Academic Science and Corporate Innovation

Seungryul Ryan Shin[1], Matt Marx[2], Lee Fleming[3]

July 2023

Abstract

How is corporate innovation shaped by scientific discoveries in academia, if at all? While much prior research links academic research and innovation in the industry, how academic science shapes firms' innovation search and outcomes is less explored. In this paper, we focus on increased exposure to academic science for firms due to the arrival of university scientists in the geographically proximate area and examine how it changes the innovation of local firms. We show that an increase in exposure to academic science is not responsible for a uniform increase in patented inventions at firms, but rather "fattens the tails of innovation," shifting firms' R&D efforts from exploitation to exploration. Firms in counties with increased exposure to academic science deliver inventions based on science, and specifically, novel inventions that are at once highly-impactful and zero-impact. This effect can be directly traced via citations to the scientific articles and fields of newly-arrived scientists. Also, firms increase reliance on science originating from a university, rather than non-university organizations such as corporate and government laboratories. Both local established firms and startups are responsible for the effect, yet established firms benefit more from academic science than startups. We provide a causal interpretation via a shift-share instrument for scientist mobility based on the distribution of surnames in the 1940 U.S. Census. Our findings move beyond the notion that universities-matter for innovation, informing R&D of the dual implications of relying on scientific discoveries: outsized breakthroughs may be increased, but so is the probability of failure.

Keywords: Academic science, Corporate innovation, Innovation search strategy, Shift-share instrument variable

[1]UNIST (Ulsan National Institute of Science and Technology). Email: srshin@unist.ac.kr
[2]Cornell University. Email: mmarx@cornell.edu
[3]UC Berkeley. Email: lfleming@berkeley.edu

INTRODUCTION

Academic research is an important source of fundamental scientific knowledge for corporate innovation (Nelson, 1982; Jaffe, 1989; Rosenberg & Nathan, 1994; Cohen et al., 2002; Fleming & Sorenson, 2004). Scientific knowledge supports firms' downstream innovation activities (Arora et al., 2021); notably, firms reduce internal research activities and, instead, rely on scientific findings originating from academia (Arora et al., 2018; Bikard & Marx, 2020). Accordingly, prior literature suggests firms adopt scientific knowledge from academia through various channels, such as conducting collaborative research with university scientists (Zucker & Darby, 1996; Zucker et al., 2002; Bikard et al., 2019), recruiting experienced university scientists (Kaiser et al., 2018), transferring discovery through contracts (Jensen & Thursby, 2001; Thursby & Thursby, 2002; Mowery & Ziedonis, 2015), and facilitating social interaction among scientists (Mohnen, 2022). Considering that academic science is frequently used for corporate innovation, a deeper understanding of how academic science influences corporate innovation is particularly important for firms in designing their innovation strategies as well as for policymakers in facilitating the use of academic science in commercial applications.

Understanding the role of academic science in corporate innovation is not straightforward as disentangling the impact of academic science from the university itself is difficult. A number of prior studies demonstrate how universities contribute to an increase in the number of inventions in the industry (Jaffe, 1989; Kantor & Whalley, 2014; Andrews, 2022); however, such an impact may operate through several varied channels other than the direct provision of academic science—for example, cultivating skilled human capital through education (Valero & Van Reenen, 2019), inducing agglomeration in the industry (Aghion et al. 2009; Kantor & Whalley, 2014), attracting laboratories for research and development (R&D) in firms (Furman & MacGarvie, 2007), and increasing startup activities (Marx & Hsu, 2022; Tartari & Stern, 2022). In fact, while Andrews (2022) demonstrates that the establishment of a university increases the number of local inventions using college site selection experiments, it provides suggestive evidence that a university influences commercial inventions not only through the invention activities of its faculty members or graduates but also through other potential channels. This suggests that the existing studies investigating university impacts on commercial innovation do not yet fully elucidate the role of academic science in commercial inventions.

Some recent studies narrow the focus to the knowledge aspect of academic science and examine how it influences firms' innovation activities. Kaiser et al. (2018) explain that the characteristics of academic scientists' knowledge depend on their prior experience; they suggest that academic scientists having experience in academic research as well as working at an industrial firm form the key input for recruiting firms' innovation performance. Hausman (2022) demonstrates how increased access to university knowledge leads to an increase in firm-level engagement with universities—such as R&D partnership and IP transfer—and firms' patent outputs using the differential increase in accessibility to university knowledge for each industry following the 1980 Bayh-Dole Act. While these studies point to the positive relationship between academic science and corporate innovation, the dynamics of the production of corporate innovation might be more nuanced than made apparent as the prior studies merely count firms' innovation activities. More specifically, how academic science is used in the production of innovation and how it shapes the subsequent innovation outcomes remain underexplored.

To address this gap in the literature, this study focuses on corporate inventors' search activities and outcome characteristics and examines how academic science that is exposed to corporate inventors shapes the dynamics of the production of corporate innovation. we begin by theorizing the relationship between exposure to academic science and corporate innovation based on the following conceptual premises: 1) Academic science builds on prior related literature and includes novel findings concerning empirical regularities on natural phenomena approached through different perspectives and methods (Arora & Gambardella, 1994; Azoulay et al., 2019) and 2) Corporate inventors have limited attention and, consequently, a limited understanding of the scientific literature (Bikard, 2018). With these premises in hand, we posit that exposure to academic science increases science-based inventions by corporate inventors. This is because such exposure entices corporate inventors to allocate their attention to academic science and enables them to search through the related scientific literature. we also posit that exposure to academic science increases science-based inventions using novel technological approaches because academic science illustrates those novel approaches either directly from its findings or indirectly by guiding corporate inventors to different perspectives and approaches. Further, we posit that exposure to academic science increases inventions on the extremes, i.e., inventions that are highly impactful and zero impact. This is because academic science shifts corporate inventors' invention activities toward explorative R&D activities involving uncertainty and cost, thus increasing the variability of resulting inventions.

We provide empirical evidence that supports our predictions based on a panel data set covering 3,107 US counties from 1996 through 2013. By tracking scientific papers that each scientist publishes over time, we capture the inter-county mobility of US academic scientists. We measure the change in the level of exposure to academic science by counting the academic scientists moving into a county each year. We capture firms' inventions and detailed characteristics based on US patents. The results of Fixed effects regressions support our predictions that firms increase inventions based on science when they are exposed to academic science. This effect can be directly traced via citations to scientific articles and fields of incoming academic scientists. The results also support that academic science leads firms to deliver inventions with novel technological approaches and fattens the tails of corporate inventions, i.e., increasing inventions at the extremes of impact distribution.

To provide a causal interpretation, we isolate the plausibly exogenous subpart of variation in the level of exposure to academic science by adopting a shift-share instrument variable (SSIV) approach (Bartik, 1991; Balsmeier et al., 2020). The SSIV of the study is constructed by interacting: i) within-US mobility of academic scientists, excluding academic scientists moving to a given county, i.e., the SSIV's common shocks, and ii) historical surname distributions within the US, i.e., the SSIV's pre-determined shares. Intuitively, while each contemporaneous mobility of academic scientists at the national level and historical surname distribution across US counties may be correlated with the contemporaneous mobility of academic scientists across US counties, they are less likely to be driven by—or correlated with—a local condition of a certain US county. Thus, this SSIV allows designing an experiment in which corporate inventors are as-good-as-randomly exposed to academic science due to the arrival of academic scientists for a reason orthogonal to other local pull factors; consequently, this SSIV enables assessing the causality between academic science and corporate innovation. We confirm the validity of the instrument following recent studies on the validity conditions of the SSIV (Adao et al., 2019; Balsmeier et al., 2020; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2021). The results of IV regressions endorse our predictions and complement findings from the Fixed effect regressions with a causal interpretation.

We perform multiple additional tests to support the robustness of the baseline findings. First, we demonstrate that academic science's impact on corporate innovation is only specific to science-based rather than non-science-based inventions. Second, we confirm that the increase in science-based inventions is not driven by inventions that universities are directly involved in. Third, we demonstrate that innovative counties do not drive the main results. Fourth, we confirm that the results of the inventions using novel technological approaches and highly impactful inventions are robust to alternative measurements.

We also attempt to empirically shed light on the mechanisms by which academic science influences corporate innovation. We provide evidence supporting the connection between academic science and corporate innovation by demonstrating that the majority of the increase in science-based inventions is inventions that rely on scientific articles or fields of incoming academic scientists. We also demonstrate that the increase in science-based inventions is mainly attributable to inventions relying upon science originating from a university, while there is no evidence that exposure to academic science increases the use of science originating from non-university organizations such as corporate or government laboratories. Finally, we show that exposure to academic science increases inventions created by both startups and established firms, yet established firms significantly benefit more from academic science than startups.

Studying how exposure to academic science shapes corporate innovation, we make two main contributions to the prior literature. First, the study adds texture to the understanding of the role of academic science in shaping corporate innovation. It theoretically explains and empirically demonstrate how corporate inventors' innovation search and outcomes change in response to exposure to academic science, thereby extending prior literature emphasizing the significance of universities and academic science in the commercial inventions of firms. In addition to the well-documented role of science as a map in technological search, this study suggests that academic science helps corporate inventors not only search for technological opportunities but also scientific literature.

Second, this study provides causal evidence of how academic science influences commercial inventions. It helps establish the linkage between academia and industry and illuminate academic science's value in commercial inventions, thereby contributing to the prior findings regarding universities' causal impact on inventions in the industry. Further, this study has implications for firm managers and policymakers that are conducive to promoting the efficient use of academic science in commercial R&D activities.

ROLE OF ACADEMIC SCIENCE IN CORPORATE INNOVATION

Science-based corporate innovation

Innovation is challenging as it involves an uncertain process of trial-and-error recombining components of technologies (Arora & Gambardella, 1994; Fleming, 2001; Dreyfuss et al., 2001). Inventors follow the trajectory of inventions and iterate R&D processes by replacing technological components or by changing methods. Even if inventors acquire experience and familiarize themselves with components by repeating the R&D processes, uncertainty lingers throughout as technological advancement is rapid and possible sets of recombination are almost infinite.

To reduce uncertainty, boundedly rational inventors often confine their search to technologically localized knowledge (March & Simon, 1993; Stuart & Podolny, 1996) because they expect that recombination and improvement using technologically proximate or familiar—rather than technologically distant—components provide more certain outcomes (Rosenkopf & Nerkar, 2001). Moreover, inventors accumulate experience as they pursue R&D activities; hence, they may anticipate potential recombination outcomes between familiar components and pursue promising opportunities while avoiding hopeless approaches. Firms attempt to overcome this tendency of local search because even if familiar ways of the search may lead to incremental improvements in their technology, such familiarity and propinquity traps impede breakthrough inventions (Ahuja & Lampert, 2001). This is well-documented in prior studies that explore various means through which firms may overcome local search of their R&D activities, such as the formation of interfirm relationships (Rosenkopf & Almeida, 2003), employee mobility (Campbell et al., 2012), and investment in external ventures (Wadhwa & Kotha, 2006).

One prominent approach for overcoming the localized search in invention processes is relying on science. According to Fleming & Sorenson (2004), science becomes a map in the process of inventions by guiding inventors' technological search. Science clarifies empirical regularities and underlying mechanisms, thereby reducing uncertainty in the R&D processes and allowing the exploration of unfamiliar knowledge areas. Further, science lends inventors ideas for new approaches to previously unsolvable problems. As recent papers demonstrate by analyzing a large-scale dataset of linkages between patents and scientific publications (Ahmadpoor & Jones, 2017; Poege et al., 2019; Marx & Fuegi, 2020), inventors frequently rely on science in their invention processes.

Academic science and corporate inventors' limited attention on scientific literature

Academic science is a distinctive type of science. According to prior literature on institutional logic, the nature of science differs by the institutional logics of the originating institution (Rosenberg & Nelson, 1994; Sauermann & Stephan, 2013). Compared to scientific research conducted in other institutions such as industrial or government laboratories, academic research in universities is mainly focused on understanding the fundamentals of natural phenomena and underlying mechanisms. Additionally, academic science focuses on contributing to the scientific literature by advancing knowledge with novel findings from different perspectives or approaches while building on prior related studies of peers (Iaria et al., 2018; Azoulay et al., 2019). This can be attributed to the different reward systems of academia that reward based on peer recognition of the work's scientific value as opposed to that of the industry that prioritizes the resultant commercial and economic values (Sauermann & Stephan, 2013; Sheer, 2022).

Due to the distinctive characteristics of academic science, corporate inventors pay limited attention to academic science and, consequently, possess a limited understanding of scientific literature. Corporate inventors recognize that translating academic science to a commercially valuable invention requires additional endeavors and risk-taking, whereas corporate science is easier to apply for their inventions as compared to academic science. As Bikard (2018) demonstrates, corporate inventors use the originating institute as a cue to select science and pay less attention to science originating from academia. Moreover, as scientific literature comprises advanced knowledge that pushes the frontier of knowledge (Waldinger, 2016; Iaria et al., 2018) and its volume is vast and advancement is rapid (Agrawal & Henderson, 2002; Jones, 2009), it is difficult for corporate inventors to understand and keep track of scientific literature—especially when they do not pay attention to the literature. Corporate inventors' limited attention to—and understanding of—scientific literature become significant bottlenecks for their use of academic science in their invention activities. In the following sections, we examine how the bottlenecks alter when corporate inventors are exposed to academic science, thus transforming their invention activities.

Impact of exposure to academic science on corporate innovation

Corporate inventors become more likely to allocate their attention to academic science when exposed to it. When corporate inventors have easier access to academic science, they pay greater attention to it. Corporate inventors may understand academic science in greater detail when tacit knowledge and information concerning the science is available (Polanyi, 1958); thus, they may recognize it as a source of technological opportunities with promising discoveries at the knowledge frontier (Chai & Menon, 2019).

Not only limited to the exposed academic science itself, but exposure to academic science also leads corporate inventors to search for other related scientific research in the literature. Academic science advances by building on related literature; hence, exposed academic science helps corporate inventors search through the scientific literature. Specifically, exposed academic science enhances corporate inventors' understanding of the specific topic or the context of the phenomenon, thereby reducing the costs required for corporate inventors to understand related scientific research. Moreover, as exposed academic science provides information on the relevant scientific literature, it narrows the range of scientific literature that corporate inventors need to keep track of. This also helps corporate inventors to search through the scientific literature.

Corporate inventors' attention to the exposed academic science and their search through related scientific literature leads to an increase in corporate inventions based on science. Academic science provides delineated explanations and findings on empirical regularities concerning a natural phenomenon, and hence, corporate inventors would use it to address technological problems that they confront in the invention process. Moreover, as academic science guides corporate inventors' search through the scientific literature, it allows corporate inventors to select the necessary science for their inventions, and hence, they become more likely to use science in the invention process. Thus, we posit the following:

Hypothesis 1. Exposure to academic science increases corporate inventors' science-based inventions.

Exposure to academic science leads corporate inventors to pursue explorative R&D activities based on science with which the inventors get familiarized. It is well-documented that science becomes a map for technological search and innovation (Fleming & Sorenson, 2004). Academic science provides an understanding of empirical regularities and underlying mechanisms from various perspectives (Mokyr, 2002), thus helping corporate inventors overcome the tendency of local search and broadening their technological search scope by providing multi-faceted means to approach a focal problem faced by the inventors (Rosenkopf & Nerkar, 2001). Moreover, a broadened search scope substantially increases sets of components to recombine; thus, academic science significantly contributes by allowing corporate inventors to understand the newly adopted technology and foresee the potential of the technology in combination with their existing knowledge. Consequently, academic science helps corporate inventors explore novel perspectives and approaches in their R&D activities, including the exploration of new technological areas, recombination of technological components in unprecedented ways, and integration of technological components from diverse technological areas (Fleming et al., 2007; Uzzi et al., 2013; Arts & Fleming, 2018).

Not only does academic science serve as a map to adopt new technological approaches, but discoveries from academic research and other scientific research in the literature also provide opportunities to translate themselves into commercial inventions (Zucker et al., 1998; Thursby & Thursby, 2002). When such opportunities become available due to increased exposure to academic science, corporate inventors adopt these discoveries and integrate them into their existing technological capabilities to create commercial inventions. Translating discovery into a commercial invention requires corporate inventors to pursue novel ways of R&D as such discovery is often at the frontier of scientific advancement and, therefore, is new to commercial inventions. In summary, academic science provides a map for explorative R&D in inventions and a novel commercialization opportunity based on the discovery itself. Thus, we posit the following:

Hypothesis 2. Exposure to academic science increases corporate inventors' science-based inventions using novel technological approaches.

Although explorative R&D is encouraging and the primary engine of technological advancement, explorative R&D based on academic science entails uncertainty and risk in creating technologically valuable inventions (March, 1991). According to prior studies, explorative search does not necessarily lead to impactful inventions (Arts & Fleming, 2018). Especially when corporate inventors use science originated from academia, integrating science in a commercial invention involves a higher cost and uncertainty than using corporate science or existing technologies. Academic research, owing to its nature—e.g., conducted under less commercial pressure—requires additional efforts from corporate inventors to find commercial opportunities or develop inventions based on the science (Rosenberg & Nelson, 1994; Sauermann & Stephan, 2013). Even when corporate inventors use academic science as a map to search for other science, maintaining the balance in their attention allocation between exploiting the science and realizing commercial potential becomes a key challenge in the invention process.

The cost and uncertainty involved in explorative R&D with science increase the variability of the resultant inventions, which may lead to an increase in both inventions with low and high impact (March, 1991; Fleming, 2001). Many attempts to apply academic science in commercial inventions result in inventions with either low or no impact on future inventions because corporate inventors frequently fail to manage the additional efforts required in translating academic science into commercial inventions—owing to uncertainty and cost. However, corporate inventors may also come up with high-value inventions if they appropriately manage the balance between academic science and commercial potential, especially when they translate discoveries at the frontier of scientific advancement into commercial invention. Moreover, commercial inventions having a solid basis in academic science may be highly valued in future inventions because of their credibility and adaptability (Arora et al., 2022). Thus, an increase in the use of academic science and explorative R&D will increase inventions on the extremes—i.e., inventions with low and high technological impact on future inventions. In summary, because exposure to academic science shifts corporate R&D activities toward explorative R&D activities and the integration of academic science is often uncertain and costly, we posit the following:

Hypothesis 3. Exposure to academic science fattens the tails of impact distribution of corporate inventions, i.e., increasing science-based inventions that are highly impactful and zero impact.

EMPIRICAL ANALYSIS

Data

This study assembles data from several sources at the US county level. Motivated by prior studies that emphasize geographically localized spillover of academic research (Jaffe, 1989; Adams, 2002; Furman & MacGarvie, 2007; Kantor & Whalley, 2014), we use geographical boundaries of US counties to estimate the changes in corporate inventors' innovation search and the outcomes in response to increased exposure to academic science in the geographical region. The US county system comprises more than 3,000 counties, each of which covers smaller geographical areas than states or Metropolitan Statistical Areas but encompasses cities or townships (more than 30 cities or townships on average), thus allowing the estimation of changes in corporate innovation in response to the change in exposure to academic science for corporate inventors due to the academic scientists moving to a nearby institution.

We begin with the bibliographic data from the Microsoft Academic Graph (MAG) database. The MAG database provides information on authors, affiliation, published year, and keywords of scholarly works including journal publications, conference proceedings, and books. An advantage of using the MAG database is that it provides unique identifiers for each author (Sinha et al., 2015), which is essential because we use the mobility of academic scientists to measure the change in the level of exposure to academic science. The RCP database complements the MAG database with a novel dataset of patent citations to scientific papers, allowing the investigation of the relationship between patents and scientific papers, i.e., commercial inventions and underlying scientific knowledge, in greater detail (Marx & Fuegi, 2020; Marx & Fuegi, 2022).

We measure our variable of interest—exposure to academic science—using the inward mobility of academic scientists in a given county and year. As prior studies find a localized spillover of academic research (Furman & MacGarvie, 2007; Kantor & Whalley, 2014; 2019), incoming academic scientists in a region increase local corporate inventors' exposure to academic science including tacit knowledge that does not transfer through publications alone (Zucker & Darby, 1996). Moreover, following Marshall (1890) emphasizing the importance of geographical proximity in knowledge transfer among individuals, prior studies find that inventors are largely influenced by the knowledge available in their local region (Moretti, 2021). Thus, we capture the change in exposure to academic science for corporate inventors using the number of additional academic scientists located in the same geographical region. This is similar to how Furman & MacGarvie (2007) use the number of Ph.D. graduates as a proxy for academic science research in a geographical region and estimate its impact on local industry.

To identify the mobility of academic scientists across US counties, we first track the geographical location history of scientists by using the papers that authors publish over time. To reduce the burden in computation, we start by excluding scientists who published only once as their location change cannot be tracked. Subsequently, the geographic location of each author and paper is inferred based on the affiliation string (see Appendix A1). We track the location of each scientist between the first and last years of their publications and create a panel for each scientist. Here, we resort to two assumptions following prior literature that capture the mobility of individuals with archival data (e.g., Hoisl, 2007; Marx et al., 2009; Moretti & Wilson, 2014). In case a scientist has multiple affiliations in a paper, we assume that the author is located in the first affiliation. In case a scientist has multiple publications from different US counties during a year, we assume that the author is at the modal county. Subsequently, we identify US university affiliations based on the affiliation string (see Appendix A2). Based on the complete publication history of each scientist, we only consider scientists with more than half of their papers published with a university affiliation as academic scientists.[4] Finally, we infer the mobility of each academic scientist using their county location changes over time. Using publication year as a timestamp, we count the number of academic scientists moving into a US county in a given year. Figure 1 demonstrates a geographical distribution of the inward mobility of academic scientists between 1996 and 2013.

Figure 1 here

To capture the commercial inventions created by corporate inventors, we use US patent data provided by PatentsView databases, which contain details on patents and corresponding

[4] Notably, 95.5% of scientists who at least publish once with a US university affiliation have published more than half of their entire papers published with the US university affiliation.

inventors such as application year, citation linkage between patents, assignee and inventor information with unique identifiers, and geographic locations. we use the full population of eventually granted patent applications filed by inventors within the US. To identify patents originating from firms in industries, we use assignee information for each patent (see Appendix A3). Of the patents considered, 93.3%, 0.4%, and 3.6% are assigned to at least one firm, both firms and universities together, and only universities, respectively. While we use the entire patents assigned to at least one firm to capture the dependent variables of interest, the results are robust to excluding patents assigned to both firms and universities together. It is worthwhile to note that results differ for patents assigned to only universities, though this is beyond the scope of this work.

We capture the dependent variable of interest based on all the patents assigned to firms combined with their information on each patent's citations to scientific papers provided by the RSP database. We define a science-based invention as a patent that has one or more citations to a scientific paper. To capture science-based inventions using a novel technological approach, we use the combination of main Cooperative Patent Classification (CPC) groups following prior studies (Fleming, 2001; Jung & Lee, 2015; Arts & Fleming, 2018). We define a science-based invention using a novel technological approach as science-based patents that have one or more pairwise main CPC group combinations appearing for the first time in the PatentsView databases. As an alternative measurement of novelty in the technological approach, we also consider science-based patents having the top 10% of originality as measured by the Herfindahl–Hirschman index using main CPC groups. For the impact of science-based inventions, we use the forward citation distribution of patents in a given main CPC group in an application year following prior studies (Balsmeier et al., 2017; Lin et al., 2020). While we define science-based inventions with no impact as science-based patents receiving no forward citation, we define science-based inventions with mediocre impact as science-based patents receiving forward citation but are not located in the top 10% of forward citation of patents in each CPC group and application year. We define science-based inventions with high impact as science-based patents located in the top 10% of forward citation of patents in each CPC group and application year (Balsmeier et al., 2017). Geographical distribution and the yearly number of science-based patents are demonstrated in Figures 2a and 2b, respectively.

Figures 2a and 2b here

The instrument variable (described in detail below) is constructed based on historic census data, which provides information on households and individuals who resided in the US during 1940. Since we use surname as the subdimension in the instrument construction, we match the surname of authors appearing in the MAG database and that of individuals in the historic data based on the text matching algorithm described in Appendix A4.

The final panel dataset comprises 3,107 US counties from 1996 through 2013. The data collected from each aforementioned source are aggregated at the US county and year level. Importantly, there were several major and minor demarcations in the US county boundaries, e.g., county consolidation, part annexation, and county code change. To address the concordance of regions over time, we use the US county boundaries in 2020 as the anchor and aggregate values for each county and year according to the county boundaries in 2020.[5]

Table 1 presents the summary statistics of the final sample. The final sample includes a total of 502,573 incidents of inward mobility of academic scientists and, on average, nine incidents of inward mobility of academic scientists in each county and year. For corporate inventions in the final sample, there are 613,445 patents based on a scientific paper, accounting for 35.8% of the entire patents. There are 3,712 science-based patents with novel recombination between the main CPC groups and 95,980 science-based patents with top 10% originality, each of which accounts for 0.5% and 15.6% of the science-based patents, respectively. Additionally, there are 212,630 science-based patents that received no forward citation, 284,435 science-based patents that received at least one forward citation but were not in the top 10% of the forward citation distribution, and 107,511, 58,924, and 14,341 science-based patents that are located within the top 10%, 5%, and 1% of the forward citation distribution, respectively. The variables show a skewed distribution; thus, we use the logarithmic transformation of one plus each variable in the following analysis.

[5] The historic county change association file is provided by Balsmeier et al. (2020).

Table 1 here

Econometric specification

To examine how academic science affects commercial invention, we estimate how corporate inventors make use of academic science and change their search strategy in response to the change in exposure to academic science due to the supply of academic scientists in the region using the following specification:

$$Y_{i,t} = \alpha + \beta AcademicScientists_{i,t-1} + \gamma_i \times \delta_t + \theta_i + \varepsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ represents dependent variables captured based on patents applied by corporate inventors resided in county i during year t. To allocate patent outcomes by the location of inventors, I divide one by the number of inventors in each patent and sum over all patent outcomes by each county i in year t.[6] $AcademicScientists_{i,t-1}$, which is the main explanatory variable of interest, is the number of academic scientists arriving in county i in year t-1. The term γ_i represents state fixed effects, whereas the term δ_t represents year fixed effects. Thus, the term $\gamma_i \times \delta_t$ controls for time-varying state conditions, such as policy changes in each state. The term θ_i represent county fixed effects, absorbing any time-invariant characteristics of each county. We cluster standard errors at the state level to account for the nature of variables clustered at the state level.[7]

Fixed effects regression results

Table 2 presents the results of fixed effects analyses that estimate Equation (1) using OLS regressions with all the fixed effects included. Model (a) presents the fixed effects regression

[6] I follow Myers & Lanahan (2022) to allocate patent outcomes by CPC groups as patents generally have multiple CPC groups. Notably, the results are consistent though I use mere count of patents without scaling by the number of inventors in each county.

[7] Notably, results are consistent when standard errors are clustered at the county level.

results of science-based inventions, showing a positive and significant correlation between exposure to academic science and the number of science-based inventions. This supports Hypothesis 1 that firms create more inventions based on science when they are exposed to academic science. To further investigate if there is a direct connection between the firms' inventions and incoming scientists, we counted only corporate patents that cite articles published by incoming scientists and articles in the scientific fields of incoming scientists. As each of Models (b) and (c) present, the number of both science-based inventions that cite articles (presented in Model (b)) and scientific fields (presented in Model (c)) of incoming academic scientists significantly increases when more scientists move into the local area.

Models (d) and (f) present the fixed effects regression results of science-based inventions using novel technological approaches. Model (d) shows the results of IV regression of science-based inventions with novel recombination of technological components. It confirms that academic science significantly increases the number of science-based inventions with novelty. Model (f) shows the results of IV regression of science-based inventions with the highest 10% originality value. It also shows a positive and significant effect of academic science on science-based inventions that are combined in an original way. These suggest how firms deliver more inventions using novel technological approaches when they are exposed to academic science, supporting Hypothesis 2.

Models (g)–(i) present the fixed effects regression results of science-based inventions by the distribution of forward citations. Model (g) presents the fixed effects regression of science-based inventions with no impact. It shows that exposure to academic science sharply increases the number of failed inventions. Model (h) presents the results of the fixed effects regression of inventions with mediocre impact. We find no evidence of the impact of academic science on inventions with mediocre impact. Models (i) presents the results of the fixed effects regression of highly impactful science-based inventions. It shows that academic science increases the number of highly impactful inventions. These results provide evidence that academic science contributes to fattening the tails of corporate inventions, rather than uniformly increasing inventions at firms.

Table 2 here

Shift-share instrument variable approach

One may concern as the estimated βs obtained from the fixed effects regression may be biased if the $AcademicScientists_{i,t-1}$ is correlated with the error term $\varepsilon_{i,t}$. For instance, change in local demands on academic research in corporate innovation may have attracted academic scientists to the region, thus increasing exposure to academic science (Alcacer & Chung, 2007). Other regional conditions, either observable or unobservable, may also be correlated with both the supply of academic scientists and corporate innovation (Azoulay et al., 2017; Orazbayev, 2017). Although county fixed effects account for any time-invariant characteristics of each county, they do not account for time-variant local factors that may influence both academic scientists moving into the region and corporate innovation. Thus, the estimation of Equation (1) using a OLS with fixed effects may still yield a biased β, hindering the identification of academic scientist effects. A source of exogenous variation for the supply of academic scientists is warranted to address such a challenge in the identification.

To exploit an exogenous variation of exposure to academic science due to the supply of academic scientists, we adopt a shift-share instrument variable (SSIV) approach. Since Bartik (1991), the SSIV approach has been adopted in prior studies to exploit a plausibly exogenous subpart of variation of a continuous treatment variable (Card, 2009; Autor et al., 2013). Extending the stream of research, Balsmeier et al. (2020) construct an SSIV that isolates the variation of the local supply of high-skilled human capital from other local confounding factors. Building on immigration literature that shows how people tend to move close to where more of their relatives lived (Darlu et al., 2011; Clark & Cummins, 2015), they construct the SSIV by summing up the shocks of within-US mobility of inventors with a given surname at the national level (i.e., “Shift”) weighted by the historical distribution of the surname over US counties (i.e., “Share”).

Following Balsmeier et al. (2020), we construct an SSIV based on the historical share of surnames in US counties (i.e., “Share”) and contemporary within-US mobility of academic scientists (i.e., “Shift”). we also applied a leave-out strategy that excludes the academic scientists moving to a given county in capturing the shift part, enabling the purge of the potentially endogenous part in the shift part. we obtain the instrument as follows:

$$\widetilde{AcademicScientists}_{i,t-1} = \sum_n \frac{P_{n,i}}{P_n} \times AcademicScientists_{n,t-1,leave-out(n,i,t-1)},$$

where $P_{n,i}$ is the population of surname *n* in county *i* during 1940, P_n is the total population of surname n during 1940; $AcademicScientists_{n,t-1,leave-out(n,i,t)}$ represents the number of academic scientists with surname n moving across US county borders, except those moving to county *i* in year *t-1*. Intuitively, as the SSIV isolates the subpart variation of supply of academic scientists in a given county in year *t* by exploiting how each county is differentially affected by common shocks of within-US mobility of academic scientists depending on the historical demographics of each county, it is unlikely to be correlated with the local condition of a certain US county. Nonetheless, we demonstrate the validity of each of the share and shift parts of the SSIV in the robustness check for validity of the SSIV section below.

As the estimation of Equation (1) includes state-year and county fixed effects, we exploit the variation of SSIV residualized after subtracting the fixed effects. we present the variation of the treatment and instrument variables in Appendix A5. As appeared in Table A5, while county fixed effects account for approximately half of the variation of SSIV, there is a significant variation in the SSIV after accounting for county and state-year fixed effects. Figures A5a and A5b further show the distribution of residualized SSIV by US states and by time periods, respectively. We exploit this source of variation to isolate the exogenously-varying subpart of the treatment variable.

Validity of the SSIV

As the validity of estimated causal impacts depends on the validity of SSIV, we check the validity of SSIV following Balsmeier et al. (2020). Building on the recent literature on the validation of shift-share instrument variables (Adao et al., 2019; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022), Balsmeier et al. (2020) provide a series of tests to address concerns about the instrument and its components, i.e., each of the shift and share parts, in establishing causality. Thus, we replicate the tests performed by Balsmeier et al. (2020) to add evidence to validate the SSIV, complementing with tests suggested by other recent literature on the shift-share instrument. Overall, the results of a series of tests provide support for the validity of SSIV.

We first include descriptive evidence on the components of SSIV to demonstrate how the SSIV is unlikely to be driven by particular shares or shifts. SSIVs in prior literature tend to have a small number of shares and shifts, which typically used shares and growth rates by industries (e.g., Autor et al., 2013) or countries (e.g., Card, 2009), respectively. As suggested by Goldsmith-Pinkham et al. (2020) and Borusyak et al., (2022), this can be problematic if some industries or countries have overly strong influence and consequently bias the estimation. The SSIV of this study does not suffer from this problem as it exploits the historical distribution of 3.3 million unique surnames in the U.S during 1940, as appeared in the 1940 Census data. Even if we consider only surnames that ever moved within-US, i.e., surnames having a value of shifts, shares of 102.0 thousand unique surnames are used as the share part. Table A6a further shows the distribution of the shares used in the construction of the SSIV for the five most and five least populous counties during 1940 included in the sample, demonstrating that each county has a sufficient number of surnames with share values spanning zero to one that prevents particular shares being overly influential. Regarding the shift part, the yearly value of the inverse Herfindahl–Hirschman index (HHI) for within-US mobility of academic scientists allows for determining the effective sample size of the shift part (Borusyak et al., 2022). Table A6b shows how the HHI index of shifts of all surnames ranges from 4.316 in 1997 and 6.623 in 2012,[8] illustrating the effective sample size and distribution of shifts.[9]

Subsequently, we test for the presence of possible bias from confounding local factors by following Breuer (2021). We regress both the treatment and instrument variables on observable local factors, income, employment, and population, along with the state-year and county fixed effects. Table A7a indicates that while income, employment, and population are significantly correlated with the treatment variable, these factors have no significant correlation with the SSIV. Moreover, residual variations of each treatment and instrument variable that are explained by each local factor, i.e., within-R^2, are significantly less for the SSIV than for the treatment. We also assess how the inclusion of the observable local factors as a control variable in models alters the estimation. As presented in Table A7b, while the estimated coefficients are consistent with

[8] Notably, I have multiplied HHI by 10,000; thus, the HHI value can lie between 0 (evenly distributed shifts) and 10,000 (highly concentrated shifts).
[9] Notably, Borusyak et al. (2022) suggest that inverse HHI value should approach zero in a sample with effective shifts.

and without each control variable, the explanatory powers of the models with each control increase substantially. This suggests that although the observable characteristics are significant determinants of the local corporate inventions, these do not seem to confound the main estimation. These results suggest that SSIV successfully reduces concerns of the estimates being confounded by local correlates (Breuer 2021). To further alleviate the concern that the results may be driven by the inherent population size difference between counties, We ran regressions weighted by historical and current populations as well as regressions excluding the ten most and ten least populous counties from the sample. The results presented in Tables A8a and A8b show consistent estimates throughout the models.

We perform a series of tests to address concerns with respect to the share part of the SSIV. In the first test, we examine whether the regional correlates of the shares predict changes in the number of science-based inventions to test the identifying assumption of the exclusion restriction for the shares. By regressing the historical characteristics of US counties on the historic share of individual surnames, I find that 6.9%, 2.6%, 55.9%, 17.0%, and 13.5% of a total of 3.3 million surname shares are significantly correlated with the ratio of male, white, and native, education level, and average family size, respectively.[10] Subsequently, to alleviate the possibility that the correlates of the shares confound the estimation, We assess whether these historical characteristics of counties predict *changes* in contemporaneous corporate innovation. As noted by Goldsmith-Pinkham et al. (2020), the correlates of the shares should not predict *changes* in the outcome variable, although they can be correlated with the *level* of the outcome variable. The results of regressions of the number of the science-based invention on each of the historic characteristics presented in Table A9a indicate no significant correlation of historic correlates with changes in the outcome variable, providing empirical evidence of exclusion restriction with respect to regional correlates. Further, to rule out the possibility that the shares correlated with each regional correlate, we re-construct SSIVs by removing the surnames of which shares are correlated with each regional correlate and estimate the baseline regressions by using the newly created SSIVs. The results presented in Table A9b demonstrate consistent results throughout the variation of SSIV in removing problematic surnames.

[10] Notably, the percentages of surnames shares correlated with each of the ratio of male, white, and education level are the same as reported in Balsmeier et al. (2022) as both of the studies use the same data for the share part.

We also test whether the marginal effects of each surname share on the mobility of academic scientists is heterogeneous by the ethnicity groups. Following the procedure of Balsmeier et al. (2020), we first obtain the size and precision level of marginal effects of each share by running regressions of mobility of academic scientists on historic surname shares for each surname. Figure A10 shows the size and precision level of marginal effects obtained from 72,951 individual regressions for each surname ever moved into a US county in the sampling period. Consistent with the notion that academic scientists would choose a location closer to their families, all of the precisely estimated ($p < 0.05$) coefficients show a positive marginal effect of surname share on the mobility of academic scientists. There are some surnames shares with negative coefficients, but they are imprecisely estimated. Using the estimated marginal effects of the shares, we test whether the marginal effects of shares significantly differ by ethnicity of the surname. The results shown in Table A10 demonstrate a lack of ethnicity bias in the share effect.

Although exogeneity of the share is a sufficient condition to establish causality when using an SSIV, as suggested by Goldsmith-Pinkham et al. (2020), we also test the plausibility of the shift part of the SSIV. Since the shift part exploits the number of within-US mobility of scientists with a given surname at the national level, it is difficult to imagine that local conditions of one out of 3,000 US counties drive the shift of academic scientists of a given surname. However, one may still have concerns about the shifts of some surnames being serially correlated or having time trends; thus, the shifts may not be as good as random. Consequently, we test the serial correlation and existence of time trends for the shift of each surname. Figures A11a and A11b plot the estimates obtained from regressions of the mobility of academic scientists on the mobility in the previous year and time trend, respectively. We find that 4.4% of surname shifts are serially correlated, and 9.1% of surname shifts have time trends. We again re-construct SSIVs by removing the surname shifts and estimating the baseline model. The results presented in Table A11 confirm that the estimation is not vulnerable to problematic surname shifts.

Although the shift part exploits the national-level mobility of academic scientists and deprives the potentially endogenous part by applying the leave-out strategy when constructing the SSIV, one may still be concerned that within-US mobility is endogenous to an unobserved local condition of a given county. To alleviate such concern, we use the international mobility of scientists instead of within-US mobility as the shift part. Further, we exclude scientists moving across the US boundaries, i.e., scientists moving into or out of the US Intuitively, the yearly number of non-US international mobility of scientists is unlikely to be correlated with the local condition of a certain US county. Table A12 confirms that the results are consistent with the alternative SSIV that uses non-US international mobility as the shift.

We conclude the validity check for the SSIV by testing the over-rejection of the null hypothesis due to the effective absorption of local conditions. Following Balsmeier et al. (2020) and Adao et al., (2019), we run three placebo tests, each of which we estimate the baseline model by shuffling the SSIV randomly across the overall sample, across counties within each year, and across years within each year. The results presented in Table A13 confirm that randomly reassigned SSIVs do not predict the treatment variable and further show that falsely instrumented treatment variables do not reject the null hypothesis.

IV regression results

Table 3 presents the estimation results of IV regressions, generally endorsing the Fixed effect regression results above but providing a causal interpretation. Model (a) presents the first stage OLS regression of exposure to academic science on the SSIV. This shows a positive and significant correlation between SSIV and exposure to academic science, supporting that the SSIV can be used to predict the change in the level of exposure to academic science. Model (b) presents the results of IV regression of science-based inventions on the exposure of academic science. The F-statistic is well above conventional levels; this suggests that the SSIV does not incur a weak instrument problem (Lee et al., 2021). Model (b) shows that exposure to academic science increases the number of science-based inventions. The estimate in Model (b) suggests that a 1% increase in exposure to academic science due to incoming academic scientists leads to a 0.41% increase in the number of science-based inventions created by corporate inventors. In absolute value, it suggests that a 100% increase in exposure to academic science increases 4.7 science-based inventions created by corporate inventors.

Models (c) and (d) present the estimation results regarding the impact of academic science on science-based inventions using novel technological approaches. These results together confirm that academic science increases the number of corporate inventions with unprecedented recombination between components in an original way. Model (e) – (g) present the estimation results regarding the impact of academic science on the quality of corporate innovation. These results demonstrate a significant effect of academic science on both extremes of citation distribution, yet no significant effect of academic science on mediocre impact was found.

Table 3 here

Robustness check on baseline findings

We conduct various robustness checks presented in Table 4 to address potential concerns and confirm the robustness of the baseline findings. First, Model (a) presents a placebo test on the effect of academic science on corporate inventions that are not based on science. One may concern that academic science may increase the total volume of inventions and thus increases the number of inventions based on science. If academic science increases corporate inventors' use of science in the production of innovation, it should not increase non-science-based inventions as much as science-based inventions do or have no influence on non-science-based inventions. The estimate of IV regression in Model (a) alleviates such concern by showing that the impact of academic science is muted for corporate inventions that are not based on science.

Second, one may concern that the increase in science-based inventions is driven by inventions in which a university is directly involved. Model (b) shows the results of IV regression of science-based inventions but excludes patents assigned to a firm and university together, showing consistent results. This shows that the results are not driven by inventions that a university is directly involved in the process of inventions.

Third, we address the concern that the results are driven by counties that are active in technological innovation. Model (c) shows results of IV regression, where we exclude the top 10 counties in terms of the number of patent applications between 1996 and 2013 from the sample. It also shows consistent results, supporting that our results are not driven by counties that are highly innovative.

Fourth, the results of additional tests for science-based inventions using novel technological approaches are presented in Model (d) and (e). In measuring novel approaches in inventions, the main analyses exploit combination patterns between CPC main groups. However, one may be concerned that CPC main group is a broad classification, and thus unprecedented or original ways of recombination may not be captured effectively. To address this concern, we count the number of inventions with novel recombination and originality based on CPC subgroup classification and test whether the results are robust to the alternative measures. Models (g) and (h) present the results of IV regression of science-based inventions with a novel approach captured by having at least one pair of unprecedented CPC subgroups and having a highest 10% originality value as measured by HHI based on CPC subgroups, respectively, confirming the robustness to alternative measurements based on CPC subgroup classification.

Fifth, Models (f) and (g) present the results of robustness check on highly impactful inventions. Models (f) and (g) consider science-based patents located in the top 5% and 1% of forward citation distribution, respectively, as they are considered a breakthrough invention in the prior literature (Singh & Fleming, 2010; Jung & Lee, 2016; Balsmeier et al., 2017). These models confirm that the result is robustness to alternative cutoffs in forward citation distribution for highly impactful inventions.

Table 4 here

Mechanisms

In this section, we evaluate potential mechanisms by which increased exposure to academic science by incoming scientists influences local corporate inventions. Although the validity of the SSIV enables identifying the causal impact of exposure to academic science on corporate inventions, it does not inform the underlying mechanisms. First, we demonstrate two channels through which incoming academic scientists influence innovation at firms: i) increasing reliance on their knowledge and, ii) facilitating spillover of knowledge about their fields. As we previewed in the Fixed effect regression results, Models (a) and (b) in Table 5 demonstrate that, in response to arrival of academic scientists, firms increase the number of patents that cite a scientific paper of incoming academic scientists (presented in Model (a)) and that cite a scientific paper in a field overlapped with incoming academic scientists' papers (presented in Model (b)). These results confirm that increased exposure to academic science by incoming academic scientists leads to an increase in patents that rely on the incoming scientist's knowledge as well as a spillover of knowledge about their knowledgeable fields. In particular, based on a back-of-the-envelope calculation, corporate inventors' use of science that overlaps with a field of incoming academic scientists accounts for 74% of the increase in science-based patents.

Second, we demonstrate that the increase in science-based inventions is mainly driven by inventions relying upon science originating from a university. We classify types of science that inventions relied upon science originating from university and non-university institutions by using the affiliation information of scientists. Non-university science is science discovered by scientists with non-university affiliations, including corporate and government laboratories. Model (c) and (d) in Table 5 show the results of IV regression of university and non-university science-based inventions, respectively. The results reveal that the increased science-based inventions are mainly inventions relying upon science originating from a university. Further, the impact of academic science is muted for the inventions relying on non-university science. These results point to corporate inventors using science from university rather than non-academic science, such as corporate science, when exposure to academic science increases.

Third, we perform a heterogeneity analysis of the effect of academic science based on the type of firms: startups vs. established firms. We separate inventions created by startups from inventions created by established firms based on the incorporate dates of assignees. We count science-based inventions assigned to an assignee who has been 5 years or younger since its incorporation as inventions created by startups, and science-based inventions assigned to an assignee who has been 6 years or older since its incorporation as inventions created by established firms. As Model (e) and (f) in Table 5 demonstrate, both startups and established firms increase science-based inventions when they are exposed to academic science. However, the effect size is significantly larger for established firms, suggesting that firms' resources and accumulated R&D capabilities help firms to adopt academic science in the production of innovation.

Table 5 here

DISCUSSION AND CONCLUSION

By examining how academic science is used in corporate innovation and providing causal evidence, this study contributes to the prior literature and provides practical implications for firm managers and policymakers. First, this study adds texture to understanding of the role of academic science in corporate innovation. Since Jaffe (1989) first noticed the significant relationship between academic research and innovation activities of firms in the industry, several prior studies examine the linkage between academia and the industry. Prior literature examines the linkage from various perspectives, including the impacts of having a university on the local inventions (e.g., Andrews, 2022), various channels through which academic science is diffused to the industry (e.g., Jensen & Thursby, 2001 for licensing; Zucker & Darby, 2006 for interaction between scientists and firms), the knowledge provided by academic scientists depending on their research experience (Kaiser et al., 2018), and firms' engagement with universities when they have access to university knowledge (Hausman, 2022). However, how academic science shapes the detailed dynamics of the production of inventions remains understudied. Extending the prior literature, this study provides a theoretical explanation of how corporate inventors use academic science to search for scientific and technological opportunities when they are exposed to academic science. Further, it demonstrates how academic science increases inventions on the extremes of impact distribution. Therefore, this study enhances the understanding of the dynamics of how academic science leads to commercial R&D activities in the industry.

As the study theoretically discusses how academic science helps search through the scientific literature, it also contributes to prior literature on search. While several prior studies emphasize the importance of search activities and suggests various dimensions that characterize the search activities in the invention processes, e.g., local vs. boundary-spanning search (Rosenkopf & Nerkar, 2001), depth and breadth of search (Katila & Ahuja, 2002), or by the type of target knowledge (Jung & Lee, 2016), Fleming & Sorenson (2004) suggest that science becomes a map that enables inventors' search processes. Prior studies also suggest how firms conduct internal scientific research to support their downstream innovation (Arora et al., 2018) as well as to acquire and utilize externally developed knowledge (Rosenberg, 1990). This study extends the literature by focusing on academic science, a specific type of science with distinctive characteristics, and examining the role of academic science in search of corporate innovation.

Specifically, this study suggests that academic science helps not only the technological search for novel approaches similar to the role of science suggested by prior studies but also the search through scientific literature.

Second, this study provides causal evidence on the relationship between academic science and commercial inventions. Although prior studies attempt to provide evidence on the causal effect of universities on economic factors, including commercial inventions (e.g., Aghion et al. 2009; Kantor & Whalley, 2014; Andrews, 2022; Hausman, 2022), it is hard to disentangle whether such university impact is attributed to the effect of academic science on corporate innovation. Though Andrews (2022) demonstrates that the establishment of a university increases local inventions using college site selection experiments[11], it does not provide a direct causal link between academic science and corporate inventions. Hausman (2022) narrows the focus down to the impact of increased accessibility to scientific knowledge in universities and demonstrates how it leads to an industry agglomeration as well as to an increase in firms' activities to acquire academic science by using the differential increase in accessibility to university knowledge for each industry after the 1980 Bayh-Dole Act. Though providing insights into how firms engage with universities when they have better access to academic science, it also does not provide causal evidence on how academic science shapes the process of corporate innovation in detail. Extending prior studies, this study provides causal evidence of how academic science influences inventions created by corporate inventors.

As the study demonstrates how academic science influences local inventions, its causal evidence also contributes to prior literature emphasizing the localized spillover of academic research. While geographically localized spillover of knowledge is well documented in many existing studies (e.g., Jaffe et al., 1993; Belenzon & Schankerman, 2013; Singh & Marx, 2013), a few studies also find geographically localized spillover of academic research from universities to the local industry (Jaffe, 1989; Furman & MacGarvie, 2007; Kantor & Whalley, 2014). Adam (2002) suggests that the spillover of academic research originating from university labs is much more localized than that of knowledge originating from the industry. Evidence of localized knowledge spillover can also be found in prior studies on how local invention activities depend

[11] College site selection experiments of Andrews (2022) compares a county selected for a site of new college establishment and the runner-up county, of which share similar regional characteristics.

on local universities (Rosenberg & Nelson, 1994; Valero & Van Reenen, 2019; Andrews, 2022) or direct interaction between star scientists and local firms (Zucker et al., 1998; Zucker et al., 2002; Zucker & Darby, 2006). This study demonstrates that the impact of increased academic science available in a given county leads to changes in the invention activities of corporate inventors within the county, thereby adding empirical evidence on how scientific knowledge diffuses throughout the geographical region and its impact on R&D activities in the industry is localized.

The clarification on the role of academic science in corporate innovation provides managerial and policy implications conducive to commercial R&D activities in the industry and knowledge flow from academia to the industry. This study suggests that firm managers pay particular attention to and manage the level of their corporate inventors' exposure to academic science depending on their desirable R&D direction and outcomes. As it demonstrates, corporate inventors' explorative R&D activities based on academic science do not always lead to successful outcomes. In fact, such activities sharply increase failed outcomes. When firm managers aim for refinement and incremental development building on prior knowledge, they might want to limit the corporate inventors' exposure to academic science. By contrast, when firm managers are willing to take a risk and develop inventions with a more significant impact, it is worthwhile to consider implementing various means to increase corporate inventors' exposure to academic science, e.g., the establishment of R&D laboratories nearby a university, formal collaboration with academic scientists, or providing incentives for corporate inventors to participate in conferences or seminar.

The findings also suggest that policymakers devise measures to support firms' R&D activities based on academic science. In other words, policymakers should consider supporting the demand side of academic science, in addition to the current policy supporting the supply side of academic science. As this study demonstrates, while academic science leads to highly impactful inventions, at the same time, it often results in failed inventions. As innovation processes are extremely expensive, imposing all the cost of innovation on a firm may hinder firms from taking risks in their R&D activities. Thus, policy initiatives that lessen the burden of the firms' cost of using academic science, e.g., implementing a tax credit for inventions using academic science, should be devised to reduce the burden on firms' innovation activities. Indeed, governments already allocate billions of dollars to academic research of universities—governments in the US, for instance, funded a total of $50.8 billion in 2020 for US universities (Higher Education Research and Development Survey, 2021).[12] Not only supporting research activities, but governments also encourage the use of academic science in the market and society. For instance, the National Science Foundation of the US established a new directorate called Technology, Innovation, and Partnerships in March 2022, aiming to help accelerate the translation of research in laboratories to technological advancement and bring it to the market and society. Along with these current supports of governments centered on the activities of universities, i.e., the supply side of academic science, it is also imperative to implement policies that help the use of academic science in the industry, i.e., the demand side of academic science, to increase corporate innovation based on academic science.

[12] https://ncses.nsf.gov/pubs/nsf22311/

REFERENCES

Adams, J. D. (2002). Comparative localization of academic and industrial spillovers. Journal of Economic Geography, 2(3), 253-278.

Adao, R., Kolesár, M., & Morales, E. (2019). Shift-share designs: Theory and inference. The Quarterly Journal of Economics, 134(4), 1949-2010.

Aghion, P., Boustan, L., Hoxby, C., & Vandenbussche, J. (2009). The causal impact of education on economic growth: evidence from US. Brookings papers on economic activity, 1(1), 1-73.

Agrawal, A., & Henderson, R. (2002). Putting patents in context: Exploring knowledge transfer from MIT. Management Science, 48(1), 44-60.

Ahmadpoor, M., & Jones, B. F. (2017). The dual frontier: Patented inventions and prior scientific advance. Science, 357(6351), 583-587.

Ahuja, G., & Morris Lampert, C. (2001). Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. Strategic Management Journal, 22(6-7), 521-543.

Andrews, M. J. (2022). How do institutions of higher education affect local invention? Evidence from the establishment of US colleges. American Economic Journal: Economic Policy.

Arora, A., Belenzon, S., & Patacconi, A. (2018). The decline of science in corporate R&D. Strategic Management Journal, 39(1), 3-32.

Arora, A., Belenzon, S., & Sheer, L. (2021). Knowledge spillovers and corporate investment in scientific research. American Economic Review, 111(3), 871-98.

Arora, A., Belenzon, S., & Suh, J. (2022). Science and the Market for Technology. Management Science.

Arora, A., & Gambardella, A. (1994). The changing technology of technological change: general and abstract knowledge and the division of innovative labour. Research Policy, 23(5), 523-532.

Arts, S., & Fleming, L. (2018). Paradise of novelty—or loss of human capital? Exploring new fields and inventive output. Organization Science, 29(6), 1074-1092.

Arts, S., & Veugelers, R. (2015). Technology familiarity, recombinant novelty, and breakthrough invention. Industrial and Corporate Change, 24(6), 1215-1246.

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. American Economic Review, 103(6), 2121-68.

Azoulay, P., Fons-Rosen, C., & Graff Zivin, J. S. (2019). Does science advance one funeral at a time?. American Economic Review, 109(8), 2889-2920.

Balsmeier, B., Fleming, L., & Manso, G. (2017). Independent boards and innovation. Journal of Financial Economics, 123(3), 536-557.

Balsmeier, B., Fleming, L., Marx, M., & Shin, S. R. (2020). Skilled human capital and high-growth entrepreneurship: evidence from inventor inflows (No. w27605). National Bureau of Economic Research.

Bartik, T. J., & Bartik Timothy, J. (1991). Who benefits from state and local economic development policies?.

Bikard, M. (2018). Made in academia: The effect of institutional origin on inventors' attention

to science. Organization Science, 29(5), 818-836.
Bikard, M., & Marx, M. (2020). Bridging academia and industry: How geographic hubs connect university science and corporate technology. Management Science, 66(8), 3425-3443.
Bikard, M., Vakili, K., & Teodoridis, F. (2019). When collaboration bridges institutions: The impact of university–industry collaboration on academic productivity. Organization Science, 30(2), 426-445.
Belenzon, S., & Schankerman, M. (2013). Spreading the word: Geography, policy, and knowledge spillovers. Review of Economics and Statistics, 95(3), 884-903.
Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. The Review of Economic Studies, 89(1), 181-213.
Breuer, M. (2021). Bartik instruments: An applied introduction. Journal of Financial Reporting, forthcoming.
Byun, S. K., Oh, J. M., & Xia, H. (2021). Incremental vs. breakthrough innovation: The role of technology spillovers. Management Science, 67(3), 1779-1802.
Campbell, B. A., Ganco, M., Franco, A. M., & Agarwal, R. (2012). Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. Strategic Management Journal, 33(1), 65-87.
Card, D. (2009). Immigration and inequality. American Economic Review, 99(2), 1-21.
Chai, S., & Menon, A. (2019). Breakthrough recognition: Bias against novelty and competition for attention. Research Policy, 48(3), 733-747.
Cohen, W. M., Nelson, R. R., & Walsh, J. P. (2002). Links and impacts: the influence of public research on industrial R&D. Management Science, 48(1), 1-23.
Dreyfuss, R. C., Zimmerman, D. L., & First, H. (Eds.). (2001). Expanding the boundaries of intellectual property: innovation policy for the knowledge society. Oxford University Press.
Fleming, L. (2001). Recombinant uncertainty in technological search. Management Science, 47(1), 117-132.
Fleming, L., Mingo, S., & Chen, D. (2007). Collaborative brokerage, generative creativity, and creative success. Administrative Science Quarterly, 52(3), 443-475.
Fleming, L., & Sorenson, O. (2004). Science as a map in technological search. Strategic Management Journal, 25(8-9), 909-928.
Furman, J. L., & MacGarvie, M. J. (2007). Academic science and the birth of industrial research laboratories in the US pharmaceutical industry. Journal of Economic Behavior & Organization, 63(4), 756-776.
Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. American Economic Review, 110(8), 2586-2624.
Hausman, N. (2022). University innovation and local economic growth. The Review of Economics and Statistics, 104(4), 718-735.
Hoisl, K. (2007). Tracing mobile inventors—the causality between inventor mobility and inventor productivity. In A study of inventors (pp. 65-119). Deutscher Universitätsverlag, Wiesbaden.
Iaria, A., Schwarz, C., & Waldinger, F. (2018). Frontier knowledge and scientific production: evidence from the collapse of international science. The Quarterly Journal of Economics, 133(2), 927-991.

Jaffe, A. B. (1989). Real effects of academic research. The American Economic Review, 957-970.

Jensen, R., & Thursby, M. (2001). Proofs and prototypes for sale: The licensing of university inventions. American Economic Review, 91(1), 240-259.

Jones, B. F. (2009). The burden of knowledge and the "death of the renaissance man": Is innovation getting harder?. The Review of Economic Studies, 76(1), 283-317.

Jung, H. J., & Lee, J. J. (2016). The quest for originality: A new typology of knowledge search and breakthrough inventions. Academy of Management Journal, 59(5), 1725-1753.

Kaiser, U., Kongsted, H. C., Laursen, K., & Ejsing, A. K. (2018). Experience matters: The role of academic scientist mobility for industrial innovation. Strategic Management Journal, 39(7), 1935-1958.

Kantor, S., & Whalley, A. (2014). Knowledge spillovers from research universities: evidence from endowment value shocks. Review of Economics and Statistics, 96(1), 171-188.

Katila, R., & Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. Academy of Management Journal, 45(6), 1183-1194.

Lin, C., Liu, S., & Manso, G. (2021). Shareholder litigation and corporate innovation. Management Science, 67(6), 3346-3367.

March, J. G. (1991). Exploration and exploitation in organizational learning. Organization Science, 2(1), 71-87.

March, J. G., & Simon, H. A. (1993). Organizations. John wiley & sons.

Marshall, A. (1890). Principles of Economics (London and New York, Macmillan).

Marx, M., & Fuegi, A. (2020). Reliance on science: Worldwide front-page patent citations to scientific articles. Strategic Management Journal, 41(9), 1572-1594.

Marx, M., & Fuegi, A. (2022). Reliance on science by inventors: Hybrid extraction of in-text patent-to-article citations. Journal of Economics & Management Strategy, 31(2), 369-392.

Marx, M., & Hsu, D. H. (2022). Revisiting the entrepreneurial commercialization of academic science: Evidence from "Twin" discoveries. Management Science, 68(2), 1330-1352.

Marx, M., Strumsky, D., & Fleming, L. (2009). Mobility, skills, and the Michigan non-compete experiment. Management Science, 55(6), 875-889.

Mohnen, M. (2022). Stars and brokers: Knowledge spillovers among medical scientists. Management Science, 68(4), 2513-2532.

Mokyr, J. (2002). The Gifts of Athena: Historical Origins of the Knowledge Economy. Princeton University Press.

Moretti, E. (2021). The effect of high-tech clusters on the productivity of top inventors. American Economic Review, 111(10), 3328-75.

Moretti, E., & Wilson, D. J. (2014). State incentives for innovation, star scientists and jobs: Evidence from biotech. Journal of Urban Economics, 79, 20-38.

Mowery, D. C., & Ziedonis, A. A. (2015). Markets versus spillovers in outflows of university research. Research Policy, 44(1), 50-66.

National Center for Science and Engineering Statistics (NCSES). 2021. Higher Education Research and Development: Fiscal Year 2020. NSF 22-311. Alexandria, VA: National Science Foundation. Available at https://ncses.nsf.gov/pubs/nsf22311/.

Nelson, R. R. (1982). The role of knowledge in R&D efficiency. The Quarterly Journal of

Economics, 97(3), 453-470.
Poege, F., Harhoff, D., Gaessler, F., & Baruffaldi, S. (2019). Science quality and the value of inventions. Science Advances, 5(12), eaay7323.
Polanyi, M. (1958). Personal Knowledge: Towards a Post-Critical Philosophy.
Rosenberg, N. (1990). Why do firms do basic research (with their own money)?. Research Policy, 19(2), 165-174.
Rosenberg, N., & Nathan, R. (1994). Exploring the black box: Technology, economics, and history. Cambridge University Press.
Rosenberg, N., & Nelson, R. R. (1994). American universities and technical advance in industry. Research Policy, 23(3), 323-348.
Rosenkopf, L., & Almeida, P. (2003). Overcoming local search through alliances and mobility. Management Science, 49(6), 751-766.
Rosenkopf, L., & Nerkar, A. (2001). Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. Strategic Management Journal, 22(4), 287-306.
Sauermann, H., & Stephan, P. (2013). Conflicting logics? A multidimensional view of industrial and academic science. Organization Science, 24(3), 889-909.
Sheer, L. (2022). Sitting on the Fence: Integrating the two worlds of scientific discovery and invention within the firm. Research Policy, 51(7), 104550.
Shin, S. R., Lee, J., Jung, Y. R., & Hwang, J. (2022). The diffusion of scientific discoveries in government laboratories: The role of patents filed by government scientists. Research Policy, 51(5), 104496.
Singh, J., & Fleming, L. (2010). Lone inventors as sources of breakthroughs: Myth or reality?. Management Science, 56(1), 41-56.
Singh, J., & Marx, M. (2013). Geographic constraints on knowledge spillovers: Political borders vs. spatial proximity. Management Science, 59(9), 2056-2078.
Sinha, A., Shen, Z., Song, Y., Ma, H., Eide, D., Hsu, B. J., & Wang, K. (2015, May). An overview of microsoft academic service (mas) and applications. In Proceedings of the 24th International Conference on World Wide Web (pp. 243-246).
Stuart, T. E., & Podolny, J. M. (1996). Local search and the evolution of technological capabilities. Strategic Management Journal, 17(S1), 21-38.
Tartari, V., & Stern, S. (2021). More than an ivory tower: The impact of research institutions on the quantity and quality of entrepreneurship (No. w28846). National Bureau of Economic Research.
Thursby, J. G., & Thursby, M. C. (2002). Who is selling the ivory tower? Sources of growth in university licensing. Management Science, 48(1), 90-104.
Uzzi, B., Mukherjee, S., Stringer, M., & Jones, B. (2013). Atypical combinations and scientific impact. Science, 342(6157), 468-472.
Valero, A., & Van Reenen, J. (2019). The economic impact of universities: Evidence from across the globe. Economics of Education Review, 68, 53-67.
Wadhwa, A., & Kotha, S. (2006). Knowledge creation through external venturing: Evidence from the telecommunications equipment manufacturing industry. Academy of Management Journal, 49(4), 819-835.
Waldinger, F. (2016). Bombs, brains, and science: The role of human and physical capital for

the creation of scientific knowledge. Review of Economics and Statistics, 98(5), 811-831.

Zucker, L. G., & Darby, M. R. (1996). Star scientists and institutional transformation: Patterns of invention and innovation in the formation of the biotechnology industry. Proceedings of the National Academy of Sciences, 93(23), 12709-12716.

Zucker, L. G., & Darby, M. R. (2006). Movement of star scientists and engineers and high-tech firm entry.

Zucker, L. G., Darby, M. R., & Armstrong, J. (1998). Geographically localized knowledge: spillovers or markets?. Economic Inquiry, 36(1), 65-86.

Zucker, L. G., Darby, M. R., & Armstrong, J. S. (2002). Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. Management Science, 48(1), 138-153.

FIGURES

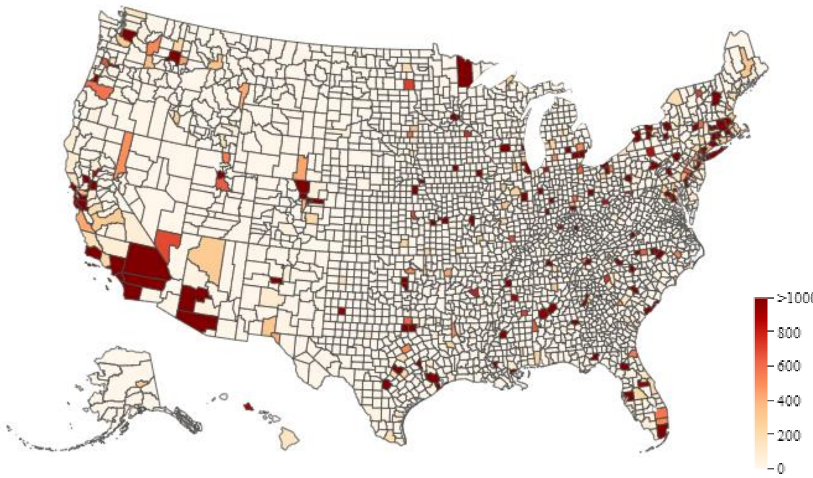

Figure 1 - Geographical distribution of exposure to academic science proxied by the number of incoming academics scientists between 1996 and 2013

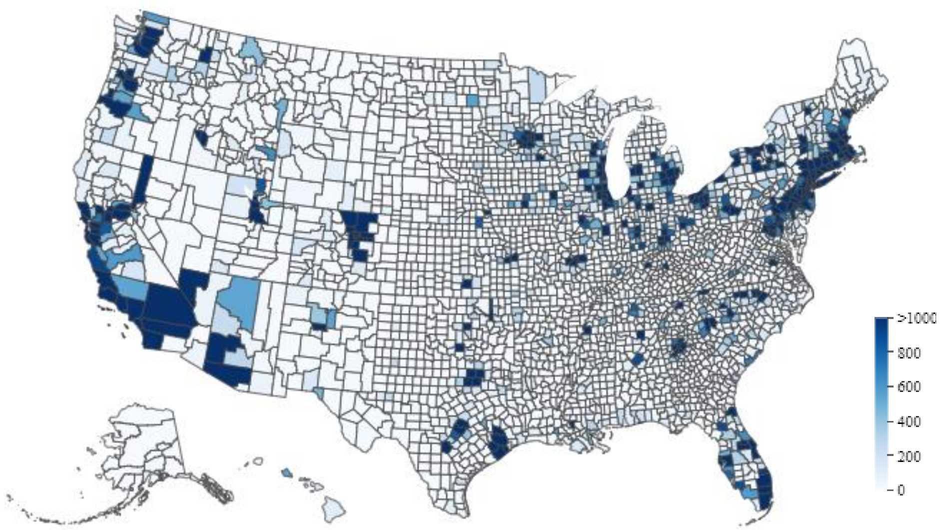

Figure 2a - Geographical distribution of science-based patents between 1996 and 2013

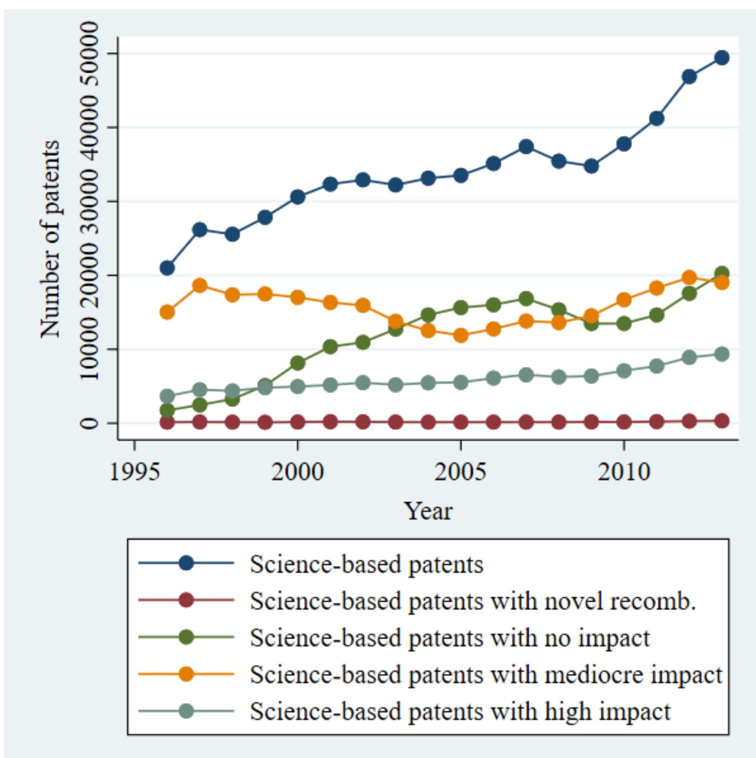

Figure 2b – Yearly number of science-based patents applied from 1996 to 2013

TABLES

Table 1: Descriptive statistics at the US county level

Variables	N	Mean	Median	Std. Dev.	Min	Max
Academic scientists	55,926	8.986	0	63.384	0	2553
Instrument	55,926	7.859	2.492	38.801	0	1506.3
Science-based inventions	55,926	10.969	0	99.425	0	5955.4
Science-based inventions (exclude university)	55926	10.863	0	98.907	0	5941.1
Non-science-based inventions	55926	18.476	.500	122.090	0	7673.6
Science-based inventions with novel recombination	55,926	0.057	0	0.474	0	35.5
Science-based inventions with top 10% originality	55,926	1.716	0	12.669	0	641.3
Science-based inventions with no impact	55,926	3.802	0	37.642	0	2146.1
Science-based inventions with mediocre impact	55,926	5.086	0	44.666	0	2649
Science-based inventions with top 10% impact	55,926	1.922	0	19.171	0	1306.5
Science-based inventions with top 5% impact	55,926	1.054	0	10.632	0	742.2
Science-based inventions with top 1% impact	55,926	0.256	0	2.6079	0	182.9

Table 2: Fixed effects regression results

Estimation method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	Science-based inventions			Science-based inventions with novel approaches		Impact of science-based inventions		
Dependent variable	Cite a paper	Cite a paper of incoming scientists	Cite a paper in the field of incoming scientists	Novel recomb.	Top 10% originality	No impact (no citation received)	Mediocre impact (bottom 90%)	High impact (top 10%)
	a	b	c	d	f	g	h	i
Academic scientists$_{t-1}$	0.071***	0.030***	0.252***	0.010***	0.080***	0.185***	0.006	0.062***
	(0.009)	(0.005)	(0.015)	(0.003)	(0.009)	(0.010)	(0.010)	(0.007)
N	55,926	55,926	55,926	55,926	55,926	55,926	55,926	55,926
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.944	0.843	0.951	0.577	0.906	0.905	0.933	0.923

Notes: The table presents OLS regressions of the number of patents. The dependent variables, Academic scientists, and SSIV are log-transformed. The sample includes 3,107 counties between 1996 and 2013. Specification (a) shows results of the fixed effects regression of patents that cite at least one scientific paper. Specification (b) shows results of the fixed effects regression of patents that cite at least one scientific paper published by an incoming scientist. Specification (c) shows results of the fixed effects regression of patents that cite at least one scientific paper in the overlapping fields of an incoming scientist. Specification (d) shows the results of the fixed effects regression of science-based patents with a novel approach, where we count the number of science-based patents that include one or more novel combinations of main CPC group pair. Specification (f) shows the results of the fixed effects regression of science-based patents with a novel approach, where we count the number of science-based patents that are located in the highest centile of originality distribution. Specification (g) shows results of the fixed effects regression of science-based patents with no impact, where we count only science-based patents that receive no citation from future patents. Specification (h) shows results of the fixed effects regression of science-based inventions with mediocre impact, where we count science-based patents that are cited but not in the highest centile (top 10%). Specification (i) shows results of the fixed effects regression of science-based inventions with high impact, where we count science-based patents that are located in the top 10% of the citation distribution. Each model includes state-year and county fixed effects. Standard errors clustered at the state level are reported in parentheses. ***, ** and * denote a significance level of 1%, 5%, and 10%, respectively.

Table 3: IV regression results

Estimation method	OLS (first stage)	IV	IV	IV	IV	IV	IV
Dependent variable	Academic scientists$_{t-1}$	Science-based inventions	Novel recomb.	Top 10% originality	No impact (no citation received)	Mediocre impact (bottom 90%)	High impact (top 10%)
	a	b	c	d	e	f	g
SSIV$_{t-1}$	0.296***						
	(0.033)						
Academic scientists$_{t-1}$		0.412***	0.075***	0.460***	1.166***	-0.072	0.342***
		(0.070)	(0.018)	(0.065)	(0.112)	(0.057)	(0.057)
N	55,926	55,926	55,926	55,926	55,926	55,926	55,926
F-statistic		82.378	82.378	82.378	82.378	82.378	82.378
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.950						

Notes: The table presents OLS regressions of the number of patents. The dependent variables, Academic scientists, and SSIV are log-transformed. The sample includes 3,107 counties between 1996 and 2013. Specification (a) shows first-stage OLS regression, where regress academic science on the SSIV. Specification (b) shows the results of the IV regression of science-based patents, where academic science is instrumented with the SSIV in the first stage. Specification (c) shows results of the IV regression, where the dependent variable is the count of science-based patents that include one or more novel combinations of CPC main groups pair. Specification (d) shows results of the IV regression, where the dependent variable is the count of science-based patents that are located in the highest centile of originality distribution as measured by the HHI index based on CPC main groups. Specification (e) shows results of the IV regression of science-based inventions with no impact, where we count only science-based patents that receive no citation from future patents. Specification (f) shows results of the IV regression of science-based inventions with mediocre impact, where we count science-based patents that are cited but not in the highest centile (top 10%). Specification (g) shows results of the IV regression of highly impactful inventions, where we count science-based patents that are located in the top 10% of citation distribution. F-statistic is the Kleibergen-Paap Wald F statistic of the first stage regression. Each model includes state-year and county fixed effects. Standard errors clustered at the state level are reported in parentheses. ***, ** and * denote a significance level of 1%, 5%, and 10%, respectively.

Table 4: Robustness checks for main results

Estimation method	IV	IV	IV	IV	IV	IV	IV
Dependent variable	Non-science-based inventions	Exclude university co-assigned inventions	Exclude top 10 counties	Novel recomb. (CPC subgroup)	Top 10% originality (CPC subgroup)	High impact (top 5%)	High impact (top 1%)
	a	b	c	d	e	f	g
Academic scientists$_{t-1}$	-0.005	0.412***	0.402***	0.279***	0.741***	0.264***	0.139***
	(0.063)	(0.072)	(0.069)	(0.055)	(0.086)	(0.043)	(0.030)
N	55,926	55,926	55,746	55,926	55,926	55,926	55,926
F-statistic	82.378	82.378	83.698	82.378	82.378	82.378	82.378
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents IV regressions of the number of patents. The dependent variables, Academic scientists, and SSIV are log-transformed. The sample includes 3,107 counties between 1996 and 2013. Specification (a) shows the results of the IV regression of non-science-based patents. Specification (b) shows the results of the IV regression, where we exclude science-based patents that are co-assigned to a university. Specification (c) shows the results of the IV regression of science-based patents, where we exclude the top 10 counties with the most patents from the sample. Specification (d) shows the results of the IV regression, where the dependent variable is the count of science-based patents that include one or more novel combinations of CPC subgroup pairs. Specification (e) shows the results of the IV regression, where the dependent variable is the count of science-based patents that are located in the highest centile of originality distribution as measured by the HHI index based on CPC subgroups. Specification (f) shows the results of the IV regression, where the dependent variable is the count of science-based patents that are located in the top 5% of citation distribution. Specification (e) shows the results of the IV regression, where the dependent variable is the count of science-based patents that are located in the top 1% of citation distribution. F-statistic is the Kleibergen-Paap Wald F statistic of the first stage regression. Each model includes state-year and county fixed effects. Standard errors clustered at the state level are reported in parentheses. ***, ** and * denote a significance level of 1%, 5%, and 10%, respectively.

Table 5: Mechanisms

Estimation method	IV	IV	IV	IV	IV	IV
Dependent variable	Relation to incoming scientists		Origin of citing paper		Type of firms	
	Cite their paper	Cite a paper in their field	University	Non-university laboratories	Startups	Established firms
	a	b	c	d	e	f
Academic scientists$_{t-1}$	0.102***	0.593***	0.646***	0.056	0.220***	0.679***
	(0.029)	(0.066)	(0.078)	(0.053)	(0.050)	(0.093)
N	55,926	55,926	55,926	55,926	55,926	55,926
F-statistic	82.378	82.378	82.378	82.378	82.378	82.378
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents IV regressions of the number of patents. The dependent variables, Academic scientists, and SSIV are log-transformed. The sample includes 3,107 counties between 1996 and 2013. Specification (a) shows the results of the IV regression, where the dependent variable is the count of science-based patents that cite a paper of an incoming academic scientist. Specification (b) shows results of the IV regression, where the dependent variable is the count of patents that cite a paper in a field that overlaps with an incoming academic scientist' paper. Specification (c) shows results of the IV regression, where we only include university science-based patents. Specification (d) shows results of the IV regression, where we only include non-university science-based patents. Specification (e) shows results of the IV regression, where the dependent variable is the count of science-based patents that are assigned to a startup. Specification (f) shows results of the IV regression, where the dependent variable is the count of science-based patents that are assigned to an established firm. F-statistic is the Kleibergen-Paap Wald F statistic of the first stage regression. Each model includes state-year and county fixed effects. Standard errors clustered at the state level are reported in parentheses. ***, ** and * denote a significance level of 1%, 5%, and 10%, respectively.