GOVERNMENTS AS PARTNERS: THE ROLE OF COLLABORATION IN CLEANTECH STARTUP INNOVATION

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ABSTRACT

Governments around the world are working towards accelerating innovation in clean energy technologies to meet rising energy demand and mitigate climate change. Policymakers shape the ecosystem in which startups innovate in various ways, ranging from R&D grants to technology and market collaborations. However, beyond government financing for R&D and the steering of market demand, there is little understanding of the role of governments as partners for joint technology development, for technology transfer through licenses, or as customers. We build on research on collaborative innovation and draw on resource dependence theory to highlight the role of collaboration with government organizations for startup innovation when compared with other firms, non-governmental research organizations and not-for-profit organizations. We develop a novel dataset of 783 US cleantech startups from 2008 to 2012 to quantify the innovation impact of technology development, licensing, and market collaborations between startups and government organizations as well as other partners. Our findings show that technology development and licensing with government organizations are associated with increased patenting activity and financial investments. Overall, the positive association between technology development, public licenses, and startup innovation extends openness and alliance perspectives on innovation and contributes to the emerging research on the role of governments in entrepreneurial ecosystems.

Keywords: Cleantech, Startups, Innovation, Public Policy, Openness, Entrepreneurship, Collaboration, Ecosystems

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INTRODUCTION

Mitigating global climate change, reducing local air pollution from fossil powered electricity and transportation, and providing reliable and affordable energy for all represent some of the major challenges of the 21st century (United Nations, 2015). There is wide consensus in political, academic, and economic arenas that technological innovation in the energy sector—and particularly in the clean power and transportation, or *cleantech* sector—is essential for addressing these challenges (Anadon, 2012; Mowery, Nelson, & Martin, 2010). The design of public policies to accelerate cleantech innovation has become a priority in countries around the world, as reflected in the 2015 Paris Agreement which recognizes that "accelerating, encouraging and enabling innovation is critical for an effective, long-term global response to climate change" (UNFCC, 2015, Article 10: 27). The high interest of governments in the cleantech sector is further explained by the fact that the provision of reliable and affordable energy is also essential for wellbeing and economic development (United Nations, 2015), even though the generation, supply and distribution of energy is largely controlled by private firms in many countries, especially in the United States (Chu & Majumdar, 2012; Koonin & Gopstein, 2011). The heterogeneity of technologies (e.g., from nuclear power plants to refrigerators), markets (e.g., from centralized electricity to personal transport), and organizations (e.g., large firms, government agencies, startups, universities) in the energy sector (Anadon & Holdren, 2009), as well as the multiple policy goals (Anadon, 2012) and coordination failures (Nanda, Younge, & Fleming, 2015) suggest that a multiplicity of policies, collaborations, and coordination efforts are needed to stimulate innovation. The most recent example of the recognition of the need for such collaboration was an initiative by the governments of 20 major global economies and 27 investors from the private sector to support cleantech innovation, announced in parallel to the Paris Agreement on climate.[1]

In the past, government-firm collaborations for innovation were characterized by a long-term and relatively stable funding for public and large private actors, linkages to government and policy, as well as close integration of R&D and use.[2] More recently, governments are seeking to promote innovation within high-risk startups—i.e., recently founded entrepreneurial firms—that are perceived to be more agile and flexible in the near-term for developing novel solutions to market opportunities (Guzman & Stern, 2015). However, while quickness and agility may be important in sectors with short development cycles (e.g., IT) (Bettis & Hitt, 1995), the cleantech sector requires a longer-term perspective due to technology development cycles that can take up to several decades (Grubler, Nakićenović, & Victor, 1999; Markard, Raven, & Truffer, 2012). In the cleantech sector, this long-term perspective is primarily offered by government organizations (e.g., National Renewable Energy Laboratory (NREL) or the Department of Energy (DOE)),[3] universities, and, to a lesser extent, other established firms (Jones, Anadon, & Narayanamurti, 2014). Government organizations have been engaged in cleantech innovation activities for decades and tend to have a longer-term view (Anadon, Bunn, & Narayanamurti, 2014; Westwick, 2003). Given the short-term imperative for achieving successful outcomes and the limited resources available to startups (Baum, 1996; Baum, Calabrese, & Silverman, 2000), [4] we consider that collaboration with government organizations might be particularly important for increasing innovation activities of cleantech

[1] This initiative is called Mission Innovation, committing the governments to accelerate public and private global clean technology innovation and double their public research and development (R&D) investments by 2020. The private sector's Breakthrough Energy Coalition, initially comprising 27 private investors, committed to investing early in technologies that can help mitigate climate change and bring in long-term 'patient' capital investments.

[2] Examples of such projects in the US include the Apollo project that took men to the Moon in 1969, research on military technologies at DARPA, or the large corporate R&D laboratories such as Bell Labs (Bonvillian, 2014; Narayanamurti & Odumosu, 2016; Riordan & Hoddeson, 1998).

[3] For example, governmental organizations such as the DOE or NREL provide assistance for technology and market readiness, and the Department of Defense (DoD) orders or acquires certain products or technologies from startups.

[4] Startup success may be indicated through new products, patents, financing deals, IPO that act as distinct signals to capital markets to attract financing within few years after founding.

startups. Yet, despite the recognition of the importance of collaboration to foster private-sector innovation in general (Powell, Koput, & Smith-Doerr, 1996) and the growing policy interest in how to replicate the level of high-impact entrepreneurial innovation occurring in local clusters like Silicon Valley, prior research on cleantech innovation has focused on the role of governments as direct financiers of startup R&D through grants (e.g., Howell, 2015) or in supporting innovation through the design of deployment (or market creation) policies for firms of all sizes (Choi & Anadón, 2014; Doblinger, Dowling, & Helm, 2016; Hoppmann, Peters, Schneider, & Hoffmann, 2013; Nemet, 2009). Thus, the question of how governments can promote cleantech innovation by being direct collaborators in terms of joint technology development, licensing, or as customers for startups has largely remained unaddressed. [5]

While the importance of collaboration in fostering innovation at the firm-level is a subject of inquiry in several streams of literature, existing research has largely overlooked the specific role of collaborating with governmental partners. These partners might not only possess key technological resources but also have different goals, since their aim is to shape innovation to meet societal goals rather than to obtain private returns. These streams of literature include research on firm openness (e.g., Chesbrough, 2003; Laursen & Salter, 2006; Laursen & Salter, 2014), interorganizational alliances (Baum et al., 2000; Powell et al., 1996), (technological) innovation systems (e.g., Bergek, Jacobsson, Carlsson, Lindmark, & Rickne, 2008; Freeman, 1987; Hekkert, Suurs, Negro, Kuhlmann, & Smits, 2007; Lundvall, 1992) , knowledge and innovation ecosystems (Adner, 2006; Clarysse, Wright, Bruneel, & Mahajan, 2014; Iansiti & Levien, 2004), and, what has emerged more recently as the concept of entrepreneurial ecosystems (e.g., Autio, Kenney, Mustar, Siegel, & Wright, 2014). The common suggestion that holds across these research streams—often derived

[5] We are interested in the effects of collaborative activities on knowledge generation and therefore do not explicitly investigate the relationship between startups and relations to financial partners. However, as access to financing (e.g., venture capital, corporate or government funding) is clearly vital for startups, we include prior financing deals as a control variable.

from empirical research in the biotech, manufacturing, or IT sectors—is that collective value creation and joint innovation within (local) networks are more productive than firms or research institutes working on their own. More specifically, research on openness and interorganizational alliances suggests that firms could generally benefit from actively searching for knowledge from many different types of knowledge channels, including those enabled by customers, suppliers, or research institutes (Baum et al., 2000; Dyer & Singh, 1998; Laursen & Salter, 2014; Powell et al., 1996). However, collaborations with suppliers, research institutes or government organizations, for example, may require different resources, as such organizations are characterized by different sets of institutional norms, habits, and rules. Thus, determining the most fruitful exchanges for firm innovation requires research to look beyond partner diversity by exploring "the importance of breadth and depth of external search to innovative performance within each channel or knowledge domain" (Laursen & Salter, 2006: 133). In other words, a better understanding of the value of different types of partners is needed. In a similar vein, research on entrepreneurial ecosystems highlights the importance of the 'context' under which startups innovate (Autio et al., 2014). Particularly key to the context is the collaborative environment of startups—i.e., their networks and collaboration with top or 'anchor' firms or public and not-for-profit organizations such as universities or research institutes (e.g., Adner, 2006; Adner & Kapoor, 2010; Clarysse et al., 2014; Iansiti & Levien, 2004). However, little is known about the relative impact of different types of partners, particularly government organizations, and of different types of collaboration on startup innovation. Therefore, given the urgency of accelerating innovation in the cleantech sector, gaining a better understanding of the relationship between different types of partners and collaborations is not only critical for startups, investors, government organizations, or policymakers, but also provides avenues for novel theoretical contributions to the openness, interorganizational alliances, and ecosystems literatures.

These knowledge gaps give rise to two questions: (1) What role do collaborations with governments—as compared to collaborations with research institutes and universities, not-for-profit organizations, or other firms (startups and established firms)— play for cleantech startup innovation activity? (2) What type of government collaborations—i.e., market- vs. technology-based—are important for startup innovation and the ability to attract financial investments? To address these questions, we develop a framework that separates knowledge flows from different types collaborations and partners to startups and hypothesize that these different types of collaborations and partners can have distinct effects. Our framework draws on resource dependence theory (Hillman, Withers, & Collins, 2009; Pfeffer & Salancik, 1978) to posit that the most *central governmental partners* hold the discretion over particularly large and useful knowledge and technological resources valuable to cleantech startups. These central governmental partners are defined as those that are established by the government to fulfill a key political mandate in their area of expertise and that have created the strongest network represented by a high number of connections to other well-connected partners.[6] In addition to enabling access to critical knowledge and technological resources (e.g., through user facilities (Koonin & Gopstein, 2011)), we argue that collaborations with government organizations might also be less prone to the typical caveats of collaboration such as appropriability concerns (Laursen & Salter, 2014) and unintended knowledge outflows via opportunistic behavior of partners (Cox Pahnke, McDonald, Wang, & Hallen, 2015). Using a novel dataset of the global collaborations of 783 US cleantech startups from 2008 to 2012, our analysis also investigates the relative benefits of collaborations with network central government organizations based on the type of collaboration, i.e., technology-based (joint technology development or licensing), or market-based (e.g., customer or procurement).

[6] We use the term *network central* government organization to express centrality in a network and not in terms of government organizations that are active at a national level.

This paper contributes to research on collaborative innovation in four ways. *First*, we extend openness and interorganizational alliance perspectives on startup innovation by providing a dynamic evaluation of the distinct impacts of different partners and collaboration types while accounting for the resource intensity of collaborating with a diverse set of partners. Our results suggest that while collaborations between cleantech startups and network central government organizations are generally more important for startup innovation than knowledge exchanges with any other partner type, this positive effect only holds when it comes to joint technology development or licensing and not for market collaborations (where governments are the customers of the startups' technologies or products). *Second,* in our analysis of collaborations we account separately for the differences between codified knowledge exchanges from acquiring licenses from governmental partners and more tacit exchanges from joint technology development. We are able to do this by quantifying the relative impact of joint technology and licensing collaborations, which have been analyzed at an aggregate level in prior research (Baum et al., 2000; Powell et al., 1996). *Third*, this paper advances the literature on entrepreneurial ecosystems by contributing to the theorization of this emerging perspective, pointing out that resource dependence theory may help explain the relative importance of governmental collaborators. Our findings suggest that governmental partners hold critical knowledge and technological resources for startups in the cleantech space that stem from their long-term experience, expertise, and commitment to their mandate to contribute to long-term societal benefit. *Fourth,* while most research on collaborative innovation has had its empirical basis in the IT, manufacturing, or biotech sectors, we provide novel insights that stem from the use of (a) a new type of data in (b) a new sector, cleantech. The cleantech sector is different from other sectors in that it is associated with commoditized goods with distinct institutional, investment, and time requirements. Our theory and empirical evidence on the importance of collaboration between network central government organizations and cleantech startups provide answers to pressing policy questions regarding the role of different governments' interventions in the energy space, particularly in the wake of the 2015 Paris Agreement.

THEORY AND HYPOTHESES

Collaborative Innovation: The Role of Different Types of Partners

The importance of co-evolving, mutually-rewarding, and long-term collaborations for innovation is supported by several streams of literature that emphasize on networks, openness, and joint value creation among different types of organizations at different levels of analysis. These streams of literature have emerged in the last decades as the understanding of innovation evolved from models exploring Schumpeter's lone and opportunity-seeking entrepreneur to models exploring the dynamic and interactive character of innovation processes that result from collaborative endeavors with distinct organizations—such as customers, suppliers, competitors, or research institutes (Cox Pahnke et al., 2015). In *macro*- or *systems-level* analyses of technological innovation systems, interorganizational collaboration represents one of many possible interactions of a system that is described by interactions and feedbacks between different governments, firms, entrepreneurs, etc. (i.e., organizations) and institutions (e.g., Bergek et al., 2008; Hekkert et al., 2007). In *firm-level* analyses, interorganizational alliances and 'ecosystems'—i.e., knowledge, innovation, business, or, more recently, entrepreneurial ecosystems—have emerged as central to innovation (Adner, 2006; Adner & Kapoor, 2010; e.g., Autio et al., 2014; Baum et al., 2000; Clarysse et al., 2014; Iansiti & Levien, 2004; Powell et al., 1996; Zahra & Nambisan, 2012). The literature on interorganizational alliances and knowledge ecosystems, which has been primarily conducted using empirical evidence from the biotech and IT sectors, recognizes that innovation is often a result of collaboration with different types of organizations primarily within local clusters. This research suggests that the locus of innovation resides in local networks rather than within individual firms (Baum et al., 2000; Clarysse et al., 2014; Powell et al., 1996), and that innovative activities can further depend on the physical and global network position of the firms themselves (Whittington, Jason, & Powell, 2009). The importance of collaboration with lead users and suppliers for increased innovation activities are a key subject of analysis in literature on openness and innovation or business ecosystems (Dyer & Singh, 1998; Laursen & Salter, 2006; von Hippel, 1988). The recently emerging literature on entrepreneurial ecosystems puts entrepreneurial innovation at its core, emphasizing the importance of collaboration with key partners and a supportive ecosystem for innovation within entrepreneurial firms or startups (Autio et al., 2014). In short, Baum et al., (2000: 267)'s well-cited recommendation "Don't Go At It Alone" nicely summarizes the suggested importance of collaboration for firm innovation prevalent across these various academic disciplines.

Firms can collaborate with several types of partners that enable distinct knowledge flows for stimulating innovation. Interorganizational collaboration therefore typically occurs with suppliers, customers, or even competitors (e.g., Adner & Kapoor, 2010; Lechner, Soppe, & Dowling, 2014; von Hippel, 1988). These partners enable access to up-to-date industry developments and market needs. Collaboration also occurs with non-private organizations such as universities, research institutes, or national laboratories (Clarysse et al., 2014; Powell et al., 1996). These collaborations typically enable boundary-spanning knowledge flows that, in combination with existing prior knowledge or technologies, can lead to higher innovation activities by firms (Jung & Lee, 2015). Overall, a greater diversity of partner types—or a firm's openness to actively seek and exploit external knowledge channels—generally increases firm innovation activities in terms of new product introductions, diversity of the new product portfolio, or new patent applications (Demirkan & Demirkan, 2012; Laursen & Salter, 2006).

However, the suggestion to 'collaborate as much with as many diverse partners as possible' may not be feasible for startups. Different types of partners typically require distinct resources as they are characterized by varying institutional norms and practices. For example, on the one hand, collaboration with suppliers and customers typically requires careful consideration of disclosure of knowledge on products and technologies and extensive mutual coordination and commitment (Dyer & Singh, 1998; von Hippel, 1988). On the other hand, collaborating with a government organization, such as a national lab or a state-level energy agency, often involves a different type of process resulting from higher levels of bureaucracy, distinct cultural attitudes, contractual rules, and costs (Glauthier & Cohon, 2015). In order to deal with these differences and to absorb knowledge, firms often need to go through a period of trial and error and develop time-intensive and costly organizational practices (Laursen & Salter, 2014). Bringing in diversity in partners may therefore be particularly challenging for startups that are generally subject to more resource constraints with limited personnel or cash flow than larger firms, even though collaboration generally represents an important approach to overcome resource constraints (Alvarez & Busenitz, 2001; Meyskens & Carsrud, 2013).

Furthermore, collaboration may even result in diminished innovation activity. Recent studies on startup innovation show that collaboration with other firms from the same industry, for example, can reduce rather than promote innovation activity because this narrower type of collaboration may contribute to startups missing important trends that are emerging outside of the industry boundaries (Stam & Elfring, 2008). Ties to venture capitalists (VC) can further reduce startup innovation activities because of information outflows to competitors and the opportunistic behavior of the VC that serves as a shared intermediary (Cox Pahnke et al., 2015).

In this paper, we suggest that different partners and different types of collaboration may be more (or less) important and have distinct effects on cleantech startup innovation activity. Prior research that has emphasized the importance of collaboration with many and diverse partners for firm innovation is often derived from research on larger firms or for biotech or IT startups. Our framework provides a more detailed analysis of the value of different types of partners and collaborations and focuses on startups. In doing so, this study is among the first to respond to the call of Laursen and Salter (2006; 2014) to separate knowledge flows from different partner types. In the following, we further extend these granular insights on partner and collaboration types by drawing on resource dependence theory (Pfeffer & Salancik, 1978) to highlight the possibility that startups may particularly benefit from collaboration with governmental partners.

Collaboration with Governmental Partners

Collaborating with specific types of partners offers startups avenues to access critical resources. Collaboration therefore serves as an important means to overcome resource dependence and to reduce uncertainty and complexity (Hillman et al., 2009; Pfeffer & Salancik, 1978). To acquire critical resources and benefit from collaboration, firms need to manage their external relations well, and forge relations with those partners that have the greatest discretion over valuable and rare resources. Alongside physical products, these resources include technological knowledge and social status or prestige (Pfeffer & Salancik, 1978). In the case of startups, the most valuable type of partner—i.e., the partner that holds critical resources for increased innovation activities of startups—largely depends on the structure and character of the startup's sector. Three key interlinked dimensions characterize the sector of cleantech startups: (1) electricity and fuels, or the product, are commodities that are often regulated as energy and transportation are key to human wellbeing and the functioning of a state; (2) the rate of innovation is slow, since new products in the energy space take multiple decades to be developed and deployed; and (3) high capital intensity and lumpiness of investments, path dependencies, and lock-ins with existing fossil fuel based infrastructures mean that changes in infrastructure and institutions are needed to make new energy sources available (Fouquet, 2013; Grubler et al., 2012; Koonin & Gopstein, 2011; Nanda et al., 2015; Unruh, 2000). These characteristics of the cleantech sector suggest that the critical resources required for startups may be held by organizations that have substantial research experience and equipment, financial and human resources, and a longer-term perspective for their activities.

We suggest that network central government organizations, such as the US Department of Energy (DOE), the US national laboratories (which are part of DOE) such as NREL, or NASA, which forge direct collaboration with startups and other firms, may possess these critical resources. In the following, we hypothesize that startups benefit in an outsized manner from collaborating with such network central government organizations for three reasons. *First,* government organizations and laboratories manage and receive funding for conducting research with longer time frames when compared to private sector firms. These governmental partners possess technological expertise in cleantech as well as related technologies that they have developed over decades (Anadon, 2012; Bonvillian, 2014). Although collaboration with government organizations might involve higher levels of bureaucracy and overhead costs than collaboration with other firms, we expect that the technological expertise and knowledge from these central partners may be particularly beneficial for subsequent startup innovation activities in the short-term. Recent studies have demonstrated that many inventions took place as a result of research conducted in government organizations such as national laboratories, which complemented the innovation activities of private-sector firms and were then successfully used by those firms (Mazzucato, 2013). Hence, these resources might be important for startups that typically only have a short time frame to achieve successful outcomes such as new products, patents, financing deals or an IPO (Baum, 1996; Baum et al., 2000). *Second*, collaboration with government organizations typically involves less conflict over knowledge and concerns about appropriability. Appropriability is widely considered a barrier to collaboration in the openness literature. For example, strict regulations from the legal departments of firms, complex negotiations, compounded with mechanisms to ensure secrecy may even restrict emergent collaboration (Laursen & Salter, 2014). Government organizations are explicitly mandated to contribute to knowledge and technology transfer (DOE, 2014). The Bayh-Dole Act of 1980, for instance, was put in place to promote private sector development and commercialization of government funded R&D by facilitating licenses of patents obtained with government-funded research to private firms (Schacht, 2009). *Third*, collaboration with government organizations involves lower risk of information leakages and knowledge outflows to competitors which otherwise represent serious threats for startups that typically depend on single technologies and products. Even though these threats can be reduced through non-disclosure agreements and other formal mechanisms to ensure IP ownership, recent research suggests that information can also leak to competitors via shared intermediaries such as VCs, with negative implications for startup innovation (Cox Pahnke et al., 2015). While collaboration with central governmental partners also bears the risk of information outflows to competitors that are also partnering with the same agencies, governments have less incentive for opportunistic behavior by leaking knowledge to competitors as they are—unlike VCs—not profit-driven. In sum, based on these arguments, we propose the following hypothesis:

Hypothesis 1: For startups in the cleantech sector, collaboration with central governmental partners is more important for short-term innovation activities than collaboration with other types of partners.

Market- vs. Technology-based Collaborations with Governmental Partners

Moreover, we submit that not all collaborations with central governmental partners are associated with increased startup innovation activities. For example, while network central government agencies such as DOE or NREL provide technological knowledge, agencies such as the Department of Defense (DoD) can order or acquire certain products or technologies from startups through mechanisms such as procurement (Bonvillian & Atta, 2011; Fuchs, 2010). Thus, to fully understand the impact of government collaboration on short-term startup innovation activities, it is important to further explore the impact of collaboration types.

Market-based Collaborations. Collaboration of startups with users or suppliers can enable unique and up-to-date insights on future market demands or technological improvement opportunities that can be important drivers of innovation. Innovation can also result and benefit from the technological knowledge embedded in acquired products (Tang & Popp, 2014). Such opportunities that are characteristically indirect and implicit can lead to higher innovation activities by firms (Malecki & Poehling, 1999; Von Hippel, 1978). There can also be benefits that stem from learning about the needs of the broader marketplace. Nevertheless, the level of technological learning and value added from market-based collaborations is likely to be lower in the short-term (over 1-2 years) as the primary goal of market relations is to deliver or acquire specific products or services and not the transfer or exchange of technological knowledge. In the case of market-based collaborations with government organizations, we expect startups that forge such collaborations to not be associated with increased levels of innovation, at least in the required short-term time frame for startups. Governmental partners typically serve as customers and not as suppliers of technologies to startups. This limits startups’ learning opportunities to niche markets for governmental applications, with often reduced commercial applicability. Moreover, while most research on government-business collaborations focuses on public procurement from large, established firms, the existing insights suggest that the value of collaboration between government organizations and startups lies in its potential to increase government—and not startup—efficiency (Lin, 2014). And finally, startups may only resort to investigating market-based collaborations with government organizations after being unsuccessful in the marketplace. In sum, startups that engage in market-based collaborations with network central government organizations typically supply products to a stable niche market that may provide limited learning opportunities. Thus, we propose:

> *Hypothesis 2: For startups in the cleantech sector, the effect of collaboration with central governmental partners on short-term innovation activity changes for market-based collaborations, such as that they are associated with reductions in innovation activity.*

Technology-based Collaborations. Technology collaborations, such as when startups engage in joint R&D, demonstration, or testing activities with other partners, enable the sharing and exchange of technological knowledge, spreading of risk, and access to complementary resources. As expected, prior research has shown how firms that forge technology collaborations with other firms, research institutes, universities, or governmental laboratories experience increased levels of innovation in terms of patenting activity and new product development (Clarysse et al., 2014; Deeds & Hill, 1996; Li-Ying et al., 2014). [7] We hypothesize that this positive view on the impact of technology collaborations on startup innovation also applies to collaborations with network central governmental partners, given the provision of complementary technological resources and reduced concerns of appropriability or of opportunistic behavior as outlined above.

However, in contrast to prior research on technology collaborations, we take a more nuanced perspective on technology-based collaborations, and distinguish between (a) joint technology development and (b) the provision of licenses for technology applications. These two collaborations involve different forms of knowledge exchanges and possibilities for spillovers—i.e., more tacit for joint technology development and more codified for licensing. Prior research shows that joint

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[7] Deeds and Hill, (1996) found an inverted U-shape relationship between the number of technology alliances and new product development for established companies.

technology development collaborations primarily with universities or research institutes are relatively more important for startup innovation than licensing collaborations in biotech startups (Baum et al., 2000; Liebeskind, Oliver, Zucker, & Brewer, 1996).[8] Baum et al. (2000: 273) further suggest that technology collaborations are "a source of up-to-date information or knowledge critical to success in patent races but too tacit to be effectively transferred through licensing." While this research has not empirically tested the relative benefits of licensing and joint technology development, Chan (2015) found that licenses from national laboratories to private firms resulted in increases in follow-on patenting activity of the licensee firms and also in follow-on patenting at other firms.

We argue that startups acquiring technology licenses from government organizations not only benefit from codified knowledge transfer but also from knowledge spillovers that are stronger when compared to those emerging from joint technology development. We suggest that startups are more likely to acquire licenses in areas that are farther from their own set of competencies when compared to areas for joint technology development, which could be associated with a greater potential to learn and to generate subsequent innovation. Thus, we suggest:

Hypothesis 3: For startups in the cleantech sector, the positive effect of collaboration with central governmental partners on short-term innovation activity is greater for licensing than for joint technology development.

[8] While Powell et al., (1996) illustrated different relationship types in biotechnology (e.g., R&D, marketing, licensing, supply/distribution, joint venture), they aggregated the relationships into R&D ties and non-R&D network experience for the purpose of their study.

Signaling Effects of Technology-based Collaborations with Governmental Partners to Private Investors

Next to the effects on startup innovation activities, technology-based collaborations in the form of joint technology development activities or licensing from central governmental partners may also increase the likelihood of startups to attract financial investments. Empirical studies have applied resource dependence theory to explain the impact of political alignment and frequent interactions with government organizations for firms to reduce dependencies or uncertainty, eventually leading to financial benefits (see Hillman et al., 2009 for a recent overview). However, besides research on the positive impact of the SBIR R&D grants from the DOE on startups' ability to acquire private sector investments (Howell, 2015), the signaling effects of technology collaborations to investors—both joint technology development and licensing—with network central government organizations are less clear.

In addition to physical and technological resources, access to social resources such as status and prestige are important for reducing dependencies and uncertainty (Hillman et al., 2009; Pfeffer & Salancik, 1978). As suggested above, government organizations might possess critical technological resources in the cleantech sector that can help further technology development. Furthermore, government reputation for technological expertise combined with direct access to critical technological resources through technology-based collaborations might represent important quality signals to investors and capital markets. Prior research suggests that technology collaborations with other firms not only increase startup performance in terms of sales or net income to sales ratio (Hagedoorn & Schakenraad, 1994; Lechner, Dowling, & Welpe, 2006), but that the signaling effects of high connectedness to key partners that possess technological knowledge can further build public confidence in the value of the startup (Stuart, 2000). Moreover, licenses from key partners are also seen as important signaling effects for private sector investors

(Conti, Thursby, & Thursby, 2013; Hsu & Ziedonis, 2013). We expect similar positive signaling effects for technology-based collaborations with governmental partners. However, the already existing codified knowledge transferred through licenses might enable more predictable assessments of the prospects of the startups than ongoing joint technology collaborations with more uncertain outcomes. As investors are faced with high levels of uncertainty and typically rely on patents or other codified forms of knowledge to assess the prospects of potential portfolio companies (Haeussler, Harhoff, & Müller, 2009; Laursen & Salter, 2014), we expect that licensing collaborations with governmental partners are stronger quality signals than joint technology development collaborations. Moreover, as stated above, market collaborations with central governmental partners might not result in increased innovation activities due to limited short-term learning opportunities. Because of the additional niche market concerns and perceived inability to sell products in the marketplace, we do not expect that market-based collaborations will result in stronger increases in private investments from investors. Given this logic, we propose:

Hypothesis 4: For startups in the cleantech sector, the positive effect of government licensing collaborations on the ability to attract private sector investments in the short-term is greater than for government joint technology development or market-based collaborations.

METHODS

Data and Measures

Description of the US cleantech startup dataset. We constructed a novel, large, and unbalanced panel of 783 US startups in the cleantech sector between 2008 and 2012. The panel includes all US startups that interacted with other firms, government organizations, research institutes, universities, and other not-for-profit organizations from the United States and globally. The startups operate in one or more of the following 17 sub-sectors: solar, wind, biomass, geothermal, hydro & marine power, nuclear, power storage, smart grid, power efficiency, advanced materials, transportation, biofuels & biochemicals, conventional fuels, fuel cells & hydrogen, air, recycling & waste, or water & wastewater. We considered a firm to be startup if it is younger than 10 years in year *t*, with t_0 being 2008. 57% of the startups were founded before t_0, and 43% entered our sample during the reported time frame. In total, our sample encompasses 3,297 observations from 783 startups over the five-year time frame (2008 to 2012). It provides very granular and time-resolved information about the type of startup partners, the types of startup collaborations, and basic firm information regarding size, age, location, and sector. We obtained the base data on the collaborations of US cleantech startups from the i3 Cleantech Group database. This relatively new database has hardly been used for research purposes in the past (see Zobel, Balsmeier, & Chesbrough, 2016, for a recent example in the US solar industry) and is, to the best of our knowledge, the richest and most thorough collection of information on the global cleantech sector. It applies various mechanisms to collect information on firms, collaborations between firms, industry development, and investments (i3 Cleantech Group, 2015). Information on collaborations is collected and constantly updated and checked by a research team or directly by the firms, and includes the names of the partners, collaboration types, a brief description of the purpose and goal of the collaboration, and the source. Furthermore, information for all potential partner types is collected using the same method, which implies that collaboration with government organizations is certainly not overrepresented in the sample. i3 Cleantech Group provided us with the startup names and collaboration information for the overall cleantech sector. We subsequently conducted manual verifications of all pieces of information covered by the database, including the type of collaboration, the year of the collaboration, and the name of the partners. We complemented the name and information on US startups with data on founding year and size from FactSet, Orbis, and, if not consistent, via an additional web search. We further expanded our dataset to include detailed information for each startup on location, patents, and financial investments by using multiple data sources (e.g., Orbis, FactSet, Thomson One, Derwent Innovation Index). Details on each of these independent and dependent variables, and how they were operationalized for our statistical analysis are described below. To examine the impact of partner and collaboration types on the dependent variables innovation activity and financing deals of startups, we used the Stata (13) software.

Independent Variables

Type of partner. Each startup enters collaborations with different types of partners. These partners were categorized into five different categories: (1) other cleantech startups, (2) other private sector businesses, (3) government organizations (e.g., DOE, DOD) and governmental laboratories or agencies (e.g., NREL, Fraunhofer), (4) universities (e.g., MIT or Princeton University) and private research institutes (e.g., Rocky Mountain Institute), or (5) NGOs or environmental groups (e.g., Sierra Club). These different partner types include organizations from the US or other countries (globally).

The collaborations included in the dataset typically last for more than one year, but duration data is only rarely reported. Thus, to evaluate the impact of these variables, it was necessary to make assumptions about their duration. Prior research in this realm has used durations between one and five years, mostly relying on three years (e.g., Choi & Anadón, 2014; Schilling & Phelps, 2007). In contrast to the majority of these panel studies that are based on established firm networks, we took a more conservative approach for our startup context and created two-year (i.e., 2008-2009, …, 2011-2012) and three-year windows (i.e., 2008-2010, …, 2010-2012) variables for each of the collaborations to test the robustness of the findings to this assumption. These two- or three-year moving windows for the annual network measures were used to account for the impact of prior (including pre-sample) collaborations and their cumulative nature (Robinson & Stuart, 2007;

Schilling & Phelps, 2007). We tested all of our statistical models (see below) for both the two- and three-year windows for the duration of the partnerships. As the results were very similar, we decided to present results using the two-year time lag windows that might be more relevant in the more short-term oriented startup context.

We used the network measure of eigenvector centrality to illustrate patterns in each two-year window for each partner and collaboration type. The eigenvector centrality for each startup captures patterns in a broader network by assigning weights to each collaboration based on the centrality measures of the partner (Bonacich, 2007). Collaboration with a well-connected partner in the strongest network thus has a higher weight than collaboration with a weakly connected partner. This allowed us to explore whether a startup was part of the network and collaborated with the most central government organizations. These startups received the highest eigenvector scores (between 0 and 1) (see Figures 1a and 1b). To check the robustness of the eigenvector centrality measures, we conducted several steps including the evaluation of additional measures of centrality—power centrality and average distance weighted reach (Bonacich, 1987; Schilling & Phelps, 2007).[9] We used the 'igraph' package in R to calculate all of the network measures (Csardi & Nepusz, 2006; R Core Team, 2015).

Insert Figures 1a and b about here

In Figure 2, we separated the full network of all global collaborations (from 2008 to 2012) will all types of partners into two ecosystems: one larger, interconnected network where all

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9 Power centrality assumes that centrality and 'powerfulness' of a firm are a function of the collaborations of a firm in its neighborhood (or ecosystem) of partners depending on selected parameters, with more collaborations with well-connected partners implying more centrality (note that the network analysis by itself is not accounting for local proximity). The power centrality measure was parameterized to mimic eigenvector centrality. While different from centrality, distance weighted reach also assigns greater value to more collaboration in that it assumes that firms collaborating with a large number of organizations over a shorter average path enable improved knowledge flows through access to faster and greater information, compared to less connected firms.

organizations are linked to the larger ecosystem, and one that is more diverse and characterized by dyadic or triadic interactions of a few organizations. As access to knowledge and information flows might differ based on the position of the startups within and outside of this larger ecosystem, we controlled for this difference for the 59% of the startups that are all interconnected and therefore part of the larger network and the 41% that operate outside of this network in the statistical models that are outlined below.

Insert Figure 2 about here

Collaboration types. The i3 Cleantech Group database provided an initial classification into collaboration types. We validated the information on collaborations with two researchers in our team, who independently assessed the description provided by the i3 database. In doing so, we re-coded some of the classifications to ensure a consistent matching of the 2,676 collaborations (2008 to 2012) to the following collaboration types for each startup in our dataset: technology-based (i.e., joint technology development or licensee) and market-based (i.e., procurement) (see Table 1 for examples).[10]

Insert Table 1 about here

Dependent variables

Patents. To examine the impact of different types of partners and collaborations on startup innovation activity, we use patents as a measure that is validated in an external examination process (Griliches, 1990). Although using patents to measure innovation activity or knowledge creation is not without challenges—for example, the propensity to patent and overall patenting activity might

[10] We also included licensors, i.e., when the startup provides the license, and project development collaborations as controls.

vary between industries (Levin, Klevorick, Nelson, & Winter, 1987)—it is a commonly used measure of innovation (Trajtenberg, 1987). This seems to be particularly true in our empirical setting, as the patenting propensity of U.S. startups has been found to be very high. Among other factors, patenting in cleantech is less contentious than in other sectors like IT and is considered to provide a signaling effect to potential investors (e.g., Conti et al., 2013; Hsu & Ziedonis, 2013). Furthermore, patent counts represent the most commonly applied measure for startup innovation (Clarysse et al., 2014; Howell, 2015; Nanda, Younge, & Fleming, 2013). We measured innovation as the number of patent applications for firm *i* in year *t*. The annual patent applications were extracted from the Derwent Innovations Index database in their year of priority application.

Private Financing Deals. We used the number of annual financing deals that each startup acquired per year to evaluate the signaling effects of collaborations on investors. The financing deals were collected and aggregated from the Thomson One, FactSet and i3 Cleantech Group databases, and primarily encompassed venture capital funding at different stages (seed, series A, B, etc.) as well as other private investments (loans, bonds, etc.). Figure 3 provides an overview of the distribution of the financial deals. We further included a measure of firm growth as a robustness check to the annual number of financing deals. We measured firm growth as the likelihood of achieving a desired growth outcome, i.e., an acquisition[11] or an initial public offering (IPO) within six years after the startup was founded (e.g., recently applied by Guzman & Stern, 2015). The data on firm growth was collected from various sources, including the i3 Cleantech Group and the FactSet database, and manually verified through a web search. Growth is operationalized as a binary variable equaling 1 for an acquisition or IPO in year *t*, and 0 otherwise.

Insert Figure 3 about here

[11] Acquisitions after bankruptcy or liquidity constraints are not included in the variable.

Control variables

Pre-sample patents. To account for the diminishing importance of earlier knowledge, we included the pre-sample patent stock as a control variable, annually depreciated at a rate of 15% (e.g., Popp, 2004; Qiu & Anadon, 2012). Following Schilling and Phelps (2007), we included the annually depreciated value of pre-sample patents (before 2008) to control for unobserved heterogeneity in firm patenting activity.

Prior private financing deals. We controlled for the impact of private investments by including the number of prior financing deals of each startup for each year. We applied an annual depreciation rate equal to the one we used for prior patents to account for the diminishing importance of financial investments over time.

Prior public financing deals. Similar to private financial deals, we also included a measure that accounted for whether the startup received prior grants or other forms of financial support from public sources. As an additional robustness check on public financing and acknowledging the central role of the DOE, we compiled information on the number of grants or other types of financial support that the startups might have received from the DOE in the examined time frame. We obtained the data from the USA Spending database and counted the number of financing deals per startup. Overall, 96 of the cleantech startups in our sample (i.e., 12% of our sample) have received one or more DOE grant or other financial assistance.[12]

Sub-sector, age, and size. Firm-level information on sub-sector, age, and size was extracted from the i3 Cleantech Group, FactSet, and Orbis databases, and complemented and verified in a web search. We included industry fixed-effects for the 17 sub-sectors in our statistical models.

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[12] These include direct payments or reimbursements.

Figure 4 shows the average number of patents per sub-sector. We measured firm size by the number of employees, and age as the time interval since the founding year.

Insert Figure 4 about here

Location. While we look at the global collaborations of US startups, we also account for the physical location of the startups, particularly in regional hotspots. For example, the Silicon Valley and San Francisco area are together home to 168 of the 783 (i.e., 21% of our sample) cleantech startups. We examined whether firms that are located in geographically dense areas have higher propensities to innovate, achieve growth outcomes, or survive. We collected information on firm addresses from the i3 Cleantech Group, FactSet, and Orbis databases, and mapped the zip codes to the respective Metropolitan Statistical Area (MSA)[13] for 2011. We applied two different approaches to account for locational influences. The first approach was to capture the variance in the concentration of cleantech startups in the different MSA by using the percentage of total firms located in the respective MSA (for a similar approach, see, for example, DeCarolis & Deeds, 1999; Folta, Cooper, & Baik, 2006). As shown in Figure 5, around 40% of the firms are located in the San Francisco-Oakland-Fremont, Boston-Cambridge-Quincy, New York-Northern New Jersey-Long Island, San Jose-Sunnyvale-Santa Clara, and Los Angeles-Long Beach-Santa Ana region, and the rest of the firms are spread across the country or located in smaller regional hubs. The second approach was to directly include fixed effects for each MSA to check the robustness of the concentration measure.

Insert Figure 5 about here

[13] We also included the same evaluation for Combined Statistical Area (CSA) distinction, which revealed similar results in our statistical models.

Figure 6 shows the average number of patents in the Top 15 MSAs. Not surprisingly, the San Jose-Silicon Valley area is among the highest in average patents per firm. However, the MSAs of Santa Rosa-Petaluma, CA, displayed an even higher average number of patents per startup.

Insert Figure 6 about here

RESULTS

A summary of the descriptive statistics and correlations for the 783 startups in our sample, averaged over time, is provided in Table 2. Our dependent variables patenting activity and financing deals are not highly correlated with any of the other variables. The startups in our sample introduced an average of 1.8 patents every year (mean = 1.84 per firm-year), and, on average, attracted more than one financing deal every two years (mean = 0.66 per firm-year). Overall, while all of our startups had collaborations in at least one of the four two-year windows (2008-2009, …, 2011-2012), 13.75% of the startups collaborated with at least one government organization between 2008 and 2012.

Insert Table 2 about here

We analyze the data with negative binomial regressions for the count variables—patenting activity and financing deals—because of overdispersion. We use robust standard errors and include time- and sector-fixed effects in our models. For each outcome variable, we calculated three different models: Models 1 and 2 for the overall impact of the controls and partner type variables respectively, and Model 3 for the granular separation in collaboration types per partner. The estimates for industry and time period effects are, although estimated, not reported to conserve space.[14] Table 3 reports the estimated coefficients of four negative binomial regression models on patenting activity. The results indicate that—compared to startup collaborations with universities or research institutes, not-for-profit partners, other public organizations, and other startups or established firms—only the startups that collaborate with and are part of the network of the most central government organizations are associated with larger cleantech startup patenting ($\beta = 2.16$, p-value < 0.01, Model 2). As negative binomial regressions model the log of incident counts, this estimate implies that a one-unit increase in centrality with governmental partners increases the log of patenting activity by approximately 2.16.[15] Thus, we found support for H1. As hypothesized in H2, we found that market-based collaborations with governments are associated with reductions in innovation activities ($\beta = -1.71$, p-value < 0.01, Model 3). H3 is only partially supported, as joint technology development collaborations ($\beta = 2.25$, p-value < 0.01, Model 3) are associated with more startup innovation than licensing collaborations ($\beta = 0.63$, n.s., Model 3). However, when the analysis is conducted separately for the 59% of startups that are part of the larger ecosystem and for the 41% of startups that are largely operating in smaller networks (dyads, triads, etc., see Figure 2), we found that governmental licensing collaborations are associated with greater startup innovation activities for those that operate outside of the larger, connected ecosystem (Model 4). This interaction is depicted in Figure 6.

Insert Table 3 about here

Insert Figure 6 about here

[14] These estimates are available from the authors upon request.

[15] This estimate can also be expressed in terms of a percentage increase, i.e., the incidence rate ratios (IRR), where percentage is determined by the amount that the IRR is either below or above 1. The IRR for collaboration with central governmental partners is 8.67 ($IRR = e^{\beta}$), which implies that patenting activity increases by approximately 767% with every one unit increase in centrality. The centrality measure is a continuous variable between 0 and 1 (see Table 2), where a one unit increase implies a large change from minimum to maximum levels of eigenvector centrality, which explains the large coefficient and IRR.

The results on the impact of collaboration with governmental partners on the ability of startups to attract financial investments are shown in Table 4 (private financing deals). The results provide only partial support for H4, as both joint technology development and market collaborations have no significant effect on subsequent financing deals. However, we found that public licensing collaborations increase subsequent financing deals ($\beta = 1.19$, p-value < 0.01, Model 3) and therefore could serve as an important signal to investors.

Insert Table 4 about here

Additional Analysis

To check the robustness of our results and to rule out alternative explanations, we specified several alternative econometric models and measures of central partners that revealed similar results, available upon request from the authors. The same models in a panel set-up using a fixed-effect specification revealed robust coefficients and comparable results without inclusion of the time-invariant variables (see Table 5). Models using a binary variable on whether the startups achieved a growth outcome (IPO or M&A within 6 years after founding) in a logit regression revealed similar results to the private financing deals models. To understand the impact of our control variable on general public financing, all of the above models were calculated including a count variable on the number of awards that the startups received from DOE in the time frame, which also provided identical results. Finally, models using power centrality and average distance weighted reach as alternatives to eigenvector centrality measures also revealed similar results.

Insert Table 5 about here

Furthermore, there may also be a concern that our dataset and the relationships we detected could be inflated due to an endogeneity problem. The ability of startups to find a governmental partner may be correlated to their innovation abilities, and we do not have access to a randomized control trial or other quasi-experimental approach (e.g., IV or DID). But our hypothesis and findings do not rely on a causal interpretation. Even if the results are explained by more innovative or capable startups pursuing collaboration with governmental partners, our results indicate that the more innovative startups see value in particular types of partners and collaborations. We further conducted propensity score matching and tested the treatment effect on similar firms based on age size, prior private and public financing deals, prior patents, and location. Our findings indicate significant Average Treatment Effects (ATE) ($p < 0.1$) for patenting activity, such as that firms with governmental partners showed a higher patenting activity. For private financing deals, our findings revealed significantly ($p < 0.05$) higher ATE of private financing deals for startups with governmental partner.

DISCUSSION

This study examines the impact of startup collaboration with network central government organizations on the ability of startups to innovate and to attract financial investments, when compared to collaboration with research institutes and universities, not-for-profit organizations, or other startups or established firms. Following the call of Laursen and Salter (2006, 2014), we develop a framework that separates the knowledge flows from these different partner types and show that each of them can have different effects on startup innovation activities. Our framework extends the emerging literature on entrepreneurial ecosystems by drawing on resource dependence theory to highlight collaboration with governmental partners that hold key resources for startup innovation. Our novel dataset on the global collaborations of 783 US cleantech startups between 2008 and 2012 enables the quantification of the relation between startup innovation outcomes and different types of collaborations with governments, i.e., market-based vs. technology-based or tacit from joint technology development vs. codified from acquiring public licenses. Overall, our study extends openness and alliance perspectives on firm innovation and contributes to the ecosystems literature in the following ways.

Openness and Alliances

Our study contributes to research on openness and interorganizational alliances with a focus on startups. Though prior research has often emphasized the benefits of collaboration with as many and diverse partners for innovation, we motivated a scenario that acknowledges that startups have more limited resources than other firms and that collaborating with a diverse set of partners is a resource intense endeavor. In this study, the relative impact of collaboration with all potential partner types on startup innovation activities not only considered potentially distinct dynamics by distinguishing knowledge flows and value appropriation from collaboration with network central government organizations and other central startups or established firms, but also between universities, private research institutes, and other not-for-profit partners such as NGOs or environmental groups. Our findings provide novel empirical evidence on the importance of collaboration with network central governmental partners that hold critical technological resources in the cleantech sector resulting from their long-term experience, expertise, and commitment. These technological resources might be highly complementary to the abilities of startups in identifying and responding to market opportunities by developing novel solutions to market needs using jointly developed or licensed technologies. Combined with the reduced concerns of appropriability and opportunistic or exploitative behavior as opposed to other firms or VCs, these unique characteristics make governments key, yet so far undervalued, partners.

Moreover, our findings on the types of collaborations and the importance of joint technology development collaborations for innovation activity and of licensing collaborations with governments for follow-on investments provide novel insights into when governmental partners are beneficial for startups, and enrich research on openness by developing even more "fine-grained items for each of the possible knowledge channels" (Laursen & Salter, 2006: 147). The quantification of the relation between joint technology development, licensing collaborations and startup innovation further provides a new perspective on the benefits of collaboration with governments through different forms of knowledge exchanges and possibilities of spillovers. While access to more implicit and tacit knowledge sources from joint technology development are more important for subsequent innovation activities than codified knowledge from public licensing, the latter is associated with an increased likelihood of attracting financial investments.

Entrepreneurial Ecosystems

Our study advances research on entrepreneurial ecosystems in two main ways. *First,* we suggest an important theoretical grounding for determining the top or 'anchor' partners that are associated with more entrepreneurial innovation by using resource dependence theory that takes an ego-centric view on organizations. With its focus on organizations' management of their external relations to ensure access to those organizations in their environment that have greatest discretion over the most valuable technological resources (Pfeffer & Salancik, 1978), resource dependence theory offers avenues to understand which type of partner and collaboration is associated with highest levels of startup innovation. Our findings show that joint technology development and licensing collaborations with governments represent the most important components of the ecosystem that contribute to increased innovation. Moreover, our dynamic perspective on entrepreneurial innovation combined with a focus on the whole network of startups rather than specific dyads contributes to the call for multiplex and dynamic applications of resource dependence theory (Hillman et al., 2009).

Second, by highlighting the role of governmental intervention for entrepreneurial innovation, we bring the tools and concepts of entrepreneurial ecosystems focused on the firm-level to study a question that was previously mostly investigated at the macro-level in technological innovation systems (TIS) research (e.g., Bergek et al., 2008; Hekkert et al., 2007). While both approaches have the focus on organizations and networks in common, there are two main differences: (1) ecosystems research focuses on the impact of a firm's collaborations with other organizations, whereas firms only constitute one of many organizations in the larger systemic context that jointly contribute to the development and diffusion of new technologies in innovation systems. (2) The ecosystems concept has been derived from a biological and ecological perspective, and generally assumes that the system develops organically and that firm interactions are primarily governed by market demands. Policy recommendations to improve ecosystem functioning are—if at all—mostly derived for local, geographically centered ecosystems. In contrast, the TIS approach takes a more macro-level perspective on organizations and their global networks, and points to specific system bottlenecks—or 'functions of innovation'—for designing adequate policies to steer system development. Our findings show that these research streams are highly complementary and can benefit from each other's views in two ways: (a) by setting the boundaries of the entrepreneurial ecosystem outside of specific geographic hotspots or local clusters (Adner, 2006; Autio et al., 2014) and (b) by identifying system failures through the study of contextual factors that affect startup outcomes (Hekkert et al., 2007; Jacobsson & Bergek, 2011). These two contributions are outlined in the following.

The TIS approach enables a systemic perspective to first identify system failures and then develop adequate policy responses to addressing these failures while recognizing the global nature of innovation (Grubler et al., 2012). The focus on public steering and the importance of central partners underlines the importance of exploring cleantech innovation on a geographic scale that moves beyond the regional clusters or 'hotspots' such as Silicon Valley. Our findings suggest that central US government organizations associated with more positive outcomes for startups, i.e., primarily the national laboratories such as NREL located in Golden, Colorado (see Figure 1), were not only acting away from regional hubs such as Silicon Valley, but collaborated with startups that are physically dispersed across the US. Furthermore, we distinguished two larger ecosystems for cleantech startup innovation. We found that the codified knowledge exchanges in the form of public licenses only affected the innovation activities of those startups that did not have access to the knowledge flows within the larger ecosystem. Thus, these findings highlight the importance for future research to set ecosystem boundaries outside of specific geographic hotspots or local clusters for studying outcomes at the firm (startup) level.

By putting the contextual factors that support increased levels of short-term entrepreneurial innovation at the center of analysis (most prominently on the types of partners and types of collaborations), the insights from entrepreneurial ecosystems research provide an avenue to account for the missing focus on entrepreneurial outcomes in TIS research (Ács, Autio, & Szerb, 2014). Much of the extant analyses on the function of 'entrepreneurial activities' in TIS are based on the pure number of new firm founding (i.e., quantity) with the implicit assumption that all startups innovate or have equal probabilities of success (e.g., Hekkert et al., 2007; Pacheco, York, & Hargrave, 2014; Sine, Haveman, & Tolbert, 2005). Resonating with the recent contribution of Guzman and Stern (2015)—highlighting the importance of studying entrepreneurial outcomes, or 'quality' rather than 'quantity'—our findings indicate that cleantech startups show different levels of innovation activities, and that the level of innovation is associated with very specific characteristics of their collaborative environment. In turn, collaboration with government organizations, which are studied at a macro-level in TIS but were largely absent from the entrepreneurial ecosystems literature, seem to be important for startup outcomes in the US cleantech sector.

Practical Implications

Our findings are important for policymakers, entrepreneurs, and investors involved in the cleantech sector. Policymakers can benefit from our results to understand what types of governmental partners and collaborations are associated with more innovative startups and follow on investments. Our results highlighting the potential role of government organizations as partners complement existing research on the role of governments as financiers of innovation activities through supply-push or demand-pull policies, providing relevant information for resource allocation. Entrepreneurs and investors can benefit from our findings that may help support resource-constrained startups in identifying the type of partner and collaboration that is associated with the highest innovation and funding outcomes.

Our findings underscore the need for policymakers to provide sufficient and stable funding for longer-term research activities for government organizations. We found that central governmental partners are the most important drivers of startup innovation activities, particularly in the form of joint technology collaborations. We proposed that government organizations possess critical technological resources for startup innovation activities that result from their long-term experience and expertise in the clean power and transportation sector. Furthermore, reduced concerns of appropriability and opportunistic behavior make government organizations key partners for startup innovation. Hence, our results point towards an approach for stimulating cleantech innovation that recognizes the importance of collaboration between historically-dominant centralized laboratories focused on national capabilities—e.g., R&D laboratories at public incumbent firms such as Bell Labs, or governmental laboratories such as NREL—with private sector activities and more recent and smaller-scale phenomenon of startups.

Our findings also indicate that access to central partners by being part of their ecosystem enables increased innovative activities—regardless of geographical proximity—at least in the cleantech sector. Hence, despite the recognized importance of geographical concentration in specific technological hotspots or physical proximity to these regions (Jaffe, 1986; Krugman, 1991; Owen-Smith & Powell, 2008; Powell et al., 1996; Saxenian, 1996), co-location in technology hotspots might be more important for startups operating in sectors that are characterized by frequent changes, high-turnover rates, and smaller capital requirements than in the energy space, such as in IT. This could be explained by the fact that clean technologies are more heterogeneous than those in other sectors (such as IT or biotech), with different technologies having very different knowledge bases ranging from semiconductor electronics and materials in solar, to aerodynamics and composite materials in wind, to enzymes and combustion in biofuels. The heterogeneity in the types of technologies in the cleantech sector may mean that different locations may be better for startups active in different technology areas; this would imply that having a critical mass of resources (including expertise) in one place for all of them might be more difficult. Hence, cleantech startups may have to resort more to collaboration, which in turn may be more geographically dispersed. Moreover, the importance of public licenses for innovation activities for those startups that are not part of the larger inter-connected network (see Figure 2) suggests that the value of public licenses differs based on the network position of the startup as compared to the geographical location of startups. Nevertheless, independent of network position or geographical location, public licenses are associated with improved follow-on investment outcomes, which could be a reflection of the fact that investors reward a particular technology ‘in hand’ more than a joint technology development collaboration.

Limitations and Future Research

As with all empirical studies, ours is not without limitations. *First*, while we look at the global collaborations of startups, we only study the impact on cleantech startups located within the US. Nevertheless, our findings regarding the value of different types of partners and collaborations provide a relatively complete picture of the cleantech startup sector given that a large majority of cleantech startups are located in the US, our sample comprises the whole country, and we consider startup collaborations to global partners. However, we see exciting opportunities for future research to conduct comparative studies and explore the impact of different types of partners and collaborations in a different country context, as cleantech startups become more prevalent outside of the United States. *Second*, while we explore the impact of collaboration types on innovation in terms of increases in the number of patents, we do not use the approach of counting patent citations to address novelty or radicalness for two reasons. (1) Patent citations are an insufficient measure of novelty as citations are often added by patent examiners rather than the inventors, and tend to also depend on the sector and expertise of examiners in addition to the quality of the patent in itself (e.g., Lemley & Sampat, 2012; Nelson, 2009). (2) While our sample is unique in its newness, the time period from 2008 to 2012 includes very recent patents for relatively new firms for which citations may not a valid measure. *Third,* our focus on the short-term impact of collaboration on startups is driven by the short-term imperative for startups to achieve successful outcomes. However, future research could extend our findings and evaluate the impact of collaboration over a longer-term focus than our time frame from 2008 to 2012. In addition, while we were able to show that particular collaborations are associated with better innovation outcomes, further knowledge of what types of resources and collaborations the ‘more successful’ firms are searching can greatly benefit entrepreneurs, investors, and policymakers alike. Additionally, even if more capable and innovative firms are those that are more likely to identify and secure such collaboration, future work may be able to determine more definitively the extent to which better partners are far-sighted enough to seek value in government collaborations or whether the collaborations themselves make partners more innovative. Future work may be able to use regression discontinuity approaches to separate firm quality from direct collaboration impact, for example, or even study the reciprocal effects. Integrating a resource dependence theoretical lens into the entrepreneurial ecosystems literature may provide important further insights into such reciprocal effects besides the outlined theoretical grounding to determine the top partners and partnerships for increased innovation. According to resource dependence theory, next to managing resources, organizations can successfully deal with uncertainty by trying to shape governmental regulations for a more favorable environment. While this strategy is typically reserved for larger, established firms that have sufficient resources for engaging in political activities, the access to the relevant governmental bodies through technology and licensing collaborations can provide a more realistic opportunity for resource-constrained startups to also shape governmental regulations (Lin, 2014 provide similar arguments for why startups should forge relationships with governmental bodies). *Fourth*, while this study already provides a fine-grained analysis of partner types by splitting network measures into collaboration types, future research could look more explicitly at the interorganizational network and explore differences in terms of collaboration with suppliers, customers, or competitors. *Fifth*, while our results point to the value of collaboration, we look at the relationship between collaboration and startup innovation activity in a specific period (2008 – 2012) that faced a global financial crisis. Although we control for time-changes in the statistical models and our results emphasize on collaboration in a time of financial resource constraints, additional research on either other sectors during the financial crisis, or on the cleantech sector in less constrained periods, could test the extent to which the results are specific to a time of limited financing.

REFERENCES

Ács, Z. J., Autio, E., & Szerb, L. 2014. National systems of entrepreneurship: Measurement issues and policy implications. ***Research Policy***, 43(3): 476-494.

Adner, R. 2006. Match your innovation strategy to your innovation ecosystem. ***Harvard Business Review***, 84(4): 98-107.

Adner, R. & Kapoor, R. 2010. Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations. ***Strategic Management Journal***, 31(3): 306-333.

Alvarez, S. A. & Busenitz, L. W. 2001. The entrepreneurship of resource-based theory. ***Journal of Management***, 27(6): 755-775.

Anadon, L. D. & Holdren, J. P. 2009. Policy for energy technology innovation. In K. S. Gallagher (Ed.), ***Acting in time on energy policy***: 89-127. Washington, DC: Brookings Institution Press.

Anadon, L. D. 2012. Missions-oriented RD&D institutions in energy between 2000 and 2010: A comparative analysis of China, the United Kingdom, and the United States. ***Research Policy***, 41(10): 1742-1756.

Anadon, L. D., Bunn, M., & Narayanamurti, V. 2014. ***Transforming US energy innovation***. Cambridge, UK: Cambridge University Press.

Autio, E., Kenney, M., Mustar, P., Siegel, D., & Wright, M. 2014. Entrepreneurial innovation: The importance of context. ***Research Policy***, 43(7): 1097-1108.

Baum, J. A. C. 1996. Organizational ecology. In S. Clegg & C. Hardy & W. Nord (Eds.), ***Handbook of organization studies***: 77-114. London: SAGE.

Baum, J. A. C., Calabrese, T., & Silverman, B. S. 2000. Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. ***Strategic Management Journal***, 21(3): 267-294.

Bergek, A., Jacobsson, S., Carlsson, B., Lindmark, S., & Rickne, A. 2008. Analyzing the functional dynamics of technological innovation systems: A scheme of analysis. ***Research Policy***, 37(3): 407-429.

Bettis, R. A. & Hitt, M. A. 1995. The new competitive landscape. ***Strategic Management Journal***, 16(1): 7-19.

Bonacich, P. 1987. Power and centrality: A family of measures. ***American Journal of Sociology***, 92(5): 1170-1182.

Bonacich, P. 2007. Some unique properties of eigenvector centrality. ***Social Networks***, 29(4): 555-564.

Bonvillian, W. B. & Atta, R. 2011. ARPA-E and DARPA: Applying the DARPA model to energy innovation. ***The Journal of Technology Transfer***, 36(5): 469-513.

Bonvillian, W. B. 2014. The new model innovation agencies: An overview. ***Science and Public Policy***, 41: 425-437.

Chan, G. 2015. The commercialization of publicly funded science:How licensing federal laboratory inventions affects knowledge spillovers. Harvard Kennedy School Working Paper. Available at: https://drive.google.com/file/d/0B-RCEGY3RGj7a09raGhaanhZSlU/view?pref=2&pli=1.

Chesbrough, H. W. 2003. ***Open innovation: The new imperative for creating and profiting from technology***. Boston: Harvard Business Press.

Choi, H. & Anadón, L. D. 2014. The role of the complementary sector and its relationship with network formation and government policies in emerging sectors: The case of solar photovoltaics between 2001 and 2009. ***Technological Forecasting and Social Change***, 82(2): 80-94.

Chu, S. & Majumdar, A. 2012. Opportunities and challenges for a sustainable energy future. ***Nature***, 488(7411): 294-303.

Clarysse, B., Wright, M., Bruneel, J., & Mahajan, A. 2014. Creating value in ecosystems: Crossing the chasm between knowledge and business ecosystems. ***Research Policy***, 43(7): 1164-1176.

Conti, A., Thursby, J., & Thursby, M. 2013. Patents as signals for startup financing. ***The Journal of Industrial Economics***, 61(3): 592-622.

Cox Pahnke, E., McDonald, R., Wang, D., & Hallen, B. 2015. Exposed: Venture capital, competitor ties, and entrepreneurial innovation. ***Academy of Management Journal***, 58(5): 1334-1360.

Csardi, G. & Nepusz, T. 2006. The igraph software package for complex network research. ***InterJournal***, Complex Systems: 1695.

DeCarolis, D. M. & Deeds, D. L. 1999. The impact of stocks and flows of organizational knowledge on firm performance: An empirical investigation of the biotechnology industry. ***Strategic Management Journal***, 20(10): 953-968.

Deeds, D. L. & Hill, C. W. L. 1996. Strategic alliances and the rate of new product development: An empirical study of entrepreneurial biotechnology firms. ***Journal of Business Venturing***, 11(1): 41-55.

Demirkan, I. & Demirkan, S. 2012. Network characteristics and patenting in biotechnology, 1990-2006. ***Journal of Management***, 38(6): 1892-1927.

Doblinger, C., Dowling, M., & Helm, R. 2016. An institutional perspective of public policy and network effects in the renewable energy industry: Enablers or disablers of entrepreneurial behaviour and innovation? ***Entrepreneurship & Regional Development***, 28(1-2): 126-156.

DOE. 2014. Strategic plan 2014-2018; Accessed June 8, 2016: http://www.energy.gov/sites/prod/files/2014/04/f14/2014_dept_energy_strategic_plan.pdf.

Dyer, J. H. & Singh, H. 1998. The relational view: Cooperative strategy and sources of interorganizational competitive advantage. ***Academy of Management Review***, 23(4): 660-679.

Folta, T. B., Cooper, A. C., & Baik, Y.-S. 2006. Geographic cluster size and firm performance. ***Journal of Business Venturing***, 21(2): 217-242.

Fouquet, R. 2013. ***Handbook on energy and climate change***. Cheltenham, UK and Northampton, MA: Edward Elgar Publications.

Freeman, C. 1987. ***Technology policy and economic performance: Lessons from Japan***. London: Pinter Publishers.

Fuchs, E. R. H. 2010. Rethinking the role of the state in technology development: DARPA and the case for embedded network governance. ***Research Policy***, 39(9): 1133-1147.

Glauthier, T. J. & Cohon, J. L. 2015. Securing America's future: Realizing the potential of the Department of Energy's national laboratories. Accessed May 20, 2016: http://energy.gov/sites/prod/files/2015/10/f27/Final%20Report%20Volume%201.pdf.

Griliches, Z. 1990. Patent statistics as economic indicators: A survey. ***Journal of Economic Literature***, 28(4): 1661-1707.

Grubler, A., Nakićenović, N., & Victor, D. G. 1999. Dynamics of energy technologies and global change. ***Energy Policy***, 27(5): 247-280.

Grubler, A., Aguayo, F., Gallagher, K., Hekkert, M., Jiang, K., Mytelka, L., Neij, L., Nemet, G., & Wilson, C. 2012. Chapter 24 - Policies for the energy technology innovation system (ETIS), ***Global energy assessment - Toward a sustainable future***: 1665-1744. Cambridge, UK, New York, USA, and Laxenburg, Austria: Cambridge University Press and International Institute for Applied Systems Analysis.

Guzman, J. & Stern, S. 2015. Where is Silicon Valley? ***Science***, 347(6222): 606-609.

Haeussler, C., Harhoff, D., & Müller, E. 2009, To be financed or not . . .: The role of patents for venture capital financing. ZEW - Centre for European Economic Research Discussion Paper No. 09-003. Available at SSRN: http://ssrn.com/abstract=1393725.

Hagedoorn, J. & Schakenraad, J. 1994. The effect of strategic technology alliances on company performance. ***Strategic Management Journal***, 15(4): 291-309.

Hekkert, M. P., Suurs, R. A. A., Negro, S. O., Kuhlmann, S., & Smits, R. E. H. M. 2007. Functions of innovation systems: A new approach for analysing technological change. ***Technological Forecasting and Social Change***, 74(4): 413-432.

Hillman, A. J., Withers, M. C., & Collins, B. J. 2009. Resource dependence theory: A review. ***Journal of Management***, 35(6): 1404-1427.

Hoppmann, J., Peters, M., Schneider, M., & Hoffmann, V. H. 2013. The two faces of market support: How deployment policies affect technological exploration and exploitation in the solar photovoltaic industry. ***Research Policy***, 42(4): 989-1003.

Howell, S. 2015. Financing constraints as barriers to innovation: Evidence from R&D grants to energy startups. Harvard Kennedy School Working Paper. Available at: http://scholar.harvard.edu/files/showell/files/howell_innovation_finance_jmp_jan17.pdf.

Hsu, D. H. & Ziedonis, R. H. 2013. Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. ***Strategic Management Journal***, 34(7): 761-781.

i3 Cleantech Group. 2015. i3 cleantech database. Accessed January 11th, 2015: https://i3connect.com/front_page?ref=%2F.

Iansiti, M. & Levien, R. 2004. ***The keystone advantage: What the new dynamics of business ecosystems mean for strategy, innovation, and sustainability***. Cambridge, MA: Harvard Business School Press.

Jacobsson, S. & Bergek, A. 2011. Innovation system analyses and sustainability transitions: Contributions and suggestions for research. ***Environmental Innovation and Societal Transitions***, 1(1): 41-57.

Jaffe, A. B. 1986. Technological opportunity and spillovers of R & D: Evidence from firms' patents, profits, and market value. ***The American Economic Review***, 76(5): 984-1001.

Jones, C., Anadon, L. D., & Narayanamurti, V. 2014. Encouraging private-sector energy technology innovation and public-private cooperation. In L. D. Anadon & M. Bunn & V. Narayanamurti (Eds.), ***Transforming US Energy Innovation***: 125-168. Cambridge, UK: Cambridge University Press.

Jung, H. J. & Lee, J. 2015. The quest for originality: A new typology of knowledge search and breakthrough inventions. ***Academy of Management Journal***, Forthcoming.

Koonin, S. E. & Gopstein, A. M. 2011. Accelerating the pace of energy change. ***Issues in Science and Technology***, XXVII(2): Winter 2011. Available at: http://issues.org/2027-2012/koonin/.

Krugman, P. 1991. Increasing returns and economic geography. ***Journal of Political Economy***, 99(3): 483-499.

Laursen, K. & Salter, A. 2006. Open for innovation: The role of openness in explaining innovation performance among U.K. manufacturing firms. ***Strategic Management Journal***, 27(2): 131-150.

Laursen, K. & Salter, A. J. 2014. The paradox of openness: Appropriability, external search and collaboration. ***Research Policy***, 43(5): 867-878.

Lechner, C., Dowling, M., & Welpe, I. 2006. Firm networks and firm development: The role of the relational mix. ***Journal of Business Venturing***, 21(4): 514-540.

Lechner, C., Soppe, B., & Dowling, M. 2014. Vertical coopetition and the sales growth of young and small firms. ***Journal of Small Business Management***, 54(1): 67-84.

Lemley, M. A. & Sampat, B. 2012. Examiner characteristics and patent office outcomes. ***Review of Economics and Statistics***, 94(3): 817-827.

Levin, R., Klevorick, A., Nelson, R., & Winter, S. 1987. Appropriating the returns from industrial research and development. ***Brookings Papers on Economic Activity***, 3: 783–820.

Li-Ying, J., Wang, Y., Salomo, S., Li-Ying, J., Wang, Y., & Salomo, S. 2014. An inquiry on dimensions of external technology search and their influence on technological innovations: Evidence from Chinese firms. ***R & D Management***, 44(1): 53-74.

Liebeskind, J. P., Oliver, A. L., Zucker, L., & Brewer, M. 1996. Social networks, learning, and flexibility: Sourcing scientific knowledge in new biotechnology firms. ***Organization Science***, 7(4): 428-443.

Lin, H. 2014. Government–business partnership formation for environmental improvements. ***Organization & Environment***, 27(4): 383-398.

Lundvall, B.-Å. 1992. ***National systems of innovation: Towards a theory of innovation and interactive learning***. London: Pinter.

Malecki, E. J. & Poehling, R. M. 1999. Extroverts and introverts: Small manufacturers and their information sources. ***Entrepreneurship & Regional Development***, 11(3): 247-268.

Markard, J., Raven, R., & Truffer, B. 2012. Sustainability transitions: An emerging field of research and its prospects. ***Research Policy***, 41(6): 955-967.

Mazzucato, M. 2013. ***The entrepreneurial state – Debunking public vs. private sector myths***. London, UK: Anthem Press.

Meyskens, M. & Carsrud, A. 2013. Nascent green-technology ventures: A study assessing the role of partnership diversity in firm success. ***Small Business Economics***, 40(3): 739-759.

Mowery, D. C., Nelson, R. R., & Martin, B. R. 2010. Technology policy and global warming: Why new policy models are needed (or why putting new wine in old bottles won't work). ***Research Policy***, 39(8): 1011-1023.

Nanda, R., Younge, K., & Fleming, L. 2015. Innovation and entrepreneurship in renewable energy. In A. Jaffe & B. Jones (Eds.), ***The changing frontier: Rethinking science and innovation policy***: 199-232. Chicago: University of Chicago Press.

Narayanamurti, V. & Odumosu, T. 2016. ***Cycles of invention and discovery***. Cambridge, MA: Harvard University Press.

Nelson, A. J. 2009. Measuring knowledge spillovers: What patents, licenses and publications reveal about innovation diffusion. ***Research Policy***, 38(6): 994-1005.

Nemet, G. F. 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. ***Research Policy***, 38(5): 700-709.

Owen-Smith, J. & Powell, W. W. 2008. Networks and institutions. In R. Greenwood & C. Oliver & K. Sahlin & R. Suddaby (Eds.), ***The SAGE handbook of organizational institutionalism***: 596-624. London, Thousand Oaks, New Delhi, Singapore: SAGE Publications.

Pacheco, D. F., York, J. G., & Hargrave, T. J. 2014. The coevolution of industries, social movements, and institutions: Wind power in the United States. ***Organization Science***, 25(6): 1609-1632.

Pfeffer, J. & Salancik, G. R. 1978. ***The external control of organizations: A resource dependence perspective***. New York: Harper & Row.

Popp, D. 2004. ENTICE: Endogenous technological change in the DICE model of global warming. ***Journal of Environmental Economics and Management***, 48(1): 742-768.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. ***Administrative Science Quarterly***, 41(1): 116-145.

Qiu, Y. & Anadon, L. D. 2012. The price of wind power in China during its expansion: Technology adoption, learning-by-doing, economies of scale, and manufacturing localization. ***Energy Economics***, 34(3): 772-785.

R Core Team. 2015. ***R: A language and environment for statistical computing***. Vienna, Austria: R Foundation for Statistical Computing.

Riordan, M. & Hoddeson, L. 1998. ***Crystal fire: The invention of the transistor and the birth of the information age***. New York et al.: Norton.

Robinson, D. T. & Stuart, T. E. 2007. Network effects in the governance of strategic alliances. ***Journal of Law, Economics, and Organization***, 23(1): 242-273.

Saxenian, A. 1996. ***Regional advantage: Culture and competition in Silicon Valley and Route 128***. Cambridge, MA: Harvard University Press.

Schacht, W. H. 2009, The Bayh-Dole Act: Selected issues in patent policy and the commercialization of technology; Accessed May 5, 2016: https://fas.org/sgp/crs/misc/RL32076.pdf.

Schilling, M. A. & Phelps, C. C. 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. ***Management Science***, 53(7): 1113-1126.

Sine, W. D., Haveman, H. A., & Tolbert, P. S. 2005. Risky business? Entrepreneurship in the new independent-power sector. ***Administrative Science Quarterly***, 50(2): 200-232.

Stam, W. & Elfring, T. 2008. Entrepreneurial orientation and new venture preformance: The moderating role of intra- and extraindustry social capital. ***Academy of Management Journal***, 51(1): 97-111.

Stuart, T. E. 2000. Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry. ***Strategic Management Journal***, 21(8): 791-811.

Tang, T. & Popp, D. 2014. The learning process and technological change in wind power: Evidence from China's CDM wind projects. ***National Bureau of Economic Research Working Paper Series 0–47***, Available at: http://www.nber.org/papers/w19921.

Trajtenberg, M. 1987. ***Patents, citations, and innovations: Tracing the links***. Cambridge, MA: National Bureau of Economic Research Working Paper 2457.

UNFCC. 2015. Adoption of the Paris Agreement; Accessed June 20, 2016: http://unfccc.int/files/essential_background/convention/application/pdf/english_paris_agreement.pdf.

United Nations. 2015. Transforming our World: The 2030 Agenda for Sustainable Development. Accessed July 10, 2016: http://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1&Lang=E.

Unruh, G. C. 2000. Understanding carbon lock-in. ***Energy Policy***, 28(12): 817.

Von Hippel, E. 1978. A customer-active paradigm for industrial product idea generation. ***Research Policy***, 7(3): 240-266.

von Hippel, E. 1988. ***The sources of innovation***. New York: Oxford University Press.

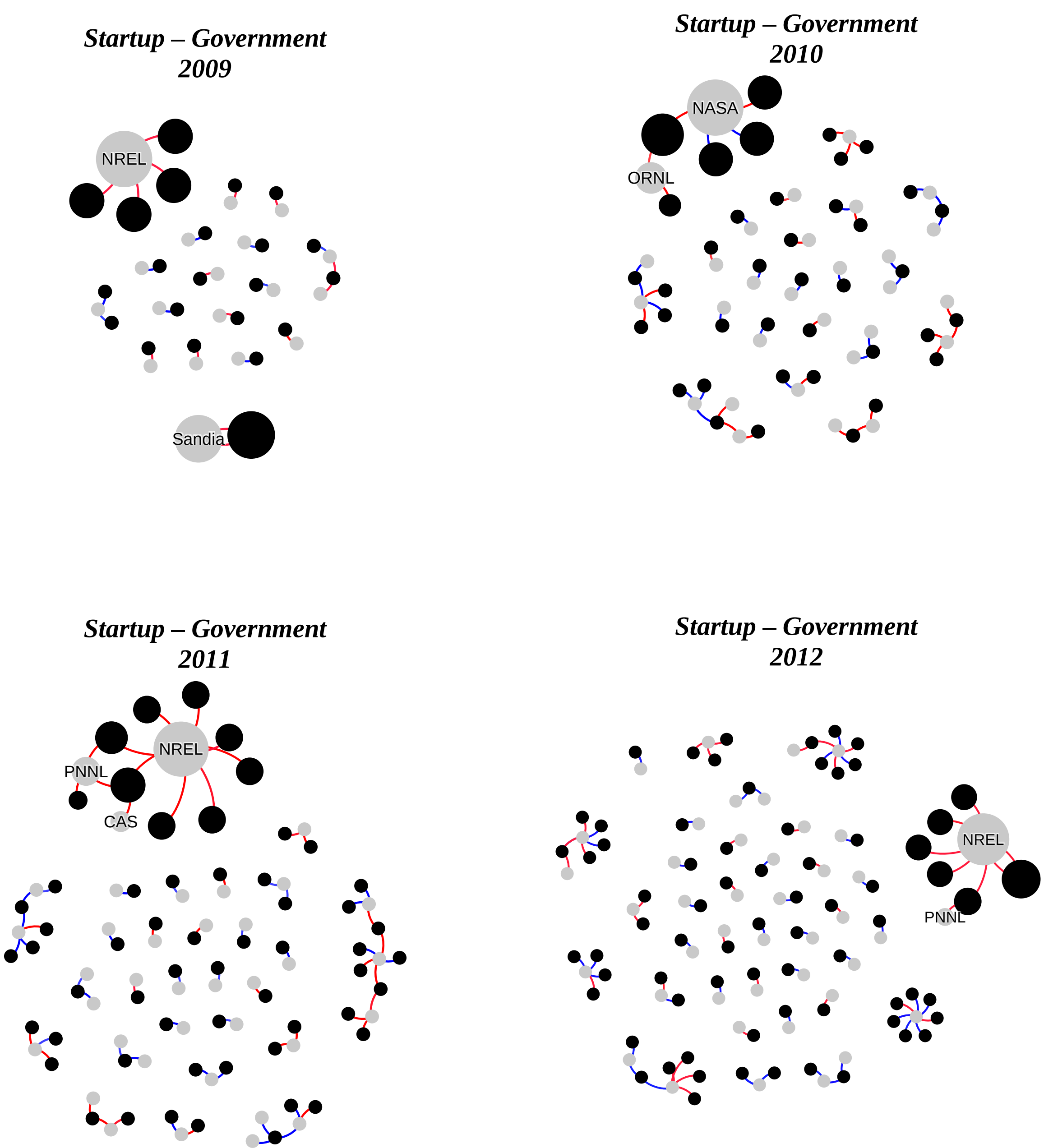
Westwick, P. J. 2003. ***The national labs: Science in an American system, 1947 - 1974***. Cambridge, MA: Harvard University Press.

Whittington, K. B., Jason, O.-S., & Powell, W. W. 2009. Networks, propinquity, and innovation in knowledge-intensive industries. ***Administrative Science Quarterly***, 54(1): 90-122.

Zahra, S. A. & Nambisan, S. 2012. Entrepreneurship and strategic thinking in business ecosystems. ***Business Horizons***, 55(3): 219-229.

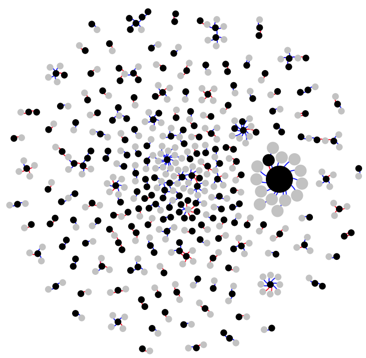
Zobel, A.-K., Balsmeier, B., & Chesbrough, H. 2016. Does patenting help or hinder open innovation? Evidence from new entrants in the solar industry. ***Industrial and Corporate Change***, 25(2): 307-331.

FIGURE 1
Network graphs

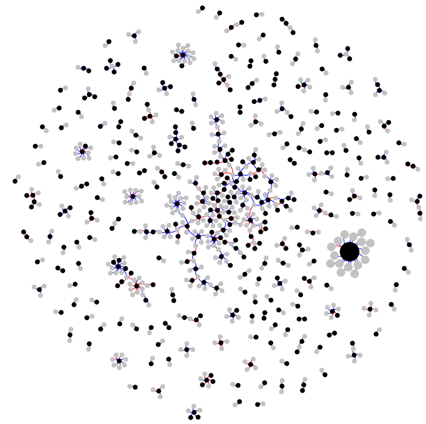


Graph of start-up (black) collaborations with governmental partners (grey) weighted by the eigenvector centrality from 2009 (top left) to 2012 (bottom-right). The collaborations are technology-based (red) or market-based (blue). The most central governmental partners with the highest eigenvector centralities are labeled.

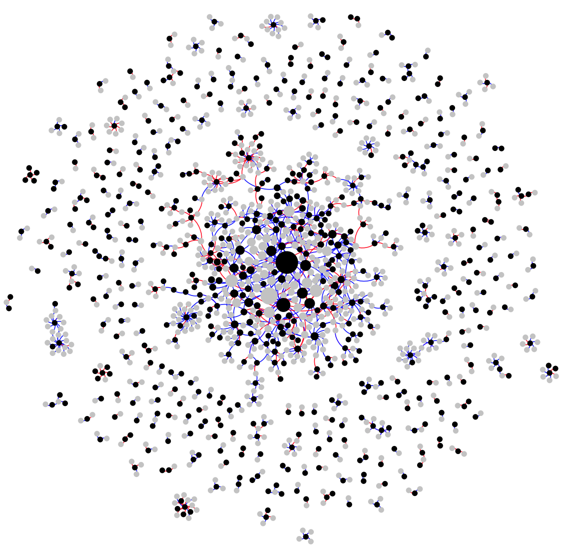
Startup – Other Firm
2009



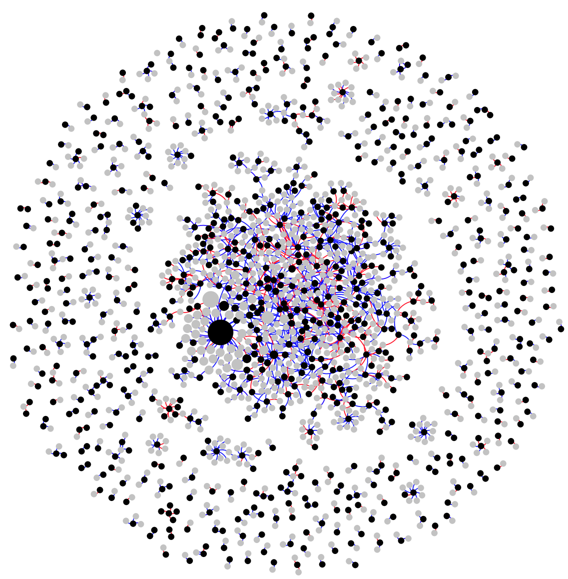
Startup – Other Firm
2010



Startup – Other Firm
2011



Startup – Other Firm
2012

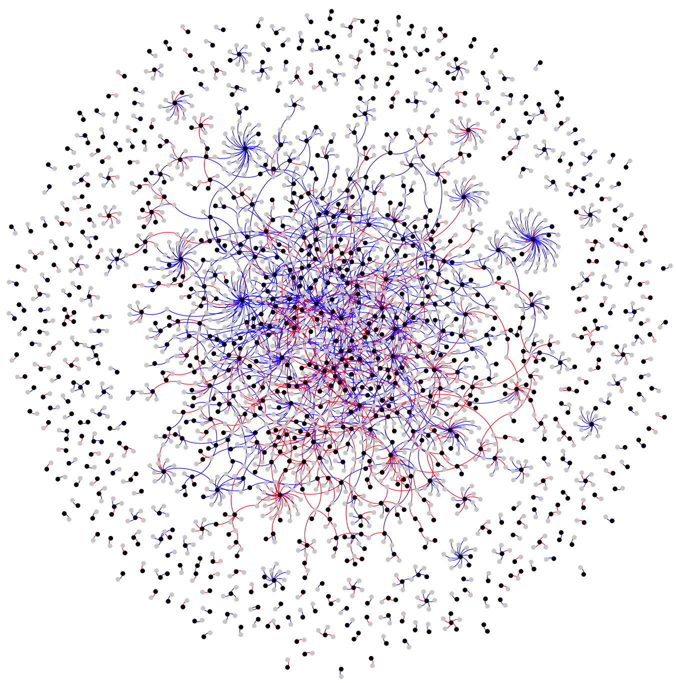


Graph of start-up (black) collaborations with other firms (grey) weighted by the eigenvector centrality from 2009 (top left) to 2012 (bottom-right). The collaborations are technology-based (red) or market-based (blue).

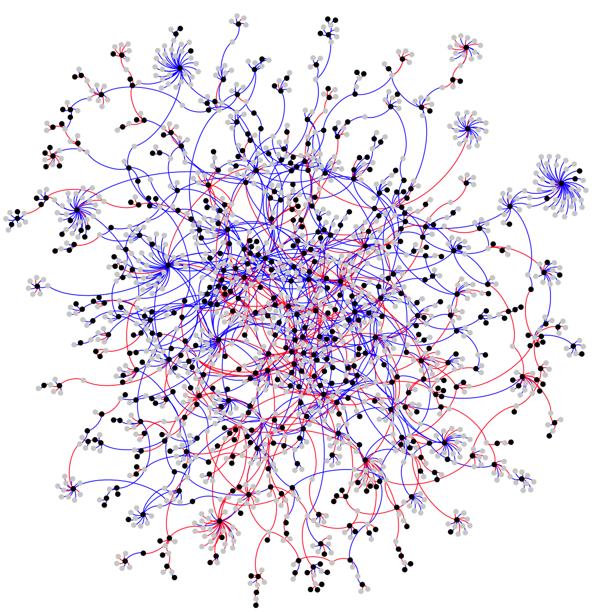
FIGURE 2

Differentiation of larger, well-connected ecosystem

Total Network



Larger Ecosystem
(59% of the US cleantech startups)



Outside of LargerEcosystem
(41% of US cleantech startups)

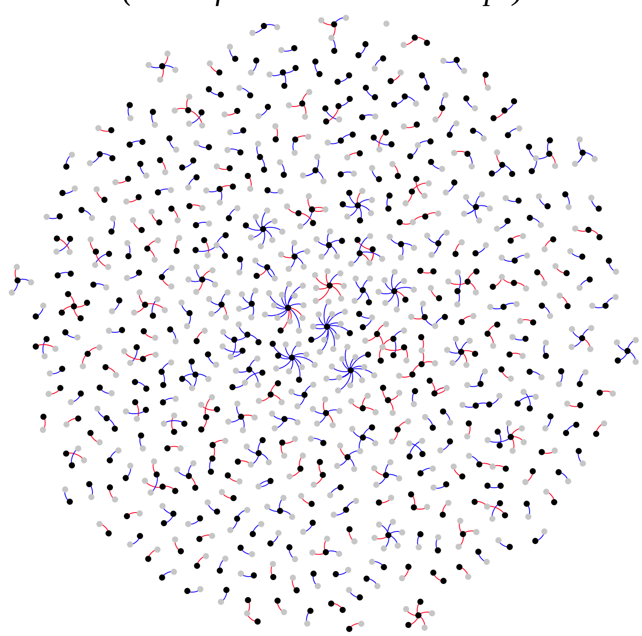


FIGURE 3

Overview of Private Investments

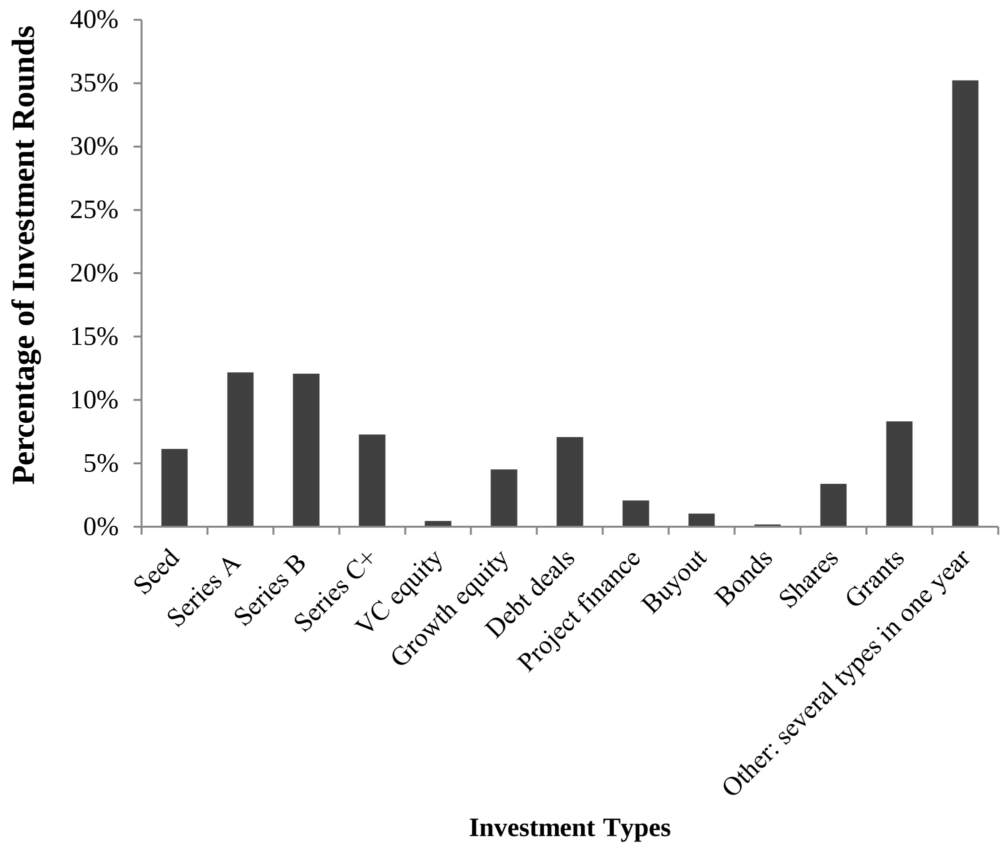


FIGURE 4

Average patenting activity per firm per sector

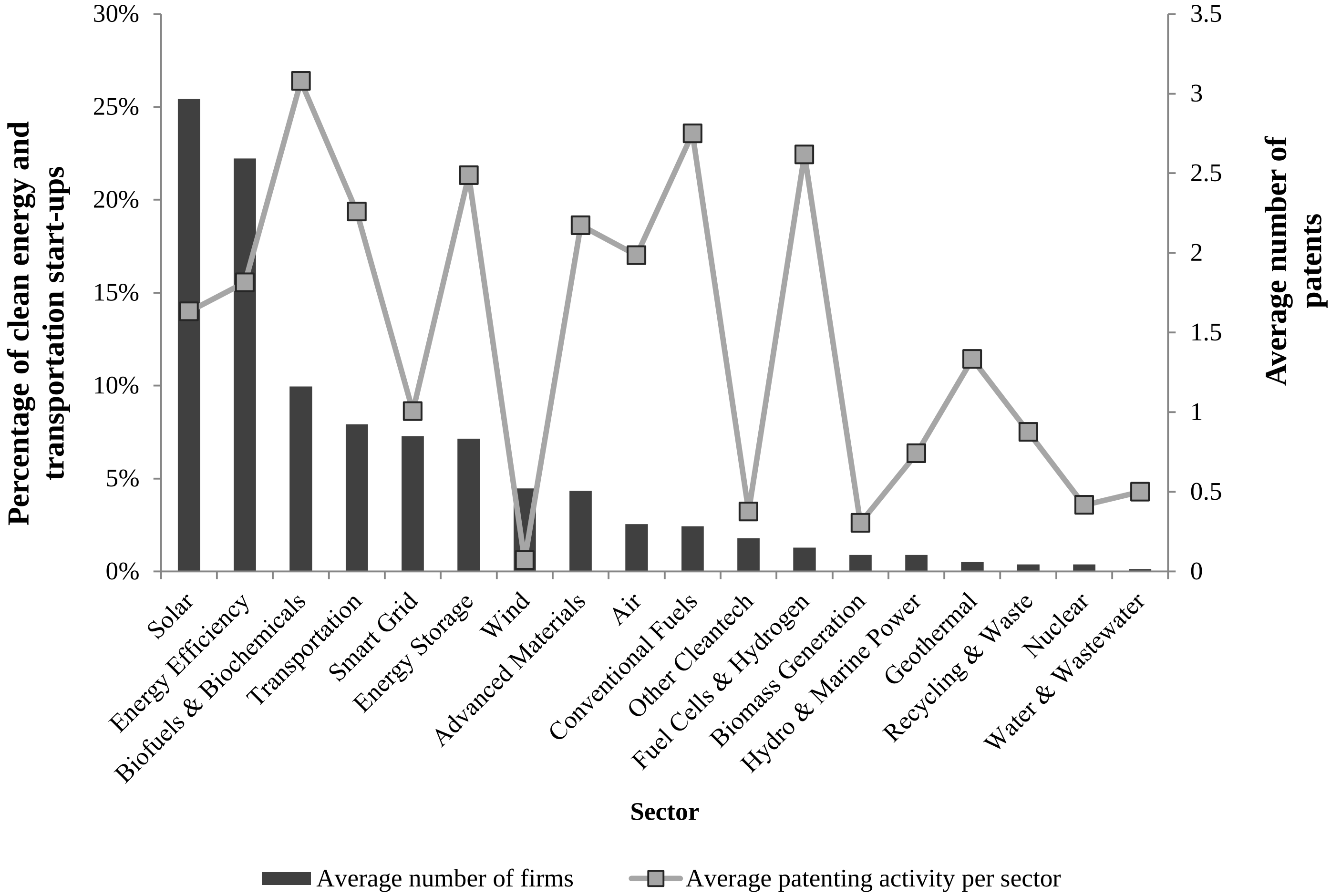


FIGURE 5

Locational distribution of US cleantech startups

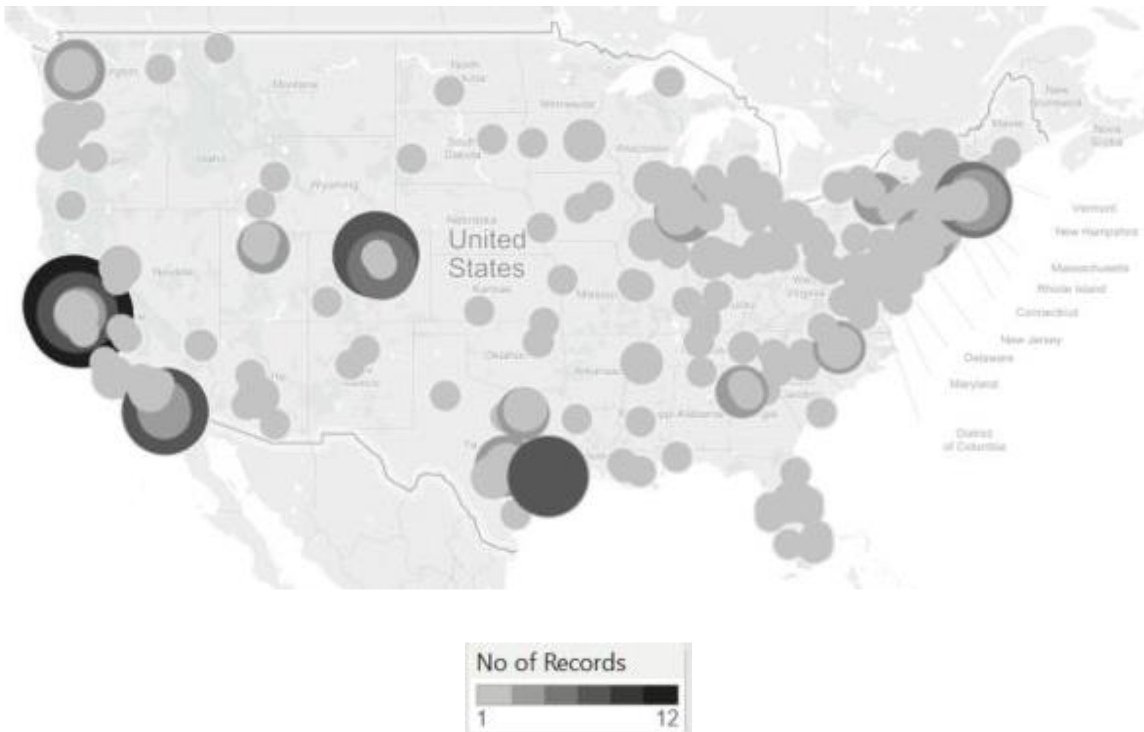
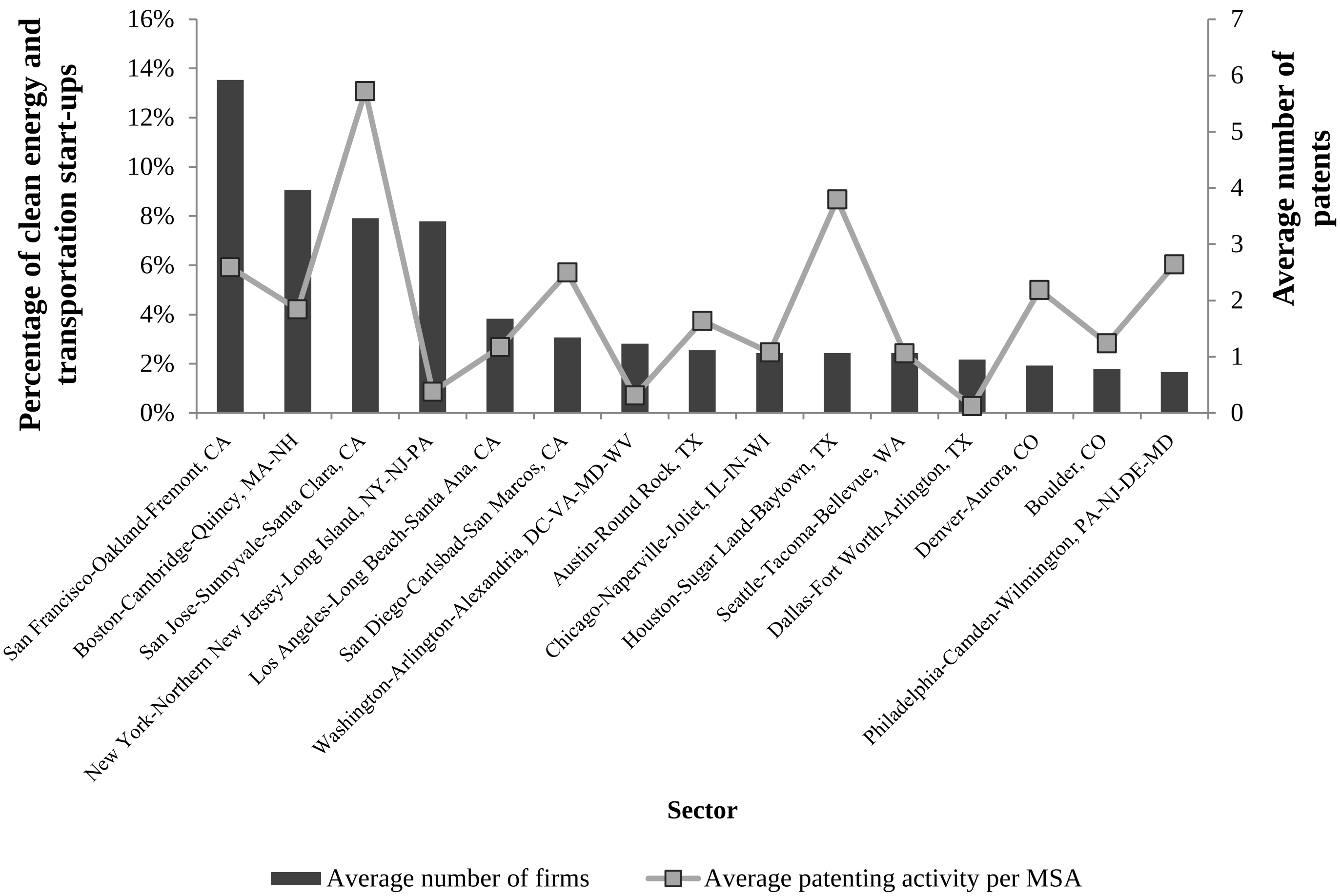


FIGURE 6

Average patenting activity per firm per Metropolitan Statistical Area (MSA) [16]



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16 For the CSA results, the patenting activity in Dayton-Springfield-Sidney, OH, Phoenix-Mesa-Scottsdale, AZ, Jackson-Vicksburg-Brookhaven, MS Springfield-Greenfield Town, MA, and Kansas City-Overland Park-Kansas City, MO-KS, Cleveland-Akron-Canton, OH was also higher than in the San Jose-San Francisco-Oakland, CA CSA.

FIGURE 7

Interaction Effect

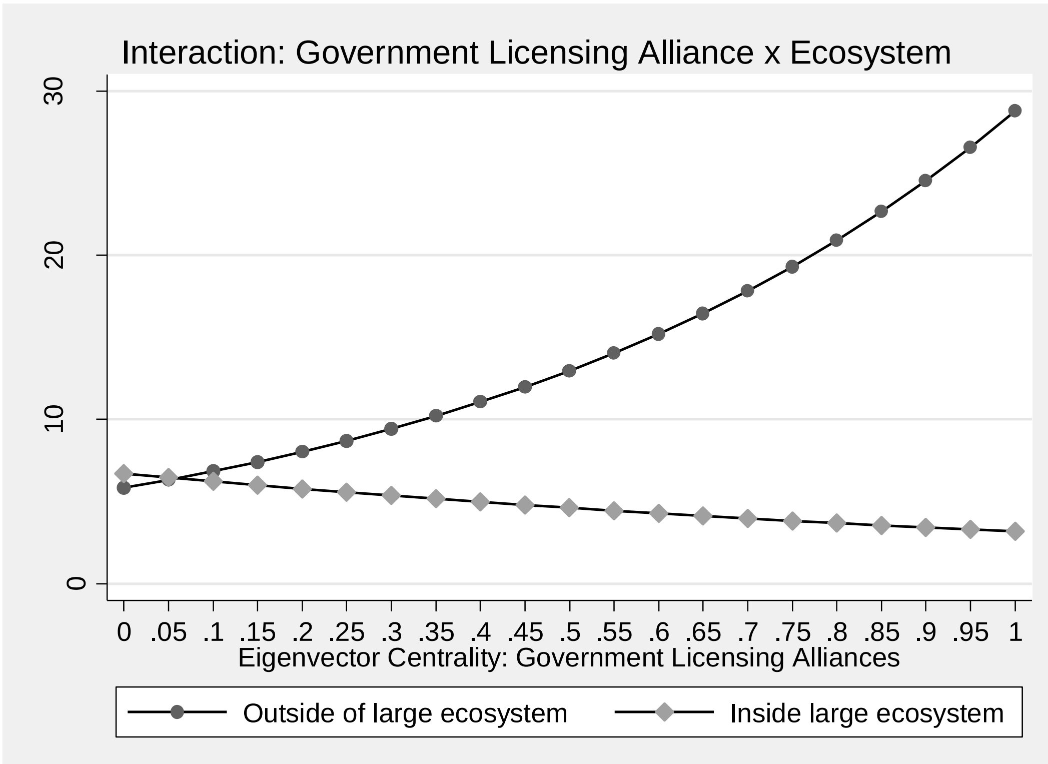

TABLE 1

Overview and explanation of the five collaboration types in the startup-database

Collaboration Type		Example
Technology-based collaboration	**joint technology development**	*Arcos Silicon and Broadcom Corporation partnered to improve the interoperability of their power-over-ethernet (PoE) products.* *Sapphire Power has partnered with University of California, San Diego to demonstrate the viability of saltwater algae in the production of biofuels.*
	licensee	*Natcore has been granted a patent license agreement from NREL to develop and commercialize a line of black silicon PV products.*
Market-based collaboration	**procurement or customer**	*As part of a purchase agreement, Sustainable Green will become exclusive distributor of MagneGas fuel over a two year period in Pacific Northwest.* *Avista Corp. is buying the power produced by the Palouse Wind project under a 30-year power purchase agreement and will take delivery of the power through a direct interconnect to the Avista 230 kV Benewah-to-Shawnee transmission line.*
Additional forms of collaboration	**licensor**	*ABB has signed a licensing agreement with ECOtality to use ECOtality's technology for ABB's EV charging network.*
	project development	*Obsidian Renewables partnered with Swinerton Builders to develop the Black Cap Solar facility.*

TABLE 2

Descriptive Statistics and Correlations of Variables Used in Regression Analysis

		N	n	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Patenting activity	2724	767	1.835	4.979	0	69	1														
2	Private financing deals	2738	771	0.666	1.175	0	13	0.21	1													
3	EC[1]: Government partner	3297	783	0.003	0.036	0	1	0.04	0.04	1												
4	EC[1]: University/research partner	3297	783	0.002	0.04	0	1	0.00	0.00	0.16	1											
5	EC[1]: Nonprofit partner	3297	783	0.002	0.04	0	1	-0.01	-0.01	0.00	0.00	1										
6	EC[1]: Other public partner	3297	783	0.002	0.035	0	1	0.00	-0.01	0.00	0.00	0.00	1									
7	EC[1]: Cleantech startup partner	3297	783	0.004	0.054	0	1	0.08	0.06	0.02	0.00	0.00	0.00	1								
8	EC[1]: Other inter-firm partner	3297	783	0.002	0.03	0	1	0.00	0.05	0.00	0.02	0.00	0.00	0.04	1							
9	Pre-sample patents	3297	783	3.868	11.004	0	94.42	0.33	0.08	-0.01	-0.01	0.00	0.04	0.02	0.01	1						
10	Prior private financing	3297	783	1.42	2.079	0	15.57	0.34	0.45	0.05	0.04	0.03	0.02	0.08	0.07	0.26	1					
11	Prior public financing	3297	783	0.051	0.258	0	3.15	0.00	0.02	0.01	0.10	0.01	0.01	-0.02	-0.01	-0.01	0.04	1				
12	DOE grants	3297	783	0.042	0.242	0	4	0.08	0.03	0.07	0.08	-0.01	-0.01	0.04	0.01	0.08	0.1	0.05	1			
13	IPO or M&A	2739	771	0.015	0.123	0	1	0.08	0.01	-0.01	-0.01	-0.01	0.03	-0.01	-0.01	0.04	0.07	-0.02	0.00	1		
14	Age	3297	783	3.873	2.794	0	10	0.17	0.06	0.02	0.02	0.03	0.01	0.03	0.03	0.29	0.32	0.08	0.03	0.08	1	
15	Size (log)	3042	716	3.13	1.612	0	8.92	0.32	0.23	0.00	-0.01	0.01	-0.01	0.05	0.08	0.28	0.36	-0.04	0.06	0.09	0.28	1
16	Location (log MSA density)	3297	783	3.094	1.456	0	4.78	0.12	0.14	0.00	0.00	0.03	-0.03	0.01	0.06	0.06	0.16	-0.06	-0.01	0.00	-0.01	0.08

[1] EC = Eigenvector Centrality

TABLE 3

Estimated Coefficients from Negative Binomial Regressions (Robust Standard Errors in Parentheses)

Patenting activity	**Model 1: Controls**	**Model 2: Partner Type**	**Model 3: Partner and Collaboration Types**	**Model 3a: Ecosystems Interaction**
Controls				
Pre-sample patents	0.06	0.07	0.07	0.07
	(0.01)**	(0.01)**	(0.01)**	(0.01)**
Prior private financing deals	0.19	0.19	0.18	0.18
	(0.02)**	(0.02)**	(0.02)**	(0.022)**
Prior public financing deals	0.09	0.10	0.10	0.10
	(0.11)	(0.109)	(0.112)	(0.112)
Part of large ecosystem	0.12	0.12	0.13	0.14
	(0.10)	(0.10)	(0.10)	(0.10)
Age	-0.04	-0.04	-0.04	-0.04
	(0.02)+	(0.02)+	(0.02)+	(0.02)+
Size (log)	0.34	0.35	0.35	0.35
	(0.04)**	(0.04)**	(0.04)**	(0.04)**
Location (log MSA density)	0.13	0.14	0.14	0.13
	(0.03)**	(0.03)**	(0.03)**	(0.03)**
Partner Types				
Government partner		2.16		
		(0.83)**		
University/research partner		-0.94		
		(0.58)		
Nonprofit partner		-0.60		
		(0.76)		
Other public partner		-4.60		
		(1.11)**		
Cleantech startup partner		0.18		
		(0.55)		
Other inter-firm partner		-1.99		
		(0.92)*		
Partner and Collaboration Types				
Government technology collaboration			2.25	2.24
			(0.65)**	(0.65)**
Government licensee collaboration			0.63	1.60
			(0.46)	(0.27)**
Government market collaboration			-1.71	-1.71
			(0.51)**	(0.51)**
Interaction Effect				
Government licensing collaboration x Ecosystem				-2.34
				(0.47)**
University/research technology collaboration			0.89	0.89
			(0.77)	(0.77)
University/research licensee collaboration			0.41	0.40
			(0.35)	(0.34)
University/research market collaboration			-1.79	-1.78
			(0.62)**	(0.62)**
Inter-firm technology collaboration			-0.16	-0.17
			(0.46)	(0.46)
Inter-firm licensee collaboration			0.96	0.81
			(0.34)**	(0.34)*
Inter-firm market collaboration			0.56	0.56
			(0.81)	(0.81)
Additional Collaborations as Control				
Nonprofit partner			-0.31	-0.32

			(0.70)	(0.70)
Other public partner			-5.15	-5.13
			(1.39)**	(1.37)**
Project development collaboration			-29.87	-29.89
			(8.74)**	(8.73)**
Licensor collaboration			-1.80	-1.63
			(1.21)	(1.24)
Time-fixed effects included	Y	Y	Y	Y
Sector-fixes effects included	Y	Y	Y	Y
Constant	-2.04	-2.08	-2.10	-2.11
	(0.19)**	(0.19)**	(0.20)**	(0.20)**
lnalpha Constant	1.07	1.06	1.04	1.04
	(0.05)**	(0.05)**	(0.05)**	(0.05)**
Observations	2,503	2,503	2,503	2,503
Cragg & Uhler's R2[1]	0.083	0.085	0.088	0.088
McFadden's R2	0.240	0.245	0.252	0.253
Log likelihood	-3,605.74	-3,598.85	-3,587.16	-3,586.04
Prob > chi2	0.000	0.000	0.000	0.000

+ *p*<0.1; * *p*<0.05; ** *p*<0.01

[1] We reported pseudo R2 (Cragg & Uhler and McFadden) as a means to compare model fit. We are aware of the fact that pseudo R2 does not provide similar information as the R2 reported after OLS.

TABLE 4

Estimated Coefficients from Negative Binomial Regressions (Robust Standard Errors in Parentheses)

Private financing deals	Model 1: Controls	Model 2: Partner Type	Model 3: Partner and Collaboration Types
Controls			
Prior patents	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Pre-sample private financing deals[1]	0.25	0.24	0.25
	(0.02)**	(0.02)**	(0.02)**
Prior public financing deals	0.08	0.08	0.09
	(0.15)	(0.15)	(0.15)
Part of large ecosystem	0.16	0.16	0.17
	(0.07)*	(0.07)*	(0.07)*
Age	-0.10	-0.10	-0.10
	(0.02)**	(0.02)**	(0.02)**
Size (log)	0.18	0.18	0.18
	(0.02)**	(0.02)**	(0.02)**
Location (log MSA density)	0.12	0.13	0.13
	(0.02)**	(0.02)**	(0.02)**
Partner Types			
Government partner		1.11	
		(0.81)	
University/research partner		-0.38	
		(0.62)	
Nonprofit partner		-1.75	
		(1.33)	
Other public partner		-0.84	
		(0.70)	
Cleantech startup partner		0.21	
		(0.39)	
Other inter-firm partner		0.04	
		(0.52)	
Partner and Collaboration Types			
Government technology collaboration			0.87
			(0.73)
Government licensee collaboration			0.91
			(0.35)**
Government market collaboration			-1.44
			(0.91)
University/research technology collaboration			-3.03
			(1.57)+
University/research licensee collaboration			0.42
			(0.44)
University/research market collaboration			0.21
			(0.53)
Inter-firm technology collaboration			0.20
			(0.56)
Inter-firm licensee collaboration			0.70
			(0.21)**
Inter-firm market collaboration			-0.51
			(0.65)
Additional Collaborations as Control			
Nonprofit partner			-1.55
			(1.41)
Other public partner			-1.23

			(0.73)+
Project development collaboration			-3.80
			(1.20)**
Licensor collaboration			-0.60
			(0.47)
Time-fixed effects included	Y	Y	Y
Sector-fixes effects included	Y	Y	Y
Constant	-1.82	-1.83	-1.85
	(0.14)**	(0.14)**	(0.14)**
lnalpha Constant	-0.12	-0.13	-0.16
	(0.10)	(0.10)	(0.10)
Observations	2,507	2,507	2,507
Cragg & Uhler's R2[1]	0.150	0.153	0.160
McFadden's R2	0.063	0.064	0.067
Log likelihood	-2,732.82	-2,729.38	-2,719.99
Prob > chi2	0.000	0.000	0.00

+ p<0.1; * p<0.05; ** p<0.01

[1] Similar to the patenting activity models, we changed the prior financing variable to include only pre-sample private financing deals to control for unobserved heterogeneity in firm patenting (e.g., Schilling and Phelps, 2007). However, including the same variable as in the patenting models (of the previous year) revealed similar results.

TABLE 5

Estimated Coefficients from Fixed-Effects Negative Binomial Regressions (Standard Errors in Parentheses)

	Patenting activity		Private financing deals	
	Model 1: Partner Type	**Model 2: Partner and Collaboration Types**	**Model 1: Partner Type**	**Model 2: Partner and Collaboration Types**
Partner Types				
Government partner	0.80		0.24	
	(0.41)+		(0.62)	
University/research partner	0.08		-0.97	
	(0.57)		(0.744)	
Nonprofit partner	-0.82		-1.80	
	(0.71)		(0.97)+	
Other public partner	-2.13		-0.08	
	(1.34)		(1.04)	
Cleantech startup partner	0.19		0.15	
	(0.32)		(0.38)	
Other inter-firm partner	0.34		0.52	
	(0.93)		(0.73)	
Partner and Collaboration Types				
Government joint technology development collaboration		0.76		0.52
		(0.41)+		(0.66)
Government licensee collaboration		0.11		0.01
		(0.43)		(0.48)
Government market collaboration		-0.23		-0.39
		(0.78)		(1.11)
University/research technology collaboration		0.12		-3.81
		(0.46)		(2.01)+
University/research licensee collaboration		0.44		-0.52
		(0.35)		(0.49)
University/research market collaboration		0.18		0.85
		(0.55)		(0.76)
Inter-firm joint technology development collaboration		0.12		-0.29
		(0.40)		(0.66)
Inter-firm licensee collaboration		0.36		0.61
		(0.25)		(0.30)*
Inter-firm market collaboration		0.26		0.22
		(0.47)		(0.74)
Additional Collaborations as Control				
Nonprofit partner		-0.67		-1.67
		(0.71)		(0.99)+

Other public partner		-2.30		-0.32
		(1.31)+		(1.03)
Project development collaboration		-4.91		-1.72
		(7.75)		(2.51)
Licensor collaboration		-2.14		-0.13
		(1.30)+		(0.77)
Time-fixed effects included	Y	Y	Y	Y
Sector-fixes effects included	N	N	N	N
Constant	0.74	0.73	1.33	1.37
	(0.12)**	(0.12)**	(0.24)**	(0.24)**
Observations	1,459	1,459	1,695	1,695
Log likelihood	-1,645.68	-1,641.50	-1,310.41	-1,302.66
Wald chi2	28.37	33.82	21.20	29.80
Prob > chi2	0.001	0.006	0.012	0.020