists. In these early stages, a startup may be funded by an angel investor who is willing to outlay significant short-term capital. This financing is meant to allow the startup more time to develop a prototype and bridge the gap until it can raise substantial venture capital.

[6]For a thorough overview of NREL's mission and history, see the following website: http://www.nrel.gov/overview/.

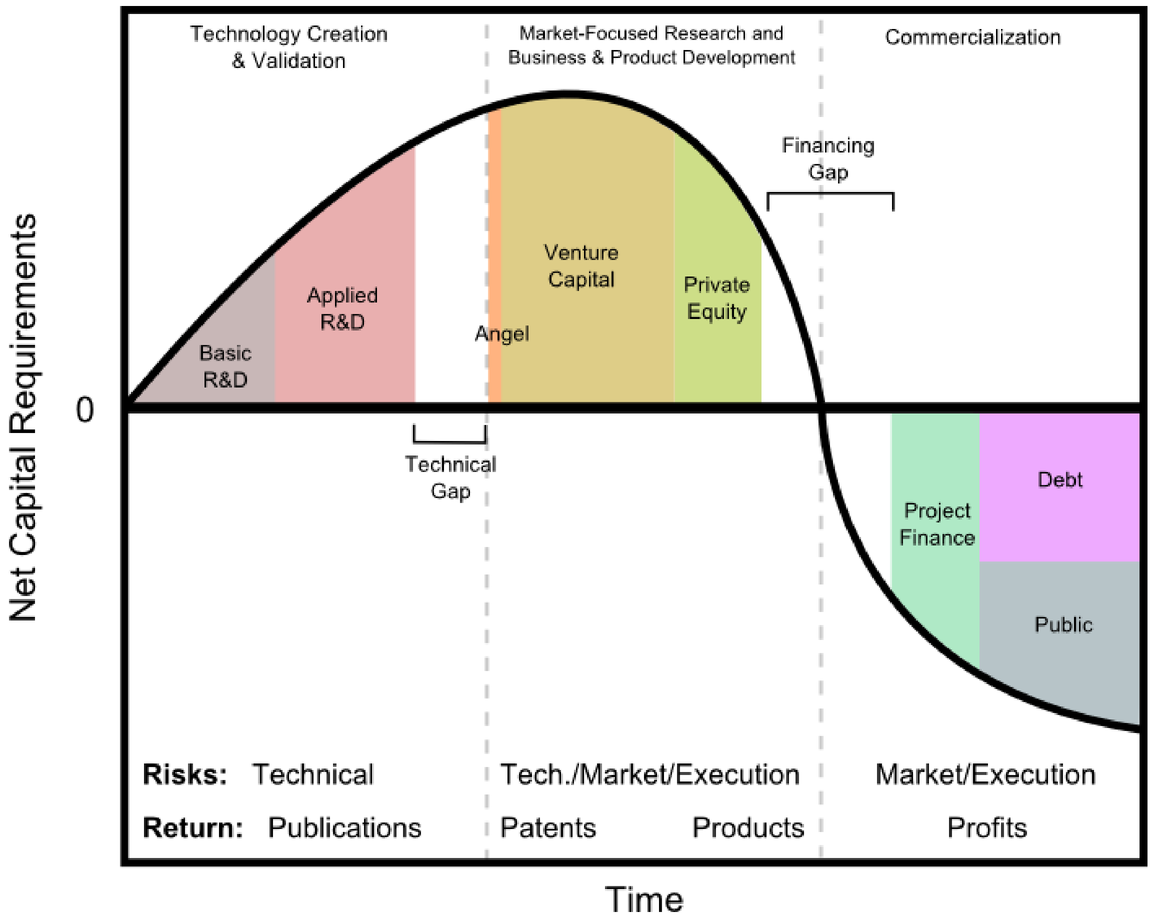

Figure 1: Technology Transfer Net Capital Requirements Over Time

To get venture capital funding, startups must convince investors that they can overcome the risk of investment and successfully build a business. There are two main types of risk associated with clean technology startups—technology risk and business risk (Murphy and Edwards, 2003). While a company's prototype may seem promising, technical infeasibilities may prevent the technology from scaling to cost-effective production. Or, the scientists and engineers that developed the prototype technology may not be well-suited to run the business operations of a new company. A startup's management team must contain a mix of business-savvy individuals and people who develop and fully understand the technology. Great technologies are not guaranteed to succeed due to any number of technological or business failings, and many companies fail to transition from a prototype technology to cash flow-positive sales that earn a significant return on the investors' capital investment (Fiet, 1995).

This combination of business and technology risk can prevent a startup from raising the funds needed to bring its product to market. Given the long development cycles associated with clean technologies, these startups may be cash flow negative for years compared to, for example, the software sector in which some startups may be able to transition from a prototype into a product with actual sales in a matter of months. For these reasons, some clean technology startups may not be an enticing investment for venture capital firms or, at least, they may be different from a venture capital firm's previous investments in software and other less cash-intensive technology areas.

VCs provide companies with capital in exchange for equity in the company; they make their money back, plus appropriate returns, when the company is acquired or has an initial public offering and their equity becomes liquid. Venture capital firms seek a high return from their companies in their investment portfolio because they expect many of them to fail, so the whole portfolio must support those failures (Sahlman, 1990). In general, early-stage companies are more likely to be prone to failure because they do not have proven products and technologies. To reduce the risk of investment, venture capitalists can hedge in several ways: by co-locating and co-investing with other VCs; diversifying across technology, development stage, and/or geography; and through other mechanisms. The quality of a VC's investments, and the ultimate return on their funds, are only as good as the information they have about their portfolio companies.

An extensive literature has characterized venture capital markets as hindered by imperfect information (Chan, 1983; Trester, 1998; Kaplan and Strömberg, 2003) and, as such, the market for venture capital funds can be characterized by the principal-agent problem. Venture capitalists do not have perfect information about a startup's technology or the business acumen of the management team, so there is risk with their investment. Similarly, startups face risks when selecting venture capital firms to work with. In addition to capital, VCs bring several resources including talent management, operational skills, sales channel development, strategic partners, and networking skills. However, VCs can also introduce unique constraints and pressures on a startup's business such as pushing a company toward liquidity. Determining which VC is the best fit for a company goes beyond the amount of capital offered, but, ultimately, neither VC firms nor startups can perfectly identify the "type" of company they do business with *a priori*. Given the existence of these two-sided information asymmetries, theory suggests that there is a suboptimal level of investment in the market for clean technology venture capital. Just as uncertainty in the selection process when hiring new employees leads to labor market inefficiencies (e.g., frictional unemployment), uncertainty in the market for venture capital can lead to suboptimal investment in startup companies (Admati and Pfleiderer, 1994). Reducing these information asymmetries would help to increase funding and drive technology transfer.

Industry groups and venture capital firms have attempted to remedy these market frictions through a variety of means, including business incubators (Allen and Rahman, 1985), the development of business clusters (Porter, 1998), syndication of venture capital funding (Lerner, 1994), and, perhaps, business plan competitions. Business incubators assist startups by providing a variety of business support services, mentoring, and networking opportunities with the investment community. These incubators are often located near business clusters, cities, or regions of inter-related companies with a specific industry focus. Co-location of startups in clusters can lead to large increases in productivity (Porter, 1988). Venture capital syndication may appeal to VCs because it allows risk to be spread among multiple firms, and it is often seen with later-stage startups due to their large funding requirements. Further, syndication allows VCs to build off of established funding networks (Bygrave, 1988). However, by reducing the stake of individual VCs, syndication also reduces the return when a startup successfully exits.

While research has analyzed the effectiveness of incubators, business clusters, and funding syndication in venture capital markets, there is a lack of research addressing the effectiveness of business competitions in performing a similar function. Frankly, while millions of dollars have been spent organizing, developing, and delivering business competitions, there are few metrics that demonstrate that they work.

1.2 Business Competitions

While there is no definitive history of business plan competitions, the University of Texas (UT) at Austin holds that its Moot Corp Competition, first held in 1984, was the first of its kind.[7] The UT Graduate School of Business wanted to develop a competition similar to "moot court" competitions that law schools hold. Students would develop a business plan that they presented to panels of venture capitalists. Those venture capitalists judged the participants based on the potential success of the company. The winner of the competition received prize money, but, more importantly, all participants could potentially make business contacts with the venture capital community. The original UT competitions appear to have been successful as both a teaching tool and a networking tool because numerous business schools now have similar competitions.

In recent years, business plan competitions have spread beyond business schools and may be affiliated with industry organizations or other entities. These new competitions may have an industry focus, such as software or cleantech industries, or they may have some other driving goal. In addition to the IGF, there are several other cleantech business competitions, although the IGF is the largest and longest running. Techcrunch Disrupt[8] and LeWeb[9] are two software-focused competitions, and Women 2.0[10] is a cross-industry startup competition that requires a female in the founding team. While each competition may have a specific goal or focus, they are all platforms for facilitating the interactions of startup companies and venture capitalists.

The IGF is part of NREL's broader commercialization efforts to facilitate technology transfer and support the clean technology industry (Murphy and Edwards, 2003). Each year, clean technology startups from around the U.S. (and, more recently, from other countries) apply to present their business plans at the IGF. In recent years, about 200 companies have applied each year, and of those, around 30 companies are chosen to present at the IGF event, which is attended by more than 500 people interested in clean technologies. After applying to present their business plans, companies are ranked and selected by a pool of more than one hundred venture capitalists and other clean technology industry figures. The number of judges who score each application depends on the company's technology type and each judge's areas of interest. While as many as 25 judges may score some companies, on average, between 10 – 12 judges typically score each application. Each judge provides a numerical score for the company based on a variety of criteria, including factors such as technological feasibility and the qualifications of the management team. The judges' scores are averaged for each company, and companies are ranked based on their average score. Once the companies have been ranked, the final group of 30 – 34 companies is selected through a large group discussion of all the judges.

While the judges' rankings are used as a guide, a variety of qualitative criteria are used in the final selection. For example, seed stage companies are often ranked much lower than later-stage companies due to the large technology risk associated with companies that may only have a prototype. The judges may choose to select lower-ranked companies to ensure a mixture of different technologies at a variety of different development stages. This is done to ensure that the IGF has a broad appeal to a variety of different investors. By using clean technology investors and insiders to select the most promising companies, we believe that the IGF selection process reduces the amount of work that VCs do to find new, quality investments. By increasing the interactions between startups and VCs, we believe that business competitions such as the IGF can reduce information asymmetries.

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[7] The Moot Corp Competition was later renamed the Venture Labs Investment Competition. For a more detailed history of the competition, see http://www.mootcorp.org/history.asp

[8] http://disrupt.techcrunch.com

[9] http://www.leweb.net/startupcompetition

[10] http://www.women2.org/pitch-competition-2010/

1.3 Research Contribution

From modest beginnings at a small number of business schools in the 1980s, business plan competitions have grown in size and scope. While the number of business plan competitions has exploded in recent years, as of yet, no one has tested the effectiveness of these competitions at increasing venture capital funding. We developed an econometric model to empirically estimate the treatment effect of participating in NREL's Industry Growth Forum. We believe that empirical validation is needed to assess efficacy of this and other business plan competitions.

Business competitions may be an effective way to reduce frictions in the venture capital market. Venture capitalists are often involved in the competition in a number of capacities, including the selection of the competing companies and the final judging of the business plans in the competition, all of which allow them to learn more about the participating companies. The competition process is also useful to startups because it allows them to refine their business pitch and it provides a direct venue for networking and information gathering with the venture capital community.

While all business plan competitions will surely tout the success of their participant companies, our research shows that most of these are case driven and that there are no significant academic analyses of the effectiveness of business competitions at helping startups secure funding. In fact, we were only able to find one analysis of business plan competitions—a paper that looks at the importance of team diversity in competition success (Foo et al., 2005). Murphy and Edwards (2003) mention the IGF in a broader discussion of reducing information asymmetries, but they do not analyze the effectiveness of the IGF. Although business competitions are common practice in business schools and some industries, the literature has not analyzed the effectiveness of these competitions at facilitating the interactions between startups and venture capital firms and actually delivering on their promise of positively influencing the success trajectory of the participating companies. Demonstrating how business plan competitions can help companies and investors may provide insights on how to make technology transfer support programs more efficient and effective.

2 Empirical Methods

In our research, we used several methods to analyze the success of the IGF at promoting interactions between investors and clean technology startups. First, we used a difference-in-differences (DD) model to estimate the treatment effect of the IGF by comparing venture capital funding for startups that presented their business plans and startups that applied but were not accepted to present at the IGF. Additionally, we tested for state-level effects and for the effect of startup participation in the Cleantech Open (CTO), a business competition focused on mentoring and cultivating seed-stage ventures. Finally, we developed a network model to analyze funding syndication in clean technology venture capital, allowing for comparisons between IGF presenters and the rest of the clean technology industry.

2.1 Data

The IGF provided a list of 1,054 applicants for the years 2004-2010, including the list of 211 companies that presented their business plans at the IGF over these years. Additionally, the IGF provided judges' rankings and scores for these years. Negotiations between startups and venture capital firms may take many months, so we chose to ignore the IGF applicants from 2010 and later years because not enough time has passed for these companies to experience any potential IGF treatment effect. So, our analysis is limited to the 2004 – 2009 IGF applicants (n=850) and presenters (n=167).

We make two caveats about the IGF data. First, some companies may apply to the IGF in multiple years. If they are not accepted, they may use feedback from the application process and re-craft their application for the next year. The selection process and our analysis treat each application as distinct and ignore the selection choices from previous years, meaning that applications from a company in multiple years are treated as distinct companies. Further, although the judges' scores are normally distributed within each year, there are year-to-year variations in the means and standard deviations of judges' scores across years. To compare scores across years, the judges' normalized score (S'_{it}) was calculated using the following equation:

$$S'_{it} = \frac{\bar{S}_{it} - \bar{X}_t}{s_t}$$

In this equation, the judges' raw mean score ($\bar{S}_{it}$) for each company (*i*) in year (*t*) was adjusted by that year's mean ($\bar{X}_t$) and standard deviation (s_t). The resulting calculated score (S'_{it}) represents the number of standard deviations that a company's score is away from the mean of zero.

Bloomberg's New Energy Finance data service was used to quantify venture capital funding raised by all IGF applicants.[11] Some applicant companies raise funding before they participate in the IGF, some raise funding after the IGF, some both, and some raise no funding at all. To test whether the IGF has an effect on venture capital funding, we categorize funding events as pre-IGF if the startup closed the venture capital financing before attending the IGF, and post-IGF if the funding was raised after they attended the IGF. Summary statistics are given in Table 1, and we note that the sample size (*n*) does not sum downward because some companies raise funding both before and after the IGF. Further, it should be noted that New Energy Finance lists many types of funding events, including government grants, initial public offerings, mergers and acquisitions. For the DD model, our analysis focuses strictly on venture capital for IGF applicants. While all types of funding can help a startup bring a product to market, the value of different funding types are not easily comparable. The value of an IPO, a merger, or an acquisition may be indicative of total company value, while venture capital funding events are capital exchanged for a partial equity stake in a company. A more accurate measure of the full treatment effect of the IGF and other business plan competitions would include all types of financing, as well as a measure of value returned to early-stage company equity investors. Unfortunately, determining a method for comparing funding types is beyond the scope of this paper and, as such, our estimate of the treatment effect of business competitions should be seen as a lower bound in estimating total company success.

[11]Bloomberg New Energy Finance supplies a variety of data focusing on the clean energy industry (http://bnef.com/).

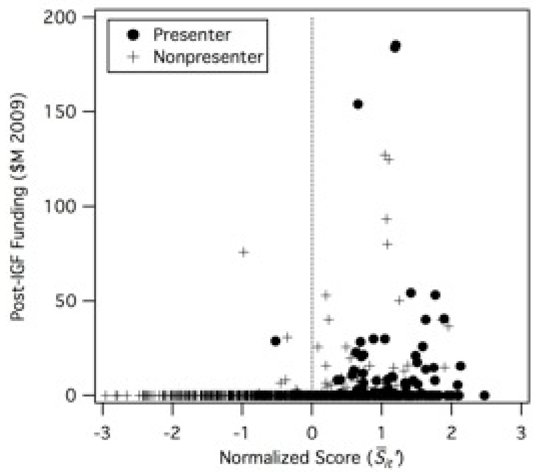
Table 1: Venture Capital Funding Pre- and Post-IGF

	Presenters		Nonpresenters	
	$M 2009	***n***	**$M 2009**	***n***
No Funding	**-**	**110**	**-**	**439**
Pre-IGF Funding (Total)	**287.6**	**39**	**370.5**	**26**
Seed stage	**12.3**	**11**	**19.3**	**10**
Bridge/Interim	**12.2**	**4**	**6.1**	**2**
Round A	**109.4**	**20**	**85.3**	**15**
Round B	**74.6**	**7**	**140.5**	**10**
Round C	**35.4**	**3**	**59.8**	**5**
Round D	**-**	**-**	**59.5**	**3**
Private Equity – Expansion capital	**43.7**	**2**	**-**	**-**
Post-IGF Funding (Total)	**1193.3**	**51**	**744.1**	**25**
Total Funding Pre- and Post-IGF	**1480.9**	**167***	**1114.6**	**479***

***Note: Total number of applicant companies, ignoring applications in multiple years**

We are most interested in post-IGF funding, as that capital may have been raised as a direct result of presenting at the IGF. We find that many companies (presenters and non-presenters) raise no venture capital funding after the IGF but companies that are ranked above average (e.g., normalized judges' score (S'_{it}) greater than zero) are more likely to raise funds (Figure 2). This suggests that the IGF's selection process—the scoring and ranking of companies—may be a relatively good indicator of later company success. On visual examination of Figure 2, it may seem that there is little funding difference between presenters and non-presenters that were ranked above-average by the IGF selection committee. However, it is important to remember the sample size of these two groups. There are a total of 479 non-presenters, only 8% of which raise post-IGF funding (these are unique companies, ignoring applications in multiple years). In contrast, there are 167 presenters, of which 34% raise post-IGF funding. On average, IGF presenters seem to be more likely to raise post-IGF funding. We seek to test whether this can this be attributed to an IGF treatment effect or is it merely an artifact of selection bias.

Figure 2: Post-IGF funding ($M 2009) by normalized score



As mentioned previously, many variables may factor into the funding success of startups, such as the co-location of startups in business clusters or near venture capital firms, the use of business incubators, and, perhaps, participation in business plan competitions. Any attempt to estimate an IGF treatment effect should control for all of these effects, and while we cannot directly control for all of these factors due to limited data, we control for state-level fixed effects and for prior participation in the Cleantech Open. Startups from states with large venture capital communities (i.e., California, Massachusetts, and New York) may have an advantage over startups located in other states merely due to proximity. In fact, a large share of the IGF applications come from startups located in those states (Table 2).

Table 2: State-level distribution of IGF applications (2004-2009)

Location	Presenters	Nonpresenters	Total
USA	154	621	775
CA	39	144	183
CO	19	132	151
NY	14	43	57
FL	11	33	44
MA	14	29	43
TX	9	18	27
PA	5	18	23
OH	3	19	22
NM	3	17	20
WA	7	8	15
other states	30	160	190
Other Countries	6	32	38
missing data	*7*	*30*	*37*
Total	167	683	850

Additionally, if a startup has participated in another business plan competitions, they may be better able to compete at the IGF. While we do not have exhaustive lists of startup participation in other competitions, we received participant lists from the Cleantech Open for all years they have operated (2006-2010). This list was cross-referenced with the IGF applicant list, allowing us to find all CTO participants that later applied to the IGF. While the IGF has a national focus, the CTO has many regional competitions that feed into a national competition. The CTO focuses on earlier-stage companies and provides hands-on mentoring for their participants. Their multi-stage, regional format allows CTO startups to interactively refine their business plans. We suspect that the CTO mentoring process improves how companies pitch their business plans, and may increase a startup's chances to be selected for the IGF or may increase later venture capital funding.

While only a small number of CTO companies applied to the IGF in 2006 and 2007, the number has increased in recent years (Table 3) with CTO companies accounting for 17% of the IGF application pool in 2010. And, in fact, the selection rate for CTO participants that apply to the IGF was much higher in

2009 and 2010: 24% and 29% for CTO participants, 10% and 15% for non-CTO companies. The list of CTO companies will allow us to estimate the effect of CTO participation on post-IGF funding success, to see whether companies that have participated in both the CTO and IGF raise more venture capital than companies only participating in the IGF.

Table 3: IGF average selection rate

Year	Applicants from CTO	Presenters from CTO	CTO Success %	Non-CTO Applicants	Non-CTO Presenters	Non-CTO Success %	Total Applications
2004	0	0	na	87	28	32%	87
2005	0	0	na	93	29	31%	93
2006	2	2	100%	104	22	21%	106
2007	1	1	100%	106	23	22%	107
2008	15	3	20%	152	33	22%	167
2009	46	11	24%	238	23	10%	284
2010	34	10	29%	163	24	15%	197

2.2 Econometric Framework

The DD model is a non-experimental technique that derives the treatment effect of a policy by comparing the outcomes for control and treatment groups before and after a policy intervention. Among other things, DD models have been used to measure the effect of tax reform on labor supply (Eissa and Liebman, 1996), the effect of an information disclosure law for hygiene score cards on restaurant profitability (Jin and Leslie, 2003), and the effect of the Mariel boatlift on labor markets in Miami (Card, 1990). We use IGF presenters as the treatment group and nonpresenters (companies that applied but were not selected to present) as the control group. The DD model is estimated with the following equation:

$$Y_{it} = \beta_0 + \beta_1 P_i + \beta_2 T_t + \beta_3 P_i T_t + \varepsilon_{it}$$

Each data point Y_{it} represents the value of venture capital financing that company i raises in time period t, where t is given by two time periods: before the IGF event and after the IGF event. The variables P_i and T_t are dummy variables with P_i equal to one for IGF presenters and zero for non-presenters and T_t equal to one for post-IGF funding and zero for pre-IGF funding. In DD models, the coefficient on the participation variable (P_i) is an estimate of the difference in pre-IGF funding between presenters and non-presenters, and the coefficient on the time variable (T_t) estimates the time trend in the control group. The interaction of these two variables, the P_iT_t term, is an estimate of the average treatment effect of the IGF.

Bertrand et al. (2004) noted that DD models are often flawed when the estimation uses time series data on either side of the policy intervention. Time series data are often serially correlated, which leads to a biased estimation of the t-statistics and significance levels. One remedy that they suggest is to average the time series data on both sides of the policy intervention, producing two data points: one before and one after the policy is implemented. Rather than time series data, our estimation uses discrete funding events, so we create pre- and post-IGF data points by summing the total value of venture capital funding that occurred before and after the IGF, which we believe addresses the concerns of biased estimation.

As previously mentioned, the IGF does not choose presenting companies randomly, so we believe there is likely a strong selection bias. The IGF selection committee chooses only the most promising startups to present at the IGF, so it may be the case that these companies would naturally raise more funding than nonpresenters even had they not presented at the IGF. To control for selection bias, we add the normalized judges' score (S'_{it}) as a covariate:

$$Y_{it} = \beta_0 + \beta_1 P_i + \beta_2 T_t + \beta_3 P_i T_t + \beta_4 S'_{it} + \varepsilon_{it}$$

On average, ten judges examine every IGF application, with each judge providing a numerical score based on the strength of the company's application. We believe the average of these scores provides a relative rating or a prediction of a company's success. So, by including the judges' scoring (normalized for the mean and standard deviation of that year's scores) as a covariate, we hope to control for the selection bias.

As previously mentioned, some may suggest a startup's success at raising venture capital funding is largely due to their location and proximity to investors, which would bias the results of the DD model. California, Massachusetts, and New York are three states with large venture capital communities, so it may stand to reason that startups from those states have an advantage over startups from other parts of the country. We test for regional effects by adding dummy variables for the states of California (CA_i), Massachusetts (MA_i), and New York (NY_i), which equal one if the company is from that state and zero otherwise.

$$Y_{it} = \beta_0 + \beta_1 P_i + \beta_2 T_t + \beta_3 P_i T_t + \beta_4 S'_{it} + \beta_5 CA_i + \beta_6 MA_i + \beta_7 NY_i + \varepsilon_{it}$$

Finally, we test the effect of the Cleantech Open on post-IGF funding to see if post-IGF success can be attributed to participation in the CTO. As noted in the previous section, CTO companies have a higher selection rate, so it raises the question as to whether CTO companies raise more venture capital funding than non-CTO companies, perhaps biasing the results of the DD model.

$$Y_{it} = \beta_0 + \beta_1 P_i + \beta_2 T_t + \beta_3 P_i T_t + \beta_4 S'_{it} + \beta_5 CTO_i + \varepsilon_{it}$$

We test for the effect of the CTO by adding a dummy variable (CTO_i) that equals one for companies that participated in the CTO before they applied to the IGF and zero otherwise.

2.3 Network Analysis

While the above DD models estimate how a startup's attributes (e.g., location and participating in the CTO) may affect their post-IGF funding, there could be differences in how VCs choose to invest in IGF startups. For example, there may be differences in funding syndication for IGF companies. Instead of one VC carrying all of the risk of a $10 million investment, two or more venture capital firms may jointly invest (or syndicate) in a startup. It may be the case that IGF startups syndicate differently as compared to the average clean technology startup. To analyze VC syndication, we create a network graph of venture capital funding with nodes (all clean technology startups and VC firms) and edges (funding events). Next, we calculate each startup's degree (D_i), the number of VC firms that have invested in the startup. While this type of analysis ignores the size of investment that each VC makes, it does give a rough measure of how startups are connected with the VCs.

$$Y_{i,post} = \beta_0 + \beta_1 D_i + \beta_2 D_i P_i + \beta_1 D_i^2 + \beta_2 D_i^2 P_i + \beta_1 D_i^3 + \beta_2 D_i^3 P_i + \cdots + \varepsilon_{it}$$

We use nonlinear least squares (NLS) to estimate the relation between degree and post-IGF funding (Equation 6). Degree regressors up to fourth-order (D_i, D_i^2, D_i^3, D_i^4) are used in the nonlinear regression, and we include presenter (P_i) dummy variables test for differences between IGF companies and all other clean technology startups.

3 Results

3.1 IGF Treatment Effect

We use ordinary least squares (OLS) to estimate the various specifications of the DD model. The simplest version of the model (Equation 2) includes each company's normalized score as a covariate so as to control for selection bias (all results are given in Table 4). In DD models, the constant term represents the baseline average funding level for non-presenting companies before the IGF. Our results show this to be positive (1.50) and highly significant at the α=0.01 level. We included the normalized judges' score as a covariate in hopes to capture the selection bias of the IGF selection process, and we find the coefficient on this term to be positive (1.77) and also highly significant at the α=0.01 level. As visual analysis of Figure 2 indicates, these results suggest that the judges' rankings are a good indicator of company success. A company with a judges' score (S'_{it}) one standard deviation above a similar company is likely to raise \$1.7 million more in funding. The presenter's dummy captures any differences between presenters and non-presenters before the IGF, and the time trend dummy captures the ability of non-presenters to raise funding post-IGF. We find that both of these variables are not significant at the α=0.05 level. Most importantly, however, the IGF treatment effect dummy is positive and highly significant at the α=0.01 level, meaning that IGF presenters on average raise around \$4.4 million more than non-presenters.

3.2 Fixed Effects

The above results suggest that IGF presenters raise more venture capital funding on average than non-presenters, even after controlling for selection bias. However, there may be additional fixed effects that reduce the IGF treatment effect. Firstly, we test for fixed effects based on location to see whether the startups in California, Massachusetts, and New York (given their large venture capital communities) have an advantage over startups located in these states. We ran a variety of specifications for Equation 4, adding and removing dummy variables for those three states (results in Table 4).

Our analysis included the dummy variables individually and jointly, however, none of those state-level dummy variables showed significant results (at the α=0.05 level) for any of the model specifications. With a complete lack of significance, we have no intuition on which model to select, so we use the Schwarz criteria to choose between model specifications. When comparing Equation 3 and all versions of Equation 4, the Schwarz criteria are minimized in the model specification with no state-level dummy variables (Equation 2). This suggests that the IGF treatment effect does not differ based on startup location. These results run counter to Porter's work on business clusters (Porter, 1998) or anecdotes by VCs who often argue that California and Boston are better environments for clean technology startups.[12] These results suggest that entrepreneurs can create viable clean technology startups anywhere in the U.S.

[12] The suggestion that California and Massachusetts are better locales for clean technology startups is largely anecdotal, but is echoed by many venture capitalists. One example we found is Shawn Lesser of Sustainable World Capital (http://cleantech.com/news/5640/top-10-cleantech-clusters).

The perceived success of states like California or Massachusetts may be due to quantity of startups and not on quality.[13]

Finally, we test the effect of participation in the Cleantech Open on post-IGF funding to see if post-IGF success can be attributed to participation in the CTO. CTO companies seem to have a higher selection rate, so it raises the question as to whether CTO companies raise more venture capital funding than non-CTO companies, perhaps biasing the results of the DD model. We estimate Equation 5 to test if CTO participants raise more post-IGF funding than other IGF startups that did not participate in the CTO (results in Table 4). As with the state-level dummy variables, the CTO variable is not significant at the α=0.05 level. Again, we use the Schwarz criteria to choose between model specifications in the event that Equation 5 adds information over Equation 3. As before, the simpler model (Equation 3) is selected.

While it appears that participation in the CTO has no significant effect on post-IGF funding, it should be noted that the CTO has only been operating since 2006, and only since 2009 have large numbers of CTO companies applied to the IGF. Due to the small sample size of CTO companies in our model, there is not enough power in the data to adequately test the effect of the CTO on IGF companies. As previously discussed, many startups that participate in the CTO are very early stage, and they receive mentoring from entrepreneurs and clean technology insiders on the most effective ways to present their business plans. Our anecdotal evidence suggests that CTO companies have a higher selection rate at the IGF, which further hints that the CTO and the IGF may provide an effective avenue for startup companies to the raise funding necessary to bring their product to market. More years of data are required to further test the effect of the CTO.

[13] As we noted in Table 2, a large number of startups are based in states traditionally known for clean technology startup success (like California, New York, and Massachusetts).

Table 4: DD regression results with fixed effects

Variable	Eq. 3	Eq. 4a	Eq. 4b	Eq. 4c	Eq. 4d	Eq. 4e	Eq. 4f	Eq. 4g	Eq. 5
Constant	1.504***	1.274***	1.503***	1.608***	1.255***	1.613***	1.384***	1.372***	1.621***
	(3.565)	(2.880)	(3.521)	(3.754)	(2.790)	(3.718)	(3.060)	(2.975)	(3.784)
Normalized Score	1.766***	1.73***	1.765***	1.789***	1.725***	1.79***	1.753***	1.75***	1.801***
	(5.677)	(5.555)	(5.664)	(5.745)	(5.525)	(5.736)	(5.618)	(5.591)	(5.778)
Presenters Dummy	-1.757	-1.790	-1.757	-1.779	-1.787	-1.781	-1.805	-1.803	-1.759
	(-1.721)	(-1.755)	(-1.720)	(-1.743)	(-1.750)	(-1.744)	(-1.770)	(-1.767)	(-1.724)
Time Period Dummy	0.698	0.698	0.698	0.698	0.698	0.698	0.698	0.698	0.698
	(1.191)	(1.192)	(1.191)	(1.192)	(1.192)	(1.191)	(1.192)	(1.192)	(1.192)
IGF Treatment	4.384***	4.384***	4.384***	4.384***	4.384***	4.384***	4.384***	4.384***	4.384***
	(3.321)	(3.323)	(3.320)	(3.322)	(3.322)	(3.321)	(3.323)	(3.322)	(3.322)
CA Dummy	-	1.110	-	-	1.129	-	1.001	1.013	-
	-	(1.727)	-	-	(1.742)	-	(1.539)	(1.543)	-
MA Dummy	-	-	0.019	-	0.284	-0.091	-	0.165	-
	-	-	(0.016)	-	(0.233)	(-0.075)	-	(0.135)	-
NY Dummy	-	-	-	-1.469	-	-1.475	-1.233	-1.221	-
	-	-	-	(-1.404)	-	(-1.405)	(-1.166)	(-1.150)	-
CTO Dummy	-	-	-	-	-	-	-	-	-1.577
	-	-	-	-	-	-	-	-	(-1.563)
Adjusted R-squared	0.038	0.042	0.040	0.041	0.042	0.041	0.042	0.042	0.038
Schwarz criteria	12,857.2	12,861.6	12,864.6	12,862.6	12,869.0	12,867.7	12,870.0	12,875.1	12,862.1

t-statistics in parentheses

* p <0.05, ** p < 0.01, *** p < 0.001

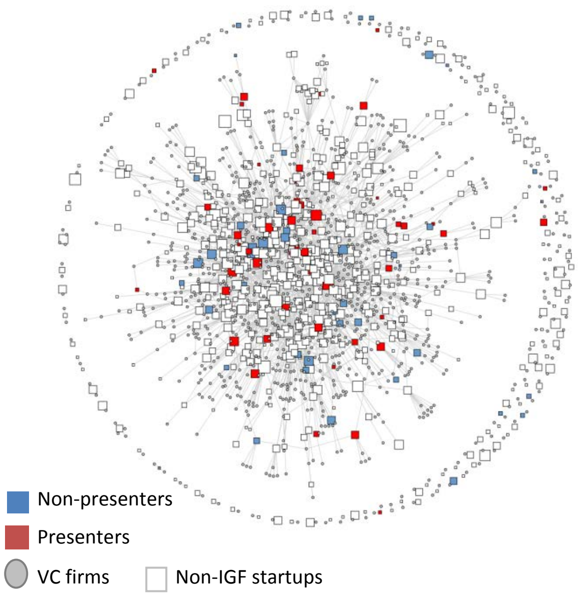
3.3 Network Regression

Next, we test for funding differences between IGF presenters and all other clean technology startups. Using igraph,[14] we constructed a syndication network for venture capital funding raised by clean technology startups between 2001-2010 and generated a series of network graphs (Figure 3).[15] Figure 3a shows the connections between all clean technology startups and venture capital firms, while Figure 3b shows the network created by IGF applicants (presenters and non-presenters). Finally, Figures 3c and 3d show the funding networks for IGF presenters and non-presenters respectively. In Figure 3a, the size of startup nodes are scaled relative to total funding raised. In these network graphs, startups that are highly connected with the venture capital community (i.e., received investment from a large number of VCs) are located close to the center of the graph. Those with fewer investors are located on the outer edge of the graph. On visual inspection of the entire network of clean technology investment (Figure 3), IGF presenters appear to be highly networked, situated close to the center of the graph. In fact, as can be seen in Figure 3c, most IGF presenters form a large network with VCs.

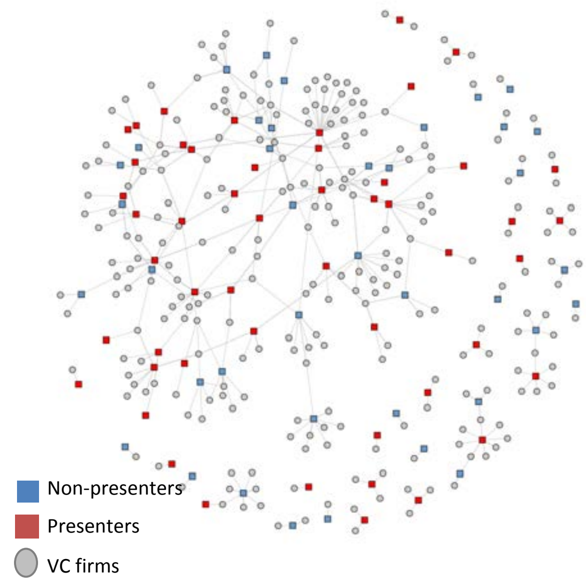
[14]The igraph library allows for complex network analysis (http://igraph.sourceforge.net/).

[15]It should be noted that Bloomberg New Energy Finance does not list investors for all 1,664 venture capital funding events over this time period. As such, our syndication network excludes the 340 venture capital funding events with no listed investor.

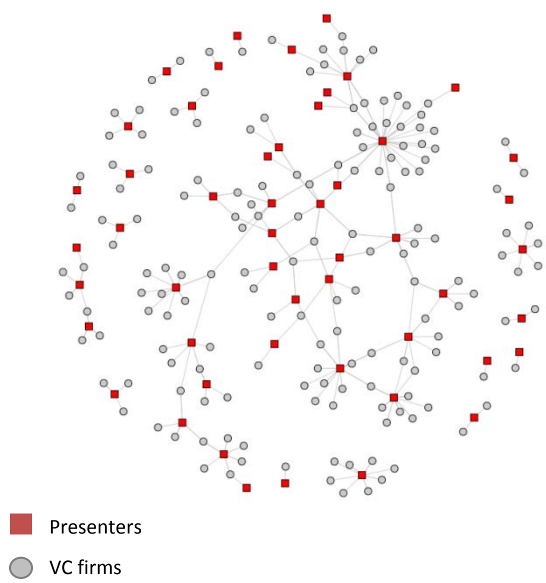
Figure 3: Network graph for clean technology venture capital syndication (2001-2010)



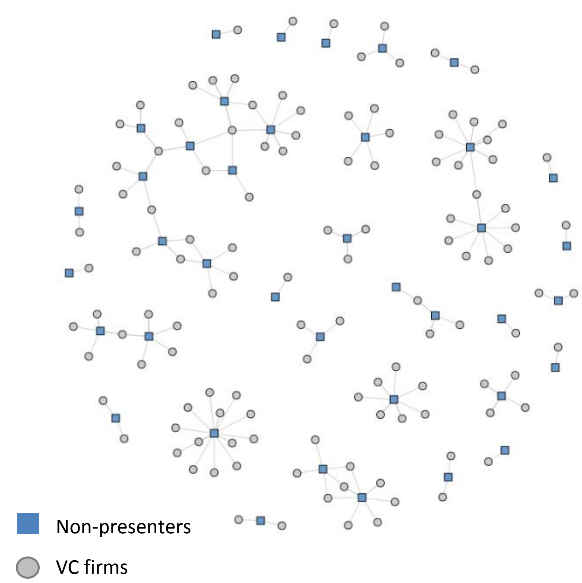
(a) All clean technology funding



(b) Funding syndication IGF applicants



(c) Funding syndication for IGF presenters



(d) Funding syndication for IGF non-presenters

After generating the funding graphs, we calculate the degree for each startup in the network analysis; a node's degree is the number of connections to other nodes. In our network, a startup's degree is the number of venture capital firms that have invested in that startup. Intuition suggests that startup degree is likely to increase as the company raises more and more funding.

To test for differences in funding syndication for IGF presenters and all other clean technology startups, we regress company degree on venture capital funding. We use NLS to estimate the relationship between funding and the number of investors, and fit the data with a variety of model specifications, including first- through fourth-order degree variables (D_i, D_i^2, D_i^3, D_i^4). We include a dummy variable (P_i) to estimate whether this relationship differs for IGF presenters, including dummy interaction terms up to the fourth-order degree variable (Equation 5).

We found no significance for any of the third- or fourth-order regressors and for most of the dummy variable interaction terms. As such, we only include second-order results in Table 5.

Table 5: Network regression results

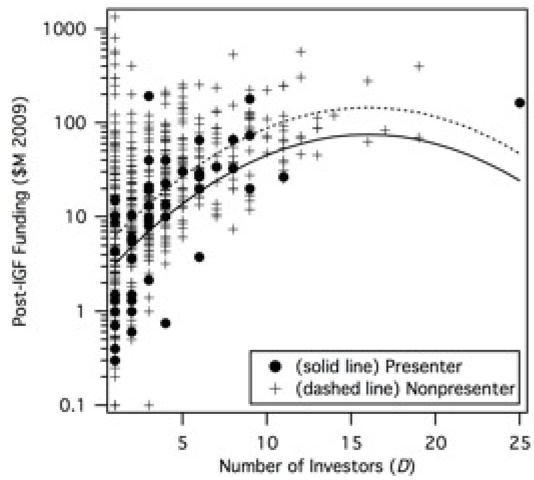
Variable	Eq. 5a	Eq. 5b	Eq. 5c	Eq. 5d	Eq. 5e
Constant	**1.719**	**1.766**	**1.343**	**1.398**	**1.381**
	(19.870)	**(20.350)**	**(11.927)**	**(12.382)**	**(12.241)**
Degree (D_i)	**0.257*** **	**0.26*** **	**0.450*** **	**0.448*** **	**0.47*** **
	(14.520)	**(14.790)**	**(10.767)**	**(10.792)**	**(11.053)**
Degree^2 (D_i^2)	-	-	**-0.014*** **	**-0.014*** **	**-0.017*** **
	-	-	**(-5.068)**	**(-4.965)**	**(-5.464)**
Presenter (P_i)	-	**-0.706*** **	-	**-0.663** **	**-1.177*** **
	-	**(-3.440)**	-	**(-3.294)**	**(-3.867)**
Presenter $*$ **Degree^2** $(P_iD_i^2)$	-	-	-	-	**0.127***
	-	-	-	-	**(2.244)**
Schwarz criteria	**2051.2**	**2045.8**	**2032.3**	**2027.9**	**2029.2**

***t*-statistics in parentheses**

*** *p* <0.05, ** *p* < 0.01, *** *p* < 0.001**

Our intuition only suggests that degree increases as companies raise more funding, so, again, we use the Schwarz criteria to select the nonlinear model that best fits the data. The model that minimizes the Schwarz criteria is listed as Equation 5d in Table 5, and is a second-order polynomial with the presenter variable only interacting with the constant term. The coefficient on the presenter variable is negative (-0.663) and significant at the α=0.01 level, meaning that the intercept differs for IGF presenters (see Figure 4). It should be noted that while $P_iD_i^2$ in Equation 5e was significant at the α=0.05 level, adding that term does not lower the Schwarz criterion, so that model was not selected. While not listed in Table 5, we tested additional model specifications, including the addition of a dummy variable for IGF non-presenters. The non-presenter variables failed to show any significance, which suggests that funding syndication for IGF non-presenters does not differ from the rest of the clean technology industry.

Figure 4: Total funding ($M 2009) by number of investors



Given the lower intercept term, for equal amounts of venture capital funding, the IGF startups have a higher degree. In other words, if one were to compare two clean technology startups with $13M in venture capital funding, the IGF presenter would have on average five investors while the other startup would have three investors on average. In short, IGF presenters are more highly connected with the venture capital community than average clean technology startups. The intuition behind this result is unclear but could be the result of several factors including increased competition for investment, better vetted business plans, or simply that presenting at the IGF reduces information asymmetries, thereby facilitating investment.

4 Conclusions

These results suggest that the IGF has a positive effect on venture capital funding. On average, startups that present at the IGF raise $4.4 million more than similar companies that applied but were not selected to present. These results do not change when we controlled for state-level fixed effects or for startup participation in the Cleantech Open. Additionally, the network analysis shows that IGF presenters have more investors than average clean technology startups, which we believe may be due to VCs competing to invest in IGF presenters. Finally, insofar as increased venture capital funding translates into improved technology transfer, the IGF seems to be an effective tool for NREL to support clean energy companies and the clean technology industry. Further work should compare the success of IGF companies using other metrics including successful capital growth and return, products and services delivered, as well as jobs created.

While these results provide some validation for the IGF, ultimately, this analysis does not predict the ability of these companies to achieve long-term success, or to predict the ability of these clean technologies to replace dirty technologies. Similarly, presentation at the IGF cannot be taken as an indication of a singular company's potential success future, but the IGF may serve as an effective tool to support technology transfer and company development. It appears that the IGF (and potentially other business competitions) is an effective tool at reducing the information asymmetries of venture capital markets. Just as presenting at the IGF is not a certain predictor of company success, the IGF alone is not a predictor of the efficacy of business plan competitions. Further work should analyze business plan competitions with different industry focuses or those competitions anchored at business schools to see how generalizable these results are.

While we are able to estimate a significant IGF treatment effect, we are uncertain on how to characterize the form of treatment effect. In short, what value does the IGF provide for startups? Unlike the CTO, which provides on-going mentoring and training as startups mature, the IGF is mostly a forum for companies to present their business plans to a national audience of potential investors. So, perhaps, companies benefit from the IGF as a networking tool. By presenting their business plans at the IGF, they are able to meet VCs that are interested in clean technology, and through those interactions are able to reduce information asymmetries and raise funding. If the IGF functions as a networking tool, then perhaps the clean technology industry would benefit from more business plan competitions. Our anecdotal evidence suggests that startups that participate in the CTO have a higher selection rate at the IGF. If further work and more years of data prove this to be true, then this suggests that these business plan competitions form an effective funding pipeline for startups to transition from seed- to late-stages.

Finally, from a public policy perspective, if the IGF had no significant effect on startup funding, then DOE funds spent on the IGF might be better used in some other activity. These positive results suggest an additional way for the Department of Energy to facilitate the adoption of clean technologies beyond the funding of research and development.

Acknowledgements

We would like to thank L. Marty Murphy, Rachel Gelman, and Mackay Miller of NREL; and Rex Northen and Annamaria Konya of the Cleantech Open for providing lists of applicant companies and the judges' scoring data.

References

Admati, Anat R., and Paul Pfleiderer. 1994. “Robust Financial Contracting and the Role of Venture Capitalists.” *The Journal of Finance* 49(2): 371-402.

Allen, David N., and Syedur Rahman. 1985. “Small business incubators: a positive environment for entrepreneurship.” *Journal of Small Business Management* (23)3: 12-22.

Bertrand, Marianne, and Esther Duflo, and Sendhil Mullainathan. 2004. “How Much Should We Trust Differences-in-Differences Estimates?” *Quarterly Journal of Economics* 119(1): 249-275.

Bygrave, William D. 1988. “The Structure of the Investment Networks of Venture Capital Firms.” *Journal of Business Venturing* 3(2): 137-157.

Bygrave, William D. 1987. “Syndicated Investments by Venture Capital Firms: A networking perspective.” *Journal of Business Venturing* 2(2): 139-154.

Carayannis, Elias G., Everett M. Rogers, Kazuo Kurihara, and Marcel M. Allbritton. 1998. “High-technology Spin-offs from Government R&D Laboratories and Research Universities.” *Technovation* 18(1): 1-11.

Card, David E. 1990. “The Impact of the Mariel boatlift on the Miami labor market.” *Industrial and Labor Relations Review* 43: 245-257.

Chan, Yuk-shee. 1983. “On the Positive Role of Financial Intermediation in Allocation of Venture Capital in a Market with Imperfect Information.” *Journal of Finance* 38(5): 1543-1568.

Eissa, Nada and Jeffrey B. Liebman. 1996. “Labor Supply Response to the Earned Income Tax Credit.” *Quarterly Journal of Economics* 111: 605-637.

Fiet, James O. 1995. “Risk Avoidance Strategies in Venture Capital Markets.” *Journal of Management Studies* 32(4): 551-574.

Foo, Maw Der, and Poh Kam Wong, and Andy Ong. 2005. “Do others think you have a viable business idea? Team diversity and judges’ evaluation of ideas in a business plan competition.” *Journal of Business Venturing* 20(3): 385-402.

Jin, Ginger Zhe, and Phillip Leslie. 2003. “The Effect of Information on Product Quality: Evidence from Restaurant Hygiene Grade Cards.” *Quarterly Journal of Economics* 118(2): 409-451.

Kaplan, Steven N., and Per Strömberg. 2003. "Financial Contracting Theory Meets the Real World: An Empirial Analysis of Venture Capital Contracts." *Review of Economic Studies* 70: 281-315.

Lerner, Joshua. 1994. "The Syndication of Venture Capital Investments." *Financial Management* 23(3): 16-27.

Murphy, L.M., and P.L. Edwards. 2003. " Bridging the Valley of Death: Transitioning from Public to Private Sector Financing." NREL/MP-720-34036.

Nemet, Gregory F. 2009. "Demand-pull, Technology-push, and Government-led incentives for Non-incremental Technical Change." *Research Policy* 38: 700-709.

Porter, Michael. 1998. "Clusters and the New Economics of Competition." *Harvard Business Review* Nov-Dec 1998.

Sahlman, W.A. 1988. "Aspects of Financial Contracting in Venture-capital Organizations." *Journal of Financial Economics* 27: 473-521.

Salmenkaita, Jukka-Pekka, and Ahti Salo. 2002. "Rationales for Government Intervention in the Commercialization of New Technologies." *Technology Analysis & Strategic Management* 14(2): 183-200.

Trester, Jeffrey J. 1998. "Venture Capital Contracting under Asymmetric Information." *Journal of Banking & Finance* 22: 675-699.