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Knowledge diffusion in nascent industries: Asymmetries between startups and established firms in spurring inventions by other firms

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Abstract

Research Summary: Research on industry evolution highlights the role of knowledge-building activities of startups and established firms in shaping knowledge evolution in a nascent industry. Yet, research thus far has overlooked the possibility that differences between startups and established firms might also shape the diffusion of the knowledge that they build. This study abductively explores this conjecture in the context of solar energy by examining the extent to which the photovoltaic cell inventions that firms create spur subsequent inventions by other firms. In contrast with existing literature highlighting differences across firms in the types of inventions they create, this study reveals asymmetries between startups and established firms in the diffusion of the knowledge underlying their inventions, even when they create inventions with similar attributes.

Managerial Summary: This study examines differences between startups and established firms in shaping knowledge diffusion in a nascent industry. Using data from photovoltaic cell patents, it shows that startups' inventions spur more subsequent inventions by other firms, even when compared to established firms' inventions with similar attributes. Findings indicate that such asymmetry is not driven by knowledge transfer mechanisms but rather by factors associated with knowledge spillovers. Specifically, findings reveal that university citations of a startup's patents draw other firms' attention to those patents, and that startups are less able to preempt rivals through cumulative inventions and less able to rely on litigiousness to deter rivals from building on their patents. These findings underscore the asymmetric influence startups have in shaping the knowledge underlying a nascent industry.

KEYWORDS

abduction, industry evolution, knowledge diffusion, knowledge spillovers, knowledge transfer

1 | INTRODUCTION

Tracing back to Schumpeter (1934, 1942), the role of startups and established firms in shaping technological change and industry evolution has been a topic of great interest to strategy scholars (e.g., Levinthal, 1992; Malerba & Orsenigo, 1995; Wu et al., 2014). More recently, the literature has emphasized the role of firms' knowledge-building activities (Cattani, 2005; Moeen, 2017) in mitigating uncertainty that firms face when new technologies emerge that might eventually support the emergence of a new industry (Kapoor & Klueter, 2021; Moeen et al., 2020). Recent studies have also revealed differences across firms in these knowledge-building activities, depending on the technological capabilities they bring to a nascent industry (Moeen & Agarwal, 2017; Moeen & Mitchell, 2020). Despite these great strides in elucidating how the knowledge that firms build in a nascent industry shapes knowledge evolution, research has yet to explore differences across firms with regard to the diffusion of their knowledge.

The conjecture that knowledge diffusion might also shape knowledge evolution is predicated on the insight that the non-rival and non-excludable public good nature of knowledge can result in a firm's inventions being a valuable input to subsequent inventions (Arrow, 1962). This insight suggests that industry evolution is shaped not only by the knowledge that firms build but also by the extent to which that knowledge is incorporated in the knowledge that other firms build subsequently. Moreover, research underscores knowledge diffusion as an important element underpinning the dynamic interplay between startups and established firms, as startups draw on the knowledge of established firms, which in turn also learn from startups (Agarwal et al., 2007; Giustiziero et al., 2019; Moeen & Agarwal, 2017). Therefore, important differences might exist between startups and established firms not only in the patterns of inventions they create, as extensively examined in prior research, but also in the extent to which their inventions spur subsequent inventions by other firms.

In this article, we investigate whether the inventions that startups create in a nascent industry are more frequently built upon than those created by established firms. As we detail in a later section, arguments in existing literature do not cohere around an answer to our research question in one particular direction. On the one hand, a vast body of research portrays startups as better able to build on new technologies, while emphasizing that established firms tend to build on existing technologies (e.g., Abernathy & Utterback, 1978; Polidoro & Yang, 2021). As new technologies arguably offer more untapped technological opportunities than technologies that firms have already extensively built upon, startups' focus on new technologies could result in their inventions indicating to other firms more opportunities for subsequent inventions. On the other hand, even if the typical established firm indeed faces challenges to draw on new technologies, those that diversify into a nascent industry are those that expect to be better able to do so, benefiting from relevant knowledge they have developed in other industries (Helfat & Lieberman, 2002; Wu et al., 2014). With this related knowledge, the inventions of established firms in a nascent industry could point to more opportunities for other firms. Moreover, unlike startups, which face higher uncertainty that can prevent other firms from paying attention to their inventions (Stuart et al., 1999), established firms are more likely to have their inventions followed and built upon by their rivals. Given ambiguity in these competing arguments, we take a question-driven approach (Graebner et al., 2023).

Our investigation focuses empirically on the context of terrestrial photovoltaic (PV) cell technologies between 1976 and 2016. Both established firms—diversifying from a variety of other industries—and entrepreneurial startups have played a critical role in building PV cell technologies. Using data on patent citations to capture the extent to which a focal patent served as a springboard for subsequent patents (e.g., Ahuja & Lampert, 2001; Jaffe et al., 1993), we examined the extent to which PV cell inventions of startups and established firms spur subsequent inventions created by other firms. We started our analysis by examining *whose* inventions, startups' or established firms', spur more subsequent inventions by other firms, and found that startups' PV cell patents received more forward citations. In light of research on the patterns of inventions that firms create (Levinthal, 1992; Malerba & Orsenigo, 1995), we probed whether this asymmetry persists after accounting for differences across patents. Using a matched sample pairing startups' patents with established firms' patents sharing similar levels in a variety of attributes that prior literature has associated with forward citations, we found that startups' patents had more citations by other firms.

We then abductively explored factors that might explain *why* startups' inventions spur higher levels of knowledge diffusion. We started with the conjecture that this asymmetry might result from knowledge transfer to partnering firms (Ahuja & Katila, 2001; Mowery et al., 1996), as startups might be more inclined to engage in alliances and acquisitions to tap into resources they lack (Moeen & Mitchell, 2020; Polidoro & Yang, 2021). We found no evidence that knowledge transfer related to alliances and acquisitions explains the higher citations of startups' patents. We then proceeded to explore factors that might result in startups being more susceptible to knowledge spillovers. We started with influences related to endorsements, as the higher level of uncertainty startups face might make them more vulnerable to endorsements, which despite their role in mitigating uncertainty (Higgins & Gulati, 2003; Stuart et al., 1999) also draw rivals' attention to firms' inventions (Polidoro, 2013; Polidoro & Theeke, 2012). Findings revealed that inventions of startups with a strong record of receiving citations from universities received more citations than patents of established firms with a similar record. We did not find evidence that scientific endorsements of a startup's PV cell produce a similar effect. We then examined differences related to preemption and deterrence, as these factors might be particularly relevant in a nascent industry, where many firms are yet to advance to commercialization and as such cannot count on their position in product markets to fend off rivals (Ethiraj & Zhu, 2008). Startups might be less able than established firms to engage in cumulative inventions to preempt rivals from capturing the technological opportunities spawn by their inventions (Ahuja et al., 2013) or to benefit from litigiousness to deter rivals from building on their inventions (Agarwal et al., 2009; Somaya, 2012). Results showed that citations to startups' patents are higher when a startup has a poor record in creating cumulative inventions. We also found that a startup's record of litigiousness does not deter but, instead, encourages forward citations. Further, we examined whether the asymmetry in knowledge diffusion we observed might be related to competitive effects shaping imitative inventions (Ethiraj & Zhu, 2008; Gallini, 1992), and found no evidence that the pattern identified in the prior analyses changes once sample firms launched PV cells into the market. Finally, we supplement our abductive analysis with inspection of differences between startups and established firms regarding *who* builds on their inventions.

In line with the question-based approach we follow, the goal of these analyses is not to provide evidence in support of a particular causal mechanism but rather to probe whether findings align with a variety of conjectures grounded in existing literature that can help elucidate our question. With that caveat in mind, we note that, in contrast with prior research on the patterns of inventions that startups and established firms create, this study shows that even when they create inventions with similar attributes, their inventions are associated with different levels of knowledge diffusion. Further, by examining mechanisms underpinning knowledge diffusion in a sample comprising both startups and established firms, in contrast with prior research largely focusing on either one firm type or the other, this study nuances understanding about known mechanisms by revealing that they play out differently across these firm types. We conclude the paper with a discussion of fruitful opportunities for future inquiry suggested by these findings.

2 | BACKGROUND: STARTUPS, ESTABLISHED FIRMS, AND KNOWLEDGE DIFFUSION

The diffusion of the knowledge underlying a firm's invention occurs because it can be a valuable input to subsequent inventive activities, potentially benefiting other firms beyond the one that created the invention (Arrow, 1962). Tracing back to Griliches's (1979) work showing that R&D spillovers are both prevalent and important, a large body of research has examined the importance of knowledge spillovers, showing that just as startups draw on the knowledge of established firms, established firms also learn from startups (Agarwal et al., 2007; Giustiziero et al., 2019). Although this effect is broadly referred to as knowledge spillovers, we denote it with the term knowledge diffusion in order to capture both *knowledge transfer*, that is, the flow of knowledge benefiting another firm that interacted with the inventing firm in market-based activities, and *knowledge spillovers*, that is, the flow of knowledge that benefits the recipient firm without providing compensation for the creating entity (Agarwal et al., 2010).

As mentioned earlier, the question-based approach we follow is predicated on the observation that prior research suggests conflicting expectations about whose inventions, startups' or established firms', spur more knowledge diffusion. These conflicting expectations have their roots in different perspectives on startups and established firms as drivers of inventions, which trace back to alternative views in Schumpeter's seminal work on this topic, sometimes emphasizing the role of startups in driving technological change and industry evolution (Schumpeter, 1934), at other times underscoring instead the impact that established firms have in that process (Schumpeter, 1942). Mirroring the former view, a large body of research portrays startups as important sources of inventions that build on new technologies (e.g., Abernathy & Utterback, 1978; Polidoro & Yang, 2021), in contrast to established firms, typically viewed as focused on existing technologies and facing challenges when trying to adapt to new technologies, which can ultimately result in their demise (Christensen & Bower, 1996; Henderson & Clark, 1990). Startups' sharper focus on new technologies implies that their inventions point to more untapped technological opportunities relative to established firms' inventions, which tend to build on known technologies whose opportunities have been already partly seized through cycles of incremental refinements. These insights appear to support the conjecture that startups' inventions can spur a greater number of subsequent inventions. Partly undermining this conjecture, though, is the inordinate uncertainty that third parties face about the activities of startups and their prospects of success (Higgins & Gulati, 2003; Stuart et al., 1999), which may discourage other firms from building on their inventions. Thus, even if the conjecture that startups' inventions spawn more opportunities is true, it does not necessarily imply that other firms recognize and seize those opportunities.

Turning to the alternative view in Schumpeter's work underscoring the impact that established firms have in driving technological change (Schumpeter, 1942), we note that there is extensive research showing their role in creating new technologies (e.g., Cohen & Tripsas, 2018; Roy et al., 2018; Wu et al., 2014). When a new technology emerges that has the potential to support the creation of a new industry, some firms that are established in other industries enter the nascent industry and conduct knowledge-building activities (Moeen, 2017; Moeen & Agarwal, 2017). Therefore, even if the typical established firm is maladaptive in the face of new technologies, those that diversify into a nascent industry represent a subset of established firms that expect to succeed in the emerging domain. Indeed, established firms that diversify and enter a nascent industry often have knowledge that is relevant to the nascent industry (Cattani, 2005; Helfat & Lieberman, 2002). Moreover, as the R&D of competitors provides a basis for firms to search for their own inventions (Ethiraj & Zhu, 2008; Gallini, 1992), established firms entering the nascent industry are likely followed by rivals across the industries in which they operate, which could also result in their inventions spurring more inventions by other firms. Partly undercutting this conjecture, though, is the observation that established firms, having more resources than startups, can capture more technological opportunities spawn by their inventions, thereby leaving fewer opportunities for other firms to capture (Ahuja et al., 2013; Alnuaimi & George, 2016).

In sum, insights in existing literature lead to ambiguous predictions about whether startups' or established firms' inventions contribute more to knowledge diffusion in a nascent industry. Thus, we follow a question-based approach, exploring this issue in the context of PV cells. We start by examining *whose* PV cell patents, startups' or established firms', receive more citations in subsequent patents of other firms. Our initial analysis shows that PV cell patents of startups received more forward citations. We then abductively explore, in different sets of analyses, factors suggested in prior literature that might help elucidate *why* startups' inventions are associated with higher levels of knowledge diffusion. Before presenting these analyses, in the next section we discuss key features of the PV cell industry and explain our data and methods.

3 | DATA AND METHODS

3.1 | Empirical setting

We examine the extent to which startups' and established firms' inventions spur subsequent inventions by other firms in the context of the terrestrial PV cell industry between 1976 and 2016. In line with the notion that the knowledge-building activities of firms in a nascent industry are critical to mitigating the uncertainty surrounding a new technology (Kapoor & Klueter, 2021; Moeen et al., 2020), firms in this setting have conducted extensive inventive activities under substantial uncertainty. The discovery of the PV effect, that is, conversion of sunlight into an electric current, opened the possibility for the production of electricity in a way that differs substantially from the conventional use of fossil fuels (Chase, 2019; Shere, 2013). Although the presentation of the first PV cell, by Bell Laboratories, occurred in 1954, it was only in the aftermath of the oil crises in the 1970s that the potential of this new technology in residential and commercial uses started being explored (Nemet, 2019). Decades later, the PV cell industry remains in emerging stage, with persisting uncertainty about its future technology landscape (Chase, 2019).

Another interesting feature of the PV cell industry is that it attracted both entrepreneurial startups and established firms diversifying from other industries (Furr & Kapoor, 2018; Guerra & Agarwal, 2022; Kapoor & Furr, 2015). The technical literature distinguishes four broad groups of PV cell technologies underlying the knowledge-building activities of these firms, namely crystalline silicon base cells, thin film cells, organic cells, and dye-sensitized cells (Chase, 2019; Wolfe, 2018). It also documents remarkable differences within the group of crystalline silicon-based cells and within the group of thin film cells. Thus, instead of aggregating PV cell technologies into four groups (Furr & Kapoor, 2018; Kapoor & Furr, 2015), our abductive analysis accounts for a more fine-grained distinction, based on the eight technologies described in Table 1.

3.2 | Data sources

Derwent World Patents Index (DWPI) provided data on successful patent applications at the US Patent and Trademark Office (USPTO) in the broad domain of solar energy.[1] We obtained additional data on these patents and their assignees from the databases of the USPTO available through Patentsview.[2] Data on patent infringement cases filed before US courts by sample firms were obtained from Thomson Westlaw. We gathered data on the performance of PV cells from the scientific journal *Progress in Photovoltaics: Research and Application*. The *World Directory of Renewable Energy Suppliers and Services* (1995–2002) and ENFsolar.com, an online directory for the solar energy industry, furnished data on when firms started commercializing specific types of PV cells. SDC Platinum was used to collect data on firms' acquisitions and alliances. As we explain later, we used VentureXpert, Crunchbase, and PitchBook, as well as press articles and firms' websites, to verify whether firms identified as assignees of PV cell patents were startups. VentureXpert also provided data on venture capital (VC) and corporate venture capital (CVC) investments made in the PV cell industry. Finally, Capital IQ was the source of data on the SIC codes recorded for sample established firms.

3.3 | Sample of PV cell patents

To build the sample of inventions in the global PV cell industry, we started by identifying all successful applications related to PV cell technologies submitted to the USPTO[3] between 1975

[1]We used the technological classes on DWPI, Electrical Patents Index—Part 3, under subject index "Solar cell".
[2]https://www.patentsview.org/download/.
[3]Prior studies (Almeida, 1996; Lahiri & Narayanan, 2013) have established that successful patent applications filed with the USPTO are representative of global inventive activities in settings in which the United States plays a major role.

TABLE 1 List of alternative PV cell technologies.

Broad group	PV cell technology	Description
Crystalline Silicon base cells	Monocrystalline Silicon	A Silicon ingot is grown from a single crystal. This ingot is sliced into Silicon wafers (octagons). This Silicon wafer is the semiconductor of the cell. To create an electrical field, the wafer is doped with impurities (e.g., boron and phosphorus).
	Multicrystalline Silicon	A Silicon block is formed by multiple crystals. This block is sliced into Silicon wafers (square). This Silicon wafer is the semiconductor of the cell. To create an electrical field, the wafer is doped with impurities (e.g., arsenic, boron, and phosphorus).
	Ribbon Silicon	The semiconductor, a Silicon wafer, is directly created and shaped by pulling crystals out of molten Silicon. To create an electrical field, the wafer is doped with impurities (e.g., arsenic, boron, and phosphorus).
Thin film cells	Amorphous Silicon	A layer of doped amorphous Silicon is deposited on a substrate (e.g., aluminum or glass).
	Copper Indium (Gallium) diSelenide	A layer of the semiconductor material Copper Indium (Gallium) diSelenide is deposited on a substrate (e.g., aluminum or glass). A thin n-type layer is deposited on top to obtain electrical current.
	Cadmium Telluride	A layer of the semiconducting material Cadmium Telluride is deposited on a substrate (e.g., aluminum or glass). A thin n-type layer is deposited on top to obtain electrical current.
Organic cells	Organic	Between two layers of electrodes, a layer of organic carbon-based compounds is printed onto a synthetic backing (e.g., plastics).
Dye-sensitized cells	Dye-sensitized	A thin layer of oxide semiconducting material (usually Titanium Dioxide) is deposited on glass together with a layer of p-type material. To increase light absorption, this film is soaked in a dye (photosensitizer) solution, which bonds with it.

Source: Chase (2019), Muller (2009), and Wolfe (2018).

and 2016. Although DWPI identifies patents related to solar energy, it does not distinguish between PV cell technologies. To identify the PV cell technology underlying a PV cell patent, we developed a list of keywords based on study of the industry literature, subsequently validated with PV cell researchers, and analyzed their incidence in the full text of the patents' title, abstract, and claims. To identify patents assigned to firms, we used data on assignee type in Patentsview, which distinguishes between patents issued to "organizations" and those issued to individuals and government institutions. By examining the names of patents' assignees we were able to separate those issued to universities and research institutes. From these PV cell technology patents assigned to firms, we only retained those of firms with at least three such patents to avoid the inclusion of firms with an incidental PV cell patent that arises due to luck and not as a result of inventive focus on that setting (McGrath & Nerkar, 2004, pp. 6–7), as well as to reduce the incidence of cases with little information to calculate lagged variables, as we discuss later. With this procedure, we identified 6116 PV cell patents, assigned to 356 distinct firms.[4]

3.3.1 | Identifying startups

To ascertain whether the assignee of a patent was a startup founded within the solar energy industry, we followed a two-step procedure. First, we checked whether the first successful patent application assigned to the firm was in the context of the PV cell industry. Second, we searched for additional evidence in VentureXpert, Crunchbase, and PitchBook that these firms were startups. This resulted in 57 firms identified as startups. Next, to account for the possibility that some startups may not have been included in those data sources, we searched for additional information on their websites and press articles, which resulted in evidence that additional 25 firms whose first invention was in the context of PV cells were also startups founded within this industry. Following this procedure, we identified a total of 82 PV cell startups.

3.3.2 | Identifying established firms as incumbents or diversifying entrants

We classified the remaining 274 firms, whose patent data indicated that they were already established in another industry before creating PV cell inventions, in two groups. Refining the broad characterization of these firms as diversifying entrants coming from other industries (Helfat & Lieberman, 2002), recent literature (Moeen & Agarwal, 2017) has proposed a distinction between two types of established firms—those that are incumbents in the industry at risk of obsolescence due to the emergence of the new industry (referred to as *incumbents*) and those that are incumbents in other industries and that, encouraged by the possession of related assets, diversify into the emerging industry (classified as *diversifying entrants*). As PV cell technologies provide the basis for alternative, renewable energy solutions that are expected to gradually substitute traditional fossil-fuel energy, we classified as incumbents those established firms that came from the oil and gas industry, and as diversifying entrants those that were previously established in other industries. Following tradition in prior research of using SIC to identify the industry in which a firm operates (Chen et al., 2012; Furr & Kapoor, 2018), we used Capital IQ to identify the SIC-code recorded for those firms prior to creating their PV cell technology patents. We identified 15 oil and gas firms[5] (i.e., *incumbents*) and 259 firms in other industries[6] (i.e., *diversifying entrants*).

3.4 | Dependent variable: Citations received

As knowledge flows leave a paper trail in patent documents, which contain citations to prior inventions that served as a springboard for a focal invention (e.g., Hall et al., 2001; Jaffe et al., 1993), prior research has largely relied on patent forward citations to observe the extent

[4]We note that Kapoor and Furr (2015) and Furr and Kapoor (2018) focus on *commercializing firms* in the global PV modules industry, not on *technology-investing* firms, and accordingly their samples have a different number of firms. Guerra and Agarwal (2022), in turn, focus on the US market, and include space PV cells and concentrators.

[5]Firms in SIC codes 2911 and 1311.

[6]Among these firms, the most frequent industries are semiconductors (51 firms) and chemicals (21 firms).

to which an invention spurs subsequent inventions (e.g., Ahuja & Lampert, 2001; Cattani, 2005). Accordingly, to measure the extent to which an invention spurs subsequent inventions by other firms, we use citations that a patent receives in subsequent patents of *other* firms, that is, excluding citations that a firm makes to its own prior patents. We counted the citations that a sample patent received in subsequent patents filed by other firms in a given year up to 9 years after its application.[7] As we discuss later, for greater ease of interpretation of results we enter the natural logarithm of *Citations received*, added by one, as our dependent variable.

3.5 | Independent variable: Startup

As discussed earlier, the sample includes patents of both startups and established firms. The dummy variable *Startup* identifies startups' patents—it is set to one if a patent was assigned to a startup founded within the PV cell industry and to zero if it was assigned to an established firm.

3.6 | Control variables

3.6.1 | Heterogeneity across firms

Startups and established firms may differ systematically in the level of capabilities they accumulate in the technology underlying a patent, which can also affect forward citations. As a firm's patents capture its technological capabilities (Griliches, 1990), we account for this potential influence with the variable *Patents in focal technology* with the count of successful patent applications that the firm had in the same PV cell technology of the focal patent by the previous year. Another possibility is that a firm's record of building upon its own prior inventions may interfere with the extent to which other firms will build on the focal patent (Hoetker & Agarwal, 2007). Models account for this conjecture by adding the variable *Self-citations in prior patents* with the average percentage of backward citations to its own patents in the focal firm's successful PV cell patent applications in the previous 5 years. To account for differences across firms in the scope of the inventions they create (Cohen & Levinthal, 1990), models include the variable *Technological scope of prior patents* which takes the average across the firm's PV cell patents in the prior 5 years of one minus the Herfindahl index of the four-digit technology classes assigned to the patent[8] (Moreira et al., 2020). Also, variation across firms in the maturity of the technologies underlying their inventions can shape the citations to the focal patent (Lanjouw & Schankerman, 2003). Models control for this potential influence with the variable *Technology maturity of prior patents* as the average ratio between the number of backward citations and the number of claims in a focal firm's prior PV cell patents in the prior 5 years (Hoetker & Agarwal, 2007). Firms can also vary in the diversity of technological domains they search when creating inventions, which can affect the number of technological opportunities

[7]Hall et al. (2005) demonstrated that the prime citation years for patents is between 3 and 5 years after grant. Hence, by observing citations received up to 9 years after application we include a sufficient number of years for the citation patterns to be informative. The analysis does not include the year of a patent's application as citations in that year might be sensitive to the specific application date within that year.

[8]The technological scope of a patent is measured as: $1-\sum_{j}^{n_i} {s_{ij}}^2$, where s_{ij} denotes the proportion of class i in patent j, out of n_i technological classes assigned to the patent.

they spawn (Polidoro & Yang, 2021). The analysis controls for this potential influence with the variable *Prior patents' originality* with the average patent originality score across a firm's patents. This score takes the value of one minus the Herfindahl index of the four-digit technology classes present in the patent's backward citations[9] (Hall et al., 2001). Further, to account for the effect of a firm's degree of collaboration across its inventors on knowledge diffusion (Polidoro et al., 2022), models add the variable *Intrafirm collaboration in prior patents*, with the average number of unique co-inventors each inventor in the focal firm had by the previous year. Finally, startups can systematically conduct inventive activities in areas that have a greater number of other firms, and being in such areas potentially exposes their knowledge to geographically proximate firms (Jaffe et al., 1993). The analysis accounts for this potential influence by adding the variable *Firms in geographic location* capturing the total number of firms with inventions in PV cell technologies in the same locations in which the focal firm has inventive activities. We add this variable in its logarithmic form to account for skewness.

3.6.2 | Heterogeneity across patents

The addition to models of the variable *Number of claims* controls for the potential effect of the boundaries of property rights provided by a patent on forward citations (Lanjouw & Schankerman, 2001). Also, as a patent that relies more heavily on prior inventions of the firm may negatively affect other firms' tendencies to build on it (Hoetker & Agarwal, 2007), models add the variable *Self-citations* with the number of citations that the patent makes to the firm's prior patents. Because the scope of a patent can indicate the scope of technological opportunities it offers for subsequent inventions (Lerner, 1994), models enter the variable *Technological scope*, measured as one minus the Herfindahl index of the four-digit technology classes assigned to the patent. Models include the variable *Backward citations*, with the number of patents it cites as prior art, to account for its effect on other firms' propensities to build on the focal patent (Lanjouw & Schankerman, 2001). The scope of the search of a focal patent, as reflected in the technological classes of that patent's backward citations, can also affect the technological opportunities spawn by that patent (Fleming & Sorenson, 2001), an influence that the variable *Technological scope of backward citations* accounts for. Further, models add the variable *Technology maturity*, measured as the number of citations made by a patent divided by its number of claims, which has been shown to affect a patent's forward citations (Hoetker & Agarwal, 2007). Additionally, as we discussed earlier, variation across patents in the diversity of knowledge upon which the invention builds, as reflected in a patent's originality score (Hall et al., 2001), can systematically relate to the number of subsequent inventions they spawn (Polidoro & Yang, 2021). The analysis accounts for this potential influence by adding the variable *Patent originality* described above. Also, as collaborative inventions can be associated with knowledge exploration (Toh & Polidoro, 2013), which in turn can result in more technological opportunities for subsequent inventions, models control for the *Number of inventors* in the focal patent. To address the possibility that an invention that relies more extensively on science (Ahuja & Katila, 2004) might spur more subsequent inventions, models include the variable *Nonpatent citations*, with the count of scientific articles and books that the focal patent cites (Narin et al., 1997). The analysis also accounts for temporal heterogeneity with the addition of year

[9]The patent originality score of a patent is measured as: $1-\sum_{j}^{n_i} t_{ij}^2$, where t_{ij} denotes the proportion of citations made by patent j that belong to class i, out of n_i technological classes assigned to these backward citations.

dummies, as well as heterogeneities across the PV cell technologies with the addition of dummies capturing the technology underlying the focal patent. Finally, as we explain below, in the longitudinal analysis we also account for additional heterogeneity across sample patents with patent-level random effects.

Table 2 reports summary statistics and correlations for the variables above. Inspection of VIF indicated average scores below 3.44, allaying concerns about multicollinearity (Greene, 2012).

3.7 | Methodology

To examine whose inventions, startups' or established firms', spur more subsequent inventions of other firms, we start with a cross-sectional analysis estimating the total of citations that sample PV cell patents received during the first 9 years since application. We then proceed with a longitudinal analysis estimating influences on the citations that each sample patent received in each of the first 9 years after its application. Models in the longitudinal analysis add lagged time-varying firm-level control variables and also account for the time-invariant attributes of patents described earlier. Following this initial set of analysis, we abductively explore additional factors suggested in prior literature that might help us refine understanding of the association we find in this initial analysis. As we explain later, these additional analyses add a variety of variables and their respective interactions with *Startup*. In line with prior literature (Giustiziero et al., 2019; Moreira et al., 2020), for greater ease of interpretation of the results, we used ordinary least square (OLS) regressions for our estimation of influences on the dependent variable.

4 | KNOWLEDGE-BUILDING ACTIVITIES IN PV CELL TECHNOLOGIES

Figure 1a displays the cumulative number of startups' and established firms' PV cell patents. The sample contains 773 patents created by 82 startups and 5343 patents created by 274 established firms, including 15 *incumbents*, that is, firms that were in the oil and gas industry before creating inventions in this setting, and 259 *diversifying entrants*, that is, firms that were previously incumbents in other industries, such as chemicals and semiconductors. These 15 *incumbents* created a total of 287 patents, which is about 4.7% of sample patents. Given the limited empirical traction in this relatively small set of firms, our analysis contrasts startups' patents with those of established firms, which include both incumbents and diversifying entrants.

Table 3 shows that both startups and established firms were active in all PV cell technologies. Startups accounted for 12.6% of all PV cell patents, ranging from 4.8% of organic cell patents and 27.2% of cadmium telluride thin-film cell patents. There is also technological diversity within firms, as several of them built on more than one technology to create PV cell inventions. Specifically, on average, startups (established firms) built on two (three) distinct PV cell technologies.

Table 3 also shows the year in which we observe the first patent building on each PV cell technology and the average year in which firms achieved commercialization of their respective PV cells in that technology. It reveals substantial differences across technologies regarding when they advance to commercialization. For example, although the commercialization of

TABLE 2 Descriptive statistics (N = 36,481).

	All firms		Startups	Established firms	Difference in means																	
Observations	**36,481**		**4954**	**31,527**																		
Unique firms	**356**		**82**	**274**																		
Variables	**Mean**	**SD**	**Mean**	**Mean**	***t-Stat***	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1. Citations received	0.19	0.44	0.26	0.17	11.28																	
2. Startup	0.14	0.34	1	0		.07																
Firm-level control variables																						
3. Patents in focal technology	24.64	41.14	11.92	26.64	−46.96	−.07	−.12															
4. Self-citations in prior patents	0.13	0.13	0.09	0.13	24.03	.09	−.12	.21														
5. Technological scope of prior patents	0.18	0.17	0.10	0.19	−43.52	−.19	−.17	.33	−.04													
6. Technology maturity of prior patents	0.94	1.11	1.43	0.86	23.32	.02	.18	−.11	−.00	−.15												
7. Prior patents' originality	0.47	0.19	0.41	0.48	25.83	−.11	−.13	.13	−.16	.57	.05											
8. Intrafirm collaboration in prior patents	4.69	2.26	4.41	4.74	−9.90	−.07	−.05	.50	.20	.23	−.00	.07										
9. Firms in geographic location	1.54	1.13	1.26	1.58	−18.05	−.13	−.10	.30	.02	.24	.10	.13	.40									
Patent-level control variables																						
10. Number of claims	17.23	13.09	22.61	16.38	26.30	.12	.16	.03	.08	−.08	.03	−.04	.05	−.06								
11. Self-citations	0.12	0.24	0.08	0.13	−15.42	.02	−.07	.11	.47	−.02	−.00	−.07	.11	.01	.05							
12. Technological scope	0.16	0.26	0.10	0.18	−23.07	−.16	−.10	.23	−.03	.59	−.09	.35	.16	.15	−.05	.02						
13. Backward citations	11.83	24.63	20.41	10.48	25.40	.01	.14	−.07	−.03	−.07	.53	.10	−.02	.05	.15	−.01	−.03					

TABLE 2 (Continued)

	All firms		Startups	Established firms	Difference in means																	
Observations	**36,481**		**4954**	**31,527**																		
Unique firms	**356**		**82**	**274**																		
Variables	**Mean**	**SD**	**Mean**	**Mean**	***t-Stat***	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
14. Technological scope of backward citations	1.57	1.09	1.27	1.61	−31.12	−.15	−.11	.26	−.03	.57	−.10	.32	.17	.16	−.04	.01	.89	−.04				
15. Technology maturity	0.94	2.25	1.43	0.86	11.81	−.01	.09	−.05	−.01	−.06	.46	.03	.00	.05	−.15	−.00	−.03	.63	−.04			
16. Patent originality	0.47	0.34	0.41	0.48	−15.48	−.07	−.07	.08	−.09	.32	.03	.52	.04	.08	−.03	−.14	.27	.10	.24	.07		
17. Number of inventors	3.31	2.04	3.03	3.35	−10.99	−.03	−.05	.16	−.02	.18	−.05	.12	.41	.20	.04	−.00	.16	−.02	.17	−.03	.08	
18. Nonpatent citations	8.80	21.94	16.18	7.64	21.68	−.02	.13	−.03	−.05	.03	.32	.14	.04	.05	.12	−.04	.04	.53	.04	.36	.13	.05

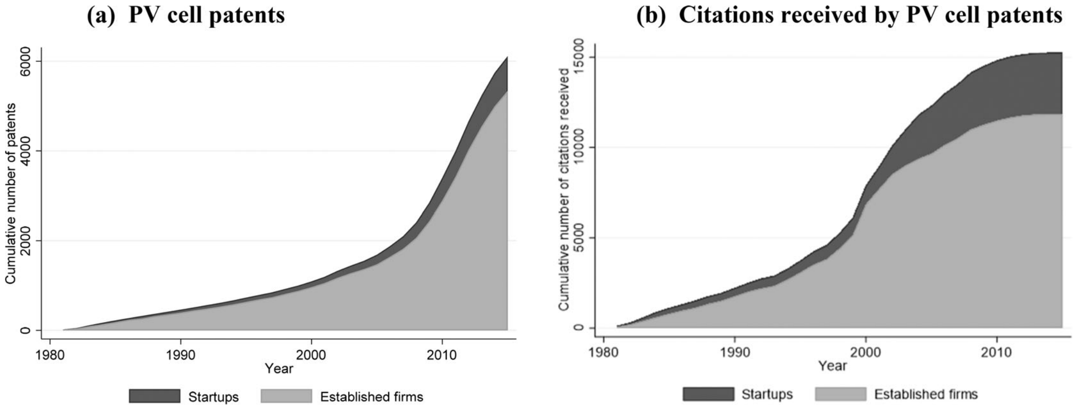

FIGURE 1 (a) Photovoltaic (PV) cell patents. (b). Citations received by PV cell patents.

monocrystalline silicon cells precedes the analysis period, many sample firms advanced to commercialization a lot later; specifically, among those firms that eventually advanced to commercialization, the average year in which they did so was 2007. By contrast, we observed the first patent building on dye-sensitized PV cell technology in 1998, and that technology achieved commercialization more than a decade later. Figure 2 shows the number of patents during the analysis period created by firms that were not commercializing PV cells in the respective technology and by firms that were already in commercialization stage. Inventions created by firms pre-commercialization account for 73% of all patents, and firms continued to exhibit robust inventive activities post-commercialization.

5 | WHOSE INVENTIONS SPUR MORE SUBSEQUENT INVENTIONS BY OTHER FIRMS?

5.1 | Inspection of descriptive statistics

We start by examining preliminary evidence in descriptive statistics about the forward citations from other firms that startups' and established firms' patents receive. Visual inspection of Figure 1a with the number of sample patents created by startups and established firms, and Figure 1b with the number of citations received by those patents, reveals that startups account for a larger share of citations than of patents. While startups account for 12.6% of the sample patents (i.e., 773 out of 6116 patents), their patents account for 22.3% of the citations received by all sample patents (i.e., 3403 out of 15,259 citations), which indicates that they are relatively more cited in subsequent inventions of other firms. Descriptive statistics in Table 2 show that observations related to startups have higher levels of *Citations received* than those related to established firms (t-statistics = 11.28). Using the *binsreg* command in STATA 17 (Starr & Goldfarb, 2020), Figure 3 shows the binned scatterplot of the *Citations received* by sample patents in each year since patent application, controlling for application year and PV cell technology fixed effects. It indicates that over time startups' patents receive more citations than established firms' even after accounting for differences across patent cohorts and across PV cell technologies.

TABLE 3 PV cell technologies: Patents and average across firms of year of first commercialization.

PV cell technology	Sample patents	Percentage of total sample patents	Proportion of patents in each PV cell technology by: Startups	Established firms	First patent	First year of commercialization (average across commercializing firms[b])
Monocrystalline Silicon	255	4.2	16.5	83.5	Before 1976[a]	2007
Multicrystalline Silicon	287	4.7	13.6	86.4	1981	1994
Ribbon Silicon	76	1.2	23.7	76.3	1982	2001
Amorphous Silicon	1243	20.3	14.4	85.6	1979	1993
Copper Indium (Gallium) diSelenide	1034	16.9	19.1	80.9	1981	2001
Cadmium Telluride	599	9.8	27.2	72.8	1977	2002
Organic	2172	35.5	4.8	95.2	1981	2003
Dye-sensitized	450	7.4	6.4	93.6	1998	2011
Total	6116	100.0	12.6	87.4		

[a]The first "official" PV cell patent was applied for in 1954 by Bell Laboratories (US2,780,765).
[b]These averages reflect sample firms that entered the corresponding PV cell technology by 2016, corresponding to 16.9% of all firms. This proportion is comparable to the 14.5% of investing firms in agricultural biotech that commercialized a product (Moeen & Agarwal, 2017).

5.2 | Cross-sectional analysis of influences on *Citations Received*

Table 4 reports the results of a cross-sectional analysis estimating influences on *Citations received* during patents' first 9 years. Model 1 enters the variable *Startup*. Model 2 enters firm-level control variables and model 3 adds both *Startup* and firm-level controls. Model 4 enters patent-level control variables, and model 5 adds *Startup* to the variables in model 4. Model 6 is the full model. Findings show a positive association between *Citations received* and *Startup*. The coefficient on *Startup* is positive in model 1 ($\beta = .254$; $p = .000$) and remains positive after addition of firm-level controls ($\beta = .235$; $p = .002$ in model 3) and patent-level controls ($\beta = .211$; $p = .001$ in model 5), as well as in the full model ($\beta = .208$; $p = .003$ in model 6). Results in model 6 reveal that a startup's patent receives 21% more citations in subsequent patents of other firms during its first 9 years since application than an established firm's patent.

5.3 | Longitudinal analysis of influences on *Citations Received*

Table 5 presents the results of patent-level random-effect OLS estimates of influences on *Citations received* by patents in each of their first 9 years. The coefficient on *Startup* remains positive after inclusion of time-varying firm-level covariates ($\beta = .097$; $p = .000$ in model 3) and time-invariant patent-level covariates ($\beta = .078$; $p = .001$ in model 5). Model 6, the full model, reveals a positive association between *Citations received* and *Startup*, indicating that a patent created by a startup receives 8.5% more citations in a given year than a patent created by an established firm.

We ran an additional analysis decomposing the overall effect for *Startup* into yearly effects. Table 6 shows positive coefficients on *Startup* in every year since application and reveals that

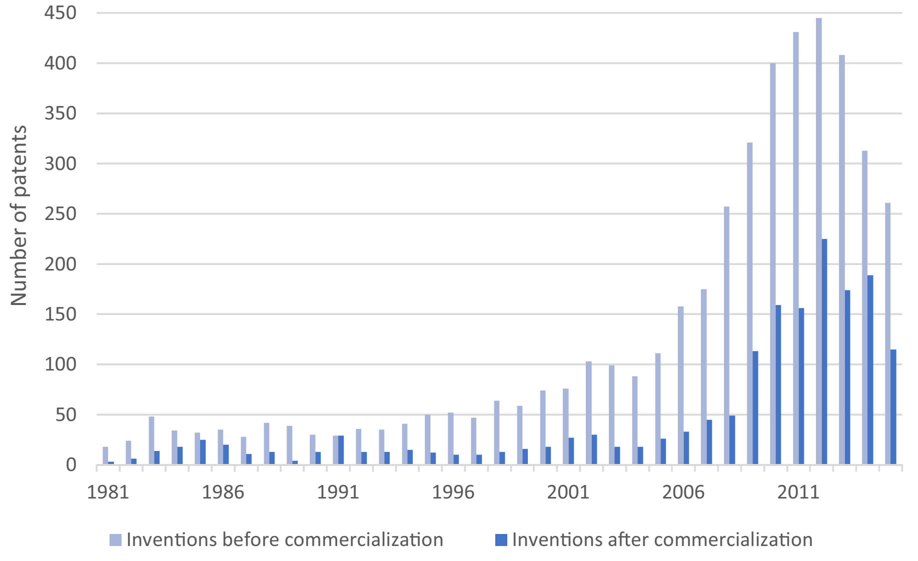

FIGURE 2 Patenting before and after firms started commercializing PV cells.

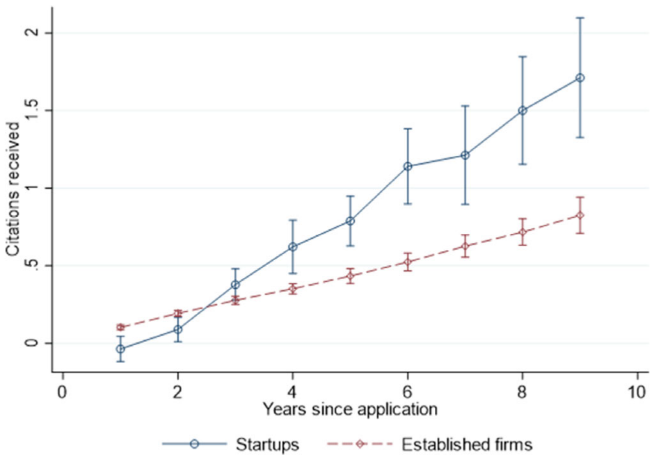

FIGURE 3 Binned scatterplot of citations received by startups and established firms, accounting for application year and technology type fixed effects.

the coefficient becomes more noticeable after the third year, with a tendency to increase after that (from $\beta = .075$; $p = .002$ in year three to $\beta = .185$; $p = .001$ in year nine).

5.4 | Accounting for differences in inventions that startups and established firms create

As discussed earlier, the parametric technique in the analyses above adds patent-level controls to account for the possibility that the higher level of citations associated with startups' patents that the analysis above revealed might result from differences between patents of startups and those of established firms. However, adding controls when there are systematic differences

TABLE 4 Cross-sectional analysis of influences on *Citations Received* ($N = 6116$).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Startup	0.254 (0.069)		0.235 (0.075)		0.211 (0.065)	0.208 (0.069)
Firm-level controls						
Patents in focal technology		−0.000 (0.000)	−0.000 (0.000)			−0.000 (0.000)
Self-citations in prior patents		−0.014 (0.111)	0.078 (0.102)			0.101 (0.115)
Technological scope of prior patents		−0.328 (0.080)	−0.303 (0.081)			−0.107 (0.087)
Technology maturity of prior patents		0.030 (0.011)	0.019 (0.013)			0.010 (0.014)
Prior patents' originality		0.144 (0.077)	0.197 (0.080)			0.164 (0.082)
Intrafirm collaboration in prior patents		0.002 (0.008)	0.000 (0.007)			−0.006 (0.007)
Firms in geographic location		−0.036 (0.012)	−0.028 (0.012)			−0.025 (0.012)
Patent-level controls						
Number of claims				0.006 (0.002)	0.005 (0.001)	0.005 (0.001)
Self-citations				−0.028 (0.036)	−0.008 (0.033)	−0.021 (0.033)
Technological scope				−0.253 (0.063)	−0.252 (0.062)	−0.246 (0.060)
Backward citations				0.002 (0.001)	0.002 (0.001)	0.001 (0.001)
Technological scope of backward citations				0.011 (0.011)	0.015 (0.011)	0.018 (0.011)
Technology maturity				0.001 (0.005)	−0.001 (0.005)	−0.002 (0.005)
Patent originality				0.023 (0.025)	0.035 (0.025)	−0.003 (0.023)
Number of inventors				0.005 (0.005)	0.005 (0.005)	0.010 (0.006)
Nonpatent citations				0.000 (0.001)	0.000 (0.001)	−0.000 (0.001)
Other controls						
PV cell technology dummies	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Constant	1.358 (0.225)	1.368 (0.226)	1.287 (0.216)	1.321 (0.218)	1.280 (0.212)	1.214 (0.208)
Number of patents	6116	6116	6116	6116	6116	6116
R-squared	.499	.497	.503	.502	.507	.509

Note: Robust standard errors, clustered at the firm level, in parentheses.

TABLE 5 Patent-level random effects OLS estimates of influences on *Citations Received* ($N = 36{,}481$).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Startup	0.094 (0.026)		0.097 (0.026)		0.078 (0.024)	0.085 (0.024)
Firm-level controls						
Patents in focal technology		−0.000 (0.000)	−0.000 (0.000)			−0.000 (0.000)
Self-citations in prior patents		0.026 (0.056)	0.050 (0.051)			0.066 (0.056)
Technological scope of prior patents		0.030 (0.033)	0.045 (0.035)			0.097 (0.038)
Technology maturity of prior patents		0.018 (0.006)	0.014 (0.005)			0.014 (0.006)
Prior patents' originality		0.028 (0.029)	0.046 (0.031)			0.043 (0.033)
Intrafirm collaboration in prior patents		0.001 (0.003)	−0.000 (0.002)			−0.002 (0.002)
Firms in geographic location		0.010 (0.007)	0.014 (0.007)			0.014 (0.007)
Patent-level controls						
Number of claims				0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
Self-citations				−0.022 (0.015)	−0.015 (0.013)	−0.031 (0.013)
Technological scope				−0.083 (0.022)	−0.084 (0.021)	−0.104 (0.022)
Backward citations				0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Technological scope of backward citations				0.005 (0.004)	0.007 (0.004)	0.006 (0.004)
Technology maturity				0.001 (0.002)	0.000 (0.002)	−0.001 (0.002)
Patent originality				0.004 (0.009)	0.009 (0.009)	−0.004 (0.010)
Number of inventors				0.003 (0.002)	0.003 (0.002)	0.003 (0.002)
Nonpatent citations				0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Other controls						
PV cell technology dummies	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Constant	0.313 (0.073)	0.299 (0.075)	0.271 (0.072)	0.301 (0.069)	0.285 (0.067)	0.249 (0.067)
Number of patents	6116	6116	6116	6116	6116	6116
X^2	2180	1696	2173	1947	2282	2622

Note: Robust standard errors, clustered at the firm level, in parentheses.

TABLE 6 Patent random-effects OLS estimates of yearly influences on *Citations Received* ($N = 36{,}481$).

Variables	Model 1
Startup × 1 year since application	0.020 (0.016)
Startup × 2 years since application	0.028 (0.019)
Startup × 3 years since application	0.075 (0.024)
Startup × 4 years since application	0.081 (0.030)
Startup × 5 years since application	0.088 (0.033)
Startup × 6 years since application	0.132 (0.044)
Startup × 7 years since application	0.088 (0.064)
Startup × 8 years since application	0.161 (0.063)
Startup × 9 years since application	0.185 (0.054)
Other controls[a]	
PV cell technology dummies	YES
Year dummies	YES
Constant	0.312 (0.069)
Number of patents	6116
X^2	3103

Note: Robust standard errors, clustered at the firm level, in parentheses.
[a]Abridged version shown above. Models contain firm-level and patent-level covariates for all other variables in Model 6 in Table 5.

across groups of observations in the levels they exhibit in these variables can still result in biased estimates and a non-parametric technique matching observations on observed attributes is warranted (Rose & Van der Laan, 2009). The *t*-statistics in Table 2 show that startups' patents and established firms' patents have different mean values in all those attributes. Therefore, we further probed this concern by using a matched sample. We note that the matching approach does not imply keeping a pair of patents the same with the only difference being that one was created by a startup and the other by an established firm. Such a goal is elusive, as two successful patent applications cannot be identical, or one of them would not meet the statutory requirement of novelty in the light of the other.[10] Using coarsened exact matching (Blackwell et al., 2009), we identified for each startup patent an established firm patent that has the same application year, that builds on the same underlying PV cell technology, and that has similar levels of the patent-level attributes expected to shape forward citations, as discussed in Section 3.6.2. This procedure resulted in matches for 295 out of the 773 patents of startups in the full sample.

As Table 7 reveals, the matching procedure resulted in startups' and established firms' patents with similar levels in attributes expected to shape forward citations. Using this matched sample, we ran a longitudinal analysis of influences on *Citations received*. Table 8 presents summary statistics and correlations for the variables used in this analysis. Average VIF scores were below 3.47, allaying concerns about multicollinearity (Greene, 2012).

[10]Prior research has also noted this point in relation to scientific publication data used to map "idea twins," as "two scientific discoveries are never exactly the same" (Bikard, 2020, p. 1535).

TABLE 7 Patents attributes in matched sample.

	Matched sample[a]		
	Startups	**Established firms**	***t*-Statistic**
Number of claims	18.97	17.80	−1.44
Self-citations	0.08	0.09	0.44
Technological scope	0.08	0.07	−0.40
Backward citations	11.94	10.80	−0.71
Technological scope of backward citations	1.20	1.19	−0.33
Technology maturity	0.76	0.68	−0.73
Patent originality	0.37	0.40	1.21
Number of inventors	2.85	2.88	0.24
Nonpatent citations	8.52	9.05	0.38
Observations	295	295	

[a]Each pair of matched patents shares the same PV cell technology and application year.

Models in Table 9 have a similar structure to those in Tables 4 and 5. The coefficient on *Startup* is positive in all models ($\beta = .059$, $p = .027$ in the full model 3), indicating that even after accounting, via matched sample, for differences between startups' and established firms' patents, there is a positive association between *Startup* and *Citations received*. Model 3 shows that a startup's patent receives in a given year 6% more citations in patents of other firms than an established firm's patent with similar levels in attributes expected to shape forward citations.

6 | MECHANISM ANALYSIS: WHY DO STARTUPS' INVENTIONS SPUR MORE SUBSEQUENT INVENTIONS BY OTHER FIRMS?

As findings in the analyses above show that startups' inventions spur more subsequent inventions by other firms than established firms' inventions with similar levels on attributes expected to shape that outcome, we abductively explored (King et al., 2021) factors that might explain *why* startups' inventions are associated with higher levels of knowledge diffusion. When doing so, we examined factors related to both knowledge transfer and knowledge spillovers (Agarwal et al., 2010). We also explored the conjecture that the asymmetry in knowledge diffusion we observed might stem from competitive dynamics in product markets, as sample firms advance to commercialization (e.g., Ethiraj & Zhu, 2008; Gallini, 1992). To ensure the influence stemming from these additional factors are not confounded with differences between patents of startups and those of established firms, we used the matched sample detailed above. Analysis using instead the full sample and accounting for sources of variation across patents through the addition of control variables produced results similar to those reported below; thereby, allaying concerns that findings might somehow be driven by the discarding of observations inherent in the matching procedure.

TABLE 8 Matched sample accounting for differences across inventions: Descriptive statistics ($N = 3580$).

	Variables	All firms ($N = 3580$)		Startups ($N = 1790$)	Established firms ($N = 1790$)	Difference								
		Mean	SD	Mean	Mean	*t-Statistic*	1	2	3	4	5	6	7	8
1.	Citations received	0.19	0.43	0.21	0.16	3.40								
2.	Startup	0.50	0.50	1	0		.06							
Firm-level control variables														
3.	Patents in focal technology	13.58	20.19	12.26	14.91	−3.92	−.03	−.07						
4.	Self-citations in prior patents	0.10	0.12	0.09	0.11	−5.78	.14	−.10	.16					
5.	Technological scope of prior patents	0.41	0.17	0.38	0.44	−9.40	−.10	−.18	.11	.02				
6.	Technology maturity of prior patents	1.07	1.25	1.13	1.01	2.91	−.03	.05	.02	−.03	−.03			
7.	Prior patents' originality	0.41	0.17	0.38	0.44	−9.40	−.04	−.16	−.01	−.10	.48	.16		
8.	Intrafirm collaboration in prior patents	4.22	1.96	4.27	4.16	1.65	−.06	.03	.41	.11	.17	.13	.01	
9.	Firms in geographic location	1.37	1.12	1.25	1.49	−6.60	−.11	−.11	.20	−.17	.11	.29	.14	.35

TABLE 9 Accounting for differences across inventions through matched sample: Patent random-effects OLS estimates of influences on *Citations Received* ($N = 3580$).

(N = 3580)			
Variables	**Model 1**	**Model 2**	**Model 3**
Startup	0.046 (0.029)		0.059 (0.027)
Firm-level control variables			
Patents in focal technology		−0.000 (0.001)	−0.000 (0.001)
Self-citations in prior patents		0.339 (0.149)	0.366 (0.135)
Technological scope of prior patents		−0.058 (0.077)	−0.026 (0.080)
Technology maturity of prior patents		0.011 (0.013)	0.009 (0.012)
Prior patents' originality		0.062 (0.066)	0.084 (0.065)
Intrafirm collaboration in prior patents		−0.001 (0.007)	−0.003 (0.006)
Firms in geographic location		0.003 (0.014)	0.008 (0.014)
Other controls			
PV cell technology dummies	YES	YES	YES
Year dummies	YES	YES	YES
Constant	0.269 (0.319)	0.265 (0.346)	0.233 (0.331)
Number of patents	590	590	590
X^2	1309	1335	1788

Note: Robust standard errors, clustered at the firm level, in parentheses.

6.1 | Knowledge transfer through acquisitions and alliances

Recent literature has shown that firms conducting knowledge-building activities in a nascent industry exhibit differences in the extent to which they engage with markets for technology and corporate control (Moeen & Agarwal, 2017; Moeen & Mitchell, 2020). This insight, coupled with research showing that acquisitions and alliances facilitate the transfer of a firm's knowledge to acquiring firms and partners (Ahuja & Lampert, 2001; Mowery et al., 1996), suggests that the higher level of citations to startups' patents we found might stem from such knowledge transfer. Although there is extensive research on this topic, from the perspective of both startups (e.g., Dushnitsky & Shaver, 2009; Polidoro & Yang, 2021) and established firms (e.g., Ahuja, 2000; Singh & Montgomery, 1987), prior research has not directly contrasted these firm types in terms of knowledge transfer through alliances and acquisitions. As existing literature does not offer sufficient evidence to support an a priori expectation, we abductively explore the influence of sample firms' alliances and acquisitions on citations that their patents receive from other firms.

Starting with acquisitions, we note that out of the 356 firms in the sample, only 8 established firms and 11 startups were the target of an acquisition during the analysis period. Combined, these 19 firms had 180 patents that were filed up to 9 years prior to the acquisition and hence could account for forward citations in the analysis. Only nine out of these 180 patents were cited by the respective acquiring firm, with a total of 25 citations. Among firms in the matched sample, we observed 14 firms—3 established firms and 11 startups—that were acquisition targets, and that only one of all patents of these 14 firms received one citation by the acquiring

TABLE 10 Analysis of knowledge transfer through acquisitions and alliances: Patent random-effects OLS estimates of influences on *Citations Received*.

Variables	Model 1[a]	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Startup	0.060 (0.030)	0.064 (0.026)	0.061 (0.026)	0.062 (0.028)	0.067 (0.027)	0.057 (0.027)	0.059 (0.026)
Firm-level controls							
Patents in focal technology	−0.000 (0.001)	−0.000 (0.001)	−0.000 (0.001)	−0.000 (0.001)	−0.000 (0.001)	−0.000 (0.001)	−0.000 (0.001)
Self-citations in prior patents	0.333 (0.152)	0.373 (0.134)	0.353 (0.127)	0.371 (0.132)	0.353 (0.127)	0.347 (0.123)	0.360 (0.127)
Technological scope of prior patents	−0.030 (0.096)	−0.018 (0.080)	−0.006 (0.079)	−0.016 (0.080)	0.003 (0.080)	0.001 (0.080)	−0.009 (0.079)
Technology maturity of prior patents	0.015 (0.016)	0.009 (0.012)	0.011 (0.012)	0.009 (0.012)	0.013 (0.011)	0.011 (0.012)	0.011 (0.012)
Prior patents' originality	0.075 (0.076)	0.079 (0.064)	0.065 (0.065)	0.079 (0.065)	0.063 (0.065)	0.067 (0.065)	0.068 (0.065)
Intrafirm collaboration in prior patents	−0.003 (0.008)	−0.002 (0.006)	−0.001 (0.006)	−0.002 (0.006)	−0.001 (0.006)	−0.001 (0.006)	−0.001 (0.006)
Firms in geographic location	0.013 (0.016)	0.008 (0.014)	0.007 (0.014)	0.008 (0.014)	0.005 (0.014)	0.007 (0.014)	0.007 (0.014)
Alliances							
Alliances		−0.011 (0.010)		−0.014 (0.012)			
Upstream alliances			−0.113 (0.038)		−0.052 (0.030)	−0.113 (0.038)	−0.113 (0.038)
Downstream alliances			0.001 (0.012)		0.000 (0.012)	−0.009 (0.012)	0.001 (0.012)
CVC partnerships		−0.013 (0.020)	−0.015 (0.019)	−0.013 (0.020)	−0.016 (0.019)	−0.015 (0.019)	−0.074 (0.052)
Startup × alliances				0.006 (0.015)			
Startup × upstream alliances					−0.119 (0.062)		
Startup × downstream alliances						0.015 (0.019)	
Startup × CVC partnerships							0.065 (0.058)
Other controls							
PV cell technology dummies	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES
Constant	0.233 (0.333)	0.231 (0.329)	0.236 (0.331)	0.231 (0.330)	0.229 (0.328)	0.236 (0.332)	0.237 (0.332)
Observations	2782	3580	3580	3580	3580	3580	3580
Number of patents	474	590	590	590	590	590	590
X^2	2318	1850	2041	1880	2080	2134	2087

Note: Robust standard errors, clustered at the firm level, in parentheses.

[a]Model 1 drops the patents of 14 firms that were the target of an acquisitions and their corresponding matching patents.

firm. Although there is little evidence that the pattern in our analysis was driven by knowledge transfer to acquiring firms, we probed the conjecture that acquisitions might affect the diffusion of knowledge to other firms. As model 1 in Table 10 reports, dropping the patents of the 14 firms that were acquisition targets and their corresponding matching patents show that the coefficient of *Startup* remains positive ($\beta = .060$, $p = .047$), assuaging the concern that this positive association with the dependent variable was driven by observations related to acquired firms.

Turning to alliances, we note that 13 out of 82 (i.e., 15.9%) startups and 51 out of 274 (i.e., 18.6%) established firms formed at least one alliance during the analysis period, which indicates that startups did not have a higher proclivity than established firms toward engaging in interfirm collaboration. Further, we identified that only 100 out of the total 15,259 (i.e., 0.7%) citations to sample patents constituted citations by a partner. Although the level of knowledge transfer to partners was very modest, we also examined the conjecture that alliances might affect the extent to which other firms, beyond alliance partners, build on an invention. Using the matched sample analysis as a baseline, we entered to models variables capturing the number of alliances that the focal firm formed in the prior 5 years, as well as variables capturing the breakdown of this total count in upstream alliances (i.e., alliances about R&D activities and technology licensing) and downstream alliances[11] (i.e., alliances focusing on electric utility services, manufacturing services, and retail). Given that firms also form CVC partnerships (Alvarez-Garrido & Dushnitsky, 2016; Polidoro & Yang, 2021), we added a variable with a firm's CVC partnerships in the prior 5 years.[12] To examine whether these collaborative deals can partly explain the higher citations that startups' patents receive, model 2 in Table 10 enters variables *Alliances* and *CVC partnerships*. Results show that the coefficient on *Startup* remains positive ($\beta = .064$, $p = .015$). Model 3, with separate variables for upstream and downstream alliances, shows a negative coefficient on *Upstream alliances* ($\beta = -.113$, $p = .003$), indicating that each additional upstream alliance a firm forms is associated with 11% less forward citations to its patents. These findings show that alliances generally do not lead to higher levels of *Citations received*; rather, they indicate that a firm's alliances focused on R&D dissuade other firms from building on its inventions. To examine the possibility that the influence stemming from alliances affects startups in a different way, models 4—7 enter interactions between these alliance counts and the dummy *Startup*. Findings do not provide evidence that these interaction terms predict the outcome, while showing that the coefficient on *Startup* remains positive.

Taken together, findings in this additional set of analysis did not align with the conjecture that the higher levels of knowledge diffusion associated with startups might result from higher levels of knowledge transfer to exchange partners. Rather, findings reveal a negative main effect associated with *Upstream alliances*, suggesting that such alliances may dissuade other firms from building on a firm's inventions. Given this result, we retain this variable in subsequent models.

6.2 | Knowledge spillovers associated with lower levels of generative appropriability

We also explore other sources of heterogeneity across firms that might explain differences in knowledge spillovers stemming from startups' and established firms' inventions. To do so, we

[11]The alliance deal synopsis in SDC provided the basis for this classification.

[12]We observed 114 CVC partnerships in the full sample, 35 involving startups, and 79 for established firms.

build on the concept of generative appropriability, defined as "a firm's effectiveness in capturing the greatest share of future inventions spawned by its existing inventions" (Ahuja et al., 2013, p. 248). Although there is research on some factors broadly associated with generative appropriability, such as research on patent litigation (e.g., Polidoro & Toh, 2011; Somaya, 2012), there is scant research juxtaposing such factors for both startups and established firms. Moreover, examining factors that can affect the extent to which rivals build on a firm's invention is particularly relevant during the nascent period before a firm achieves commercialization, as it cannot count on its position in product markets or structural features of product markets to fend off rivals (Ethiraj & Zhu, 2008). Building on the conceptual framework about generative appropriability proposed by Ahuja et al. (2013), we explore differences across firms in preempting rivals from seizing the technological opportunities that their inventions spawn and by deterring rivals from capturing those opportunities.

Before examining these two factors, we consider that other firms' successful efforts to build on a focal firm's inventions imply that other firms pay attention to those inventions. But, given that third parties face substantial uncertainty surrounding startups (Stuart et al., 1999), which is compounded by the uncertainty typical of a nascent industry (Kapoor & Klueter, 2021; Moeen et al., 2020), it is not immediately clear that other firms will pay attention to startups' inventions. We thus consider that startups might be more susceptible to endorsements to help mitigate the uncertainty that third parties such as investors and other resource providers face (Higgins & Gulati, 2003), in turn also drawing the attention of other firms to their inventions (Polidoro, 2013). Arguably, endorsements may play a larger role in driving attention to startups' patents than to patents of established firms, whose track record of performance can help mitigate uncertainty about their viability in a nascent industry. When exploring these conjectures, we distinguish between endorsements of the knowledge underlying the inventions that firms create and endorsements of the resulting products (Polidoro, 2013; Polidoro & Theeke, 2012).

6.2.1 | University endorsements of a firm's knowledge

Prior research has shown that academia plays an important role in endorsing the knowledge underlying firms' inventions (Higgins & Gulati, 2003; Polidoro, 2013). Informal conversations with PV cell industry experts corroborated those insights. Specifically, these experts highlighted that the future of the industry as a whole remained unclear for a long period of time, with substantial uncertainty about the viability of the alternative technologies being proposed by industry players. In that context, universities and research institutions often verified the impact of firm's inventions on PV cell properties such as stability, decay, or efficiency, helping validate a company's approach and drawing attention to its inventions. In the words of one of these experts, "*It's kind of an awakening that is going on, where you realize that this good work needs to be used.*" These experts acknowledged that they closely followed university-based research to monitor developments in PV cell technologies, with patents being important tools in this effort. Thus, following the insights in prior literature on academic endorsements and contextual evidence about the role of universities in validating PV cell technologies, we created the variable *University citations of the firm's patents* with the number of citations by universities to a firm's inventions by the prior year, excluding citations to the focal patent, to measure endorsements of a firm's knowledge. Higher values of this variable indicate that the firms' overall portfolio of inventions gained more academic endorsements. To account for skewness, this variable takes the natural logarithm of the count added by one.

Results in Table 11 align with the conjecture that university citations might have a stronger effect in attracting attention to the inventions of startups. Specifically, model 2 shows that the coefficient on the interaction term *Startup* × *University citations of the firm's patents* is positive ($\beta = .056$; $p = .002$) and almost three times larger than the coefficient on *University citations of the firm's patents*, indicating that university citations have a stronger effect on the citations from other firms received by a startup's patent relative to those received by an established firm's patent.

A potential concern is that universities may be more likely to cite patents that are inherently superior and accordingly more heavily built upon by other firms. We note, though, that the analysis controls for a variety of attributes of the patents of the focal firm, as well as of the focal patent, such that the effect captured by university citations is net of those potential influences. Moreover, the average in *University citations of the firm's patents* is higher among established firms,[13] thereby allaying lingering concerns that additional heterogeneity might result in startups achieving higher levels of university citations to patents in its portfolio and forward citations to a focal patent.

The more positive association between *University citations of the firm's patents* and *Citations received* observed for startups might simply reflect that startups have more connections with universities (Agarwal & Shah, 2014; Mindruta, 2013), which could result in startups' patents relying more heavily on universities' patents. Contrary to that conjecture, inspection of citations sample patents make to universities' patents revealed similar values for startups' and established firms' patents (*t*-statistic = 1.04). Similarly, results could reflect that startups' inventors have closer ties to universities due to prior employment or collaboration. But, examination of each PV cell inventors' patents prior to their first patent[14] revealed that startups and established firms had similar values in both the absolute number of inventors and the proportion of inventors that appeared in earlier patents of universities or research institutes (respectively, 1.52 vs. 4.15, *t-statistic* = −1.83 and 0.21 vs. 0.18, *t-statistic* = 0.92).

We also probed an implication of the conjecture that university citations to a firm's patents draw more attention to the focal patent—if university citations in fact draw attention to startups' inventions, we would observe a positive association between these citations and firms citing startups' patents for the first time. We found that the number of new citing firms is higher among startups with high values in *University citations of the firm's patents*. Moreover, if the effect we found in the analysis arises because universities enhance the visibility of patents to other firms, then such effect should be stronger among other firms that build more extensively on universities' patents and thus are more likely to attend to what they cite. In alignment with this conjecture, when inspecting whether the patents citing the sample patents also cite patents of universities, we found a higher number of university backward citations among citing patents in observations with high values of *University citations of the firm's patents*.

6.2.2 | Scientific endorsements of a firm's product

To explore the influence that scientific endorsements of a firm's product might have on citations that its patents receive from other firms, we created the dummy variable *Attested highest cell*

[13]Mean values of 1.39 and 1.58, respectively, for startups and established firms (*t*-statistic = −4.08).

[14]Proportions were also similar when only considering inventions in the prior 3 or prior 5 years, which could indicate more recent connections with universities.

TABLE 11 Analysis of factors related to generative appropriability and commercialization: Patent random-effects OLS estimates of influences on *Citations Received* ($N = 3580$).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6[a]	Model 7	Model 8
Startup	0.059 (0.023)	0.118 (0.032)	0.060 (0.023)	0.061 (0.022)	0.059 (0.023)	0.110 (0.033)	0.072 (0.027)	0.090 (0.038)
Startup × university citations of the firm's patents		0.056 (0.018)				0.048 (0.022)		
Startup × attested highest cell efficiency			0.064 (0.065)			0.031 (0.069)		
Startup × low cumulative inventions				0.136 (0.050)		0.060 (0.059)		
Startup × litigiousness					0.154 (0.073)	0.181 (0.072)		
University citations of the firm's patents	0.021 (0.014)	0.020 (0.010)	0.021 (0.014)	0.022 (0.013)	0.021 (0.014)	0.021 (0.010)	0.027 (0.016)	0.027 (0.016)
Attested highest cell efficiency	−0.060 (0.037)	−0.037 (0.037)	−0.054 (0.035)	−0.048 (0.038)	−0.062 (0.037)	−0.034 (0.035)	−0.050 (0.037)	−0.055 (0.038)
Low cumulative inventions	0.139 (0.027)	0.136 (0.027)	0.139 (0.027)	0.135 (0.028)	0.137 (0.028)	0.134 (0.028)	0.151 (0.029)	0.150 (0.028)
Litigiousness	0.105 (0.066)	0.100 (0.081)	0.089 (0.059)	0.067 (0.068)	0.090 (0.042)	0.059 (0.046)	0.102 (0.045)	0.090 (0.047)
Firm-level control variables								
Patents in focal technology	−0.001 (0.001)	−0.000 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.000 (0.001)	−0.000 (0.001)	−0.000 (0.001)
Self-citations in prior patents	0.277 (0.127)	0.214 (0.121)	0.273 (0.128)	0.248 (0.125)	0.276 (0.127)	0.207 (0.121)	0.278 (0.130)	0.303 (0.128)
Technological scope of prior patents	0.001 (0.078)	0.024 (0.079)	0.004 (0.078)	0.011 (0.078)	0.000 (0.078)	0.026 (0.079)	−0.008 (0.078)	−0.016 (0.076)
Technology maturity of prior patents	0.013 (0.011)	0.008 (0.010)	0.013 (0.011)	0.010 (0.010)	0.013 (0.011)	0.008 (0.010)	0.011 (0.011)	0.011 (0.011)
Prior patents' originality	0.051 (0.065)	0.036 (0.067)	0.046 (0.065)	0.052 (0.065)	0.049 (0.065)	0.035 (0.067)	0.033 (0.067)	0.037 (0.066)
Intrafirm collaboration in prior patents	−0.008 (0.005)	−0.008 (0.005)	−0.009 (0.005)	−0.007 (0.005)	−0.008 (0.005)	−0.008 (0.005)	−0.007 (0.006)	−0.007 (0.006)
Firms in geographic location	−0.003 (0.012)	−0.003 (0.011)	−0.003 (0.012)	−0.006 (0.011)	−0.003 (0.012)	−0.005 (0.011)	−0.006 (0.012)	−0.006 (0.012)
Upstream alliances	−0.116 (0.043)	−0.128 (0.046)	−0.116 (0.043)	−0.120 (0.044)	−0.116 (0.043)	−0.128 (0.046)	−0.126 (0.043)	−0.126 (0.042)

TABLE 11 (Continued)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6[a]	Model 7	Model 8
Commercialization variables								
Commercialization in focal PV cell technology							−0.072 (0.033)	−0.071 (0.032)
Startup × commercialization in focal PV cell technology								−0.044 (0.045)
Other controls								
PV cell technology dummies	YES	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.373 (0.310)	0.387 (0.329)	0.377 (0.311)	0.350 (0.309)	0.374 (0.310)	0.379 (0.329)	0.442 (0.327)	0.451 (0.331)
Number of patents	590	590	590	590	590	590	590	590
X^2	3986	3920	3993	3772	7213	7560	4500	4527

Note: Robust standard errors, clustered at the firm level, in parentheses.
[a]The coefficients for the interaction effects are jointly significant ($p = .000$; $X^2 = 22.02$) based on a Wald test.

efficiency set to one if the focal firm had its PV cell listed in *Research in Photovoltaics: Progress and Application* as having the best efficiency in its respective PV cell technology[15] and to zero otherwise. Although endorsements of a firm's product signal its viability to other parties, they can also indicate to rivals that the focal firm has a higher chance in capturing the potential inherent in that product, which functions as a deterrent (Polidoro, 2013). These conflicting effects add ambiguity about the overall effect stemming from endorsements of a firm's PV cell.

We found that startups are less likely than established firms to have their PV cell recognized as having the best efficiency in its corresponding technology (respectively, 0.03 and 0.05, t-statistic = −3.20). Model 3, which enters the interaction *Startup* × *Attested highest cell efficiency*, does not support inference that its coefficient is different from zero. Model 6, the full model, shows this same pattern. Therefore, findings do not provide evidence that scientific validation of the performance of a firm's product might be a factor contributing to startups' patents receiving more citations by other firms than those of established firms.

6.2.3 | Low levels of cumulative inventions

We now turn to examination of whether the extent to which a firm engages in cumulative inventions, which can preempt other firms from seizing the technological opportunities spawn by its inventions (Ahuja et al., 2013), might explain the asymmetry in knowledge spillovers associated with startups. To explore this conjecture, we created a variable capturing the extent to which a firm has a low level of cumulative inventions, thereby leaving more technological opportunities for other firms to seize. Specifically, the variable *Low cumulative inventions* for firm i in year t measures the average across technological domains of the extent to which other firms $-i$, not the firm i itself, have built inventions capturing the technological opportunities that its prior inventions have spawn in that technological domain. This variable is calculated as follows:

$$\text{Low cumulative inventions}_{it} = \frac{\sum_{s=1}^{S}\left[\frac{c_{-is\,t-5}}{(c_{is\,t-5}+c_{-is\,t-5})}\right]}{S}$$

In the notation above, S is the number of distinct technological subclasses of the patents citing patents of firm i in the previous 5 years, $c_{is\,t-5}$ is the number of times subclass s is present in patents of the firm i that cited its own patents in the previous 5 years, and $c_{-is\,t-5}$ is the number of times subclass s is present in patents of other firms -i that cited the firm i's patents in the previous 5 years.[16] Thus, higher values indicate that the firm has lower levels of cumulative inventions.

When a startup has low levels in the variable *Low cumulative inventions*, other firms may anticipate it will leave fewer untapped technological opportunities stemming from the focal invention for them to capture. Conversely, when a startup has high levels of *Low cumulative inventions*, rivals may perceive that it lacks the resources to capture the opportunities spawn by

[15]We note that this form of endorsement does not reflect the commercial success of a firm's PV cells, as a PV cell can have its efficiency tested even if it has not been launched into the product market, not to mention that other considerations, such as manufacturing costs, are critical for success in commercializing those cells (Wolfe, 2018).

[16]When prior patents of firms had not received any forward citation by the focal year (354 observations), we could not calculate a proportion of opportunities not appropriated by the focal firm. Considering that the firm did not forgo any opportunity up to then—no opportunity was claimed by either the focal firm or another firm—we replaced the missing values with 0. Analysis dropping these observations showed fully robust results.

its inventions, which can encourage them to build more heavily on the focal invention of the startup. By contrast, rivals may perceive that an established firm has the resources to capture the opportunities that its inventions spawn, such that when it exhibits a record of low cumulative inventions its inventions are associated with fewer promising opportunities, or the established firm would have captured those opportunities. Alternatively, rivals may perceive an established firm as not needing to preempt rivals from capturing those opportunities because they have a superior ability to deter rivals' imitative efforts. Both possibilities would result in an established firm's record of low cumulative inventions contributing less to encouraging rivals to build on its invention relative to similar effect stemming from a startup's low cumulative invention, partly explaining a positive association between *Citations received* and *Startup*.

We found that startups and established firms exhibit similar values of *Low cumulative inventions* (respectively, 0.63 and 0.64, t-statistic = −0.85). Results in model 4 in Table 11 reveal a positive coefficient on the interaction term *Startup* × *Low cumulative inventions* ($\beta = .136$, $p = .006$), thereby showing that the association between *Citations received* and *Startup* is more positive for startups that exhibit a record of low cumulative inventions, which aligns with the conjecture discussed above. These findings indicate that a 1 SD increase in *Low cumulative inventions* (0.38) is associated with an 85% increase in the additional citations received by a startup's patent relative to an established firm's patent.[17]

Further, *Low cumulative inventions* and the variable *Litigiousness*, discussed later, are only weakly correlated (0.02), thereby providing weak indication that preemption and deterrence might function as substitutes. We also probed the possibility that the coefficient on *Startup* × *Low cumulative inventions* might have been driven by a subset of established firms' observations having concomitantly high values of *Low cumulative inventions* and of *Litigiousness*, in which case such substitution effect is more likely. Models dropping observations capturing established firms' patents with values in the top quartile in both variables and the corresponding observations of startups with which they are matched showed robust results. These findings align with the conjecture above that low cumulative inventions play a greater role in encouraging more citations for startups because in the case of established firms with low cumulative inventions rivals perceive relatively fewer promising opportunities to be captured, not because they perceive such record as reflective of lower inclination to preempt those opportunities due to superior ability to deter.

6.2.4 | Litigiousness

We also investigate whether the extent to which a firm resorts to litigiousness as a form of deterrence (Polidoro & Toh, 2011; Somaya, 2012) helps explain higher levels of citations to startups' patents. Imitation deterrence entails an important tradeoff, as the same efforts that a firm takes to protect its inventions can also reveal to other firms the strength of its inventions (Clarkson & Toh, 2010). Whether litigations against infringements of intellectual property rights deter other firms beside the defendants in those lawsuits (Lemley & Shapiro, 2007) depends on the extent to which a firm establishes a reputation of litigiousness and demonstrates "a credible commitment to follow through with the reputational strategy" (Agarwal et al., 2009, p. 1353). In contrast to the litigiousness of established firms, startups' "threats of litigious action will be perceived as less credible" (Agarwal et al., 2009, p. 1350). Lacking bargaining chips in battles to assert exclusionary rights and deep pockets to sustain costly litigations (Lanjouw & Schankerman, 2001), cases of patent

[17]Specifically, $(0.061 + 0.136 \times 0.38)/0.061 = 1.85$.

infringement involving a startup's patents can tilt the balance between deterring imitation and revealing the strength of its inventions that could have remained "*hidden*" from other firms (Clarkson & Toh, 2010, p. 1202, emphasis in original) in the direction of the latter, thereby drawing other firms' attention to its technologies (Awate & Makhija, 2022). Established firms, by contrast, are better able than startups to build a reputation for litigiousness (Agarwal et al., 2009; Ganco et al., 2020). Therefore, startups' patent litigations can be less effective in deterring other firms from building on their inventions, and may even result in more firms doing so.

To investigate this conjecture, we created the variable *Litigiousness* with the proportion of the firm's patents, excluding the focal patent, that the firm claimed an infringement for before a US court by the prior year (Clarkson & Toh, 2010; Ganco et al., 2020).[18] We found that startups and established firms have similar levels of this variable (mean value of 0.01 in both cases, t-statistic = 1.57). Model 5 shows a positive coefficient on the interaction *Startup* × *Litigiousness* ($\beta = .154$, $p = .035$), indicating that a 1 SD increase in *Litigiousness* (0.07) is associated with an 18% increase in the additional citations received by a startup's patent relative to an established firm's patent.[19] These results align with the conjecture that for startups litigiousness can encourage other firms to build on its invention.

6.3 | Commercialization

We now turn to the conjecture that the asymmetry between startups and established firms in the extent to which the knowledge they build is further built upon by other firms might be contingent on whether firms have launched PV cells into the market. To investigate this conjecture, we created the dummy variable *Commercialization in focal PV cell technology*, set to one if the focal patent relates to a firm that had already commercialized a PV cell building on the focal technology, and to zero otherwise. We found that the mean value of this variable is higher for startups than established firms (respectively, 0.47, 0.31, t-statistic = 9.97). Thus, sample startups were present in PV cell markets to a greater extent than established firms. This could imply that the higher level of knowledge spillovers associated with startups' patents might be attributable to competitive effects in product markets, as rivals seek to create imitative inventions. Model 8 in Table 11 shows that the coefficient on the interaction *Startup* × *Commercialization in focal PV cell technology* does not support that interpretation that it is more positive for startups ($\beta = -.044$, $p = .325$). These findings do not align with the conjecture that competition in product markets might partly explain the asymmetry in knowledge spillovers that we found in this study.

7 | SUPPLEMENTAL ANALYSIS: WHO BUILDS ON STARTUPS' AND ESTABLISHED FIRMS' INVENTIONS?

Having abductively explored factors that might explain the asymmetry between startups and established firms in the extent to which their patents are built upon by other firms, we now turn to examination of potential differences regarding *who* cites those patents. One possibility we explore is that, unlike established firms, startups do not benefit from technological capabilities

[18]We note that none of the patents in the sample was the subject of a patent infringement lawsuit.

[19]Specifically, $(0.059 + 0.154 \times 0.07)/0.059 = 1.18$.

TABLE 12 Supplemental analysis exploring who cites PV cell inventions.

	Startups	Established firms	*t-Statistic*
Technological domains of citing patents distinct from cited patent	4.50	3.42	2.21
Percentage citations received from universities	0.11	0.09	4.72
Percentage local citations	0.24	0.15	3.51

accumulated in other industries (Helfat & Lieberman, 2002; Moeen & Agarwal, 2017), which can result in other firms citing their inventions in technological domains that lie outside of the original domain of the focal patent. Table 12 reveals that startups' patents receive relatively more citations from patents in other technological domains (t-statistic = 2.21).

Another conjecture is that startups' patents may be more heavily cited by universities, reflecting a greater inclination of startups to be founded in geographic proximity of universities (Audretsch & Stephan, 1996). Table 12 reports that startups' patents exhibit a higher proportion of citations from universities when compared to established firms' patents (t-statistic = 4.72).

Finally, another conjecture is that the tendency of knowledge spillovers to be geographically proximate to the source firm (Jaffe et al., 1993; Polidoro et al., 2022) is more pronounced for startups, given that lower visibility relative to established firms can make it even more difficult for entities located farther away to gain access to the knowledge underlying their inventions. As Table 12 reports, startups' patents received a higher proportion of citations within a 200-mile radius (Adams, 2002) than established firms' patents (t-statistic = 3.51).

In sum, while the task of investigating factors explaining who builds on startups' and established firms' patents is beyond the scope of this study, we found preliminary evidence that differences exist between these groups of firms not only in the number of citations they receive, as reported in the analyses above, but also in *who* cites their patents.

8 | DISCUSSION

We investigated differences between startups and established firms in the diffusion of the knowledge they build in a nascent industry by examining *whose* inventions spur more subsequent inventions by other firms. Focusing empirically on citations that PV cell patents received in subsequent patents of other firms, we found that forward citations were higher for startups' patents than for established firms' patents. We also found that this pattern persisted when using a matched sample pairing startups' patents with established firms' patents sharing similar levels on a variety of attributes associated with forward citations. Through a series of abductive analyses, we then probed factors that might explain *why* startups' inventions are associated with higher levels of knowledge diffusion, including factors related to both knowledge transfer and knowledge spillovers. Starting with knowledge transfer associated with firms' alliance and acquisition activity, we found evidence suggesting that a firm's upstream alliances dissuade other firms from building on its patents. When examining factors related to knowledge spillovers, we considered that startups' inventions might attract more attention from other firms, and that startups might be less able than established firms to preempt or to deter other firms from capturing the technological opportunities spawn by their inventions. We found that startups' inventions received more citations than established firms' patents when startups had a stronger record of receiving forward citations from universities, which aligns with the notion that the uncertainty typical of nascent industries renders startups particularly susceptible to endorsements drawing the attention of other firms. On the other hand, we did not find evidence that scientific endorsement of a startup's PV cell produces a similar effect. We also found that forward citations to startups' patents are higher when a startup has a poor record in creating cumulative inventions and when it has a record of litigiousness. Additionally, we found no evidence that whether firms have launched PV cells into the market changes the pattern identified in the prior analyses. In a final set of analysis, we examined differences between startups and established firms in terms of *who* builds on their inventions. We found that startups' patents are relatively more likely to receive citations from a technological class different from that of the original patent, and to have a higher percentage of citations coming from universities and geographically proximate firms.

8.1 | Limitations and generalizability

This study's findings are subject to a few caveats. An important merit of the abductive approach we followed is the opportunity to explore a greater variety of factors that can help elucidate our question. But, findings do not warrant interpretation as evidence of causality, as addressing endogeneity concerns surrounding each of the factors we explore in our analyses is beyond the scope of a single study. The opportunity remains for future inquiry to establish causal evidence of the mechanism underlying the factors probed in this study. Further, future studies can investigate whether these findings generalize beyond the context of PV cell technologies. An interesting feature of this setting is that, several decades after the introduction of the first solar cell, distinct PV cell technologies still vie for dominance and solar energy still plays a modest role in replacing fossil-fuel technologies. Such technological diversity during a prolonged period of time is also present in other settings.[20] In settings wherein new technologies present a more imminent threat to existing technologies, established firms may face stronger incentives to diversify into the nascent industry to avoid market decline, a conjecture worth examining in future studies.

8.2 | Managerial implications

Existing literature has extensively examined the patterns of innovations that startups and established firms create, oftentimes portraying startups as important sources of inventions that build on new technologies while recognizing their limitations in capturing the value of their inventions in *downstream* product markets (Lampert et al., 2020; Teece, 1986). The findings in this study, however, alert entrepreneurs to the fact that startups in nascent industries may face limitations in capturing the *upstream* value of their inventions, which produce a greater level of knowledge spillovers benefiting other firms. It is possible, however, that startups face a tradeoff

[20]For example, the incubation of knowledge supporting the development of RNA-based therapies has comprised a variety of technological approaches, from ribosomal RNA to messenger RNA to RNA interference over the course of several decades (Melnikova, 2007).

as by generating more spillovers their inventions may have increased chances of becoming more dominant in the nascent industry, a conjecture worth examining in future research.

8.3 | Theoretical implications and opportunities for future research

This study advances the emerging and rapidly growing literature on knowledge-building activities in nascent industries (e.g., Moeen, 2017; Moeen & Agarwal, 2017; Moeen & Mitchell, 2020). While this literature has uncovered the role of technology-investing firms in building knowledge in a nascent industry, thereby shaping knowledge evolution in that industry, our study focuses on a second-order effect of these knowledge-building activities in shaping knowledge evolution, as the knowledge that these firms build is subsequently built upon by other firms.

The analyses of *whose* inventions spur more subsequent inventions reveal that startups asymmetrically contribute to knowledge diffusion in a nascent industry. We found that even when startups and established firms create inventions with similar attributes, those created by startups disproportionately contribute to knowledge diffusion. That is, while this pattern could be attributed to startups exhibiting higher propensities to create inventions that have a higher potential for spawning subsequent inventions in the first place, the analyses show that startups' inventions are more heavily built upon by other firms even when compared to inventions of established firms that share similar attributes expected to shape forward citations. This asymmetric effect of startups on knowledge diffusion further underscores the importance of startups in shaping the evolution of a nascent industry (Agarwal et al., 2007; Giustiziero et al., 2019).

In abductively exploring factors that can explain *why* such asymmetry arises, this study also offers insights for the literatures that inform the conjectures we explore. Starting with research on alliances and acquisitions, we note that in contrast with prior studies demonstrating that these transactions facilitate the transfer of a firm's knowledge to partnering and acquiring firms (e.g., Ahuja & Katila, 2001; Mowery et al., 1996), this study shows that these market-based mechanisms have little effect in promoting the diffusion of the firm's knowledge to other firms. Rather, findings provide evidence that R&D alliances that a firm forms dissuade other firms from building on its inventions. This effect might be attributable to other firms' expectations that partners or acquiring firms, as existing literature shows, will benefit from those transactions to build on the knowledge underlying the focal firm's inventions, thereby reducing opportunities for them to build on that knowledge, a conjecture worthy of future inquiry.

Advancing prior literature showing that knowledge spillovers are relevant to both startups and established firms (Agarwal et al., 2007, 2010; Giustiziero et al., 2019), this study provides evidence that startups experience a higher level of knowledge spillovers than established firms. Additionally, to the best of our knowledge, this is the first study to empirically examine factors expected to shape knowledge spillovers in a sample comprising both startups and established firms. In doing so, it offers insights on factors leading to spillovers. First, while prior research has shown the benefits accruing to startups that receive endorsements (Higgins & Gulati, 2003; Stuart et al., 1999), this study reveals a link between endorsements and knowledge spillovers—if, on the one hand, startups can obtain legitimating benefits when universities build on their inventions, which is particularly beneficial in a nascent industry when uncertainty about the emerging industry compounds the uncertainty surrounding startups, on the other hand, these citations can result in their inventions drawing greater attention from other firms. Second, the analyses reveal that the inventions of startups with lower abilities to engage in cumulative inventions are more frequently built upon by other firms, thus linking differences in knowledge spillovers to differences across firms in the preclusive component of generative appropriability (Ahuja et al., 2013). A third point is that, despite extensive research showing that litigation for patent infringement helps firms deter imitation (e.g., Lanjouw & Schankerman, 2001; Lemley & Shapiro, 2007), findings vindicate the notion that for startups "threats of litigious action will be perceived as less credible" (Agarwal et al., 2009, p. 1350), aligning with the insight that, for startups, efforts to deter rivals can reveal to other firms the strength of their inventions (Clarkson & Toh, 2010).

The task remains for future research to investigate long-term consequences of knowledge spillovers for startups. Strictly from the viewpoint of generative appropriability, with other firms benefiting more heavily from their inventions as a springboard for subsequent inventions, startups appear to have lower abilities to capture the generative value of their inventions (Ahuja et al., 2013; Arrow, 1962). An alternative interpretation we raised when outlining managerial implications is that startups, by having their inventions more frequently built upon, might indirectly have higher chances of asserting the superiority of their inventions in the competition against potential substitutes (Polidoro & Toh, 2011), a possibility that future research can explore. Another possibility is that, by disproportionally contributing to knowledge spillovers, startups might have a larger pool of knowledge they can learn from in the form of knowledge spillins (Alnuaimi & George, 2016).

Further, the preliminary evidence we found about differences between startups and established firms in the types of citations they receive suggests future research can investigate differences between these groups of firms in terms of who benefits the most from the knowledge spillovers associated with their inventions. Additionally, future studies can explore differences between startups and established firms as recipients of knowledge spillovers, for example in terms of whose knowledge spillovers they most benefit from. Recent literature underscores that important learning effects arise not only between startups and established firms but also within each of these groups (Giustiziero et al., 2019). Thus, established firms need to balance efforts to capture spillovers generated by startups with efforts to outlearn other established firms. It is possible that they focus on knowledge spillovers from startups to learn about the technological frontier in a particular domain, while looking at other established firms with knowledge accumulated in other domains to learn about how knowledge can be applied across domains.

Finally, future studies can explore the extent to which knowledge spillovers help established firms shape the technological trajectory of an emerging industry in ways that favor complementarities with their pre-entry knowledge. The literature has shown how pre-entry capabilities facilitate firms' adaptation (Cattani, 2005; Helfat & Lieberman, 2002) and influence the types of knowledge investments they make during the incubation of a nascent industry (Moeen, 2017; Moeen & Agarwal, 2017). The findings in this study suggest that established firms might also use pre-entry capabilities as a shield that protects them from the potentially destabilizing effects of technological change, as they may be able to warp the emerging trajectory by deliberately exploring the generative potential of inventions building on a new technology in combination with their pre-entry technological capabilities. This scenario suggests that the level of knowledge complementarities observed in a nascent industry may arise endogenously, partly from established firms' efforts to influence technological trajectories in ways that favor their pre-entry knowledge investments, an intriguing conjecture that warrants further investigation.

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