Signaling by Early Stage Startups:
US Government Research Grants and Venture Capital Funding

Abstract

Entrepreneurship researchers have documented that early stage startups rely on signals to demonstrate the transitions in their identities that they must make when they cross organizational life cycle thresholds. However, early stage startups in emerging industry contexts tend to have few good signals upon which to rely. Public agencies can play a valuable role in this process, but prior research has not sufficiently examined how startups effectively leverage this support. In this paper, therefore, we develop a framework to investigate the role that signals can play for early stage startups when they win prestigious government research grants. We test this framework in the setting of the emerging U.S. clean energy sector and find that in comparison to a matched sample of clean energy startups that have not won prestigious research grants, startups with these grants were 12 percent more likely to acquire subsequent venture capital (VC) funding. Another significant result is that the value of this signaling is greater for startups that have fewer patents. The important contribution of this finding is that it shows that signaling has the potential to *redistribute* benefits rather than just provide an additional accrual of advantages to the already high status actors. Together these results highlight the advantages for startups in emerging industries of pursuing signaling strategies with public agencies when they attempt to make important transitions through the stages of their organizational life cycles.

Signaling by Early Stage Startups: US Government Research Grants and Venture Capital Funding

1. Introduction

Early stage startups seeking to acquire resources struggle to demonstrate the legitimacy they need to transition from conceptualization to commercialization (Kazanjian, 1998; Fisher et al., 2016). They must efficiently cross thresholds over the organizational life cycle to assure their survival and growth. Entrepreneurship researchers have demonstrated that the strategies they use to cross these thresholds involve costly efforts to signal the quality of their ventures (Plummer et al., 2016; Rao, 1994; Stuart et al., 1999). They must take initiatives that demonstrate their technology and market potential in order to overcome informational disadvantages and to distinguish themselves from their peers (Marcus et al., 2013). However, the strategic use of signals is nuanced and depends upon the resource requirements at particular stages of development. Early stage startups that have yet to commercialize a technology or secure clients have few signals available to them. As a result, it is not surprising that much of the academic attention has been placed on signaling strategies by later stage startups that are frequently found in mature industries. Such firms are more likely to have attained signal-worthy accomplishments and have a willing audience of knowledgeable resource providers to interpret and respond to such signals. This paper departs from this literature by advancing the notion that early stage startups in emerging sectors also have signal-worthy options. These signals are founded within their affiliation with third-party institutions. These institutions bestow upon selected startups the tangible and symbolic resources they need to transform their identities and promote the legitimacy they seek.

The strategic use of signals by startups can be based more upon the prominence of the third-party institution they affiliate with than the on-going support or monitoring that these institutions provide (Higgins and Gulati, 2003; 2006). For early stage startups, these institutions are increasingly public agencies that tend to hold broader social and economic objectives than the commercial success of a particular startup. The startups that public agencies choose to support reveal the agency's policy preferences and priorities. In the past, these preferences and priorities shaped the trajectory of emerging technology industries such as semiconductors and flat-panel displays (Murtha et al., 2001; Lerner, 2009).

In this paper, we study the value that signals have for startups in an emerging technology industry by examining the impact of government research grants on the recipients' ability to attract subsequent venture capital (VC) funding. Competition among research proposals is substantial with leading experts drawn from academia, public and private domains to make the assessments.[1] Startups that prevail in this competition typically are funded for well-defined technical projects that have clear guidelines on how to use the funds awarded. Winning such a grant is an important and highly sought after recognition that is well-publicized and elevates the startup's status.

Winning the grant is important because startups that win them can, at their discretion, use the award as an externally-validated signal of accomplishment. While using the funds to advance their technology, they can catalyze efforts they must make to establish new sets of ties with key resource providers (Hallen and Eisenhardt, 2012). The information revealed via the granting process can bolster the objective data available about startups and substitute for those that lack such data when startups transition from conceptualization to commercialization stages.

[1] For instance, the initial grant solicitation by the Obama Administration's Advanced Research Projects Agency-Energy (ARPA-E) in 2009 received 3700 applications for its first round of 37 grants. Its assessment team included a thermodynamics expert from Intel, a Massachusetts Institute of Technology electrical engineering professor, a clean-tech venture capitalist, a nanotechnology professor from the University of California, Berkeley, and a biochemistry professor from Duke University.

Specifically, we make the novel proposition that a government research grant can substitute for a history of patenting and that VCs are receptive to this type of signal. VCs value this alternative information and identify grant-winning ventures as technologically competent and have increased confidence the grant winners will be able to make the transition to market-oriented norms (Fisher et al., 2016). Moreover, signals from further in the past are drowned out by prior signals and are less likely to resolve critical uncertainty and promote a startup's legitimacy that underlies VCs' funding decisions.

We empirically test predictions on the relationships between government grant award announcements and VC funding decisions of startups in the U.S. clean energy sector from 2005 to 2011. Using a propensity score matching approach, we find that startups that received government grants were more likely to receive subsequent VC funding than similar startups that did not receive grants. We also find that VCs acted relatively quickly in response to grant announcements, as the effects we found were most pronounced in the two-quarter periods following receipt of the grants. Moreover, our findings show that the benefits were most distinct for startups with fewer patents.

Our study makes several contributions to the entrepreneurship literature on resource acquisition and signaling. First, we examine how early stage startups leverage support from third-party organizations, like public agencies, to generate valuable signals of venture quality and build the legitimacy needed to establish ties and obtain funding from key resource providers. We show that the benefits were most distinct for startups with fewer patents and thus demonstrate that signals from government grants redistribute benefits rather than provide a Matthew Effect-like accrual of advantages to already high-status actors (Merton 1968; Bothner et al., 2011). In addition, we contribute to the theory of entrepreneurial resource acquisition (e.g. Lounsbury and

Glynn, 2001; Villanueva et al., 2012) by integrating it with an organizational life cycle stages framework (e.g. Greiner, 1972; Kananjian and Drazin, 1990; Koberg et al., 1996; Fisher et al., 2016). In doing so, we show how government grants can be especially useful in emerging industry contexts where the transition from conception to commercialization is pronounced. Finally, we demonstrate how winning a contest, like a grant competition, can be used effectively as a proof point in tie formation (Hallen & Eisenhardt, 2012). We provide support for contests and grand innovation challenges (Boudreau et al., 2011; Murray, Stern, Campbell and MacCormack, 2012) as increasingly popular methods to rapidly progress technology development.

In the sections that follow, we develop a theoretical framework that focuses on use of signals as proof points in tie formation with external resource providers. We then describe the empirical context, data, and methods we used, provide the results, and conclude with a discussion of implications.

2. Theory and hypotheses

2.1 Identity transition for startups in emerging industries

Startups are beset with vast challenges that stem from a lack of operation and production history (Santos and Eisenhardt, 2009; Zheng et al., 2010; Zott and Huy, 2007; Villanueva et al., 2012), limited knowledge of their environments (e.g., Stinchcombe, 1965), insufficiently developed relationships with suppliers and customers (e.g., Aldrich and Auster, 1986), and immature and unrefined methods and routines (Aldrich and Fiol, 1994). These challenges are magnified for early stage startups in emerging industries as they struggle to validate unproven technologies and commercialize products in nascent markets.

Inherent to these challenges is the necessity for these startups to effectively transform their identities over time to ones congruent with the new audiences from which they seek to obtain resources. The nature and degree of legitimacy required as new ventures mature must evolve with the expectations of different audiences and with the requisite norms, standards and values that prevail at different startup life cycle stages (Fisher et al., 2016). For instance, the factors that make early stage ventures successful in attaining needed resources in a university incubator setting are less likely to be effective during later startup life cycle stages. From this perspective, the survival and growth of startups from conception through commercialization and long-term growth is a chameleon-like process where startups cross legitimacy thresholds within each stage of their development as they meet the increasing and distinct demands of different resource providers.

Unlike earlier conceptions of the dynamics of venture legitimacy (Zimmerman and Zeitz, 2002), the evolving expectations view of different resource providers helps to better explain failure as startups struggle to redefine their identities in response to changing legitimacy criteria in life cycle stage transitions. This perspective highlights those critical junctures that startups encounter as they attempt to survive and grow (Vohora et. al, 2004). In addition, it builds upon research in stage-based models of new venture development because changes are required in routines and practices to ensure successful progression to the following stage (Van de Ven et. al, 1984). Furthermore, this perspective brings focus to the challenges that startups encounter when straddling life cycle stages as they are pushed to maintain multiple identities to satisfy their incumbent resource providers while trying to make themselves attractive to potential, new resource providers. Periods of transition between life cycle stages can be particularly tenuous as split identities may confuse both current and new resource providers who may question the legitimacy of the venture resulting in confusion brought on by institutional pluralism (Kraatz and Block, 2008; Fisher et al., 2016). Survival is contingent on timely transitions between stages because the longer startups have their legitimacy questioned, the more likely they will encounter obstacles in obtaining the requisite external resources.

Industry context further influences how timely these transitions can be made. Mature industries are teeming with comparable organizations that act as ideal types against which prospective resource providers compare transitioning startups. Additionally, startups in these industries are more likely to have experience through previous ventures that can be used as evidence for achieving efficient identity transitions. The benefits available in mature industries have less influence in emerging industries as appropriate norms, values, and practices still are being established and fewer comparable organizations have transitioned between stages. To further complicate matters is that gaining scale in emerging industries is likely to be difficult and costly as the ecosystem of suppliers, manufacturers and distributors is still underdeveloped (Murtha et. al, 2001). The result in emerging industry contexts is that transitioning startups may have to straddle identities for longer durations. That is, they face greater uncertainty than companies in mature industries, leading to higher failure rates. Therefore, the dynamics of venture legitimacy are explained both by evolving expectations of different audiences at different stages of the life cycle (Fisher et al., 2016) and the differences in the degree to which startups have to endure institutional pluralism, which varies by the stage in industry development.

2.2 Using signals to bridge identity transitions

Startups in emerging industries that are seeking to bridge stages of development and avoid protracted periods of institutional pluralism often engage in projective strategies aimed at establishing key relationships. These relationships minimize the information gap between themselves and prospective resource providers (Rawhouser et. al, 2016). Startups that are able to more efficiently establish ties with resource providers can focus their scarce resources on improving their operations rather than obsessing over tie formation (Hallen and Eisenhardt, 2012). These startups often are challenged, however, at demonstrating unambiguous measures of their potential and consistency with organizations that resource providers would deem legitimate (Stuart et al., 1999).

Heightened imperfections in the informational environment of emerging industries create substantial asymmetries between startups and resource providers. Past research has shown how startups can overcome these informational asymmetries with costly and informative signals that potential investors and financial markets take seriously when making resource allocations (e.g., Shane and Stuart, 2002; Gulati and Higgins, 2003; Plummer et al., 2016). These signals have included affiliations with prestigious investment banks (Pollock et al., 2010) and private equity placements (Janney and Folta, 2006). They involve corporate governance characteristics (Sanders and Boive, 2004), business plan comprehensiveness (Kirsh et. al, 2009), and length of IPO lockup periods (Arthurs et. al, 2009). These signals boost the reputation of startups because their track records are short and emerging sector contexts often means that they are pursuing commercialization of technologies whose merits have not yet been proven.

The value placed on a signal comes from its ability to resolve a critical uncertainty about the startup's prospects and its likelihood to effectively transition venture life cycle stages. Hallen and Eisenhardt (2012) demonstrate how startups adopt strategies to catalyze ties with investors by timing their interactions around proof points when the startup is best able to signal a "substantial accomplishment of an unusually critical milestone that is validated by an external party." For these proof points to be effective in establishing ties with investors, the accomplishment is typically related to an identity-transforming event that launches the startup towards its next stage of development. Such a signaling strategy can be especially important when a startup lacks strong direct ties with resource providers, which often is the case in an emerging sector context.

2.3 The signaling value of government grants as a proof point

Much of the attention of the extant research on signaling strategies has been placed on startups at later stages of their life cycle and in mature industries (Sanders and Boivie, 2004; Arthurs et. al, 2009; Certo, et. al, 2009). This focus is not surprising as these settings provide greater opportunity to engage resource providers, such as VCs or institutional investors, and the startups are more likely to have attained signal-worthy accomplishments. Although the importance of these accomplishments makes it appear that such strategies may be limited for early stage startups in emerging industry contexts, in this paper we suggest that an alternative source of external validation does exist. It may come in the form of research grants from public organizations that support startups with high degrees of technical and commercial uncertainty (Graffin and Ward, 2010) and are motivated by efforts to accelerate the pace of innovation and to promote national competitiveness. Such policies enabled the U.S. government to accelerate needed technologies in emergent industries such as semiconductors, telecommunications, electronics, and the Internet (Henderson and Newell, 2011; Fabrizio and Mowery, 2007). Government agencies design competitions to attract promising startups that are seeking funds to advance their technologies to commercialization. These competitions not only apply the internal scientific and technical capabilities of public agencies but also draw on highly prestigious external review partners that are able to better inform the process (Pahnke et al., 2015; Howell, 2014).

Studies have demonstrated that the grant selection process is highly competitive and based on meritorious criteria (Hsu, 2006), often involving startups undergoing numerous rounds of rankings by expert teams that are shielded from overt political pressure. The outcome of this vetting conveys a strong signal of scientific and technical merit and provides useful information for prospective VCs seeking to invest in startups (Lerner, 1999; Feldman and Kelley, 2003). Winning a grant provides successful startups with the type of unique and externally substantiated accomplishment that their management can use in trying to establish and catalyze ties with prospective VCs should they be actively seeking venture funding. If such relationships are already underway, the grants function as proof points that further expedite the process.

The signaling mechanism that underlies this proof point emanating from the receipt of a government research grant has attributes that are typical to the signaling literature but yet some differences are worth noting. Unique to this context is that the signal is a result of the joint process of a startup applying for a grant and then having its technology validated by winning the contest. The latter step introduces an external gatekeeper into the signaling mechanism, who conceptually should prevent low quality startups from being able to falsely signal a higher quality type and benefit from this strategy. Consequently, the mechanism considered here should only benefit high quality startups and prevent a noisy signaling environment that would undermine a signal's value. Therefore, while the mechanism, by design, does not allow for a test of the traditional separating equilibrium it does ensure that we do not observe a pooling equilibrium that prevents outsiders from distinguishing startup types.

This signaling mechanism, nevertheless, does espouse the two central characteristics of an efficacious signal: observability and costliness (Connelly et. al., 2011). The attainment of a coveted grant is clearly observable as the announcement of recipients is well publicized by both the public agency dispensing the grant and recipient firms' public relations efforts. VCs are now made aware that the startup applied for the grant and was successful at impressing a highly discerning evaluator. Furthermore, seeking out and positioning to win a grant is a costly process, especially for early stage startups that have limited resources for activities that are outside their core priorities. These costs, however, are different from those typically considered in the literature. Government applications are comprehensive, multi-staged, and can be expected to take ten to twelve weeks of dedicated effort to complete (National Academies of Sciences, Engineering, and Medicine, 2016). Success in the grant process can take practice, which may involve multiple iterations of failing applications before finally reaching a successful result. Yet the successful completion of this costly process brings with it two features that are coveted in the signaling literature: a veracious signal (Busenitz et al., 2005) that is accompanied by a valuable interorganizational tie (Park & Mezias, 2005).

The case of Alphabet Energy, an early stage clean tech startup, in the late 2000s is revealing about this signaling process. This San Francisco-based startup was in its early stages of development of a waste-heat recovery technology that had the potential to vastly reduce the cost of present technologies. The technology had potential applications in the automotive, aerospace, power generation, and manufacturing sectors. Shortly after its founding in 2009, Alphabet Energy successfully applied to the U.S. Department of Energy (DOE) for a research grant of $150,000 to support its technology. As part of the celebratory announcement of the grant, Alphabet Energy took the opportunity to publicly point out that the "award represents the growing recognition— at the highest levels of energy and technology policy— of heat as a valuable resource in a wide range of industrial sectors" (Alphabet Energy, 2010a). The government relationship brought with it ties to the U.S. Army and Navy, who might become important customers for the startup's technology. A short three months after receiving the grant, Alphabet Energy secured $1 million in seed financing from Claremont Creek Ventures to support manufacturing a commercial prototype which would help the company transition to the commercialization stage (Alphabet Energy, 2010b). Although the startup was known to the VC community, the information that the award revealed signaled an accomplishment which provided further proof about its prospects and offered more details about the venture's quality. The grant positioned the startup to transition its identity from the logic of conceptualization to the logic of commercialization and in this way it helped to attract needed resources from a well-reputed VC.

Prevailing in the competition for an award such as the one Alphabet Energy won, reveals novel tacit information about young firms on multiple dimensions. First, the award of the grant demonstrates the industriousness and vision of the management team that has sought out this form of support, when more traditional forms may not be available. Successful grant applications send strong signals because VC funding decisions of early stage startups are not necessarily swayed by sound business plans but by strength of the management team (Shepherd, 1999; Chen et. al, 2009, Kirsch et al., 2009). Second, the grant award signals that the startup will display a high level of discipline and sound governance because it is accountable to public oversight and responsible for periodic activity reporting about the use of funds (Lerner, 1999). This obligation can be attractive to VCs, as the government provides oversight, yet is not mandated to meddle in the startup's activity. Finally, government support for a startup is likely to indicate a preference for a specific technology (e.g., solar power), which VCs may, in turn, interpret as a direction for future policy support that will continue to benefit the recipient startup. Together, these signals that are conveyed by a startup prevailing in a contest for a government research award position it to transition its identity from the logic of conceptualization to the logic of commercialization.

Once its identity is more firmly rooted in the latter stage, it is better able to attract the needed financial resources from VCs and avoid the issues associated with prolonged institutional pluralism.

> *Hypothesis 1: Startups in an emerging sector that are able to signal the support of a public agency are more likely to receive VC funding in a subsequent period compared with competing startups that do not have such a signal.*

2.4 The dynamic value of a signal

The prior hypothesis conforms well to existing literature. Where the literature on signaling amongst startups has been relatively silent is on the dynamic aspects of this resource acquisition strategy. The focus has been on the observability and costly nature of the signal and its ability to reduce information asymmetries. Yet, the value of this information can diminish over time as new information is revealed and context changes. In their study of the signaling value of private placements by post-IPO firms, Janney and Folta (2006) recognize that the value that underlies a signal at one point in time may erode if the assumptions under which it was assessed have changed. The recency of information, thus, takes on relevance because recency is able to resolve a critical uncertainty of immediate concern (Kahneman, et. al, 1982; Pollock, et. al, 2008). Once the information is even slightly dated, it may have less influence.

Spence's (1973) original treatise on signaling in which he focuses on education as a signal to the job market is inherently dynamic as it involves a learning process. In his model, the employer's expectations of potential employees and the value of an education are continuously updated as new data arrives from iterations of applicants and the performance of previously employed ones. However, as the context of the organization evolves and further confounding information is revealed, the value of prior signals becomes less pertinent (Feldman and Kelley, 2003). As a result, should applicants choose not to swiftly leverage their costly and informative signal to seek employment, they risk challenges in the future job market. Therefore, agency is required by applicants to use the signal and benefit from the cost that they incurred in attaining it.

For a startup in an emerging sector that seeks to establish a tie with a VC, the cachet associated with attaining a government grant is an accomplishment that the startup has to swiftly act upon if it desires to attain VC funding and avoid the complications of further institutional pluralism. The signal that the grant presents offers a bridge to a new identity and to later stages in the venture's life cycle by demonstrating technological progress, market potential, and consistency with future policy preferences. Such startups are now armed with new funds and relationships that distinguish them from others and enable options that were not previously available. Hallen and Eisenhardt (2012) identified how tie formation strategies that time efforts around meritorious proof points are amplified by recency of information revealing events. The premium placed on recent information is consistent with the argument by Pollock et al. (2010) who provide an attention-based explanation for the value of signals. Although casual conversations or even negotiations may have been ongoing between startups and VCs, a startup empowered by the signal of obtaining a prestigious grant would likely now seek to quickly finalize a round of funding.

From the VC perspective, their capacity to achieve extraordinary returns is contingent on their ability to quickly identify and invest in the most promising startups (Gompers and Lerner, 2004). Therefore, we expect that effective use of a signaling strategy around proof points, such as the receipt of a prestigious grant, has to be acted upon quickly. Accordingly, the signaling value of receiving a research grant from a public agency is likely to be most pronounced shortly after receipt, when signal fidelity is greatest.

Hypothesis 2: The signaling value created by the support of a public agency upon subsequent VC funding will be most pronounced in the period immediately following the receipt of that signal.

2.5 Characteristics of the Startup

Startups vary in the perceptible attributes on which venture capitalists rely to evaluate their legitimacy and make investment choices. Hence, informational problems vary for different startups as does their ability to effectively transition across identities. We posit that the signal from a public agency helps to reveal further legitimizing information about a startup's underlying technology. Therefore, if a startup lacks easily attainable information on this attribute, it is more likely to engage in a strategy of tie formation focused on a proof point such as obtaining a government grant as it otherwise suffers from uncertainties surrounding its prospects.

Venture capitalists are attracted to the most technologically competent startups with strong commercial prospects. One objective measure of firms' technical outputs is their patenting activity (Heeley et al., 2007). Previous research has demonstrated that startups with higher numbers of patents are more likely to obtain VC funding (Kortum and Lerner, 2000; Engel and Keilbach, 2007; Cockburn and MacGarvie, 2009). Startups that more actively patent their technologies are prioritized in VC funding decision and are able to raise more backing from investors (Baum and Silverman, 2004; Mann and Sager, 2007). The underlying assumption is that firms with many patents have greater scientific capability and are likely to have high-quality scientific staff who are able to consistently develop cutting-edge technologies (Arthurs et al., 2009). However, startups that are still progressing towards the commercialization stage are less likely to have had the opportunity to protect their intellectual property let alone develop a robust portfolio of patents. In an emerging sector context, many of these startups rely on basic research as they explore various novel commercial applications that they would continue to innovate. This dependence can contribute to the larger gap that such startups must traverse as they cross the stages from conceptualization to commercialization.

The lack of a technological track record challenges efforts at tie formation with VCs who are seeking demonstrated technological progress. As a result, although tie formation strategies that embrace critical milestones may be universally beneficial, they are likely to be inordinately valuable to startups that face greater uncertainty surrounding their prospects due to few or no patents. Such ventures may be just as prepared as those startups with patents to transition to a later stage but suffer to a greater degree from informational asymmetries and would benefit more from the external validation embedded in the signal of a grant from a public agency.

> *Hypothesis 3: The signaling benefits associated with the support of a public agency will be more pronounced for those startups with fewer patents or no patents than for their cohorts with many patents.*

3. Methodology

3.1. Empirical context

The empirical context to test our hypotheses' is the U.S. clean energy sector. It was still emerging in the period we carried out our study, and thus the information asymmetry between startups and venture capitalists is higher compared with more established industries. The startups we examine are from biofuels, energy efficiency, geothermal, materials, solar, storage, tidal, wind, fuel cells, membranes, and smart grid subsectors. This sector is distinct because the initial capital requirement for technology development is comparable with the capital needed for information or biomedical technologies, yet commercializing this technology incurs both significant costs and longer lead times (Kirsner, 2010). The commercialization costs can often run ten times as large as the initial development cost, creating an insatiable need for capital, well before a proven track record is established (Ghosh and Nanda, 2010).

The U.S. government also has played an active role in supporting the sector. Over the past decades, the government, especially the DOE, has provided various forms of support, from the funding of basic science in national laboratories, to the liberalization of the wholesale energy markets that encouraged renewable energy development, and, providing research grants directly to startups.

3.2. Sample

We extracted the data sample of startups from Energy Acuity's *Power Database.* This database contains the most comprehensive information on clean energy startups that have received government research grants. To ensure the startups in our sample were truly in the emerging clean energy sector, we cross-checked the nature of their activities from the profiles in the Energy Acuity's databases and in two other proprietary databases: Cleantech Group's *i3 Platform* and Bloomberg's New Energy Finance's *Insight Data*. When data were incomplete, we examined the information from company websites and the *Bloomberg Businessweek* Private Firm database. In some cases, we contacted the firms to ensure the validity of our coding.

For our empirical analysis, we applied the following criteria to include a firm from Energy Acuity's *Power Database* as a startup. First, we eliminated all firms that were older than ten years as of 2010. Second, the organization had to have purely commercial aspirations with an intention to seek VC funding so we eliminated educational institutions, public research laboratories, and non-profit research institutions. Third, we omitted all foreign entities because the U.S.-based startups would only qualify for U.S. government grants. Based on this information, we created quarterly panel data for each of the qualifying startups starting from the date of founding.

3.2.1. Dependent Variable

To examine whether government research grants increase the likelihood of obtaining subsequent VC funding (H1), we created a set of binary indicator variables that were set to 1 if a startup receives any VC funding: (a) within the first two quarters, (b) between quarter three and four, or (c) between quarter five and six following a focal quarter, and set to 0 otherwise. These variables are named *VC_1-2Q*, *VC_3-4Q*, and *VC_5-6Q*, respectively. That is, for each focal quarter, we look ahead to first two, third and fourth, and five and six quarters' time windows to observe whether the startup received any VC funding. Startups that had already received VC funding in an earlier quarter (i.e. *VC_1-2Q*) are subsequently removed from the analyses for the later windows because those startups are less likely to receive another round of VC funding during the following quarters. The three mutually exclusive and progressively distant time windows enable us to test the dynamic element of our predictions (H2). We also coded a categorical variable (*VC_2_4_6_Q*) that we set to 0 if a focal start-up does not receive any government grant, while we set it to 1, 2 or 3 when the startup received grant in within the first two quarters, between quarter three and four, or between five and six, respectively. We use this alternative categorical variable in the robustness checks. Data on the timing of VC funding came from the proprietary databases referenced above.

3.2.2. Independent Variables

The key independent variable is *GRANT*, a binary indicator variable that identifies whether a startup received a government research grant from one of the agencies in a focal quarter. This variable was set to 1 if a startup received a grant in that quarter, and set to 0 otherwise. We sourced the information on research grants from Energy Acuity's *Power Database* and confirmed it using the U.S. federal government's www.grants.gov website. Our analysis includes 128 government grants: 101 (78.9%) are DOE grants, 11 (8.6%) are the Department of Defense (DOD) grants, and the remaining 16 grants are from various other agencies.[2]

To examine how patents may influence the signaling effects of government research grants (H3), we created *PATENTS*, a continuous variable that counts the cumulative number of patent applications a startup has made since its founding. We sourced the patent data from the *PatentEdge* database. Although an increase in the number patents applied for would increase a startup's knowledge pool, this increase is likely to be at a decreasing rate. We transformed this variable logarithmically to account for this non-linear relationship.

3.2.3. Control Variables

We include several control variables and fixed effects to account for observable and unobservable variation in the panel. First, we created a binary indicator variable, *PAST_VC*, that identifies whether a startup had previously received VC funding. It is switched from 0 to 1 when a startup received VC funding and is then set to 1 for the remainder of the panel. Second, we created a variable called *VC_FUND*, which is the cumulative amount of VC funding a startup received prior to the focal quarter. We transformed this variable logarithmically to account for the plausible non-linear relationship between the amount of VC funding and the likelihood of receiving a grant. Third, we included a binary indicator variable, *PAST_GRANT,* that is set to 1 if the startup had previously received a government grant, and 0 otherwise. Fourth, we included a

[2] The design of the grant processes across these agencies is quite comparable in their objectives and eligibility. However, some requirements do differ with respect to the expectations placed upon later stage startups that have applied for DOD funded grants for the third phase of grant awards. Such startups have an expectation of seeking alternative public or private funding in addition to the Phase III grant. In unreported analyses we focus exclusively on DOE grants, which do not have such an expectation, and find quantitatively and qualitatively similar results when the awards come solely from that source.

continuous variable, *AGE*, which measures the number of years since the founding of a startup. This variable is likely to account for the resources and capabilities that a firm may acquire as it ages. We logarithmically transformed this variable to account for a non-linear relationship between age and the likelihood of receiving VC funding. Fifth, a startup's likelihood of receiving VC funding is contingent on the overall venture capital market. Because the U.S. venture capital market follows a cyclic pattern, under the "hot" market condition, chances of receiving a round of VC funding would be higher (Gompers and Lerner, 2004; Nanda and Rhodes-Kropf, 2013). To account for this possibility, we control for the total amount of VC investment in a year (*TOTAL_VC*) in all sectors in the U.S. Finally, we included a series of fixed effects to account for unobserved variation that correlate with the receipt of a government research grant. These include regional effects (*REGION*), sectoral effects (*SECTOR*), and temporal effects (*YEAR*).

3.2.4. Empirical Strategy

The disbursement of government research grants is not randomly determined but involves an intensive application process initiated by the startup and a subsequent evaluation process performed by the government agencies. Therefore, estimating the impact of receipt of a grant on follow-on VC funding will be biased due to this endogenous selection process.

We use the propensity score analysis approach (Rosenbaum and Rubin, 1983), which accounts for this endogeneity issue by creating a matched-sample based on a set of observable factors (matching variables). Specifically, the underlying algorithm considers the matching variables and creates two groups of startups, both of which are equally likely to receive government research grants in a focal quarter, whereas, in reality, only one group received grants. We then estimate the effects of receiving a grant on follow-on VC funding in subsequent quarters using the matched sample to assess the hypothesized relationships.

The first step of this approach is to generate the propensity scores that we used to match between two groups— those that received grants and those that did not. For this purpose, we selected the following variables: whether the startup previously received VC funding (*PAST_VC*), previously received a government research grant (*PAST_GRANT*), the number of patents the startup applied (*PATENTS*), the age of the startup (*AGE*) and three fixed effects that identify the sector (*SECTOR*), U.S. region (*REGION*) and year (*YEAR*). We used a logistic regression, wherein the dependent variable is an indicator variable set to 1 if the startup received a government grant, and 0 otherwise. In the regression, we included all 128 startup-quarters, when startups received grants, and all other observations for startups that never received grants.[3] The conditional probabilities or nonzero propensity scores yielded from this step were used in the next matching process.

The second step involves the matching of each grant recipient startup-quarter with a different startup-quarter that did not receive a grant, based on the closeness of their calculated propensity scores in order to make the two groups as comparable as possible. We used the nearest neighbor approach within a caliper of 0.2 times the standard deviation matching without replacement. This step yielded 128 non-grant recipient startup-quarters that were used to create a matched sample of 256 observations. We chose the nearest neighbor within a caliper of 0.2 times the standard deviation of the logit of the propensity score and matched the sample without replacement. Austin (2011) recommended this to be the minimum caliper width to minimize the mean squared error (MSE) when at least one of the covariates is continuous, as in our case. Furthermore, this specification also yielded the most precise matching among the four alternative greedy matching algorithms (Guo and Fraser, 2010). We matched without replacement because

[3] During the sample period, out of 109 startups, 95 received one grant each, ten received two grants each, three of them received three grants each, and one startup received four grants.

we had a sufficiently large number of startup-quarters when startups did not receive grants compared with when they did (3,350 vs. 128), and we avoided adjusting for estimated variance in cases of multiple matches of untreated observations (Hill and Reiter, 2006).

The final step involves estimating a second set of logistic regressions to identify the likelihood of receiving follow-on VC funding using the constructed matched sample.[4] The estimated coefficient of the independent variable *GRANT* enabled us to examine the signaling value of government support (H1). We used differing dependent variables to assess the dynamic elements of the signal (H2). For control variables in this model, we included all the matching variables, and the total amount of VC funding the startup received in the past (*VC_FUND*) and the total amount of VC investment in the focal year across all sectors (*TOTAL_VC*). These controls are represented as the vector $\mathbf{X}_{it}$ in the equation below. Also included are regional and sectoral fixed effects. We estimated the following equation:

$$VC\_\#\_QUARTERS_{it} = \beta_1 GRANT_{it} + \beta_2 \mathbf{X}_{it} + e_{it} \qquad (1)$$

To assess the predicted relationship for H3, we estimated the same model as in (1) but included the interaction of *GRANT* with *PATENTS*. For this model, we estimated the following:

$$VC\_\#\_QUARTERS_{it}=\beta_1 GRANT_{it}+\beta_2 PATENTS_{it}+\beta_3 GRANT_{it}\_X\_\ PATENTS_{it}+\beta_4 \mathbf{X}_{it}+e_{it} \qquad (2)$$

4. Results

The first step of our empirical strategy was to construct a matched sample of startups that received government research grants and those that did not. For this first stage, we calculated

[4] As the dependent variables – three different time windows – are time dependent across periods, an alternative approach would be to estimate the model jointly with a multinomial logistic regression. The difference between these two approaches are subtle but substantive in testing our predictions. The primary difference is in the interpretation of the results as the logistic models conform better to the theoretical design. Thus, we preferred the logistic regressions specifications but in robustness checks we estimated a multinomial logistic model and found consistent results. We also find consistent estimates with event history model. These models are described in more detail as part of our robustness analysis.

propensity scores based on a regression of receiving grant (*GRANT*) on whether the startup received VC funding before (*PAST_VC*), number of patent applied for (*PATENTS*), whether the startup received a government grant before (*PAST_GRANT*), age of the startup (*AGE*), and fixed effects for geographic region, sector and year. Table 1 presents the estimates based on this specification in Model 1.

-------------------Insert Table 1 about here-------------------

Having received VC funding (*PAST_VC*) or government research grants in the past (*PAST_GRANT*) were positively correlated to receiving grants in the subsequent period. Similarly, the number of patents (*PATENTS*) that a startup applied for was also correlated to the likelihood of receiving a government research grant. We followed a more conservative approach in specifying the fixed effects in Model 2 by interacting the year and sector indicator variables to evaluate variation across years within different clean energy sectors. This alternative approach captures time variant features of particular sectors, such as if a sector is prioritized over others in the granting process. The three variables found significant in Model 1 remained so in Model 2.

We used propensity scores generated from Model 2 in our baseline analysis to construct a matched sample of 256 start-up quarters using the nearest neighbor matching approach. Among the matched observations, half of them received government research grants while the other half did not. The means and standard deviations of the matched sample are found in Table 2.

-------------------Insert Table 2 about here-------------------

An important identifying assumption of the matched sample approach is that the observable characteristics of the two groups match as closely as possible. To check whether the matched observations were statistically similar on the matching variables, we used a *two-sample t-test with equal variances* for continuous variables and a *two-sample test of proportion* for indicator variables. We found that the two sets of observations were statistically indistinguishable from one another on all the matching variables except for one of the regions (South Central) and one of the clean energy sectors (Storage). Considering that we use 25 matching variables, we can conclude that the propensity score approach yielded an appropriate matched sample. Table 3 presents descriptive statistics and a correlation matrix of the matched sample.

-------------------Insert Table 3 about here-------------------

Table 4 presents the estimates from logistic regression models using the matched sample. Models 1, 2, and 3 used the same covariates with different dependent variables—whether the startup received VC funding in first two quarters (*VC_1-2Q*), between quarter three and four (*VC_3-4Q*) or between five and six (*VC_5-6Q*). We refer to the first three models when testing Hypotheses 1 and 2, and the latter three models (Model 4, 5, and 6) to test Hypothesis 3, where we now have included the interaction term between whether a startup received a government research grant and the number of patents it applied (*GRANT_X_ PATENTS*).[5] As Zelner (2009) points out, interpreting the coefficients of interaction terms in a non-linear model, such as a logistic regression, is challenging and distinct from a linear model because neither the sign of the interaction coefficient nor the standard error provide direct information regarding the effect. Therefore, we used a simulation-based technique (Tomz et. al, 2003) to graphically depict the interaction and its standard errors in Figure 1. This technique was conducted in STATA using the

[5] Note that the sample size is reduced from 256 startup-quarter observations to 252 in Model 1 because two clean energy subsectors had no VC funding in the subsequent two quarters. As a result, the dependent variable has no variation, leading to exclusion of those observations. Similarly, in Model 2 and Model 3 observations drop to 173 and 159 respectively because there were no VC funding in two regions and three subsectors in the former case and two regions and two subsectors in the latter case. In addition, we also drop startups that had already received VC funding in an earlier quarter (i.e. *VC_1-2Q*) for the later windows because those startups are less likely to receive another round of VC funding during the following quarters. For the same reasons, the sample size is reduced in Model 4, 5 and 6. In an alternative analysis, we included three indicator variables to identify three dominant sectors (solar, biofuel, and storage) to avoid eliminating some of the observations, and found consistent results.

Clarify program that applies a Monte Carlo simulation to provide a more precise calculation of the probability distribution. It uses both the parameter estimates and variance-covariance matrix of the model to make 1000 random draws of estimates from a multivariate normal distribution. The simulated distribution is then used to estimate the predicted probability of receiving VC funding at specified values of the covariates (i.e. *PATENTS)*. Changes to predicted probabilities are then computed by finding the difference in predicted probabilities as discrete changes are made to these covariates. The logic of this procedure is analogous to a survey-based approach that is able to improve the accuracy of its estimate of a population by increasing sample size. However, in this case the focus is on the probability distribution, which when properly accounted for in nonlinear models, like a logistic regression, improves statistical interpretation. This approach to the interpretation is preferable to the analytical delta method which is technically demanding and can lead to biased results if the Taylor series is not approximated beyond the second order (King et al. 2000).

-------------------Insert Table 4 about here-------------------

Model 1 presents strong support for both Hypotheses 1 and 2. The coefficient of the key independent variable *GRANT*, whether the focal startup received a grant, is positive and significant ($p < 0.05$) in this model but not in either Model 2 or Model 3. Government grants are an effective signal during the two quarters following receipt of a grant but this effect is not apparent after the first two quarters. The economic significance of the signaling effect is noteworthy, as startups that received government research grants were, on average, 11.98 percent more likely to receive VC funding within two quarters, compared with their matched counterparts that did not receive grants.[6]

[6] Given the use of a non-linear estimator, we calculated the marginal effect of *GRANT* using the Margins postestimation command in STATA.

The coefficient of the control variable *PAST_VC*, whether the focal startup received prior VC funding, is positive and significant ($p < 0.01$). This suggests that having received prior VC funding enabled those startups to demonstrate their identity and legitimacy to some extent in the market for entrepreneurial finance, leading to subsequent rounds of funding. We checked whether multicollinearity between *VC_FUND* (cumulative VC funding), and *PAST_VC* (whether the focal startup previously received VC funding), biased our estimation by calculating the variance inflation factors (VIFs). None of the VIFs was above 10, the commonly used maximum limit. In addition, we included these two variables separately in Model 1 and found that the positive coefficient of *GRANT* variable remains significant ($p < 0.05$) in both cases.

Models 4 to 6 show estimations of the conditional relationship where we interacted *GRANT* with *PATENTS*. As discussed above, standard approaches cannot be applied to interpret these coefficients thus we defer interpretation to the graphical representation in Figure 1. This figure is constructed using the output of the simulation based approach that depicts the difference in the predicted probability of receiving VC funding in the following two quarters between startups that received government grants and those did not. We focus on applying this approach to Model 4 because we argue for the immediacy of the signaling effect. In an unreported analysis, we applied the same approach to Models 5 and 6 and found the interactions were not statistically significant for the other two time-windows.

In Figure 1, the x-axis represents the range of *PATENTS* (logged number of patents a startup applied) and the y-axis represents the difference in the predicted probability in receiving VC funding in the following two quarters between startups that received government grants from those that did not. The fact that the values of the solid line are positive (i.e. difference in the probability is greater than zero) throughout its range is consistent with our earlier finding but also demonstrates that for a given level of patenting the grant recipients are more likely to receive follow-on VC funding. The downward slope, however, represents the interaction effect and indicates that the difference in this positive probability of follow-on VC funding between grant and non-grant recipients decreases as the number of patents increases. The dotted lines above and below the solid line represent a 95 percent confidence interval; the bottom dotted line (representing the lower bound of the confidence interval) crosses the zero threshold at 2.1 patents which identifies that this conditional relationship is only statistically significant ($p < 0.05$) for startups scoring between 0 and 2.1 on *PATENTS*. Given that this measure is a natural logarithm, this finding corresponds to a range of startups that have not applied for any patents to those that have applied for up to seven patents. When we look a little closer at the values of the difference in probabilities that underlie this figure we can begin to better understand the economic significance of this finding. For instance, the left most point of the solid line on Figure 1 demonstrates that a grant recipient startup with no patent applications would be seven percent more likely (i.e. the value of the y-axis is 0.070) to receive follow-on VC funding in next two quarters than a similar startup that has not received a grant. However, this privileged position as represented by the difference in the predicted probability of receiving VC funding for a grant recipient relative to a non-grant recipient decreases by 15 percent (i.e. the value of the y-axis is 0.059) when we move across the line to the end of its statistical significance where the startups are at 2.1 on the *PATENTS* measure. This finding offers support for H3.

-------------------Insert Figure 1 about here -------------------

4.1 Robustness Tests

In this section, we conduct a series of robustness tests to ensure that the above findings are not contingent on the specific choices we made in our empirical analysis. Our focus in this discussion is on the main effects (H1 and H2), but the findings apply across generally to include the conditional relationship (H3).

First, we considered alternative estimators to assess the predicted relationships. We used a multinomial logit model to jointly estimate the odd ratios of receiving VC funding between three pairs of alternatives: (a) receiving VC funding in the first two quarters versus no VC funding at all for the year and a half after receipt of a grant by a recipient startup or its non-recipient peer, (b) between quarter three and four versus no VC funding, and (c) between quarter five and six versus no VC funding. The interpretation of this model was distinct from our primary analysis because it did not focus on the probability of receiving VC funding in a particular two-quarter window; rather, it contrasts the likelihood of receiving VC funding in a time window vis-à-vis no funding at all. As a result, this estimation approach is less flexible in that it excludes the possibility that VC funds may come in one of the other two windows. In addition, the multinomial logit model relies on the strong assumption of independent of irrelevant alternatives (IIA). In our empirical context, it means that the odds of preferring one time-window over another does not depend on the presence or absence of the other "irrelevant" time-windows. With these caveats, we present the estimates from a multinomial logit model (Model 1) in of Table 5. We find consistent results with our preferred model as the coefficient of *GRANT* is positive and significant at 5% level, but not significant in the other two alternative time windows presented in Model 1. We also present results of a discrete time event history model in Model 2, which depicts a statistically significant ($p < 0.01$) result where grant recipients are 7.2% more likely to receive VC funding than non-recipients. In unreported models, we found similar results with a continuous time Cox hazard model.

Second, the hypothesized relationships we observe could be driven by the size of the government grant. In our theoretical development, we were agnostic to the grant amount because we were primarily concerned with its signaling value. Therefore, the use of a binary indicator variable was appropriate. However, it is possible that larger grants may have garnered differential attention from VCs. We assessed this possibility directly by replacing the binary indicator variable *GRANT* with the natural logarithm of the amount of the grant. For those non-recipient matched peers that would otherwise have a zero we included the natural logarithm of 1. Estimates from this alternative specification are presented in Models 3, 4 and 5 in Table 5. The estimated coefficient for *GRANT* (*continuous*) is statistically significant ($p < 0.05$) only in Model 3 but not in Model 4 and 5. This finding further suggests that the signaling value of a grant is short-lived.

-----------------Insert Table 5 about here--------------

Third, we considered whether the signaling value of receiving a government grant is founded in the affiliation with the public agency on its own or whether the receipt of multiple grants has any additional impact. We redefine the GRANT variable as (i) an indicator variable that identifies startups' first research grant (FIRST_GRANT) and (ii) an indicator variable that identifies the receipt of subsequent research grants (NOT_FIRST_GRANT). Model 6 and Model 7 of Table 5 present logistic regression models for the two quarters following the receipt of either a first grant or a follow-on grant and demonstrates that the main effects (Hypotheses 1 and 2) have been maintained ($p < 0.05$) in the case of startups' first grant but not for subsequent grants. This finding suggests that the information revealed at the time of the initial signal was particularly useful for startups in attaining VC funding and is robust to the exclusion of follow-on grants.

Fourth, the result may be biased due to unobserved factors that may drive the government agency's decision in distributing grants. To assuage such a concern, we calculate Altonji et al.'s (2005) selection on unobservables to selection on observables ratio for the first stage model. For the Model 2 in Table 1, omitted unobservable factors would need to explain 4.6 more variation in the dependent variable than the included variables to explain the estimated effect size. This ratio is well in excess of Altonji et al. (2005) rule of thumb for a robust estimate of 1.0.

Finally, the results could have been influenced by the choice of caliper chosen in the matching procedure. As a result, for the nearest neighbor matching we tried two alternative calipers – 0.25 times of standard deviation of the logit of the propensity scores and 0.1 – to generate two different sets of matched samples. These alternate samples yielded consistent results. Relatedly, we tested the robustness of the results to the matching algorithm by creating matched samples using three alternative greedy matching techniques suggested by Guo and Fraser (2010) rather than the nearest neighbor approach and found consistent results.

5. Discussion and Conclusion

In this paper, we explore signaling by early stage startups in an emerging sector through the acquisition of highly competitive government research awards and investigate the value of obtaining these awards for the subsequent VC funding of these startups. We provide a better understanding of the strategies startups use to meet the expectations of audiences upon which they depend for resources to advance from conceptualization to commercialization stages in the organizational life cycle. Our theoretical development and empirical examination are based on a view of evolving expectations of different resource providers. We have found that startups in the U.S. clean energy sector that received federal grants were 12 percent more likely to benefit from follow-on VC funding in the next two quarters than those that did not. Moreover, we have found that a grant recipient with no history of patent applications was seven percent more likely to receive VC funding as compared to a similar startup that had not received a grant. Together, these results suggest that despite the heavy burden of the liability of newness in an emerging industry context there are proven catalyzing strategies that leverage the signals provided by policymakers to allow some startups to overcome significant hurdles.

5.1. Contribution to Theory and Practice

Our paper complements prior studies on signaling that have demonstrated its benefit, but have generally overlooked how it relates to the changing expectations of external resource providers over time. We argue that the choice to seek and ultimately win a government grant, in light of the limited resources and other activities that an early stage startup can pursue, has value beyond the monetary award if it can be used as an identity transforming event to avoid languishing for extended periods in a state of institutional pluralism. Moreover, our results suggest that this strategy is available for less proven firms and moves beyond the literature's "rich get richer" characterization of signaling strategies.

The conception by Fisher et al. (2016) of differing levels and types of legitimacy required by startups to grow and thrive at different stages of the organizational life cycle has opened a fruitful area of study to which the analysis in this paper contributes. From a theoretical perspective, our focus on an emerging technology sector context shines light on how identity transitions differ based upon gradations in industry development. In an emerging industry context, the legitimacy threshold external resource providers confront is opaquer and therefore it is greater than it is in mature industries, leading to wider identity transition gaps. This position is consistent with the attention that practitioners and policymakers have placed on the "Valley of

Death" (Ghosh and Nanda, 2010), which is the protracted period that precedes commercial viability in emerging industries.

The dynamic aspect of the signaling strategy that we study in the context of early stage startups contributes insight to when such firms extract value from signals. The fact that government grants act as a proof point that has its greatest value to catalyze negotiations with VCs within two quarters highlights how signals are time dependent. This may not only result from the novelty of the information, but also the degree to which the startup has developed relationships with external resource providers. It is highly unlikely that the grant announcement was the initiation of a relationship between a recipient startup and a VC but rather a strategic decision by both parties to consummate the relationship when this new information is revealed. The practical implication for startups is that given the long lead times between the application for a grant and its award it would be prescient for them to engage in regular contacts with the VC community well before award announcements.

Finally, our findings offer interesting implications for policymakers responsible for designing research grant programs. Previous literature has debated whether government funding supplements or complements startups' external sources of finance (Lerner, 1999; Wallsten, 2000). We demonstrate that government grants have positive impacts on startups obtaining VC financing. Given the signaling value of grants, policymakers may consider involving VCs in the design of these programs.

5.2. Limitations and Extensions

Although our paper offers an important contribution to the existing literature, we recognize that it has several limitations. First, several factors may limit the generalizability of our theoretical framework and empirical findings. We have limited our model to the U.S., although we are unaware why the framework would not necessarily apply to other countries, especially those with similar institutional environments. Moreover, the empirical setting is within a single industry that may reduce the generalizability of the study to other contexts. However, we believe that the key insights from the theoretical framework can potentially be useful in understanding signaling strategies in other emerging industries. Second, signals— in the form of government grants— increase the likelihood of receiving VC funding in subsequent periods. Given this premise, we would expect that startups that receive grants are likely to receive higher valuations by VCs compared to similar startups that receive VC funding without receiving government grants. This relationship would be interesting to investigate, yet is one we are unable to pursue. Finally, we develop the theoretical framework within a context of an emerging industry where the hurdle to appear legitimate to a new audience is more pronounced for early stage startups. However, our empirical estimation would be more accurate if we could measure the value of this signaling strategy in two contexts—one where the industry is emerging and another that is more mature.

We see a few ways to extend the current study. First, our study focuses only on the signaling value of government research grants on startups' subsequent VC funding. However, such strategies may also help these startups acquire different external resources and improve their commercial prospects in other ways; for instance, by obtaining angel funding or by forming strategic alliances or licensing their technologies to third parties. Therefore, future studies could complement our study by focusing on other benefits and performance implications of this type of signal. For instance, researchers may investigate how the grants are used: that is, to what extent do VCs value grants solely as signals and to what extent do they carefully watch and observe the outcomes of how startups use the grant proceeds? Alternatively, future studies may consider other factors that may invoke heterogeneity among these startups when employing this type of signaling strategy. For instance, a study may consider the presence of prominent scientists in the startups.

5.3. Conclusion

In sum, our study opens up many avenues of future research in this important area of the interaction between public and private funding of startups. Governments around the world are establishing larger pools of funds to catalyze innovative efforts and support early stage startups. This is especially the case in the area of clean technology where the proceeds of carbon taxes or cap-and-trade schemes are being directed towards promising technologies that lower greenhouse gas emissions. We show that the VC community picks up on the signals that underlie these types of government grants and startups can use these as proof points as they seek to transition across life cycle stages. Significantly, these proof points appear to compensate for a weakness that startups otherwise may have. That is, we find that startups with fewer or even no patents are likely to benefit from additional VC funding in comparison to startups with more patents. The signal sent by the grant then has the important effect of redistributing the benefits of VC funding rather than to simply advantage already well-endowed actors. The role that the government can play in tipping the balance in the direction of less well-endowed startup ventures is an intriguing finding that deserves follow up for it points to an alternative strategic route that startups can take to move through the organizational life cycle.

References

Alphabet Energy. 2010a. Alpabet Energy awarded government grants totaling $320,000. Accessed September 15 2016 at https://www.alphabetenergy.com/press-releases/financing-press-releases/.

Alphabet Energy. 2010b. Alpabet Energy attracts $1 Million from Claremont Creek Ventures. Accessed September 15 2016 at https://www.alphabetenergy.com/press-releases/financing-press-releases/.

Aldrich, H., Auster, E.R., 1986. Even dwarfs started small: Liabilities of age and size and their strategic implications. Res. Organ. Behav. 8, 165–198.

Aldrich, H.E., Fiol, C.M., 1994. Fools rush in? The institutional context of industry creation. Acad. Manage. Rev. 19, 645–670.

Altonji, J.G., Elder, T.E., Taber, C.R. 2005. Selection on observed and unobserved variables. J. Pol. Econ. 113, 151-184.

Arthurs, J. D., Busenitz, L. W., Hoskisson, R. E., & Johnson, R. A. 2009.Signaling and initial public offerings: The use and impact of the lockup period. J. Bus. Venture. 24(4), 360-372.

Austin, P.C. 2011. Optimal caliper widths for propensity-score mathcing when estimating differences in means and differences in proportions in observational studies. Pharm. Stat. 10, 150-161.

Baum, J.A., Silverman, B.S., 2004. Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. J. Bus. Venture. 19,411–436.

Bertoni, F., Colombo, M.G., Grilli, L., 2011. Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects. Res. Policy 40,1028-1043.

Bothner, M.S., Podolny, J.M, Smith, E.B. 2011. Organizing for status: The Matthew Effect vs. the Mark Effect. Manage. Sci. 57, 439-457.

Boudreau, K. J., Lacetera, N., & Lakhani, K. R. 2011. Incentives and problem uncertainty in innovation contests: An empirical analysis. *Management Science*, *57*(5), 843-863.

Busenitz, L.W., Fiet, J.O, Moesel, D.D. 2005 Signaling in venture capitalist-new venture team funding decisions: Does it indicate long-term venture outcomes? Entrep. Theory Pract., 29: 1-12.

Certo, S.T., Holcomb, T.R., Holmes, R.M. 2009. IPO research in management and entrepreneurship: Moving the agenda forward. J. Manage. 35, 1340-1378.

Chen, X.P., Yao, X., Kotha, S., 2009. Entrepreneur passion and preparedness in business plan presentations: A persuasion analysis of venture capitalists' funding decisions. Acad. Manage. J. 21,199–214.

Cockburn, I.M., MacGarvie, M.J., 2009. Patents, thickets and the financing of early-stage firms: Evidence from the software industry. J. Econ. Manag. Strategy 18,729–773.

Connelly, B.L., Certo, S.T., Ireland, R.D, Reutzel, C.R. 2011. Signaling Theory: A review and assessment. J. Man. 37,39-67.

David, P.A., Hall, B.H., Toole, A.A. 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. Res. Policy 29,497–529.

Davila, A., Foster, G., Gupta, M. 2003. Venture capital financing and the growth of startup firms. J. Bus. Vent. 18, 689-708.

Engel, D., Keilbach, M., 2007. Firm-level implications of early stage venture capital investment—An empirical investigation. J. Emp. Finance 14, 150–167.

Fabrizio, K., Mowery, D., 2007. Financing innovation in the United States, 1870 to the present. In The Federal Role in Financing Major Innovations: Information Technology During the Postwar Period, eds. Lamoreaux, N., & Sokoloff, K., MIT Press.

Feldman, M.P., Kelley, M.R., 2003. Leveraging research and development: Assessing the impact of the US Advanced Technology Program. Small Bus. Econ. 20, 153–165.

Fisher, G., Kotha, S. and Lahiri, A., 2016. Changing with the times: An integrated view of identity, legitimacy and new venture life cycles. Acad. Manag. Rev., 41, 383-409.

Ghosh, S., Nanda, R., 2010. Venture Capital Investment in the Clean Energy Sector. Harvard Business School Working Paper, 11-020.
Gompers, P., Lerner, J., 2004. The Venture Capital Cycle (MIT Press: Cambridge, MA).
Graffin, S., Ward, A., 2010. Certifications and reputation. Organ. Sci. 21, 331–346.
Gulati, R., Higgins, M.C., 2003. Which ties matter when? The contingent effects of interorganizational partnerships on IPO success. Strat. Manage. J. 24, 127–144.
Guo, S., Fraser, M.W., 2010. Propensity score analysis: Statistical methods and applications. Guo SY, Fraser MW, eds. Advanced Quantitative Techniques in the Social Sciences series, Vol. 11 (Sage Publications: Thousand Oaks, CA), xviii.
Hallen, B.L., Eisenhardt, K.M. 2012. Catalyzing strategies and efficient tie formation. Academy of Management Journal 55, 35-70.
Heeley, M.B., Matusik, S.F., Jain, N., 2007. Innovation, appropriability, and the underpricing of initial public offerings. Acad. Manage. J. 50, 209–225.
Henderson, R., Newell, R., eds. 2011. Accelerating Energy Innovation (National Bureau of Economic Research, University of Chicago Press: Chicago).
Higgins, M.C., Gulati, R., 2003. Getting off to a good start: The effects of upper echelon affiliations on underwriter prestige. Organ. Sci. 14, 244–263.
Higgins, M.C., Gulati, R., 2006. Stacking the deck: The effects of top management backgrounds on investor decisions. Strat. Manage. J., 27, 1-25.
Hill, J., Reiter, J.P., 2006. Interval estimation for treatment effects using propensity score matching. Stat. Med. 25, 2230–2256.
Howell, S.T., 2014. Financing Constraints as Barriers to Innovation: Evidence from R&D Grants. Department of Economics Working Paper, Harvard University.
Hsu, D.H., 2006. Venture capitalists and cooperative start-up commercialization strategy. Manage. Sci. 52, 204–219.
Janney, J.J., Folta, T.B. 2006. Moderating effects of investor experience on the signaling value of private equity placements. J. Bus. Vent. 21, 27-44.
Kahneman, D., Slovic, P., & Tversky, A. 1982. Judgment under uncertainty: Heuristics and biases. Cambridge and New York: Cambridge University Press
Kazanjian, R. K., & Drazin, R. (1990). A stage-contingent model of design and growth for technology based new ventures. *Journal of business venturing*, *5*(3), 137-150.
King, G., Tomz, M., & Wittenberg, J. 2000. Making the most of statistical analyses: Improving interpretation and presentation. Am. J. Polit. Sci. 44, 341–55.
Kirsch, D., Goldfarb, B., Gera, A., 2009. Form or substance: The role of business plans in venture capital decision making. Strat. Manage. J. 30, 487–515.
Kirsner, S., 2010.With venture backers still reluctant, it could be a rough-and-tumble year for clean tech. The Boston Globe, March 14.
Koberg, C. S., Uhlenbruck, N., & Sarason, Y. (1996). Facilitators of organizational innovation: The role of life-cycle stage. *Journal of business venturing*, *11*(2), 133-149.
Kortum, S., Lerner, J., 2000.Assessing the contribution of venture capital to innovation. Rand J. Econ. 31, 674–692.
Lerner, J., 1999.The government as venture capitalist: The long-run impact of the SBIR Program. J. Bus. 72, 285–318.
Lerner, J., 2009. Boulevard of Broken Dreams: Why Public Efforts to Boost Entrepreneurship and Venture Capital Have Failed—And What to Do about It (Princeton University Press, Princeton, NJ).

Lerner, J., 2010. The future of public efforts to boost entrepreneurship and venture capital. Small Bus. Econ. 35, 255–264.
Marcus, A., Malen, J., Ellis, S., 2013. The promise and pitfalls of venture capital as an asset class for clean energy investment: research questions for organization and natural environment scholars. Organ. Environ. 26, 31-60.
Mann, R.J., Sager, T.W., 2007. Patents, venture capital, and software start-ups. Res. Policy 362, 193–208.
Murray, F., Stern, S., Campbell, G., MacCormack, A. 2012. Grand Innovation Prizes. Res. Pol. 41, 1779-1792.
Murtha, T.P., Lenway, S.A., Hart, J.A. 2001. Managing New Industry Creation. Stanford: Stanford University Press.
Nanda, R., Rhodes-Kropf, M. 2013. Investment cycles and startup innovation. J. Fin Econ. 110, 403-418.
National Academy of Sciences, Engineering, and Medicine. 2016. SBIR/STTR at the Department of Energy. (The National Academies Press: Washington).
Nielsen, R., Sheffield, J., 2009. Matching with time-series cross-sectional data. In Conference on Political Methodology.
Pahnke, E., Katila, R., Eisenhardt, K.M. Who takes you to the dance? How funding partners influence innovative activity in young firms. Adm. Sci Quar. *Forthcoming*
Park, N.K., Mezias, J.M. 2005. Before and after the technology sector crash: The effect of environmental munificence on stock market response to alliances of e-commerce firms. Strat. Manage. J. 26, 987-1007.
Plummer, L.A., Allison, T.H., Connelly, B.L. 2016. Better together? Signaling interactions in new venture pursut of intial external capital. Academy Management Journal 59, 1585-1604.
Pollock, T.G., Chen, G., Jackson, E.M., Hambrick, D.C., 2010. How much prestige is enough? Assessing the value of multiple types of high-status affiliates for young firms. J. Bus. Ventur. 25, 6–23.
Pollock, T.G., Rindova, V.P. and Maggitti, P.G., 2008. Market watch: Information and availability cascades among the media and investors in the US IPO market. Academy of Management Journal 51, 335-358.
Rao, H., 1994. The social construction of reputation: Certification contests, legitimation, and the survival of organizations in the American automobile industry—1895–1912. Strat. Manage. J. 15, 29–44.
Rawhouser, H., Villanueva, J., Newbert, S.L. 2016. Strategies and tools for entrepreneurial resource access. Int. J. Man. Rev. Forthcoming.
Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41–55.
Sanders, W.G., Boivie, S., 2004. Sorting things out: Valuation of new firms in uncertain markets. Strat. Manage. J. 25, 167–186.
Santos, F.M., Eisenhardt K.M., 2009. Constructing markets and shaping boundaries: Entrepreneurial power in nascent fields. Acad. Manage. J. 52, 643–671.
Shane, S., Stuart, T., 2002. Organizational endowments and the performance of university start-ups. Manage. Sci. 48, 154–170.
Shepherd, D. A., 1999. Venture capitalists' assessment of new venture survival. Manage. Sci., 45, 621-632.

Sorenson, O., Stuart, T.E., 2001. Syndication networks and the spatial distribution of venture capital investments. Amer. J. Sociol. 106, 1546–1588.

Spence, M. A. 1973. Job Market Signaling. The Quarterly Journal of Economics, 87: 355-374.

Stinchcombe, A.L., 1965. Organizations and social structure. Handbook of Organizations 44, 142–193.

Stuart, T.E., Hoang H., Hybels, R.C., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. Admin. Sci. Q. 44, 315–349.

Tomz, M., Wittenberg, J., King, G., 2003. CLARIFY: Software for interpreting and presenting statistical results. J. Stat. Softw. 8, 1–30.

U.S. Department of Energy 2015. Energy Efficiency & Renewable Energy, Award Management. Accessed at: http://www1.eere.energy.gov/financing/m/award_management.html

Villanueva, J., Van de Ven, A.H., Sapienza, H. J. 2012. Resource mobilization in entrepreneurial firms. J. of Bus. Ventur. 27, 19-30.

Van de Ven, A.H., Hudson, R., Schroeder, D. 1984. Designing new business startups: Entrepreneurial, organizational, and ecological considerations. J. Man. 10, 87-108.

Vohora, A., Wright, M., Lockett, A. 2004. Critical junctures in the development of university high-tech spinout companies. Res. Pol. 33, 147-175.

Wallsten, S.J., 2000. 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, 82–100.

Zelner, B.A., 2009. Using simulation to interpret results from logit, probit, and other nonlinear models. Strat. Manage. J. 30, 1335–1348.

Zheng, Y., Liu, J., George, G. 2010. The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology start-ups. J. of Bus. Ventur. 25, 593-609.

Zimmeraman, M.A., Zeitz, G.J. 2002. Beyond survival: Achieving new venture growth by building legitimacy. Acad. Manag. Rev. 27, 414-431.

Zott, C., Huy, Q.N., 2007. How entrepreneurs use symbolic management to acquire resources. Admin. Sci. Q. 52, 70–105.

TABLE 1: Logistic Regression Estimates of the Likelihood of Receiving Grant

VARIABLES	(Model 1)	(Model 2)
PAST_VC	0.622**	0.536*
	(0.294)	(0.290)
PATENTS	0.236**	0.263**
	(0.110)	(0.108)
PAST_GRANT	2.829***	2.870***
	(0.402)	(0.395)
AGE	-0.178	-0.177
	(0.223)	(0.211)
Constant	-4.984***	-3.190***
	(0.649)	(0.630)
Region Fixed Effects	YES	YES
Sectoral Fixed Effects	YES	NO
Year Fixed Effects	YES	NO
Year X Sector Fixed Effects	NO	YES
Observations	3309	3309
Wald chi2	146.79	136.45
Prob. > chi^2	0.0001	0.0001
Log pseudo likelihood	-469.61275	-474.26531
Pseudo R2	0.2111	0.2033

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10

Table 2: Matched Samples (after propensity score matching)

	Government Grant Recipients		Government Grant Non-Recipients	
Matching Variables	Mean	Std. Dev.	Mean	Std. Dev.
PAST_VC	0.586	0.494	0.508	0.502
PATENTS	1.184	1.391	1.115	1.501
PAST_GRANT	0.227	0.420	0.234	0.425
AGE	1.418	0.565	1.457	0.589
Region				
New England	0.203	0.404	0.203	0.404
Mid-Atlantic	0.125	0.332	0.141	0.349
East North Central	0.078	0.269	0.094	0.293
South Atlantic	0.055	0.228	0.047	0.212
South Central	0.055	0.228	0.008	0.088
Mountain	0.086	0.281	0.094	0.293
Pacific	0.398	0.492	0.414	0.494
Sector				
Biofuel	0.180	0.385	0.227	0.420
Efficiency	0.047	0.212	0.063	0.243
Geothermal	0.016	0.125	0.000	0.000
Materials	0.023	0.152	0.047	0.212
Solar	0.414	0.494	0.367	0.484
Storage	0.203	0.404	0.094	0.293
Tidal	0.008	0.088	0.008	0.088
Wind	0.016	0.125	0.055	0.228
Others	0.094	0.293	0.141	0.349
Year				
2006	0.055	0.228	0.031	0.175
2007	0.219	0.415	0.250	0.435
2008	0.195	0.398	0.172	0.379
2009	0.391	0.490	0.422	0.496
2010	0.141	0.349	0.125	0.332
Observations	128		128	

Table 3: Descriptive Statistics and Correlation Matrix (Matched Sample)

		Mean	Std. Dev.	Min.	Max.	1	2	3	4	5	6	7	8	9	10
1	*VC_1-2Q*	0.203	0.403	0	1										
2	*VC_3-4Q*	0.098	0.297	0	1	-0.166*									
3	*VC_5-6Q*	0.859	0.281	0	1	-0.155*	-0.101								
4	*VC_2_4_6_QUARTERS*	0.656	0.970	0	3	0.179*	0.457*	0.743*							
5	*GRANT*	0.500	0.501	0	1	0.155*	-0.040	0.001	0.040						
6	*PATENTS*	1.150	1.445	0	5.844	-0.033	0.040	0.005	0.015	0.024					
7	*VC_FUND*	1.512	1.665	0	5.816	0.061	0.114	0.151*	0.226*	0.018	-0.042				
7	*AGE*	1.437	0.576	0	2.398	-0.094	-0.098	-0.187*	-0.262*	-0.034	0.350*	0.016			
8	*PAST_VC*	0.547	0.499	0	1	0.148*	0.114	0.111	0.228*	0.079	-0.065	0.740*	-0.066		
9	*PAST_GRANT*	0.230	0.422	0	1	-0.069	-0.055	-0.102	-0.151*	-0.009	0.171*	0.064	0.160*	-0.042	
10	*TOTAL VC*	34.361	4.364	29.295	43.385	0.007	-0.095	-0.061	-0.108	0.025	-0.004	-0.005	0.068	-0.030	0.035

N= 256; * Significant at 5%

Table 4: Logistic Regression Estimates of the Likelihood of Receiving Venture Capital Funding

VARIABLES	VC in 1-2 Quarters (Model 1)	VC in 3-4 Quarters (Model 2)	VC in 5-6 Quarters (Model 3)	VC in 1-2 Quarters (Model 4)	VC in 3-4 Quarters (Model 5)	VC in 5-6 Quarters (Model 6)
GRANT	0.821**	-0.090	0.023	0.849**	-0.998*	-0.285
	(0.365)	(0.489)	(0.531)	(0.458)	(0.778)	(0.630)
PATENTS	-0.013	0.298*	0.014	0.002	-0.056	-0.098
	(0.137)	(0.222)	(0.287)	(0.170)	(0.238)	(0.284)
GRANT_X_PATENTS				-0.026	0.780**	0.263
				(0.234)	(0.383)	(0.393)
AGE	-0.148	-0.004	0.461*	-0.148	0.018	0.475**
	(0.151)	(0.180)	(0.298)	(0.152)	(0.172)	(0.286)
VC_FUND	-0.318	-0.853**	-1.802***	-0.316	-1.023**	-1.828***
	(0.302)	(0.434)	(0.666)	(0.300)	(0.474)	(0.678)
PAST_VC	1.168***	0.650	0.038	1.167***	0.759	0.059
	(0.495)	(0.716)	(1.064)	(0.494)	(0.763)	(1.072)
PAST_GRANT	-0.464	0.631	-0.727	-0.470	0.775	-0.735
	(0.561)	(0.769)	(1.135)	(0.550)	(0.825)	(1.129)
TOTAL_VC	0.017	-0.088	-0.075	0.017	-0.099*	-0.074
	(0.041)	(0.076)	(0.089)	(0.041)	(0.064)	(0.088)
Constant	-2.938**	0.911	1.161	-2.949**	1.549	1.222
	(1.490)	(3.149)	(3.496)	(1.517)	(2.707)	(3.427)
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	252	173	159	252	173	159
Wald chi2	23.27	28.53	25.21	23.73	30.09	27.29
Prob. > chi^2	0.226	0.027	0.090	0.254	0.0256	0.074
Log pseudo likelihood	-116.743	-67.592	-57.308	-116.738	-57.921	-46.120
Pseudo R2	0.090	0.165	0.211	0.090	0.190	0.287

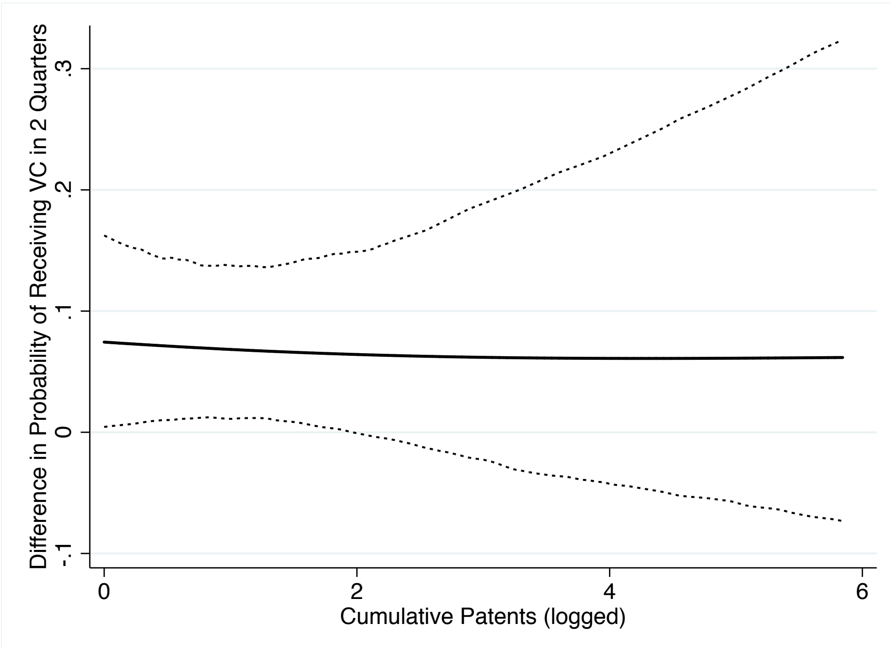
Note: Robust standard errors in parentheses. One-tailed test. *** p<0.01, ** p<0.05, * p<0.10

Table 5: Robustness Tests of the Likelihood of Receiving Venture Capital Funding

	Multinomial Logit Model			**Discrete Time Event History Model**	**Logistic Models**			**Logistic Models**	
VARIABLES	VC in Q1-Q2	VC in Q3-Q4 (Model 1)	VC in Q5-Q6	(Model 2)	VC in Q1-Q2 (Model 3)	VC in Q3-Q4 (Model 4)	VC in Q5-Q6 (Model 5)	Only 1st Grant VC in Q1-Q2 (Model 6)	Not 1st Grant VC in Q1-Q2 (Model 7)
GRANT (Dummy)	0.861**	0.144	0.219	1.605***				0.814**	0.220
	(0.396)	(0.464)	(0.507)	(0.621)				(0.382)	(2.694)
GRANT (Continuous)					0.053**	-0.017	0.009		
					(0.024)	(0.035)	(0.036)		
PATENTS	0.035	0.195	0.114	0.033	-0.008	0.296*	0.017	0.047	-2.116**
	(0.145)	(0.229)	(0.235)	(0.099)	(0.137)	(0.223)	(0.284)	(0.144)	(1.135)
VC_FUND	-0.058	0.113	0.556**	1.208***	-0.151	-0.004	0.460*	-0.131	-1.173*
	(0.159)	(0.191)	(0.301)	(0.177)	(0.150)	(0.180)	(0.299)	(0.162)	(0.809)
AGE	-0.765**	-1.152***	-2.097***	-1.291***	-0.338	-0.866**	-1.796***	-0.256	2.228
	(0.346)	(0.469)	(0.695)	(0.331)	(0.303)	(0.438)	(0.667)	(0.304)	(2.810)
PAST_VC	1.214***	0.535	-0.304	-2.468***	1.172***	0.675	0.020	1.050***	31.946***
	(0.514)	(0.720)	(1.050)	(0.733)	(0.496)	(0.710)	(1.071)	(0.518)	(6.753)
PAST_GRANT	-0.559	0.250	-0.974	-1.395**	-0.443	0.660	-0.736	-0.339	0.354
	(0.582)	(0.638)	(1.014)	(0.641)	(0.561)	(0.779)	(1.128)	(0.626)	(1.089)
TOTAL_VC	0.004	-0.080	-0.061	0.899***	0.020	-0.089	-0.075	0.021	0.286***
	(0.043)	(0.082)	(0.076)	(0.105)	(0.041)	(0.075)	(0.090)	(0.042)	(0.115)
Constant	-2.010*	0.931	0.962	-38.970***	-3.029**	0.998	1.142	-2.956**	-89.743***
	(1.536)	(3.365)	(2.684)	(4.173)	(1.494)	(3.113)	(3.536)	(1.574)	(1.053)
Quarter-Year Fixed Effects		No		Yes	No	No	No	No	No
Region Fixed Effects		Yes		Yes	Yes	Yes	Yes	Yes	Yes
Sectoral Fixed Effects		Yes		Yes	Yes	Yes	Yes	Yes	Yes
Observations		256		1184	252	173	159	214	26
Log pseudo likelihood		-221.253		-250.010	-116.924	-59.597	-46.259	-101.875	-5.650
Pseudo R2		0.186		0.276	0.089	0.166	0.276	0.085	0.6269

Note: Robust standard errors in parentheses. One-tailed test. *** p<0.01, ** p<0.05, * p<0.10

Figure 1: Marginal effect of receipt of a grant on probability of subsequent venture capital funding in quarters 1 and 2, conditional on value of cumulative patents



Note: Dotted lines represent a 95% confidence interval.