THE IMPACT OF DEMAND-PULL AND TECHNOLOGY-PUSH POLICIES ON FIRMS' KNOWLEDGE SEARCH

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ABSTRACT

The manner in which firms search for knowledge critically affects their innovative performance as well as the evolution of technological trajectories. Previous studies provide important insights into the antecedents of firms' knowledge search. Yet, we still know little about how such search activities are affected by public policies. Against this background, this study examines the impact of demand-pull and technology-push policies on the scope and distance of firms' knowledge search. We hypothesize that in times of strong policy support in a technological field, firms will narrow their attention and search scope. Moreover, we argue that technology-push policies enhance search distance, while demand-pull policies reduce it, and that the influence of policies on search scope will be moderated by the breadth of firms' existing knowledge base. We test and find broad support for our hypotheses based on the analysis of a global sample of 245 publicly listed firms in the solar photovoltaics industry from 1988 to 2012. Our findings suggest that, while innovation policies play an important role in knowledge generation and industry emergence, they may have unintended effects on firm knowledge search. We discuss the implications of these findings for the literature on organizational search, innovation policies, and technology life-cycles.

Keywords: Knowledge Search; Innovation Policy; Technology-Push; Demand-Pull; Solar Photovoltaics

1. INTRODUCTION

Firms' ability to develop new products and processes is critically important for their performance and the advancement of technologies (Damanpour, 1991; Mitchell *et al.*, 1993; Smith *et al.*, 2005). The literatures on the knowledge-based view and the behavioral theory of the firm suggest that developing such innovations requires firms to engage in a process of "search" to identify, recombine, and integrate knowledge (Dahlander *et al.*, 2016; Katila *et al.*, 2002; Laursen *et al.*, 2006). Two important parameters in this process are the scope and distance of search chosen by the firm. *Search scope* (narrow vs. broad) describes the number of knowledge sources a firm attends to when developing new technologies (Katila *et al.*, 2002), while *search distance* (local vs. distant) is the extent to which firms search for knowledge far from their existing knowledge base (e.g., Helfat, 1994a; Piezunka *et al.*, 2015).

Firms tend to search for new knowledge narrowly and locally, which primarily results in incremental innovations and short-term performance improvements (Ahuja *et al.*, 2004; Benner *et al.*, 2002; Nerkar *et al.*, 2005; e.g., Stuart *et al.*, 1996). To develop more radical innovations and be successful in the longer run, firms need to explore further from their existing knowledge base (Afuah *et al.*, 2012; Fleming, 2001; Fleming *et al.*, 2004; Laursen, 2012; Leiponen *et al.*, 2010; Singh *et al.*, 2010). Given these important ramifications of different search processes for innovative outcomes and firm performance, scholars have begun to unpack the antecedents of firm knowledge search. For example, research has shown that distant search may be triggered by employee turnover, alliances, or mergers and acquisitions (Rosenkopf *et al.*, 2003). So far, however, we know little about how a firm's knowledge search may be influenced by public innovation policies, i.e. formal institutions implemented to foster innovation in an industry.

The broader literature on technological change suggests two generic ways through which policies may affect innovation: technology-push and demand-pull (Dosi, 1982; Mowery *et al.*, 1979; Rosenberg, 1969, 1974). *Technology-push policies* comprise those policy measures that aim to increase the supply of technologies by directly fostering advances in science and technology, e.g. through public R&D funding (Nemet, 2009). *Demand-pull policies* include those measures that aim to stimulate technological innovation by altering market conditions, e.g. through direct demand incentives or shifts in factor prices (Edler *et al.*, 2007). Thus far, however, the literature on technology-push and demand-pull policies has concentrated on investigating the impact of these policies on innovative activities at the industry or country level (e.g., measured as the number of patents filed) and does not provide quantitative tests of how such policies affect knowledge search by individual firms. Shedding more light on how innovation policies affect firms' knowledge search, however, is critical if one seeks to understand whether different policies contribute to incremental or radical innovation, which in turn is important for deriving recommendations for policy makers on when to use which type of policy.

In this paper, we build on the knowledge-based view and the behavioral theory of the firm to argue that besides stimulating innovation, technology-push and demand-pull policies affect the scope and distance of firms' knowledge search. First, with regard to *search scope*, we reason that by increasing the knowledge available in a technological field (e.g., Peters *et al.*, 2012), both technology-push and demand-pull policies reduce firms' search scope. Broader availability of knowledge multiplies the possibilities for knowledge recombination, theoretically giving firms an incentive to search more broadly (Fleming, 2001; Hargadon *et al.*, 1997). In practice, however, we posit that firms actually tend to *reduce* their search scope in the face of proliferating policy-induced knowledge, since such plenitude allows them to find solutions to specific problems more quickly, threatens information overload, and increases the risk of oversearching (Huber *et al.*, 1987; Laursen, 2012; Piezunka *et al.*, 2015).

Second, with regard to *search distance*, we argue that technology-push policies increase search distance, while demand-pull policies reduce it. Studies suggest that, unlike technology-push initiatives, changes in demand trigger innovation primarily within established technological trajectories (Freeman, 1996; Mowery *et al.*, 1979). More recent work points out that the impact of technology-push policies may be limited, due to "crowding out" (Czarnitzki *et al.*, 2013; David *et al.*, 2000; Görg *et al.*, 2007), and that demand-pull policies may also trigger distant search (Hoppmann *et al.*, 2013). Still, we contend that demand-pull policies induce firms to invest primarily in local search, while technology-push policies trigger more distant search activities, since the incremental nature of changes in demand is less suited to fostering radical deviations from the status quo (Nemet, 2009).

To test our hypotheses, we draw on panel data for a global sample of 245 firms in the global solar photovoltaic ("PV") industry from 1988 to 2012. The PV sector is particularly well suited for testing the relationship between policy and firm search, since (a) it was heavily dependent on policy support during this period and (b) PV technologies were not yet competitive with alternatives at a larger scale, requiring firms to engage in a process of innovation and search (Branker *et al.*, 2011; Peters *et al.*, 2012). Besides testing how innovation policies affect search scope and distance, we investigate how the existing knowledge base of firms moderates the relationship between policies and firm search.

We find that a higher prevalence of both technology-push and demand-pull policies is associated with a narrower search scope. Moreover, in line with our expectations, technology-push policies increase the distance of firms' knowledge search, while demand-pull policies reduce it. A broader existing knowledge base reduces the negative effect of technology-push policies on search scope but also enhances the negative effect of demand-pull policies.

Our study contributes to the literature on organizational search, innovation policy, and technology life-cycles. Previous work on *organizational search* has largely neglected the impact of institutions on firms' search for knowledge (Garriga *et al.*, 2013; Laursen, 2012). We show that public policies may decisively influence both the scope and distance of search. Similar to recent findings on crowdsourcing (Piezunka *et al.*, 2015), we show that incentivizing the generation of copious external knowledge reduces the scope of firms' knowledge search. In contrast to these findings, however, we show that the driver behind external knowledge generation can lie at the industry rather than firm level, and that there are ways to stimulate knowledge generation that do not compromise firms' search distance.

Our study also contributes to the literature on *innovation policy*. While previous work has provided anecdotal evidence of a differential effect of technology-push and demand-pull policies on innovation, to our knowledge we provide the first empirical tests of how search scope and distance are influenced by the two types of policies, allowing us to draw conclusions on their influence on radical and incremental innovation. Finally, our study also makes contributions to the literature on *technology life-cycles*. We provide quantitative evidence that the relative importance of technology-push vs. demand-pull throughout life-cycles may contribute to the emergence of technological paradigms and increasing rates of incremental innovation among firms.

2. THEORY AND HYPOTHESES

One of the main tenets of organizational research following the tradition of the behavioral theory of the firm is that organizations are limited in their ability to perceive, retrieve, and process knowledge (Cyert *et al.*, 1963; Simon, 1982; Simon, 1991). Rather than optimizing based on complete information, firms engage in a process of search that is often local and path-dependent (Cyert *et al.*, 1963; Gavetti *et al.*, 2000). Since the nature of search determines which information organizations consider when taking decisions, understanding the process of search is critical to understanding organizational problem-solving and learning (Huber, 1991).

In the original behavioral theory of the firm, the concept of search was used to better understand organizational decision-making and behavior more broadly. In recent years, however, much research following the knowledge-based view of the firm has applied the concept to understand how firms develop technological innovations (Macher, 2006). It has been argued that new products and services are the result of firms recombining knowledge from different sources and technological domains (Fleming, 2001; Hargadon *et al.*, 1997; Nelson *et al.*, 1982; Von Hippel, 2007). The source of the knowledge eventually integrated into a product thus depends on the search process applied by those within the firm who develop that product (Katila *et al.*, 2002; Rosenkopf *et al.*, 2001). For example, it has been found that firms differ sharply with regard to their search scope and search distance. Generally, firms' knowledge search tends to be rather narrow and local, leading to incremental innovations and short-term improvements in financial performance (Ahuja *et al.*, 2004; Benner *et al.*, 2002; Helfat, 1994b; Nerkar *et al.*, 2005; Piezunka *et al.*, 2015; Stuart *et al.*, 1996). At the same time, however, a broader and more distant search for knowledge has been found to lead to more radical innovations and a higher rate of new-product introduction, which are important drivers of long-term firm performance (Afuah *et al.*, 2012; Dahlander *et al.*, 2016; Laursen *et al.*, 2006; Leiponen *et al.*, 2010; Li *et al.*, 2013; Rosenkopf *et al.*, 2001; Singh *et al.*, 2010). Specifically, the prior literature shows that a strong focus on local search and incremental innovations may contribute to organizational lock-ins and inertia that threaten firm survival, especially in times of environmental discontinuities (Lavie *et al.*, 2010; Mitchell *et al.*, 1993).

2.1 Antecedents of firm knowledge search

Given the importance of knowledge search for innovation and organizational performance, recent work has started to shed more light on the antecedents of search. In this context, it has been shown that search is affected by factors residing both within organizations and in their environment.

Empirical studies on *firm-internal factors* indicate that slack resources, external partnerships and alliances, employee mobility, firm size, and financial performance may all affect firm search. Firms with more slack resources, defined as "the pool of resources in an organization that is in excess of the minimum necessary to produce a given level of organizational output" (Nohria *et al.*, 1996), have been found to engage in broader, more distant knowledge search (Chen *et al.*, 2007; Garriga *et al.*, 2013; Troilo *et al.*, 2014). External partnerships, mergers and acquisitions, and employee mobility facilitate more distant search for new knowledge (Almeida *et al.*, 1999; Rosenkopf *et al.*, 2003; Song *et al.*, 2003; Stuart *et al.*, 1996). Lastly, many of the above antecedents are influenced by firm size, since larger firms tend to have more slack resources, more partnerships, or a higher degree of diversification (Leiponen *et al.*, 2010).

Research on *environmental factors* has focused on understanding how patterns in search processes are related to conditions in the industry, such as changes in markets or the rate of technological innovations. Studies indicate that higher industry dynamism and technological change tend to be associated with broader and more distant firm search (Jansen *et al.*, 2006; Leiponen *et al.*, 2010; Sidhu *et al.*, 2007).

2.2 Demand-pull and technology-push policies and their effect on firm search

While the literature provides clear evidence of the impact that different types of search have on firm performance and has investigated a number of antecedents of firm search, we currently know very little about how it might be influenced by public policy (Lavie *et al.*, 2010). Generally, work in the field of technological change suggests that policies affecting firm innovation can be categorized into two broad categories: technology-push and demand-pull policies (Dosi, 1982; Kim *et al.*, 1992; Mowery *et al.*, 1979; Nemet, 2009). *Technology-push* policies aim to increase the supply of new technologies by reducing the private cost of research and development (Nemet, 2009). Typical technology-push policy instruments include public R&D funding; tax reductions for R&D investments; incentives for cross-organizational knowledge exchange (e.g., in the form of policy-initiated industry platforms); and financial support for employee training and pilot projects (Nemet, 2009). *Demand-pull* policies aim to increase the private rents and reduce the uncertainty of future returns associated with innovations by stimulating the adoption of technologies on the demand side (Edler *et al.*, 2007). Demand-pull policies typically include standard-setting instruments (e.g., performance standards or the protection of intellectual property); federal procurement programs; and subsidies or tax credits for end consumers (Jaffe *et al.*, 2002; Peters *et al.*, 2012).

Some initial studies have started to link technology-push and demand-pull policies with the literature on organizational learning and firm-level innovation (Hoppmann *et al.*, 2013; Nemet, 2009). Currently, however, we lack systematic, quantitative evidence on how different forms of search are related to these two types of policy interventions. Testing the effect of policy seems particularly important, as public policies have been found to have a profound impact on innovations in a large number of fields (Mazzucato, 2013; Salter *et al.*, 2001). We therefore draw on the literature on the knowledge-based view and the behavioral theory of the firm to derive four hypotheses that relate technology-push and demand-pull policies with two characteristics of knowledge search, namely search scope and search distance. Acknowledging the heterogeneity of firms' starting knowledge bases, we also develop two hypotheses on how the effect of public policies might differ depending on the breadth of the firm's existing knowledge base.

2.2.1 Effect on search scope

Search scope (narrow vs. broad) describes the number of knowledge sources a firm attends to when developing new technologies (Katila *et al.*, 2002; Piezunka *et al.*, 2015). By stimulating innovation activities, both technology-push and demand-pull policies increase the amount of knowledge available in a technological field (Freeman *et al.*, 1988; Jaffe *et al.*, 2002; Mowery *et al.*, 1979; Salter *et al.*, 2001). Schmoch (2007), for example, shows that industries typically follow a so-called "double-boom cycle," i.e., technology developments are driven first by technology-push and later by demand-pull factors. Similarly, studying inventions in the renewable-energy industry, Peters et al. (2012), Costantini et al. (2015), and Cantner et al. (2016) provide empirical evidence that patenting activities were driven by both technology-push and demand-pull policies. We argue that this increase in knowledge leads to a narrower search scope among firms in the industry affected by policy support.

At first glance, the idea that an increase in knowledge due to public innovation policies leads to narrower firm search might sound counterintuitive, since a larger knowledge stock multiplies the possibilities for knowledge recombination, thereby potentially creating an incentive for firms to broaden their search (Fleming, 2001; Gruber *et al.*, 2008; Hargadon *et al.*, 1997). Indeed, previous studies have shown that firms draw heavily on publicly funded research as a source of new ideas (Narin *et al.*, 1997; Salter *et al.*, 2001). The more knowledge is created by policy incentives, the greater the variety of valuable innovations that can potentially be created by drawing on and combining these knowledge elements (Katila *et al.*, 2002; Klevorick *et al.*, 1995). Therefore, one might expect firms to widen their search scope to take advantage of the enhanced opportunity set (Leiponen *et al.*, 2010).

Still, there are several reasons why, in practice, firms might actually *reduce* their search scope in the face of proliferating knowledge. First, increasing the number of potential solutions in the environment may lead to a situation where *firms can find a solution to specific problems more quickly*, hence reducing the need for broader search. According to the behavioral theory of the firm, organizations engage in "satisficing" rather than optimizing behavior (Cyert *et al.*, 1963). As a result, they may be less interested in attaining the best potential innovation from all possible knowledge combinations than in finding satisfactory solutions to their most immanent problems (Laursen, 2012). Thus, expanding the knowledge in a technological field through public policies may reduce the time it takes firms to find a satisfactory solution—rather like adding more balls to an urn from which a firm draws potential solutions (Klevorick *et al.*, 1995).

Second, innovation policies may *narrow a firm's attention*. As has been pointed out in the behavioral theory of the firm, organizations possess limited capacity to process information (March *et al.*, 1958; Ocasio, 1997; Sullivan, 2010; Van Knippenberg *et al.*, 2015). Particularly if the amount of knowledge in a firm's environment becomes too great—so-called "crowding" (Ocasio, 2011)—firms may be unable to attend to all the opportunities available, and may narrow their search to a specific subset (Grant, 1996; Huber *et al.*, 1987). Recent research on crowdsourcing, for example, shows that when firms receive a larger number of suggestions, the resulting information overload forces them to filter them more strictly (Piezunka *et al.*, 2015). The level of attention a firm pays to individual solutions has been found to decrease with the number of solutions it is confronted with (Hansen *et al.*, 2001; Sullivan, 2010). By stimulating the generation of knowledge, public innovation policies may hence narrow firms' search scope rather than broadening it.

Third, innovation policies *raise the risk of "oversearching"* (Laursen *et al.*, 2006). As described above, a key objective of both technology-push and demand-pull policies is to speed up innovation in a particular industry. Searching for and integrating a larger amount of knowledge, however, has been shown to take considerable time and effort (Katila *et al.*, 2002). An enhanced speed of innovation in their environment puts pressure on firms to bring products to the market more quickly (Laursen *et al.*, 2006). Public innovation policy may thus force firms to reduce the scope of their search and focus on a smaller number of knowledge elements (Dahlander *et al.*, 2016). Overall, therefore, there is good reason to believe that public innovation policies reduce the search scope of firms. Accordingly, we formulate our first two hypotheses:

H1a: The greater the funding for technology-push policies, the narrower a firm's search scope.
H1b: The greater the funding for demand-pull policies, the narrower a firm's search scope.

2.2.2 Effect on search distance

Search distance describes the technological proximity of the knowledge integrated into a new product to the existing knowledge base of the firm (Helfat, 1994a; Piezunka *et al.*, 2015; Stuart *et al.*, 1996). Distant search aims at integrating technological knowledge that resides outside the firm's current technological focus and competence (Afuah *et al.*, 2012; Gruber *et al.*, 2013). In contrast, local search focuses on integrating technological knowledge close to the existing knowledge base, thereby usually leading to incremental innovations within existing technological trajectories (Rosenkopf *et al.*, 2001).

There are some indications that demand-pull and technology-push policies have different effects on search scope. In the literature on technological change, technology-push policies are generally regarded as means of variety creation, believed to spur innovation outside existing technological trajectories (Freeman, 1996; Freeman *et al.*, 1988; Mowery *et al.*, 1979). For example, in renewable energy, technology-push policies have been used to incentivize research in radically new technologies far from the market, such as tidal and wave power or nuclear fusion. One would expect that by fostering the emergence of new technological fields, technology-push policies might alter the distance of search firms engage in. In particular, if new, promising fields emerge as a result of policy interventions, this should raise the likelihood of firms engaging in more distant search to look beyond the technologies in their portfolio and integrate knowledge from the newly emerging technologies (Köhler *et al.*, 2012).

Two mechanisms, however, may dampen the positive effect of technology-push policies on search distance. First, especially if the technological knowledge generated through technology-push policies is technologically distant from that already present in the firm, this may reduce the likelihood that it is considered by the firm in its search process (Kotha *et al.*, 2013). In fact, previous research building on the knowledge-based view of the firm shows that knowledge originating in public research funding is often encoded in specific ways and disconnected from commercial applications, such that firms require specific capabilities to be able to identify, interpret, absorb, and exploit it (Link *et al.*, 2007). Second, and closely related to the first point, studies on "crowding out" suggest that public research funding often exhibits extensive overlaps with private research funding. This is because firms may try to influence the areas for which public research funding is available, and may systematically enter research projects on technologies close to their existing portfolio (Czarnitzki *et al.*, 2013; David *et al.*, 2000; Görg *et al.*, 2007). While these two effects mitigate the impact of technology-push policies on firms, we would still expect the overall impact of technology-push policies on firms' search distance to be positive.

In contrast to the findings on technology-push policies, research suggests that *demand-pull policies* serve as a selection mechanism that predominantly fosters local search along existing technological trajectories (Freeman, 1996; Mowery *et al.*, 1979). Based on a study of patent activities in the California wind power industry, for example, Nemet (2009) suggests that demand-pull policies may lead firms to primarily exploit existing technologies, and may even reduce explorative search for new ones. This view is in line with the traditional literature on technological change, which argues that demand-pull cannot explain the emergence of radical innovations (Dosi, 1982, 1988). Although it is acknowledged that changes in demand may trigger innovations, researchers claim that changes in the needs of consumers do not occur abruptly, such that market-oriented knowledge search is primarily associated with imitations or incremental improvements (Köhler *et al.*, 2012; Lukas *et al.*, 2000; Macher, 2006; Nickerson *et al.*, 2004).

Recent research has started to question the view that demand-pull policies predominantly foster incremental innovation. Hoppmann et al. (2013), for example, argue that demand-pull policies influence firm innovation activities not only by signaling changes in user needs but, more importantly, by providing the firm with the necessary financial resources. By allowing firms to generate revenues and attracting investors to an industry, demand-pull policies raise the capital available to firms that can be used to finance distant search and the development of radical innovation (Hall *et al.*, 2009; Hoppmann *et al.*, 2013). Still, while these studies suggest that demand-pull policies boost firms' distant search in absolute terms, they also acknowledge that, relatively speaking, demand-pull tends to foster local search activities more strongly. Hence:

H2a: The greater the funding for technology-push policies, the larger a firm's search distance.
H2b: The greater the funding for demand-pull policies, the smaller a firm's search distance.

2.2.3 Moderating effect of the firm's knowledge base on search scope

While the previously mentioned hypotheses suggest an impact of technology-push and demand-pull policies on firm search, it seems likely that the effect of public innovation policies on search differs between firms with different characteristics. In particular, in this study, we suggest that the breadth of firms' existing knowledge, defined as "the extent to which the firm's knowledge repository contains distinct and multiple domains" (Zhou *et al.*, 2012: 1091) affects the relationship between innovation policies and firms' search. We focus on the breadth of firms' knowledge base, since recent research shows that it is directly related to firms' search processes. Specifically, we would expect the breadth of the knowledge base to affect the influence of innovation policies on a firm's search scope, for several reasons.

First, previous research in the tradition of the knowledge-based view and behavioral theory of the firm demonstrates that a broader knowledge base facilitates the search for and integration of knowledge (Grant, 1996). The literature on absorptive capacity, for example, suggests that a firm's ability to integrate new knowledge sources is tightly coupled to its existing knowledge base, as existing knowledge facilitates the decoding and interpretation of new knowledge sources (Cohen *et al.*, 1990; Katila *et al.*, 2002; Zahra *et al.*, 2002). Moreover, as Grant (1996) argues, the greater the common knowledge base a firm can draw on, the easier it will be for the firm to share and integrate aspects of knowledge that is not common among its employees. As a result, existing knowledge may significantly speed up the process of search, hence reducing the risks resulting from oversearching (Macher, 2006; Zhou *et al.*, 2012). Second, closely connected to greater absorptive capacity, we would expect firms with a broader knowledge base to be able to attend to a broader range of different sources at the same time. Since this mitigates information overload, we expect firms with broader existing knowledge to be less likely to narrow their attention and reduce their search scope in response to public innovation policies (Ocasio, 2011). This leads to our last two hypotheses:

H3a: The broader the firm's knowledge base, the less technology-push policies reduce its search scope.
H3b: The broader the firm's knowledge base, the less demand-pull policies reduce its search scope.

3. METHODS

To test our hypotheses, we drew on a unique set of panel data on 247 firms in the global solar photovoltaic (PV) industry from 1988 to 2012. These data were analyzed using negative binominal and fractional probit regression models. In the following, we provide more details on the research context, data collection, variables, and statistical methods.

3.1 Research setting

We assessed our hypotheses within the context of the global PV industry between 1988 and 2012. The PV industry offers a suitable empirical context for examining the effect of policies on knowledge search since innovation in PV technologies plays a major role for combating global climate change, which is why policy makers have invested considerable funds into both technology-push and demand-pull policies (Choi *et al.*, 2014; Herrmann *et al.*, 2017). At the same time, the detailed impact of policy support in the PV industry remains controversially debated, calling for studies that investigate in more detail how policies have affected firm-level innovative behavior.

Solar PV allows electricity to be generated from sunlight, thereby emitting much less CO_2 than conventional energy sources such as coal, nuclear, or gas. As a result, this technology has long been considered a promising candidate for improving the environmental footprint of the energy sector. Yet, until 2012, PV technologies were not cost-competitive with conventional sources of electricity, except in small niche applications (Branker *et al.*, 2011). Therefore, to foster the broader development and diffusion of environmentally benign PV technologies, policymakers therefore implemented comprehensive support programs, using both technology-push and demand-pull policies. While technology-push and demand-pull support has also been used in other sectors (such as biotech or health care), the volume of funding that has been used to support PV is particularly high, amounting to more than hundred billion USD in Germany alone (Hoppmann *et al.*, 2014). In fact, given the large amount of funding that has gone to PV, the effectiveness of policy support has been heavily debated with some scholars questioning the innovation effect of demand-pull policies and suggesting that a stronger focus on technology-push policies would have led to a more effective and efficient use of public funds (Frondel *et al.*, 2008). On the contrary, other point to the positive innovative effect of demand-pull policies (Hoppmann *et al.*, 2013). By studying the impact of technology-push and demand-pull policies on firms' knowledge search, our study helps resolve this debate by showing how both types of policies differentially impact search scope and distance.

As the time period for our investigation, we selected 1988 until 2012, since during this time countries were making use of both technology-push and demand-pull policies and firms strongly engaged in innovation. While the period before 1988 was strongly dominated by technology-push policies, in the time after 2012 demand-pull policies have become very dominant. Since our interest is in both types of policies, we therefore decided to select a time frame during which both policies have been used and which was characterized by a limited competitiveness of PV technologies with alternatives, requiring firms to engage in processes of knowledge search. This choice is in line with other studies that have investigated policy support in the PV industry (Hoppmann *et al.*, 2020). Second, our choice was limited by the fact that data on important firm controls is not available for the years before and after the period we selected. Concretely, for our control variables we collected data on firms' production capacity and alliances from the industry magazine Photon, which is not available after 2012.

Technology-push support for PV was particularly important during the early years of the industry, from the 1970s to the early 1990s. In response to the two oil-price shocks in 1973 and 1979, governments in several countries significantly increased their public R&D funding for solar photovoltaic technologies, leading to, on average, 16-percent annual increases in patent filings from 1974 to 1985 (Peters *et al.*, 2012). In the US in particular, initial policy measures such as tax credits were also implemented to foster technology diffusion. However, the PV market remained very small until the end of the 1980s, primarily because of the very high cost of PV-generated electricity.

In the 1990s, Japan and Germany introduced comprehensive demand-pull programs—namely the "Sunshine program", the "1,000 roofs program," and the "100,000 roofs program"—that led to a significant upsurge in market size (Jäger-Waldau, 2007). Market growth accelerated even further when, in 2000, Germany implemented its "Renewable Energy Sources Act," which granted owners of PV panels a fixed price—significantly above the market rate—for selling their electricity. As a result of this new legislation, annual demand-pull funding for PV in Germany rocketed from less than 50 million USD in 1992 to about 10 billion USD in 2012 (Hoppmann *et al.*, 2014).

Other countries, especially in the EU, followed suit, leading to an increase in the global market for PV panels from 20 megawatts of annual installed capacity in 1992 to 30 gigawatts in 2012—an average annual growth rate of 44 percent (EPIA, 2014). At the same time, the annual funding for technology-push policies fell drastically in the mid-1980s, before slowly recovering in the 1990s. Since then, funding has crept up by about 2 percent per year (IEA, 2015). Although several governments implemented special R&D programs for solar PV in response to the financial crisis of 2008, in an increasing number of countries demand-pull funding significantly outweighed technology-push by 2012.

PV technologies can be categorized into first-, second-, and third-generation depending on their maturity (Green, 2006). Crystalline silicon ("c-Si") PV represents the most mature, first-generation technology. Following its invention in the 1950s, c-Si's development was supported by the integrated circuit industry, which had a long history of manufacturing and processing these materials (Bagnall *et al.*, 2008). Second-generation or thin-film technologies are less material-intensive due to thinner light-absorbing layers and more thoroughly automated manufacturing processes (Tyagi *et al.*, 2013). However, since the technology dates from the 1970s, it is less mature, and conversion efficiencies are lower than for first-generation PV. Third-generation technologies are the least mature and least competitive, but could further reduce material use and increase efficiency (Tyagi *et al.*, 2013). So far, no single PV technology has emerged as a clear winner, inducing firms in the industry to search for new technological solutions within and across all three technologies. Thus far, however, it remains unclear how innovation policies have affected this search process.

3.2 Data collection

To analyze the relationship between public policy and knowledge search in the PV industry, we relied on multiple sources of data. In line with previous studies (e.g., Katila *et al.*, 2002; Rosenkopf *et al.*, 2001), we used patent citations to measure knowledge search. Patent citations are a good measure to retrospectively assess firm knowledge search, because each patent represents the solution to a stated problem. As a result, analyzing the citations listed in patents provides insights into the sources firms drew on when developing a specific invention, which allows us to draw conclusions about the scope and distance of knowledge (Katila *et al.*, 2002).[1] Global PV patent data was extracted from the "Thomson Innovation" database using a previously developed search string (see Table A1 in the appendix) that combines international patent classification codes (IPC) related to PV with keywords that were applied to patents' title and abstract. In total, we extracted 96,771 patents. For each patent, we removed the examiner citations, as these are not added by the inventor and hence are not indicative of firm search (Alcacer *et al.*, 2006). Previous research indicates that examiner citations often represent a large proportion of total citations and can hence significantly bias analyses (Jaffe *et al.*, 1998).

Data on technology-push and demand-pull policies was obtained from the International Energy Agency's "Energy technology research and development" database (IEA, 2015) and the European Photovoltaic Association (EPIA, 2014) respectively. The former database contains data on public R&D investments in PV for 15 OECD countries since 1975, and covers 80–90 percent of global public R&D investments in recent years (Breyer *et al.*, 2013).

Moreover, we used Thomson Reuters EIKON to extract firm-level data on factors other than policies that previous research had found to influence knowledge search. For this purpose, from our patent database we extracted all names of publicly listed firms that had filed at least one patent in PV

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[1] The degree to which inventions are patented differs across industries. Similar to the semiconductors industry, however, propensity to patent in the PV industry is high, such that patents provide a good measure of inventive activity. In addition, although the propensity to patent has been shown to differ across countries, these differences do not lead to a bias in our results, since in our models we use firm fixed effects, implying that time-invariant differences in patenting activity across firms and countries are taken into account by our empirical model.

technologies.[2] Using the firm name, we then extracted data on firm size, profitability (e.g. operating and gross profit), solvency (e.g. assets, cash, long-term debts), and R&D spending from EIKON. To obtain data on alliances, we manually screened the press database Factiva as well as the two leading industry magazines, *Photon* and *PV magazine*, for announcements of partnerships and joint ventures in PV. This effort resulted in the compilation of a database containing 2,672 alliances among 1,943 firms. Finally, we drew on Thomson Reuters EIKON, Zephyr, and Mergerstat to gather data on mergers and acquisitions (M&A) in the PV industry. The M&A data was manually cleaned and consolidated into a single database that contains detailed information on 1,314 M&A deals in the PV industry. The firm-level and policy data from the different data sources was manually matched with the patent data to yield a longitudinal panel data set for the years from 1988 to 2012. The final database contains data on 247 publicly listed companies active in the PV industry over an average period of 9.2 years.

3.3 Variables and measures

Our hypotheses imply the assessment of two dependent variables, *search scope* and *search distance*, and three independent variables, *technology-push policy funding*, *demand-pull policy funding*, and *breadth of firms' knowledge base*.

3.3.1 Dependent variables

In line with previous work, we measure search scope by counting the number of patent citations in a firm's patents for a specific year (Katila *et al.*, 2002). [3]A higher number of patent citations indicates broader search, whereas a lower number of citations indicates narrower search.

To measure *search distance*, we constructed a variable that measures the Euclidean distance between the existing patent portfolio of firm *i* and the citations contained in the firm's patents in a specific year *t* using the following formula:

[2] Private firms were not considered in the analysis for reasons of data availability.

[3] It should be noted that, in contrast to Katila et al. (2002), we measure search scope by counting all patent citations, rather than only new ones. We do so, since in our study we use a separate variable *search distance* to measure the extent to which the knowledge firms search is novel. Restricting the variable search scope to novel citations would have led to an overlap in the two variables, thereby adversely affecting construct validity.

$$d_{i,t} = \frac{\sqrt{\sum_{k=1}^{4}\left(\frac{\sum_{t_0}^{t} p_{t,k}}{\sum_{t_0}^{t} p_{t}} - \frac{c_{t,k}}{c_t}\right)^2}}{\sqrt{2}}$$

In this formula, t denotes the focal year and i the focal firm for which to calculate the search distance d. p describes the number of patents a firm has filed in a specific technology category k. c is the count of citations contained in the firm's patents in a specific technology category k. The formula then calculates the share of patents a firm has filed in a specific technology category up to the year of interest and compares this ratio with the number of citations to patents in the same technology category relative to the total number of citations contained in the firm's patents in the year. The division by $\sqrt{2}$ in the formula is done to scale the distance values such that they take values between 0 and 1. For example, a firm that has only patented in one technology category in a focal year, and whose patents in that year contain only citations to patents within the same category, will have a search distance of 0 (i.e., the patent portfolio exactly resembles the portfolio of patent citations in year *t*). A firm that, up to the focal year, has patented in only one technology category but whose patents in that year contain only patents from a different category will have a search distance of 1 (i.e., the patent portfolio shows no overlap with the portfolio of patent citations in year *t*).

The categorization of patents and cited patents into technological domains was done using a self-developed algorithm. By searching for specific keywords (see Table A2 in the appendix) in the title and abstracts of all patents in our database, all patents held by the 247 firms in our sample were assigned to one of four technological domains: (1) c-Si PV; (2) thin-film PV; (3) third-generation PV; and (4) generic PV technologies (e.g., inverters, racks, absorbers). The patents cited in these patents were categorized in a similar way. In contrast to the patents, which included only PV patents, however, when categorizing the citations we added a fifth category for all citations to patents outside the PV sector.

3.3.2 Independent variables

Technology-push policies were measured by the annual amount of R&D funding dedicated to PV technologies in a specific country. Using country-level data to measure the effect of technology-push policies on firm search is reasonable, since previous work indicates that technology-push policies exert an effect on innovation and knowledge generation primarily within national boundaries (Peters *et al.*, 2012).

Compared to technology-push, data on demand-pull funding in the PV industry is not as easily available, since a plethora of different instruments operate at different levels, such as feed-in tariffs, renewable portfolio standards, public procurement, and financing schemes. We therefore followed the procedure used by Hoppmann *et al.* (2020) and measure demand-pull policies in a top-down way by calculating the cost difference between electricity generated from PV and from conventional sources, then multiplying it by the total amount of electricity generated from the PV plants installed in the focal year. The assumption behind this measure, which is also used by those governments that monitor and publish data on demand-pull policies on PV, is that, for PV plants to be installed in the first place, demand-pull policy incentives have to cover the gap between the cost of electricity from PV and the (lower) cost of electricity from conventional technologies in the market. For example, if in the US during 2001, PV plants were installed that generate 885,000 MWh of electricity over their lifetime, the cost of electricity from these plants is 0.34 USD/kWh, and the cost of electricity from conventional sources is 0.05 USD/kWh, the annual amount of demand-pull funding required to make investments in PV profitable is (0.34-0.05)*(885,000,000) = USD 256.56M. Using this method, based on country-specific investment costs and irradiation conditions (Branker *et al.*, 2011), we calculated the annual cost differences for solar PV for each of the countries and years in our sample to obtain measures for demand-pull funding. The values for the individual countries were then added up to yield a global, annual measure for demand-pull funding. This was done because previous research indicates that, in contrast to technology-push policies, demand-pull policies in a specific country have a global effect on knowledge generation (Peters *et al.*, 2012).

Finally, firm *knowledge breadth,* as a moderating variable, was measured as the number of technological domains within PV in which a firm held patents at the time of interest. To count the technological domains, we relied on the categorization of patents also used for our measure of search distance, excluding those that fell outside the realm of PV (category 5). Based on the categorization of patents, we then calculated the knowledge breadth for all firms over time by counting the number of domains in which a firm was active, ranging from 0 (not active in any PV domains) to 4 (active in all four PV domains).

3.3.3 Control variables

In our analysis, we control for a large number of factors other than public innovation policy and knowledge breadth, which in previous research have been identified as influencing firms' knowledge search. Extant studies suggest that, although the direction of the effect is still controversial, financial performance can influence firm search behavior. While some scholars argue that strong financial performance leads to broad and distant search, other scholars argue that strong performance is likely to encourage managers to maintain their current course, and hence exerts a negative effect on search scope and distance (Katila, 2002). In line with previous work, we measure financial performance by including firms' return on assets.

A firm's *slack resources* have been found to encourage both broad and distant search (Chen *et al.*, 2007; Garriga *et al.*, 2013; Troilo *et al.*, 2014). In this study, we controlled for a firm's slack resources by including the firm's ratio between cash and long-term debt.

R&D intensity, i.e. a firm's R&D expenses divided by sales, is also included as a control variable because this variable is closely related to a firm's capacity to identify and develop new knowledge (Gilsing *et al.*, 2008). A high R&D intensity is connected with broader and more distant search (Mudambi *et al.*, 2014).

Search is also facilitated by *R&D alliances,* as they serve as a means for firms to tap external knowledge sources and thereby enhance their capacity to engage in broader and more distant search (Rosenkopf *et al.*, 2003). To control for the effect of alliances on search, we included the number of R&D alliances in the field of PV a firm was active in one year prior to the year of interest. Since data on the discontinuation of alliances was not available, in line with previous research we assumed alliances to have a duration of three years (Lavie *et al.*, 2011).

Mergers and acquisitions, similar to alliances, provide the firm with access to external and thus new knowledge (Arora *et al.*, 2014). To control for this effect, we included the cumulative number of M&A deals a firm had completed in the field of PV at the time of interest.

Employee mobility has also been found to be an important mechanism to help firms overcome local search (Rosenkopf *et al.*, 2003). We therefore included a control variable to count the number of inventors named in the firm's patents during a specific year who had filed a patent with another firm in the solar industry before.

Firm size is a commonly used control variable because it can affect search in multiple ways, e.g., by facilitating internal collaboration (Leiponen *et al.*, 2010). We measured firm size by including the natural logarithm of the number of employees.

Finally, knowledge search might be driven or hampered by *environmental uncertainty*. Uncertainty in a firm's environment may make it difficult for it to predict future sales and technology developments. On the one hand, such uncertainties may provide an incentive for firms to search for alternatives to existing technologies (Jansen *et al.*, 2006). On the other hand, in the face of uncertainty, firms may postpone investment decisions in innovations and hence reduce their search activities (Hoffmann *et al.*, 2009). In line with previous work, we used the standard deviation in the change of market size over the preceding four years as a proxy for environmental uncertainty (Eisenhardt *et al.*, 1996).

3.4 Model estimation

We used two types of models to assess our hypotheses. For the models including search scope as the dependent variable (Hypotheses 1a, 1b, 3a and 3b) we used a negative binominal regression model, since the dependent variable takes the form of count data. Generally, negative binominal and Poisson regression models are suitable candidates for the analysis of count data. However, a log-likelihood test of our independent variables pointed to the presence of over-dispersion, which can lead to an underestimation of standard errors (Cameron & Trivedi, 2010). Hence, we selected the negative binominal regression over the Poisson model. For the analysis of search distance (Hypotheses 2a and 2b) we used fractional probit regression. Fractional probit regression can be used to estimate models with dependent variables that take values between 0 and 1. Two alternative models that can be used to estimate models with such data structure are the beta distribution and the zero one inflated beta. However, in contrast to these two models, fractional probit regression includes the boundary values (0 and 1) and does not assume zero- or one-inflation.

Hypotheses 1 and 3 were tested with the full sample, i.e. considering all firm-years of the 247 firms over the time period 1988 to 2012 (N=3,480). To test Hypothesis 2, we only investigated those firm-years in which we actually observed search activity by firms (N=745), since measuring search distance is only possible in those years where search takes place. To control for unobserved variances, we included firm-fixed effects. For those models that test the effect of technology-push policies, we also included year-fixed effects. Since our demand-pull policy variable takes the same value for all firms in a specific year, using year-fixed effects is not possible when testing the effect of this variable. Therefore, for those models that test the impact of demand-pull variables we controlled for time effects by including a trend variable rather than year dummies. In line with earlier studies, all independent variables were lagged by one year. Moreover, for all hypothesis tests we used heteroscedasticity-robust estimation techniques. Table 1 shows the descriptive statistics and correlations for all variables.

4. RESULTS

4.1 Hypotheses tests

In the following, we separately present the results of the hypotheses tests for the two dependent variables *search scope* and *search distance*. For both variables, we first show a base model including only the control variables (Models 1 and 8 respectively). Then, we add the two independent variables (*demand-pull* and *technology-push policies*) and the interaction terms.

Hypotheses 1a and 1b suggested that technology-push and demand-pull policies are negatively related to search scope. Table 2 summarizes the results of the negative binominal regression models for *search scope*. As explained above, we tested technology-push policies using a model that contains both firm- and year-fixed effects, thereby also controlling for demand-pull policies that are only time-variant (see Model 2). In contrast, to test the impact on demand-pull policies, we did not use year-fixed effects, but instead included a time trend (see Models 3 and 4). The resulting coefficients for technology-push policies in Model 2 (β=-0.00141, $p<0.05$, incidence rate ratio (IRR)=exp(-0.00141)= 0.9986) and demand-pull policies in Model 4 (β=-0.000057, $p<0.01$, IRR=exp(-0.000057)= 0.9999) are both negative and significant. Hypotheses 1a and 1b are thus supported by our data.

TABLE 1: Descriptive statistics

		Obs.	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Search scope	4,566	32.869	360.228	0	13,100	1												
2	Search distance	809	0.39	0.195	0	1	-0.029	1											
3	Demand-pull policies	4,566	13461.1	18655.21	61.52	66918.81	-0.03	-0.03	1.00										
4	Technology-push policies	4,566	75.085	67.096	0	365	0.002	0.005	0.35	1									
5	Firm size	4,566	4.041	0.893	0.699	6.342	0.032	0.009	-0.01	-0.037	1								
6	Financial performance	4,566	-0.018	0.469	-13.94	3.47	0.008	-0.039	-0.01	-0.048	0.267	1							
7	Slack resources	4,566	43.46	455.894	-0.05	15,562.29	-0.002	0.047	0.01	0.04	-0.065	0.001	1						
8	R&D intensity	4,566	0.391	8.945	0	428.86	-0.001	-0.074	-0.01	0	-0.09	-0.009	0.007	1					
9	Knowledge breadth	4,566	0.923	1.203	0	4	0.173	-0.004	0.44	0.209	0.208	0	-0.001	-0.014	1				
10	R&D alliances	4,566	0.129	1.085	0	33	0.019	-0.015	0.05	-0.034	-0.019	0.003	-0.011	-0.002	0.101	1			
11	M&A	4,566	0.018	0.18	0	7	0.074	0.033	0.05	0.054	-0.031	0.005	-0.001	-0.003	0.093	0.081	1		
12	Employee mobility	4,566	0.917	4.39	0	106	0.08	-0.021	0.09	0.031	0.136	0.019	-0.013	-0.007	0.38	0.111	0.101	1	
13	Environmental uncertainty	4,429	0.971	1.928	0	15.876	-0.002	0.052	0.02	-0.046	-0.003	0.007	-0.018	0.008	-0.065	-0.005	0.006	-0.062	1

TABLE 2: Results of negative binominal model testing effect of innovation policies on search scope

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Firm size	0.363***	0.359***	0.351***	0.343***	0.358***	0.341***	0.339***
	(0.0712)	(0.0711)	(0.0706)	(0.0703)	(0.0713)	(0.0708)	(0.0711)
Financial performance	0.301	0.286	0.128	0.110	0.295	0.287	0.302
	(0.254)	(0.253)	(0.233)	(0.229)	(0.253)	(0.255)	(0.258)
Slack resources	-0.000297†	-0.000295†	-0.000266	-0.000264	-0.000282†	-0.000283†	-0.000267
	(0.000172)	(0.000172)	(0.000163)	(0.000163)	(0.000171)	(0.000171)	(0.000170)
R&D intensity	2.64E-03	2.46E-03	0.00209	0.00175	0.00228	0.00301	0.00281
	(0.00405)	(0.00405)	(0.00377)	(0.00383)	(0.00411)	(0.00397)	(0.00403)
Knowledge breadth	0.483***	0.485***	0.467***	0.471***	0.425***	0.697***	0.631***
	(0.0386)	(0.0387)	(0.0378)	(0.0379)	(0.0491)	(0.0458)	(0.0549)
R&D alliances	0.00876	0.00434	0.000277	-0.00888	0.00610	0.0111	0.0139
	(0.0285)	(0.0285)	(0.0287)	(0.0290)	(0.0282)	(0.0283)	(0.0279)
M&A	0.164	0.211	0.159	0.246†	0.180	0.230	0.196
	(0.142)	(0.146)	(0.141)	(0.145)	(0.146)	(0.146)	(0.145)
Employee mobility	0.0301***	0.0296***	0.0330***	0.0325***	0.0298***	0.0349***	0.0349***
	(0.00291)	(0.00292)	(0.00272)	(0.00273)	(0.00291)	(0.00301)	(0.00300)
Environmental uncertainty	0.0473	0.0419	0.0221	0.0163	0.0444	0.0410	0.0429
	(0.031)	(0.0311)	(0.0269)	(0.0268)	(0.0312)	(0.0318)	(0.0317)
Technology-push policies		-0.00141*		-0.00292***	-0.00347**	-0.00142*	-0.00343**
		(0.000623)		(0.000601)	(0.00123)	(0.000629)	(0.00115)
Demand-pull policies			-5.89e-05***	-5.67e-05***			
			(4.06e-06)	(4.10e-06)			
Technology-push policies X knowledge breadth					0.000764*		0.000826*
					(0.000384)		(0.000382)
Demand-pull policies X knowledge breadth						-1.65e-05***	-1.66e-05***
						(2.07e-06)	(2.08e-06)
Constant	-6.050***	-5.976***	-363.9***	-365.0***	-5.893***	-5.890***	-5.804***
	(0.779)	(0.779)	(32.41)	(31.93)	(0.781)	(0.778)	(0.780)
Year fixed effects	Yes	Yes	No	No	Yes	Yes	Yes
Time trend	No	No	Yes	Yes	No	No	No
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,480	3,480	3,480	3,480	3,480	3,480	3,480
Number of Firms	245	245	245	245	245	245	245
AIC	7960.765	7957.463	8049.958	8026.375	7955.489	7896.237	7893.571

Standard errors in parentheses, *** $p<0.001$, ** $p<0.01$, * $p<0.05$, † $p<0.1$

Hypothesis 2a suggested a positive relationship between technology-push policies and search distance. The results of the fractional probit model estimation for *search distance* as a dependent variable are contained in Table 3. Again, the effect of technology-push policies was tested including firm- and year-fixed effects (Model 9), whereas the effect of demand-pull policies was measured by including a time trend (Models 10 and 11). As shown in Model 9, the coefficient for *technology-push policies* is positive and significant—albeit at a weak significance level of 10% (β=0.000800, p<0.1). Thus, Hypothesis 2a is (weakly) supported by our analysis. Hypothesis 2b predicted a negative relationship between demand-pull policies and search distance. Model 11 shows a negative and significant effect of *demand-pull policies* on *search distance* (β=-0.00000525, p<0.05). Hence, we also find support for Hypothesis 2b.

TABLE 3: Results of fractional probit model testing effect of innovation policies on search distance

Variables	**Model 8**	**Model 9**	**Model 10**	**Model 11**
Firm size	-0.061	-0.055	-0.0457	-0.0382
	(0.155)	(0.158)	(0.157)	(0.160)
Financial performance	-0.309*	-0.337*	-0.256†	-0.272*
	(0.139)	(0.141)	(0.133)	(0.136)
Slack resources	0.000122	0.000120†	0.000109	0.000106
	(0.0000766)	(0.0000705)	(7.39e-05)	(7.16e-05)
R&D intensity	-0.0781**	-0.0843**	-0.107***	-0.110***
	(0.0265)	(0.0263)	(0.0251)	(0.0252)
Knowledge breadth	0.0164	0.0208	0.0150	0.0171
	(0.0337)	(0.0336)	(0.0352)	(0.0351)
R&D alliances	0.134	0.138	0.135	0.135
	(0.12)	(0.121)	(0.121)	(0.122)
M&A	-0.177	-0.181	-0.161	-0.163
	(0.163)	(0.16)	(0.161)	(0.158)
Employee mobility	0.00154	0.00232	0.00148	0.00193
	(0.00363)	(0.0035)	(0.00382)	(0.00374)
Environmental uncertainty	0.0045	0.00673	0.0141	0.0142
	(0.0108)	(0.0111)	(0.0107)	(0.0107)
Technology-push policies		0.000800†		0.000356
		(0.000484)		(0.000386)
Demand-pull policies			-5.04e-06**	-5.25e-06**
			(1.68e-06)	(1.68e-06)
Constant	0.0847	0.0221	-2.616	-0.0964
	(0.758)	(0.772)	(13.88)	(14.20)
Year fixed effects	Yes	Yes	No	No
Time trend	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	745	745	745	745
Number of Firms	247	247	247	247
AIC	1479.221	1480.917	1403.371	1407.279

Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Hypotheses 3a and 3b suggested that a broader knowledge base within the firm reduces the negative effect of technology-push and demand-pull policies on its search scope. To test the interaction effects, we used models that include technology-push policies in combination with firm- and year-fixed effects (demand-pull policies are included in the latter). Model 7 lends support for the buffering effect on technology-push policies. The coefficient of the interaction term for *technology-push policies* and *knowledge breadth* is positive and significant (β=0.000826, $p<0.05$, IRR=exp(0.000826)=1.083). To investigate whether this finding holds for the entire range of possible values, we followed the methodology suggested by Zelner (2009), also used by York *et al.* (2018) and Hoppmann *et al.* (2020), and plotted the predicted values for our model with search scope as the dependent variable for the entire range of technology-push policies and high (mean+1 standard deviation) and low (mean–1 standard deviation) knowledge breadth. This exercise confirmed that the interaction between technology-push policies and knowledge breadth never becomes insignificant, since the confidence intervals of the graphs for weak and strong knowledge breadth do not overlap.

At the same time, however, we do not find support for Hypothesis 3b, since the coefficient for *demand-pull policies* is negative and significant (β=-0.0000166, $p<0.001$, IRR=exp(-0.0000166)=1). Again, we used the methodology by Zelner (2009) to confirm that this finding holds for the entire range of values for demand-pull policies and high (mean+1 standard deviation) and low (mean–1 standard deviation) knowledge breadth. Figure 1 summarizes the findings of our hypothesis test.

4.2 Robustness tests

To glean more insights into the mechanisms driving our results and investigate the extent to which our results are robust against using alternative measures, we conducted several robustness checks. First, as an alternative to measuring demand-pull funding based on cost differences, we used the annual market size in gigawatts, since this measure has been used to operationalize demand-pull policies in previous studies (Dechezleprêtre *et al.*, 2014; Klaassen *et al.*, 2005; Peters *et al.*, 2012). This measure is highly correlated with the measure based on cost differences (Pearson correlation coefficient of 0.94), since the cost of electricity from PV has been considerably above wholesale electricity prices for many years (Branker *et al.*, 2011), such that the market for PV technology would have been negligible without demand-pull support. The results are almost identical when using market size as an operationalization of demand-pull policies instead of cost differences (see Models

12–22 in the appendix). The only difference is that the coefficient of *technology-push policies* in explaining *search distance* becomes insignificant in these models.

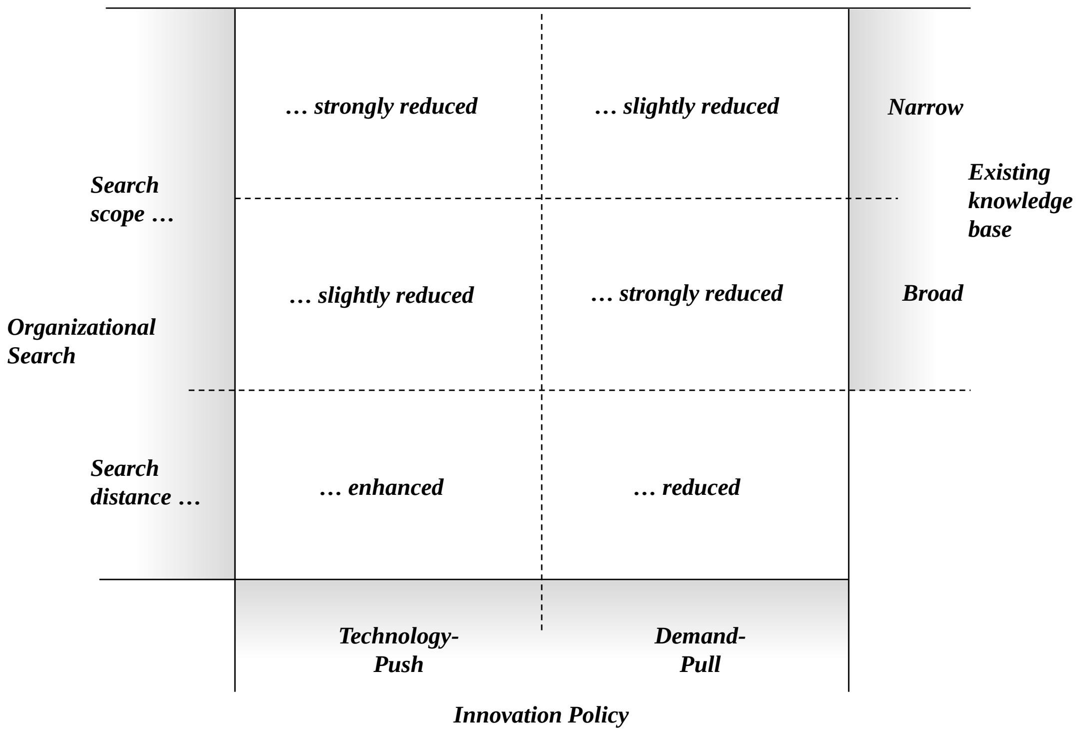

FIGURE 1: Summary of impacts of innovation policy on organizational search depending on firm's existing knowledge base

Second, as pointed out in our hypothesis section, we expected that demand-pull and technology-push policies enhance innovative activity in an industry. One of the mechanisms driving the rise in innovative activity is entry of innovative start-ups. In other words, entry serves as one of the mechanisms connecting innovation policies and firms' search behavior, rather than as an alternative explanation, which is why we do not control for entry in our original models. However, to understand the extent to which innovation is driven by entry, we tested alternative models in which we controlled for entrepreneurial entry. These analyses showed that the results remain the same when controlling for entrepreneurial entry, with the only difference that the impact of demand-pull policies on search distance is significant at the 10-percent instead of the 5-percent level. This indicates that, although entry plays a role, it is not the main mechanism connecting innovation policies and search.

Third, one might expect that technology-push and demand-pull policies do not only shape firms' search behavior separately, but that the effect of each of the two factors depends on the other. To investigate this possibility, we ran exploratory models that include an interaction effect of the two independent variables. We find that the interaction effect is not significant, neither in the models for search scope nor for search distance. A potential explanation for this finding is that, while both types of policies are important for firms, the mechanisms through which they affect search are very different. Whereas technology-push policies directly stimulate R&D and knowledge search (e.g., as firms engage in public R&D programs), demand-pull policies indirectly shape search behavior, as they stimulate demand for specific products, raise firms' revenues, and thereby increase firms' capacity to conduct R&D.

Fourth, our models include independent variables at two levels, the firm- and the country-level, which is why we ran multi-level models with fixed level 1 and level 2 predictors with randomly varying intercepts as alternatives to the models presented in section 4.1. Unfortunately, the multi-level fractional probit regression model failed to converge when including firm-fixed effects, which is a phenomenon that is common when estimating multi-level models. We therefore estimated the model without firm-fixed effects. Similarly, the multi-level negative binominal regression model only converged when leaving out firm- and time-fixed effects, which is why we estimated this model without firm and time dummies. The results obtained when using multi-level models are similar to the ones presented in section 4.1, except that the interaction effect between technology-push policies and knowledge breadth is no longer statistically significant (such that Hypothesis 3a is no longer supported) and that the weak significance of the positive impact of technology-push policies on search distance disappears (such that Hypothesis 2a would no longer be supported).

Given these differences, the question arises whether the original models (that include firm- and time-fixed effects), or the multi-level models (that do not include firm- and time-fixed effects) better fit our data. To investigate this question, we conducted a Hausman test to investigate the hypothesis that the firm-level effects are adequately modeled by a random-effects model. The results of this tests showed that the hypothesis is rejected at a very high level of significance (Prob>chi2 = 0.0000). This finding indicates that leaving out firm-fixed effects would lead to endogeneity problems and biased estimators, such that firm-fixed effects should be used. In addition, whereas multi-level regression allows for separate intercepts across countries, models including firm-fixed effects systematically vary intercepts at the lower level of firms. As a result, models including firm-fixed effects can be expected to be more accurate in capturing unobserved variance than two-level models that include fixed level 1 and level 2 predictors with randomly varying intercepts, since models including firm-fixed effects automatically control for unobserved variance at higher levels. For these reasons, we ultimately decided to not present the multi-level models as our main models but use these models as a robustness test.

5. DISCUSSION

In the following, we discuss the implications of our findings for the literature, present implications for practitioners, discuss limitations, and suggest some avenues for future research.

5.1 Organizational search

This study makes several contributions to the literature on organizational search, which is rooted in the knowledge-based view and the behavioral theory of the firm (Cyert *et al.*, 1963; Macher, 2006). First, it broadens our understanding of how factors in a firm's environment, in particular public policies, influence organizational search for knowledge. Previous research on the antecedents of search has primarily looked at firm-internal variables, such as a firm's performance and slack resources (Garriga *et al.*, 2013; Laursen, 2012). Only recently have scholars begun to investigate the broader environmental context in which knowledge search takes place (Piezunka *et al.*, 2015; Sidhu *et al.*, 2007). Our study adds to this emerging research stream by showing that environmental conditions, e.g. in the form of formal institutions, can exert a strong influence on a firm's propensity to engage in different forms of search. The fact that firms' search is affected by the environment suggests that organizational members may have less agency in setting search strategy than the current strategy literature suggests. Instead, in line with the original literature on the behavioral theory of the firm, search processes may be conditioned and influenced by the environmental context a firm operates in.

Second, our study provides detailed evidence on how technology-push and demand-pull policies influence a firm's search scope and search distance. More specifically, we find that both technology-push and demand-pull impulses lead to a narrower search scope, and that search distance is positively affected by technology-push policies and negatively affected by demand-pull policies. The former finding supports our argument that by raising the amount of knowledge public innovation policies may (1) allow firms to find a solution to specific problems more quickly; (2) prompt firms to narrow their attention to prevent information overload; and (3) raise the risk of oversearching. As a result, our findings extend previous findings in the literature on the behavioral theory of the firm

(Cyert *et al.*, 1963) and crowdsourcing (Piezunka *et al.*, 2015). In line with the idea of satisficing behavior, firms may primarily invest in search to the extent that is required to solve more immediate problems. Thus, more knowledge in a firm's environment may not necessarily lead to broader search. On the contrary, as more knowledge becomes available, less search is necessary to develop innovations that satisfy the requirements of the firm. In fact, by speeding up the development of knowledge in a technological field, innovation policies may even require firms to narrow down their search to bring products to the market more quickly and avoid "oversearching." Complementary to this view, recent work on crowdsourcing demonstrates that soliciting large amounts of information may narrow firms' attention (Piezunka *et al.*, 2015). It seems possible that public policies show an effect similar to crowdsourcing initiatives at the industrial level. Like crowdsourcing initiated by firms, innovation policies implemented by policy-makers may increase the knowledge available to firms, but require them to reduce their search scope to prevent information overload.

Third, our findings contribute to a better understanding of how a firm's existing knowledge base influences its search behavior (Zhou *et al.*, 2012). We find that a broader knowledge base within the firm reduces the influence of technology-push policies on search scope, while enhancing that of demand-pull policies. A potential explanation for the latter finding might lie in the different effects that each policy type has on innovation. As shown by our analysis of search distance, compared to demand-pull policies, technology-push policies lead to the generation of more diverse knowledge and radical innovations outside existing technologies. Firms who already possess broad knowledge can more easily absorb the diverse knowledge generated by technology-push policies. Therefore, we would expect the effect of technology-push policies on the reduction of search scope to be less pronounced for firms with a broader knowledge base. To absorb the relatively uniform knowledge resulting from demand-pull policies, however, a broad knowledge base may be unnecessary, or even inefficient. Therefore, firms with a broad knowledge base, in particular, might face a strong incentive to reduce their search scope in response to demand-pull policies.

5.2 Technology-push and demand-pull policies

Besides contributing to the literature on search, our research also has important implications for the literature on innovation policies. This literature suggests that demand-pull serves as a selection mechanism that fosters incremental innovation primarily within established technological trajectories, whereas technology-pull serves as a variety-creating mechanism that may induce more radical innovation (Freeman, 1996; Mowery *et al.*, 1979). Although these claims have been taken up by the more recent literature on innovation policies, we currently lack empirical tests that support them. In this regard, to our knowledge this study is among the first to empirically test the influence of technology-push and demand-pull policies on search distance, thereby supporting important conclusions about their potential to foster incremental vs. radical innovations. In line with the predominant view in the literature, we find that technology-push policies exert a positive effect on search scope, and demand-pull policies a negative one. Despite the fact that technology-push policies may crowd out private R&D funding, and that the resulting knowledge may be difficult for firms to decode, it thus seems that such policies can incentivize firms to search in a more distant way. Demand-pull policies, on the other hand, seem to primarily set an incentive for local search, despite increasing the financial resources available to the firm. In this sense, our findings are in line with recent studies that suggest that demand-pull policies may raise the risk of technological lock-ins (Hoppmann *et al.*, 2013).

5.3 Technology life-cycles

Finally, our findings also have implications for the literature on technology evolution and life-cycles. Traditionally, this literature has been interested in understanding the patterns and drivers of technological evolution. It has been pointed out that processes of organizational attention and search may play an important role in the emergence of technological trajectories and paradigms (Kaplan *et al.*, 2008). So far, however, we lack empirical data describing the ways in which these processes contribute to technology evolution. Our research suggests that as technology-push and demand-pull factors lead to the accumulation of knowledge in industries over time, firms tend to alter their behavior toward narrower search. As searches narrow, so knowledge becomes increasingly specialized, which may result in the emergence of distinct technological paradigms. Moreover, previous research indicates that industries evolve from being primarily reliant on technology-push factors at the beginning toward a dominance of demand-pull factors in more mature stages (Dosi, 1982). Our findings indicate that as the focus shifts from technology-push toward demand-pull, firms' search may become more local, leading to more incremental innovation. As a result, our findings provide some explanation at the firm level for why innovation patterns over the course of the technology life-cycle shift toward more incremental innovation, potentially resulting in the emergence of dominant designs.

5.4 Practical implications

In more practical terms, our study offers some insights for policymakers and corporate managers. We confirm that innovation policies can serve as important means to foster knowledge search and innovation. At the same time, our findings show that this positive effect of technology-push and demand-pull policies comes at a cost, since the use of innovation policies can lead firms to consider fewer sources in their search for innovations. Moreover, our results indicate that demand-pull policies in particular run the risk of reducing the extent to which firms search for knowledge outside their focal technology domain. Demand-pull support for firms should therefore be complemented with technology-push support if narrow search is considered undesirable (see also Hoppmann *et al.*, 2013).

Our findings are relevant for corporate managers, since they point to an important role for policies and the firm's knowledge base in knowledge search. Managers of firms that operate in industries affected by innovation policies should be aware that their firm's search processes might easily be affected by policy incentives. Firms operating in a country that makes heavier use of demand-pull policies may find that this narrows their search scope and distance. Since both search scope and distance are positively related to firm innovation and long-term competitiveness (Lavie *et al.*, 2010; Mitchell *et al.*, 1993), national policy conditions may negatively affect a firm's position in international markets. In fact, there is evidence that in the case of the PV industry, the intensive use of demand-pull policies in some countries, e.g., Germany, might have adversely affected firms' search behavior (Hoppmann *et al.*, 2013). Our research indicates that building a broader knowledge base might be a way to reduce such unintended negative effects, since it allows firms to absorb more knowledge resulting from technology-push policies. Therefore, if a firm wishes to maintain a broader search scope, its managers might think about deliberately investing in the diversification of knowledge (e.g., by entering new technological fields).

5.5 Limitations and future research

This study has some limitations that may provide starting points for future research. First, our study is limited to the PV industry. While this industry is particularly well suited to answer our research question, the PV industry differs from other industries in a number of important ways (Huenteler *et al.*, 2015; Malhotra *et al.*, 2019). For example, despite a high propensity to patent, previous research has found a high degree of knowledge spillover between firms, which may influence the patterns of search we observe. Future research should therefore explore the generalizability of our findings to other industries.

Second, while our study provides evidence that public policies influence firm search behavior, our research design does not allow us to uncover the relative importance of the different mechanisms that lead to our findings. For example, our analysis does not provide insights into whether the reduction of search scope resulting from innovation policies is due to firms being able to find solutions more quickly, experiencing information overload, or incurring a higher risk of oversearching. Future research should therefore extend our study by shedding more light on the mechanisms connecting policies and firm search—e.g., by using in-depth qualitative case studies.

Third, since this study is among the first to assess the effects of policies on firm search, we focused on *search scope* and *search distance* as the most important dependent variables. Clearly, there are a number of other constructs that represent important dimensions of firm search (e.g. search within vs. across organizations; search across geographical boundaries) or moderating factors (e.g. hierarchical structure). Future research might also categorize the sources of knowledge in terms of inventors (e.g., firms, research institutes, universities, individuals) and assess how public policies affect the extent to which firms draw on knowledge from different groups.

6. CONCLUSION

This study investigates the impact of demand-pull and technology-push policies on the search scope and search distance of firms, taking into account the breadth of their existing knowledge base. Our results provide a number of important insights into how firms' search is affected by public policies. While previous studies show that demand-pull and technology-push policies foster innovative activity and the generation of knowledge, we find that both types of policies lead to narrower knowledge search by firms. Moreover, we provide quantitative evidence that technology-push policies may increase a firm's search distance, while demand-pull policies may reduce it.

We explain these findings by positing that enhanced availability of knowledge resulting from policy incentives may allow firms to find a solution to specific problems more quickly, lead to attention-narrowing information overload, and raise the risk of oversearching. In this sense, our findings are in line with the traditional literature of the behavioral theory of the firm, which suggests that actors engage in satisficing rather than optimizing search. Moreover, the finding that technology-push policies lead to more distant, technology-spanning search may be due to the variety-enhancing effect of such policies, which often aim to foster innovation in fields relatively remote from the market. Demand-pull policies, on the other hand, may reduce firms' search distance by exerting a selection pressure, inducing firms to pursue innovation primarily along established trajectories.

Overall, our findings provide a first step toward better understanding how factors in a firm's environment may influence knowledge search. Today, a large number of innovations are developed in ecosystems and supported by public policies. We therefore believe that there is both ample opportunity and a compelling need for future research that deepens and extends the findings presented in this study.

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APPENDIX

TABLE A1. Keyword used to extract solar PV patents

Patent search	Search String
Solar PV patents	IPC=(B23K* OR B28D* OR C01B-033* OR C23C* OR C30B* OR E04D-013* OR H01L-031* OR H01L-021* OR H01L-025* OR H01L-051* OR H02M* OR H02J* OR H02N*-006* OR H01R* OR G01B* OR G01R* OR G05F-001*) AND TITLE/ABSTRACT =("solar cell*" OR "solar power*" OR "solar module*" OR "photovoltaic*" OR "solar panel*" OR "solar grade" OR "solar electr*")

TABLE A2. Keywords used in the categorization of patents

Category	Search String	Priority*
C-Si PV	“silicon solar cell*” OR “Si-solar cell*” OR “ribbon” OR “Si solar cell” OR “Si substrate” OR “silicon substrate” OR [(“ Si “ OR “silicon” OR “Si-solar”) AND (“single crystal” OR “single-crystal” OR “monocrystalline” OR “monocrystal” OR “ crystalline” OR “back surface passivation” OR “rear surface passivation”)] OR [(“ Si “ OR “silicon” OR “Si-solar”) AND (“polycrystalline” OR “multicrystalline” OR “multi-crystalline” OR “multi crystalline” OR “poly-crystalline” OR “poly-crystalline” OR “polycrystal” OR “poly crystal” OR “multicrystal” OR “multi crystal” OR “Emitter wrap through” OR “Metal wrap through”)]	0
Thin-film PV	“steel substrate” OR “roll-to-roll” OR “roll to roll” OR “vacuum depos” OR “deposit” OR “vacuum chamber” OR “lamina” OR “epitaxially grown” OR “thin film” OR “thin-film” OR “ film “ OR “plastic substrate” OR “semiconductor film” OR “sputter” OR “glass substrate” OR “flexible substrate” OR “PECVD” OR “PVD” OR “solid phase crystallization” OR "laser crystallization” OR “a-Si” OR “amorphous” OR “microcrystal” OR “silicon-film” OR “Staebler” OR “Cadmium” OR “Telluride” OR “CdTe” OR “ CdS “ OR “Sulphide” OR “ Se “ OR “ Cd “ OR “ Te “ OR “ CIGS “ OR “CI(G)S” OR “indium” OR “selenide” OR “ CIS “ OR “CuInSe” OR “Copper indium gallium diselenide” OR “CuInGeSe” OR “Copper zinc tin sulfide” OR “CZTS” OR “chalcopyrite”	1
Third generation PV**	"lens" OR "CPV" OR "concentrator" OR "upconver" OR "up-conver" OR "downconver" OR "down-conver" OR "concentr*" OR "hot carrier" OR "hot-carrier" OR "GaAs " OR "Ga-Al-As" OR "gallium arsenide" OR "germanium" OR "crystalline thin-film" OR "crystalline thin film" OR "GaSb" OR "dye-sensitiz" OR "dye sensitiz" OR " organic" OR "dye" OR "nano" OR "tio2" OR "quantum dot" OR "droplet epitaxy" OR "polymer" OR “titanium dioxide” OR “titanium oxide” OR “Graetzel” OR “perovskite” OR [(“steel substrate” OR “roll-to-roll” OR “roll to roll” OR “vacuum depos” OR “deposit” OR “vacuum chamber” OR “lamina” OR “epitaxially grown” OR “thin film” OR “thin-film” OR “ film “ OR “plastic substrate” OR “semiconductor film” OR “sputter” OR “glass substrate” OR “flexible substrate” OR “PECVD” OR “PVD” OR “solid phase crystallization” OR "laser crystallization”) AND (Si “ OR “silicon” OR “Si-solar”] AND [“single crystal” OR “single-crystal” OR “monocrystalline” OR “monocrystal” OR “ crystalline “)	2
Generic	“storage” OR "mounting" OR "roof" OR "solar tracker" OR "fuel cell" OR “inverter” OR "absorber" OR "glazing" OR "antireflect" OR "metal evaporation" OR "filter" OR "Gasochromic"	3

* In the case that an abstract contained keywords of several of the categories, it was assigned to the category with the highest priority since keywords in higher groups indicate work on more advanced technologies. The “generic” category captures the publications on topics that are applicable to all PV technologies.

** Includes concentrating PV, dye-sensitized PV, organic PV, nano PV, c-Si thin-film PV

TABLE A3: Results of negative binominal regression model on effect of policies on search scope with demand-pull policies operationalized as market size

Variables	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
Firm size	0.363***	0.359***	0.363***	0.356***	0.358***	0.349***	0.347***
	(0.0712)	(0.0711)	(0.0707)	(0.0706)	(0.0713)	(0.0710)	(0.0713)
Financial performance	0.301	0.286	0.171	0.157	0.295	0.290	0.307
	(0.254)	(0.253)	(0.242)	(0.240)	(0.253)	(0.254)	(0.256)
Slack resources	-0.000297†	-0.000295†	-0.000288†	-0.000287†	-0.000282†	-0.000293†	-0.000274
	(0.000172)	(0.000172)	(0.000166)	(0.000167)	(0.000171)	(0.000172)	(0.000170)
R&D intensity	2.64E-03	2.46E-03	0.00215	0.00195	0.00228	0.00288	0.00264
	(0.00405)	(0.00405)	(0.00384)	(0.00386)	(0.00411)	(0.00398)	(0.00406)
Knowledge breadth	0.483***	0.485***	0.463***	0.465***	0.425***	0.585***	0.507***
	(0.0386)	(0.0387)	(0.0380)	(0.0381)	(0.0491)	(0.0422)	(0.0509)
R&D alliances	0.00876	0.00434	0.000312	-0.00533	0.00610	0.00984	0.0137
	(0.0285)	(0.0285)	(0.0288)	(0.0289)	(0.0282)	(0.0283)	(0.0279)
M&A	0.164	0.211	0.149	0.205	0.180	0.212	0.169
	(0.142)	(0.146)	(0.142)	(0.145)	(0.146)	(0.146)	(0.145)
Employee mobility	0.0301***	0.0296***	0.0310***	0.0307***	0.0298***	0.0328***	0.0331***
	(0.00291)	(0.00292)	(0.00279)	(0.00280)	(0.00291)	(0.00301)	(0.00300)
Environmental uncertainty	0.0473	0.0419	0.0370	0.0339	0.0444	0.0408	0.0432
	(0.031)	(0.0311)	(0.0266)	(0.0266)	(0.0312)	(0.0318)	(0.0317)
Technology-push policies		-0.00141*		-0.00165**	-0.00347**	-0.00138*	-0.00405***
		(0.000623)		(0.000560)	(0.00123)	(0.000625)	(0.00119)
Demand-pull policies			-0.160***	-0.155***			
			(0.0117)	(0.0118)			
Technology-push policies X					0.000764*		0.00105**
knowledge breadth					(0.000384)		(0.000385)
Demand-pull policies X						-0.0417***	-0.0445***
knowledge breadth						(0.00761)	(0.00770)
Constant	-6.050***	-5.976***	-285.5***	-284.9***	-5.893***	-5.930***	-5.817***
	(0.779)	(0.779)	(25.96)	(25.68)	(0.781)	(0.779)	(0.780)
Year fixed effects	Yes	Yes	No	No	Yes	Yes	Yes
Time trend	No	No	Yes	Yes	No	No	No
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,480	3,480	3,480	3,480	3,480	3,480	3,480
Number of Firms	245	245	245	245	245	245	245
AIC	7960.765	7957.463	7968.604	7961.474	7955.489	7927.948	7922.449

Standard errors in parentheses, *** $p<0.001$, ** $p<0.01$, * $p<0.05$, † $p<0.1$

TABLE A4: Results of fractional probit regression model on effect of policies on search distance with demand-pull policies operationalized as market size

Variables	Model 19	Model 20	Model 21	Model 22
Firm size	-0.115	-0.106	-0.0908	-0.0740
	(0.252)	(0.255)	(0.254)	(0.260)
Financial performance	-0.498*	-0.545*	-0.435*	-0.476*
	(0.229)	(0.233)	(0.217)	(0.224)
Slack resources	0.000197	0.000193†	0.000165	0.000158
	(0.000123)	(0.000113)	(0.000120)	(0.000115)
R&D intensity	-0.137**	-0.146**	-0.182***	-0.188***
	(0.0483)	(0.0475)	(0.0442)	(0.0442)
Knowledge breadth	0.0249	0.0317	0.0180	0.0228
	(0.055)	(0.0548)	(0.0578)	(0.0578)
R&D alliances	0.228	0.235	0.233	0.234
	(0.203)	(0.206)	(0.208)	(0.211)
M&A	-0.303	-0.309	-0.275	-0.280
	(0.277)	(0.271)	(0.278)	(0.271)
Employee mobility	0.00264	0.00391	0.000977	0.00169
	(0.00603)	(0.00582)	(0.00719)	(0.00703)
Environmental uncertainty	0.00749	0.0111	0.0247	0.0252
	(0.0176)	(0.0181)	(0.0175)	(0.0176)
Technology-push policies		0.00129		0.000727
		(0.000799)		(0.000649)
Demand-pull policies			-0.0171**	-0.0185**
			(0.00552)	(0.00568)
Constant	0.22	0.121	3.776	8.742
	(1.23)	(1.251)	(21.00)	(21.39)
Year fixed effects	Yes	Yes	No	No
Time trend	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	745	745	745	745
Number of Firms	247	247	247	247
AIC	1417.185	1416.893	1375.279	1379.139

Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, † p<0