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Government R&D spending as a driving force of technology convergence: a case study of the Advanced Sequencing Technology Program

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Abstract

This study investigates the impact of government R&D spending on promoting technology convergence. We test the hypotheses that a government funding program positively affects technology convergence, and that the effects vary depending on the participant (i.e., academic and industrial inventors). We used the Advanced Sequencing Technology Program (ASTP) as an example to investigate this issue. We develop a novel dataset by linking the ASTP grantee information with the PATSTAT patent database. On this basis, we develop inventor-level characteristics for propensity score matching, selecting a control group of inventors from among those enrolled in the ASTP. Then, we employ difference-in-difference models to assess the program's impact on the matched sample. The results support the program's role as a driving force of technology convergence. The findings also indicate that the program has a greater influence on industry inventors than on academic counterparts. Furthermore, we conceptualize the program's "leverage effect" and demonstrate that it can attract more external industrial inventors than academic inventors. The work advances our understanding of the role of a government-funded program in encouraging convergence and has implications for developing convergence-related R&D programs in the future.

Keywords Technology convergence · NIH program · Policy analysis

JEL Classification O33 · O38

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Introduction

Technology convergence refers to the emergence of overlapping trends in at least two technological fields. Following Kodama's (1995) seminal perspective, which states that combining existing technologies can spawn novel ones, technology convergence is considered a source of innovation. Notably, given the complementary nature of contemporary general-purpose technologies (GPTs) (e.g., nanotechnology and information technology, IT), new technologies are expected to be developed through the form of convergence. The concept of innovation-as-combination can be traced back to Schumpeter's (1939) notion: "… innovation combines factors in a new way, or that it consists in carrying out new combinations." By emphasizing innovation as the sine qua non of economic development and firms as a carrier of implementing innovation, Schumpeter (1939) metaphorized firms as human beings that are constantly being born and destined to die. In the case of firms, they die as they cannot keep up with the pace at which they innovate and are eventually overtaken by others. Hence, policymakers and corporate management (e.g., entrepreneurs) need to keep an eye on technology convergence as one of the roots of innovation to promote economic growth and stay ahead of the competition.

Several researchers laid the theoretical groundwork for technological convergence and taxonomies (Curran & Leker, 2011; Karvonen & Kässi, 2013), whereas others contributed to methodological development for understanding historical patterns or forecasting future convergence opportunities (Eilers et al., 2019; Kim & Lee, 2017; Kim & Sohn, 2020; Kim et al., 2014, 2019a, 2019b; Ko et al., 2014; Lee et al., 2020; Passing & Moehrle, 2015; Preschitschek et al., 2013; Zhou et al., 2019). One of the primary goals of understanding technology convergence is to assist business entities in detecting and exploiting new opportunities, organizing research and development (R&D), and surviving in the current dynamic business environment. From another perspective, the convergence processes, as a source of innovation, can give birth to innovation that can either create untapped niche markets or drastically transform people's lives.

The perceived importance of technology convergence and academic efforts to conceptualize and quantify it may point to a more fundamental and pivotal question of what drives technology convergence (Jeong & Lee, 2015; Sick & Bröring, 2021). Drawing on Curran and Leker's (2011) four-stage sequential process (i.e., science, technology, market, and industry), growing cross-disciplinary research collaborations will erode the boundary and reduce the distance between science areas, eventually leading to technology convergence. The framework implies that convergence can be driven by both scientific push and market pull. Song et al. (2017) classified convergence drivers into four categories: technological advancement, regulation and policy, market expectations, and changes in the social environment. Although these works provide a starting point for investigating the drivers of convergence, only a few studies provided empirical evidence and explanations for what triggers the convergence (Caviggioli, 2016; Jeong & Lee, 2015). Moreover, previous research on this topic yielded only broad conclusions, stating that convergence can be driven by closely related technological fields, a lower level of technological readiness, and a longer R&D time horizon.

Indeed, endogenous growth economists believe that the R&D sectors can steer technological innovation by leveraging human capital and the existing stock of knowledge, resulting in sustainable and pervasive economic growth (Romer, 1986; Aghion et al., 1998). The non-rivalry nature of technological knowledge as a driver of macroeconomic growth necessitates government support for R&D to increase the private return on R&D investment to a societal-wide level. Because technology convergence facilitates technology spillovers at the societal level, understanding the impacts of the government support program on convergence technology, not only on program participants but also on society as a whole, is crucial. To this end, we attempt to uncover the underlying mechanism by which a government-funded program affects the behavior of industrial and academic inventors, who are the primary players in the convergence process.

The program we explore in this study is the Advanced Sequencing Technology Program (ASTP) (or the Advanced Sequencing Technology awards), which is funded by the US National Human Genome Research Institute (NHGRI). Although the program has been credited with its contribution to reducing the costs of genome sequencing, it is also recognized as an endeavor that constantly accentuates multidisciplinary collaborations and guides public–private partnerships (Hayden, 2014). Several programs' distinctive features, such as mandatory grantee meetings, benefit knowledge transfer across the sectors and promote information dissemination to external entities. In these ways, ASTP is a better fit for our goal of examining the effects of government R&D investment on promoting technological convergence.

The government-funded R&D program has been identified as one of the drivers of technology convergence (Jeong & Lee, 2015); however, its mechanism remains under-investigated. To that end, this study contributes to a better understanding of how government programs can drive convergence by examining the various roles of universities and private firms in developing and disseminating converged technologies to society. We conduct an empirical analysis using the ASTP as a target example because the program has successfully promoted the development of Next-generation sequencing (NGS) technology (convergence of IT and BT) by emphasizing multidisciplinary team participation and university–industry (U–I) collaborations (Hayden, 2014; Nature, 2014). The results suggest that the program would (1) encourage industrial firms to produce more convergent outputs than academic counterparts and (2) entice more industrial players to participate than academic scholars. The study's findings are expected to serve as a foundation for justifying the role of government funding in promoting convergence.

The remainder of this paper is structured as follows. Sect. "Literature review" reviews the literature on technology convergence and its drivers and the study's hypotheses. Sects. "Data" and "Methodology" present an overview of the program under study and an illustration of the process for constructing the dataset and models for analyzing the ASTP. Sect. "Methodology" shows the empirical results and an analysis of the impact and implications of government R&D spending. Finally, Sect. "Results" summarizes and discusses the findings of the study.

Literature review

Technology convergence and its drivers

Although the definition of technology convergence differs depending on the managerial scope (Hacklin, 2008), we refer to it in this study as a combination of existing technologies. Spillovers between fields eventually lead to convergence when different technological boundaries erode. One classic example of technological convergence is the birth of digital photography, which uses an electronic sensor to replicate the traditional chemical-based film process, revolutionizing the film industry (e.g., the rise and fall of Kodak). Unlike the traditional approach, which seeks breakthroughs through a linear R&D pattern, the convergence approach focuses on emerging new technologies by combining disparate ones. Hence, this approach is more complementary and collaborative (Kodama, 1992). Additionally, Schumpeter (1934) maintained in his seminal work, The Theory of Economic Development, that innovation is a combination of existing resources. As a result, technology convergence could be viewed as an instance of the combinatorial process in this context by explicitly emphasizing the hybridization of technologies. The demise of the adage "one technology, one industry" clearly demonstrates the increasing exposure of the convergence phenomenon (Kodama, 1992).

Sick and Bröring (2021) thoroughly reviewed the literature on technology and innovation management convergence. Prior works on technological convergence have made significant efforts in methodological development to identify historical convergence patterns or anticipate future convergence possibilities through patent analysis (Eilers et al., 2019; Karvonen & Kässi, 2013; Ko et al., 2014; Preschitschek et al., 2013). Acknowledging their great implications for enterprises and policymakers, we must return to the central topic in convergence research, namely, which drivers promote the convergence process. From the evolutionary perspective, Hacklin (2008) conceptualized the convergence process into four phases: knowledge, technological, applicational, and industrial convergence. Curran et al. (2010) then presented a four-stage model that depicted the sequential order of science, technology, market, and industry convergence. The model suggests that technological convergence may be fueled by science/technology push and market pull, which Mowery and Rosenberg (1979) have identified as an innovation driver. Song et al. (2017) proposed a taxonomy of four groups to account for the numerous factors contributing to convergence: technological progress, regulation and policy, market expectation, and social change. In terms of technological advancement, the rapid growth of the information and communications technology (ICT) industry can be viewed as the primary source and driver of convergence, as evidenced by the recent digital transformation (Han & Sohn, 2016). Furthermore, other GPTs, such as IT and nanotechnology, may serve as a vital knowledge provider to various fields (Appio et al., 2017) due to their high technological generality (Gambardella & Giarratana, 2013). Meanwhile, market expectations emphasize demand-side convergence. Dowling et al. (1998) asserted that increased purchasing power could result in a significant market demand for products with integrated functions, motivating firms to adopt and coordinate a variety of technologies. Regarding social change, convergence is propelled by the challenges and needs that society faces. For example, the recent expansion of green technology necessitates the convergence of various GPTs.[1]

Policy and technology convergence

The policy can be designed to eliminate both artificial and technological barriers between various technological fields. One example of removing artificial barriers would be the Telecommunications Act of 1996, which unlocked the restriction between the telephone sector and the IT industry. In this case, policymaking may be more closely aligned with deregulation. Another definition of technological barriers is the distance between distinct

[1] OCED: https://www.innovationpolicyplatform.org/www.innovationpolicyplatform.org/content/bio-nano-and-converging-technologies-green-innovation/index.html.

technological domains and the costs of combining them. Discipline-specific terminology, theories, and cognitive differences can result in significant transaction costs when attempting to achieve convergence in a multidisciplinary setting (Nordmann, 2004). Furthermore, Jeong et al. (2011) asserted that even within the same organization, researchers are hesitant to collaborate with colleagues from different backgrounds when technology readiness is high. The government can encourage technological convergence through public R&D funding or a multidisciplinary incentive program. According to Littler and Coombs (1988), government-supported programs typically cover a broader range of technical fields than private-sector projects but are developed with a modest speed. Metzger and Zare (1999) questioned the efficacy of such programs in promoting technological convergence. However, Jeong and Lee (2015) empirically demonstrated that government-funded R&D initiatives with a longer time horizon or a lower budget positively impacted convergence. Moreover, Kim et al. (2017) showed that standards can drive technology convergence by directing technological trajectories.

In addition to these two barriers, the uncertainties and costs associated with convergence should be considered. Ambiguity in the market and technological scope are two types of uncertainty frequently highlighted. Technological uncertainty refers to the incapacity to fathom some facets of technological environments (Song & Montoya-Weiss, 2001). This is a common occurrence in the context because convergence has the potential to connect previously unrelated fields (Hacklin et al., 2013). Another source of concern is market uncertainty, which occurs when extremely innovative products initially attract only the least profitable customers (Bores et al., 2003). Furthermore, realizing convergence potential necessitates a significant initial investment, which may cause enterprises to reallocate resources to other endeavors (e.g., more promising near-term product development). Companies may suspend or even discontinue these initiatives to avoid potential market failure, resulting in underinvestment in knowledge creation through convergence. From this perspective, government-supported programs featured with U–I knowledge exchange can aid in reducing R&D market failures and ensure investments' benefits (Martin & Scott, 2000). Jeong (2014) showed that firms are more likely to develop converging technologies when collaborating with public organizations such as universities and government research institutes. The peer-review process adopted by government agencies, such as the National Science Foundation (NSF) and the National Institutes of Health (NIH), has also been cited as a critical factor in success (Metzger & Zare, 1999). Empirical evidence suggests that NIH review panels can effectively access the most outstanding impact projects; that is, the higher the review scores, the better the quality, and the higher the productivity (Li & Agha, 2015; Park et al., 2015).

In summary, the existing literature on the impact of government policy on technology convergence provided a hint that deregulations and public funding programs may be a driver of convergence. However, we found that related empirical works on this topic are still scarce, which motivated us to devote efforts to this field.

Hypotheses

According to the literature review presented in Sect. "Policy and technology convergence", scholars have investigated the relationship between government funding programs and technological convergence. Multidisciplinary cooperation, which provides a knowledge foundation for convergence, is one of the most critical characteristics of technology convergence. The participation of specialists from various backgrounds may spark novel ideas and inspirations while collaborating. However, a multidisciplinary configuration implies that developing convergence-related projects will be more hazardous and time-consuming (Schmoch et al., 1994). That is, participants require more time to become acquainted with people from diverse backgrounds and more cycles of testing and failure to identify suitable solutions. Veugelers and Wang (2019) argue that novel combinatorial invention has a high-risk/high return nature by demonstrating that novel research combining atypical knowledge sources is more likely to have a greater technological impact. However, it also faces a high level of failure because it scouts for uncharted waters. Uncertainty and risks would be less of an issue if the capital market functioned flawlessly, allowing industrial firms and investors to accurately assess and allocate funds to convergence projects with high expected returns (Arrow, 1962; Greenhalgh & Rogers, 2010). However, it is difficult for the private sector to finance convergence projects in the real world. For starters, the complexities of developing converging technologies may result in significant information asymmetry between investors and innovators (Tuncalp & Ercek, 2014). In other words, investors would have to rely heavily on the judgment of the innovator's team because they are the only ones who understand the project. Second, if the costs of developing converging technology (fixed costs) are disproportionate to the marginal costs of producing it (variable costs), competitive market pricing becomes irrelevant (Greenhalgh & Rogers, 2010). Under this situation, it is difficult for firms even to reach a break-even point when demand for this new technology is flat. With these threats, industrial firms are more likely to shift their focus to short-term and insured endeavors, resulting in an underinvestment of convergence. In this regard, government funding programs that provide longer-than-usual grant durations can allow innovators to conduct in-depth studies rather than focusing on quick success. In the early decades of the twenty-first century, government-supported initiatives (e.g., those held by the NSF, NIH, and others) that incorporated a multidisciplinary setup (primarily focusing on the convergence of nanotechnology, biotechnology, BT, and IT), typically provided a long-term funding plan (Roco & Bainbridge, 2002).

Furthermore, because technological convergence is primarily commercial, it necessitates the commercial potential and feasibility of interdisciplinary knowledge. In this light, the experience of the US government's innovation programs can be learned, which fostered commercial applications and attracted nonfederal investment in R&D by promoting U–I collaborations or directly sponsoring industrial enterprises (Roessner, 1989). The inclusion of industrial entities emphasizes the commercial viability of developed projects, thereby encouraging technological advancement. Furthermore, U–I collaborations improve knowledge diffusion between academia and industry. This influence could be bidirectional. On the one hand, firms can stay abreast of cutting-edge academic research findings and recruit highly competent and well-matched personnel. On the other hand, academic scholars can gain insight into what is happening in the industry sector, understanding the potential applications of their work. Moreover, this case may allow some academics to transition from pure scientific exploration to technological research. Hence, we propose the following hypothesis:

H1 A government-funded R&D program has a positive impact on promoting technology convergence.

Second, university and industry are regarded as two of the most critical pillars of technological progress. As a result, we want to break down the analysis further to investigate the roles of academic and industrial inventors in the convergence process. Typically, government-funded R&D programs include an explicit goal of knowledge creation. However, their management practices (e.g., reciprocal information-sharing mechanisms) could facilitate mutual learning across disciplines and sectors, thereby potentially reducing the cognitive distance between academic and industrial participants. Local search routines (the preferential attachment effect) frequently constrain firms, causing them to search in a unidimensional space close to their business field and knowledge base (Katila & Ahuja, 2002; Kim et al., 2019a, 2019b). In this sense, the shortened cognitive distance will enable companies to gain higher absorptive capacity and go beyond their knowledge domains, quickly acquiring new value or knowledge and translating it into innovation (Cohen & Levinthal, 1990). Furthermore, unlike science-based knowledge, which is sufficiently codifiable, firm-based knowledge is more implicit, making dissemination more challenging (Kani & Motohashi, 2020; Kogut, 1988). According to Jeong and Lee (2015), convergence is more likely to occur at the basic science stage than at the application stage. A higher technology readiness level (TRL) indicates greater technological complexity and diversity, resulting in high transaction costs when recombining distinct technological knowledge (Brousseau, 1993). Furthermore, unlike scientific knowledge, which is considered a public good, technologies are frequently protected by intellectual property laws, adding to the transmission difficulty. In this regard, a government-supported R&D program with a clear convergence focus could encourage industrial inventors to develop relevant development plans at an early stage.

Another consideration is that the efficacy of reduced cognitive distance to university scholars may be hampered in several ways. Several initiatives have been launched to promote multidisciplinary collaboration in universities. However, current assessment mechanisms continue to place a premium on individual achievement, disincentivizing faculty and departments to work across fields (Klein & Falk-Krzesinski, 2017; Pfirman & Martin, 2017). Arnold et al. (2021) noted that tenure/promotion committees in a unidisciplinary setting may assess an academic worker more objectively than in a multidisciplinary setting by comparing the productivity and impact of scholarly work to that of colleagues within a discipline. In addition, jumping into an unfamiliar field is risky for an academic researcher. Furthermore, unlike scientific knowledge, which is generally considered a public good, technology is frequently protected by various tools (e.g., patents and trade secrets) to achieve commercial value. Hence, as a source of new technologies, technological convergence inherently bears a part of commercial purposes. In this sense, university researchers frequently place a high value on publishing activity because it carries a higher level of prestige than commercialization (Sauermann & Stephan, 2013). However, companies typically prioritize the technology's commercialization potential. Moreover, programs that encourage industrial forms for convergence-related projects would encourage businesses to shift from short-run to long-run convergence innovation activities. Firms were previously less likely to engage in such long-term activities due to the risks and high initial investment (Feldman & Kelley, 2006). Therefore, firms are more compelled to engage in technology development and patenting activities. This notion leads us to our second hypothesis:

H2 Among the funded inventors, a government-funded R&D program has a greater impact on industrial inventors than university inventors.

H2 aims to describe the behaviors of the funded inventors. We then want to study how a program influences the behavior of inventors outside of the program, which can be divided into university and industry groups. Existing research has shown that, from a resource standpoint, industrial firms are more likely to engage in new technology development after perceiving diverse external knowledge (Gittelman & Kogut, 2003; Wirsich et al., 2016). However, such knowledge is not appropriable unless someone can accurately evaluate its commercial viability (Poyago-Theotoky et al., 2002). According to Rikkiev and Mäkinen (2013), business managers are hesitant to take on convergence projects if they lack market-side perception. In this case, an R&D program that funds not only academic researchers but also companies could send a signal to external parties (Long, 2002). Involving industrial players would highlight the commercial feasibility of developed projects, increasing the likelihood of attracting outside firms' attention. In addition, even if new markets and demands created by converged technologies appeal to firms (Park, 2017), skeptics in the private sector may be hesitant to accept convergence ideas at this early stage due to high uncertainty. In this regard, a program's scholarly peer-review process may increase the authority of concepts, reducing information asymmetry between insiders and outsiders (Greenhalgh & Rogers, 2010). Moreover, the program itself can serve as a conduit for the external audience to see and obtain reassurance about related results and accomplishments, shifting their mindset from risk-averse to risk-neutral.

We further conceptualize the attractive force to external players as "leverage effects." That is, the government takes the initiative to invest in convergence ideas and then discloses internal progress and conclusions to pique external parties' interest. Given the enormous costs of developing technologies through convergence, government spending may be a drop in the bucket. However, the government can use a funding program to increase the input force (government R&D spending) to provide a larger output force (potential private investors, industrial and academic participants), resulting in social benefits. Because of the commercial nature of technology convergence, external industrial inventors are expected to see greater leverage effects than university inventors. Finally, we propose the following hypothesis:

H3 Government R&D spending has a more significant impact on attracting external industrial inventors than academic inventors. In other words, the program's leverage effects are more effective/visible to external industrial inventors than to university inventors.

Conceptualization

Figure 1 depicts the positions of the three hypotheses. Although convergence can generate new technologies, it is frequently accompanied by barriers, uncertainties, and substantial initial investments. H1 maintains that a government-funded R&D program could drive technological convergence. In this regard, we argue that the program's implementation of several mechanisms (e.g., multidisciplinary teams, U–I collaborations) may help mitigate the aforementioned uncertainties and costs. Subsequently, we examine how the program affects the behaviors of internal and external participants in the convergence scenario, as illustrated by H2 and H3. H2 states that the program will encourage academic and industrial inventors to participate in convergence activities, fostering technological development and research. Then, H3 is concerned with the external participants, declaring that the program as a whole could be a critical channel for disseminating internal knowledge and assuring authorities of convergence concepts, thereby motivating external participants to participate. We believe it will significantly impact external industrial players but will be limited to external academic researchers. Accordingly, we further conceptualize these as a "leverage

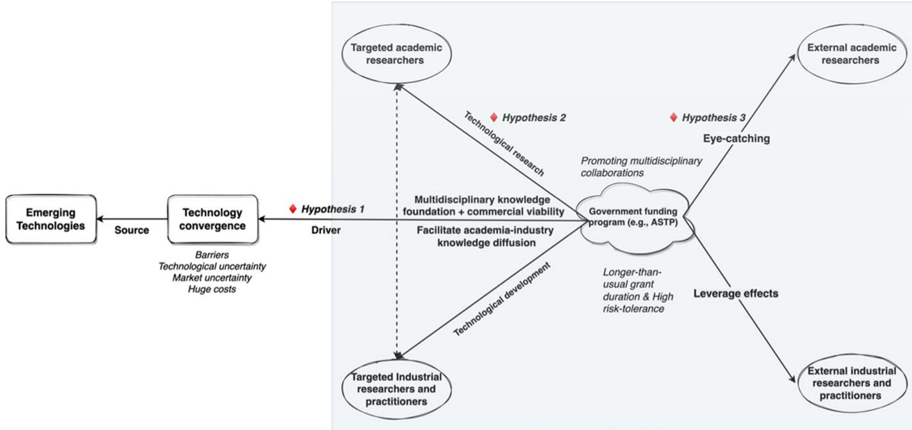


Fig. 1 Conceptualization of the role of government R&D spending in promoting technology convergence and the position of each hypothesis

Table 1 Behavioral conceptualization of the role of specific innovators in promoting convergence

A government-supported R&D program featured with multidisciplinary setup and U–I participation	
Inventor type	Behavioral conceptualization
Internal academic researchers	Interacting with industrial inventors may induce academic researchers to start technological research rather than pure scientific research
	Receiving guaranteed funding makes them more willing to join in multidisciplinary projects, which are generally riskier than single-field projects
Internal industrial researchers and practitioners	Multidisciplinary setup and interaction with academic researchers help industrial inventors escape local search constraints, enabling them to go beyond their knowledge domains and gain higher absorptive capacity
	Receiving guaranteed funding allows them to shift from short-term product development to long-term convergence projects
External academic researchers	Some external academic researchers may try to explore the achievements produced by the program. However, most of them may only witness convergence due to high risk and huge costs
External industrial researchers and practitioners	The achievements generated by the program may prove the converged technologies' feasibility
	Some Industrial pioneers would actively join in developing converged technologies, enabling them to establish strong positions in the field before other entrants to the market (first mover advantage)

effect" for industry and an "eye-catching effect" for academia. Table 1 summarizes how public funding influences a specific innovator's behavior to promote technological convergence.

Data

Our empirical test is based on the ASTP at the NIH. The following section presents the context of ASTP, which is considered a potential convergence driver in this study.

Advanced sequencing technology program from 2004 to 2014

The Human Genome Project (HGP) cost approximately $3 billion when it was completed in April 2003. In the same year, the US National Human Genome Research Institute (NHGRI), an institute of NIH, announced two broad visions for future genomics research: "elucidating the structure and function of genomes" and "translating genome-based knowledge into health benefits." This event highlighted the potential for transforming biomedical and clinical practice if sequencing costs can be significantly reduced (Collins et al., 2003). Subsequently, in 2004, the NHGRI launched a funding program to reduce costs by two to four orders of magnitude. The ASTP program consists of two requests for applications (RFAs): "Near-Term Technology Development for Genome Sequencing" (the $100,000 genome[2]) and "Revolutionary Genome Sequencing Technologies" (the $1000 genome[3]). The NHGRI emphasized multidisciplinary team collaborations and encouraged the formation of teams with a wide range of expertise, including biochemistry, chemistry, physics, mathematical modeling, software development, and others, to achieve its goal of sequencing cost reduction. Furthermore, the program used unusually aggressive grant mechanisms, providing substantial grants for longer periods. For example, R01 and P01 grants under the program were allowed to request up to 2 million dollars per year (with a maximum duration of 5 years), whereas a typical NIH R01s only provided a total amount of up to $600,000.[4] Besides, unlike traditional funding programs exclusively awarded to academia, the ASTP offered grants to academic, industry, and foreign investigators. Most grants were allocated to academic researchers and small companies, but several research projects within large companies (e.g., Intel and IBM) were also eligible. To manage the risks, NHGRI staff evaluated progress through quantifiable milestones, timelines, and annual meetings. Grants could be shortened but not usually terminated if milestones are not met. Notably, NHGRI's annual grantee meetings were regarded as a major feature of the program, with entities sponsored by ASTP being required to share their findings. Researchers could receive feedback from peers more quickly without waiting for the lengthy publication process, resulting in a shorter development cycle. Meanwhile, industrial representatives could gain access to interact with scholars to test proof-of-concept data on ongoing scientific research, thereby cultivating the commercial viability of early-stage research projects (Schloss et al., 2020). Participants were later expanded to include people outside the program, such as investigators, investors, and others. This event served as a link in the knowledge transfer process between academic and industry investigators.

[2] https://grants.nih.gov/grants/guide/rfa-files/RFA-HG-04-002.html.

[3] https://grants.nih.gov/grants/guide/rfa-files/RFA-HG-04-003.html.

[4] https://report.nih.gov/nihdatabook/report/158.

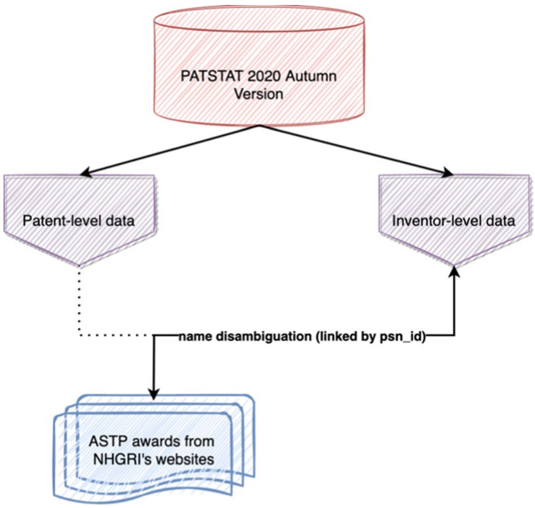


Fig. 2 Data collection and processing

Next-generation Sequencing

The Sanger-based sequencing approach (i.e., capillary array electrophoresis, CAE) was employed for the HGP, which was heavily dependent on the field of biochemistry and is also known as First-Generation Sequencing (Schloss, 2008). Although the Sanger CAE method produced high-quality results, electrophoresis only allowed for a limited amount of parallelization, resulting in low efficiency and high sequencing costs. Compared with traditional Sanger sequencing, NGS, which employs massively parallel techniques (also known as cyclic-array strategies), significantly increases data throughput, scalability, and efficiency (Shendure & Ji, 2008). The success of NGS implementation depends on a synergy of biochemistry, IT, and nanotechnology. For example, IT is involved in library preparation, which is typically the first stage of a sequencing operation (van Dijk et al., 2014). Furthermore, the growing volume of NGS data presents bioinformatics with new challenges in sequence quality assessment, alignment (i.e., re-sequencing), assembly, and data analysis. In this regard, the evolution of NGS could be referred to as a "convergence age."

Data and measures

In studies of technology convergence, patent data, which indicate knowledge accumulation and development in a specific technical field, are frequently used as a proxy for monitoring convergence (Karvonen & Kässi, 2013). Regarding methodology, patent co-classification, content analysis, and citation are three major approaches to measuring technology convergence. The co-classification method is based on well-defined patent classification systems (e.g., the international patent classification), with convergence visible as an increase in the co-occurrence of different IPC codes in patents (Han & Sohn, 2016; He et al., 2022; Jeong et al., 2015). Text-mining techniques and deep learning models have been widely used in patent content analysis to identify convergence from growing semantic overlaps between different technological domains (Eilers et al., 2019; Zhu & Motohashi, 2022). Finally, researchers working on citation-based methods have investigated convergence patterns by quantifying interfield citations among various technical fields (Ko et al., 2014). The citation-based method is used to measure technology convergence in this study because it can better depict knowledge flows across fields and fits nicely into our subsequent regression setups. We specifically collect interfield citations between IT and BT, the two primary technologies NGS uses. We extract the IT and BT patent data and citation information from the PATSTAT 2020 Autumn version, keeping in mind that the US Patent and Trademark Office publish all patents collected. We define the boundary of IT and BT patents using WIPO's technology classification concepts. The time window of the data is set from 1996 to 2019 to collect enough information to build patent indicators. The grant lists for the ASTP data are crawled from the NHGRI's websites, which provided detailed records for the ASTP awards from 2004 to 2014. We manually disambiguate the ASTP inventors and link them to the PATSTAT database. Figure 2 depicts the data collection process. We collected 64 ASTP inventors and 1,037,658 patent applications in total.

Methodology

Reduction of selection bias using propensity score matching

The first hypothesis of the causality effects of government R&D spending on promoting technology convergence can be seen in inventors enrolled in the program becoming more likely to form interfield backward and forward citations. Before testing this hypothesis, we must remove the bias introduced by the selection process of ASTP review offices. Applicants for the ASTP had to go through a peer-review process in which they were evaluated by review panels based on five criteria: Significance, Approach, Innovation, Investigator, and Environment.[5] The first three criteria are relevant to the project outlined in the RFA, whereas the remaining two are specific to the investigator (i.e., their level of experience) and their surrounding community (i.e., the collaborativeness of the surrounding environment). We select and design variables based on these criteria and apply propensity score matching to the dependent variable ASTP (1 if a given individual is enrolled in the program and 0 if otherwise). The selected covariates can be divided into three categories: patent portfolio, inventor, and environment. The following are the descriptions for each group of variables.

Patent portfolio-level variables are relevant to the first three criteria. For example, in terms of Innovation, the following questions are "Does the project employ novel concepts, approaches, or methods?" and "Are the goals unique and innovative?" These are evaluated based on the project outline in the RFA. However, we cannot rate the project's quality based on these criteria, and the data for the reviewing results is also not disclosed. More importantly, such information is unavailable to those who have never applied for the program. Therefore, we assume that some metrics can be found in one's previous works. For example, we estimate an inventor's innovativeness by aggregating (i.e., averaging) the innovative scores across his or her past patent portfolio. Based on this, four variables are created: originality, radicalness, number of coinventors, and number of institutions. Trajtenberg et al. (1997) developed an indicator to assess patent originality by arguing that an invention that relies on diverse knowledge sources (i.e., a wide range of technology fields) is more likely to be original. Shane (2001) proposed the radicalness index, which states

[5] These criteria are the same for the abovementioned two RFAs.

that the more radical an innovation is, the more it is based on paradigms other than the one to which it is applied. For the variable number of coinventors, we set up a list of ASTP inventors coinventors, and the number of coinventors will be measured in terms of this list. The idea is that if someone coauthored with the coinventors of the ASTP inventors, he or she may share similar characteristics with the ASTP inventors. Meanwhile, the case is similar to coinventors for the variable number of institutions, but we consider the ASTP inventors' institutions associated with the patent assignee information. Notably, these variables will be examined first at the patent level before being aggregated to the personal level based on one's patent portfolio.

Inventor-level variables are related to the Investigator criterion. Six variables are created in this group: experience, degree centrality, betweenness centrality, PageRank, local betweenness centrality, and local PageRank. The variable experience denotes the number of patents published up to the specified timestamp. The remaining five variables are network statistics derived from an undirected coinventor network.. Specifically, degree centrality (number of collaborators), betweenness centrality (role as a bridge), and PageRank (importance of an inventor) are referred to as global measures. The global coinventor network provides these variables. Such network can be further subdivided into several interconnected components known as local networks or communities. Then, from these connected components, local betweenness centrality (role as a bridge within his/her community) and local PageRank (importance of an inventor (node) within his/her community) are computed. Global and local network statistics are developed to account for the situation in which one may have a low PageRank (global importance) but actively serves as a bridge in his or her community (large value of local betweenness centrality).

Environment-level or community-level variables are related to the Environment criterion. The network statistics presented in the preceding section are calculated for each node. This section will create environment-level variables based on network statistics for a connected component (community). Then, we propose four variables: diameter (community size), average clustering coefficient (the likelihood that an inventor's two neighbors are also connected within the community), efficiency (how efficiently an inventor can reach others within the community), and community diversity. The first three are common network statistics, while the fourth was inspired by Aggarwal et al (2020). Aggarwal et al. (2020) demonstrated a method for measuring knowledge diversity within and across teams. In our case, each inventor in a community would be represented by a characteristic vector first. Each element demonstrates his or her experience in each subgroup of the International Patent Classification. The cosine diversity score is then computed to determine the level of diversity in a community (as described in further detail later in the "Appendix"). Because all of the variables in this group are network-level statistics, inventors in the same community will have the same values.

The program had multiple application receipt dates from 2004 to 2014. Hence, the matching process must be implemented for each year separately. Note that an inventor may receive the ASTP award more than once. In this case, we only count the earliest time for each inventor being enrolled in the ASTP. For each application year, we recompute the matching variables based on the information prior to that timestamp. We use the R package "MatchIt" to implement an optimal pair-matching strategy in which the sum of the pairwise distances in the matched sample is minimized. Each treated observation would be paired with two controls. Finally, we combine the matched samples from each year into a single dataset.

Table 2 Before and after matching results of the sample in 2004

Variables	Before matching			After matching		
	Mean treated	Mean Control	Std. Mean Diff.	Mean treated	Mean Control	Std. Mean Diff.
Propensity score	0.2857	0.0004	0.6086	0.2857	0.2857	0.0000
Originality	0.0051	0.0191	−0.7357	0.0051	0.0000	0.2673
Radicalness	0.0632	0.1901	−0.7742	0.0632	0.3290	−1.6221
Number of coinventors	4.6429	0.0197	0.8385	4.6429	1.8214	0.5117
Number of institutions	0.4286	0.0899	0.5241	0.4286	0.3571	0.1105
Experience	2.2143	1.4864	0.2476	2.2143	2.2143	0.0000
Betweenness centrality	0.2537	0.0475	0.2303	0.2537	0.0029	0.2802
Local betweenness centrality	0.1183	0.0255	0.3782	0.1183	0.0201	0.3999
Degree centrality	0.0543	0.0476	0.1047	0.0543	0.0705	−0.2555
PageRank	0.0449	0.0476	−0.0519	0.0449	0.0463	−0.0265
Local PageRank	0.0398	0.1902	−1.8710	0.0398	0.0995	−0.7418
Community diameter	4.6429	2.7053	0.2609	4.6429	4.7143	−0.0096
Community average cluster	0.4114	0.7382	−0.7634	0.4114	0.6882	−0.6466
Community efficiency	0.2229	0.7843	−2.0337	0.2229	0.5636	−1.2344
Community diversity	0.2162	0.1206	0.3357	0.2162	0.2258	−0.0337

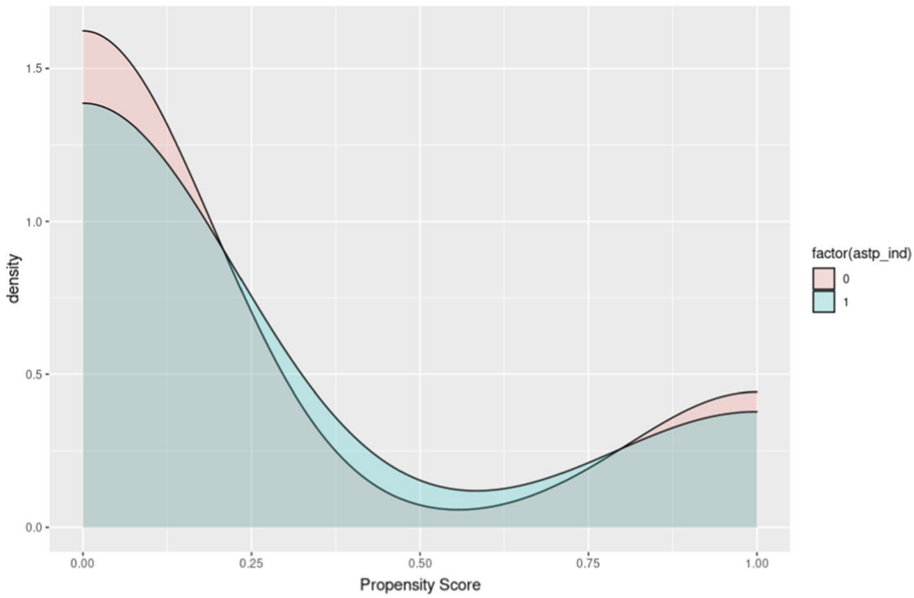


Fig. 3 Distribution of propensity scores after matching

Matching results

After estimating the propensity scores, one treated observation is matched with two control observations for each year. In some cases, a nontreated observation is matched multiple times to treated observations in different years. Hence, we only keep unique individuals in the final combining process by removing the repeated nontreated observations. In addition, there are exceptional cases where two ASTP inventors are matched into control groups before enrolling in the program. For these two cases, we simply delete them from the control group. In total, we obtained 54 observations in the treatment group (ASTP inventors) and 70 in the control group (matched inventors). Table 2 reports the results before and after matching for the first year (2004), where propensity scores differ substantially between treated and nontreated inventors before the matching. After matching, the gap in propensity scores between treated and untreated units is well alleviated, which can also be seen from other variables. Figure 3 shows the distribution of propensity scores after matching (number 0 stands for the control group, and number 1 stands for the treated group), which also evidently proves matching quality. In particular, the mean values for the treatment and control groups before matching reveal some characteristics of the selected ASTP inventors in that year. In terms of the past patent portfolio, the ASTP inventors, on average, have relatively lower originality and radicalness values than inventors outside the program. Moreover, ASTP inventors are more likely to act as a "bridge" than others from the larger values of betweenness centrality (normalized) and local betweenness centrality. Finally, in terms of the community environment, Table 2 shows that ASTP inventors are in a more extensive and diversified community than external inventors on average.

Regression models

We expect that a government R&D program will promote technology convergence, as observed by the increasing number of interfield citations after enrollment. We further categorize interfield citations as backward and forward citations. The backward citations demonstrate the participation in interfield innovation activities, while the forward citations demonstrate their impact on the external environment. As the ASTP had multiple application receipt dates, we adopted a difference-in-differences (DiD) specification with multiple periods to estimate the relation between the ASTP and the interfield citation counts. The regression setup is as follows:

$$\log\left(1 + Y_{it}\right) = \alpha + \beta D_{it} + \delta X_{it} + \mu_i + \lambda_t + \epsilon_{it}, \tag{1}$$

where $i = 1, \ldots, 124; t = 2000, \ldots, 2019$. In Eq. 1, Y_{it} is a measure of convergence activity intensity of person i in year t, which can be either interfield backward or forward citation counts. Backward and forward citations are counted at the patent level first, then aggregated to the inventor level by taking the sum over one's patent portfolio. We use a fixed window to normalize patent citation counts when dealing with forward citations (count forward citation accrued to the patent of interest from the patent application date to 5 years thereafter). λ_t and μ_i are the year and individual fixed effects, respectively, and ϵ_{it} is the error term. The variable of interest is D_{it}, a dummy variable that equals 1 if years after the person was first enrolled in the ASTP and 0 if otherwise. The coefficient, β, therefore indicates the impact of the ASTP on technology convergence. X_{it} is a set of time-varying person-level control variables, and the variable δ's are coefficient of the control variables. Control variables are used to ensure a reliable estimate of ASTP's impact on enrolled inventors. The variables are chosen to control three aspects: an inventor's patent quality, an inventor's characteristics in the global and local networks, and an inventor's surrounding network characteristics. Most variables are chosen from those used for matching. Furthermore, we must account for the increase in total citation counts. To control the effects of citing scientific papers, we also include variable science, which represents the number of backward citations of nonpatent literature (NPL). Karvonen and Kässi (2013) suggested that the count of NPL evaluates the proximity between technological innovation and scientific research, and can thus be used to measure the science-technology linkage to some extent. However, applicants may include NPL to intentionally broaden patent coverage or because of the examiners' standard practices (Meyer, 2000). Table 3 displays the predictors' correlation matrix. No critical multi-collinearity is observed as the absolute values of the correlations are less than 0.7.

Results

Empirical results

Our first analysis examines the effects of a government funding program on promoting technological convergence. Tables 4 and 5 show the impact of the ASTP on changes in interfield citations. When considering interfield backward citations, models 1–5 show that the coefficients of the treated variable D_{it} are positive and statistically significant at the 5% significance level. As a result, we found evidence that enrollment encouraged inventors to engage in multidisciplinary innovation activities. The variable science has statistically

Table 3 Correlation matrix

	log(#InterBWD + 1)	log(#InterFWD + 1)	Originality	Radicalness	Science	degCentNorm	btwnCentNorm	btwnCentLocal	Community avgcluster	Community efficiency	Community diversity
log(#InterBWD + 1)	1										
log(#InterFWD + 1)	0.631	1									
Originality	0.334	0.069	1								
Radicalness	0.411	0.215	0.382	1							
Science	0.679	0.656	0.073	0.214	1						
degCentNorm	0.451	0.428	−0.020	0.126	0.561	1					
btwnCentNorm	0.321	0.269	0.052	0.078	0.371	0.411	1				
btwnCentLocal	0.178	0.107	0.154	0.171	0.127	0.217	0.058	1			
Community avgcluster	0.360	0.277	0.145	0.263	0.271	0.542	0.117	0.083	1		
Community efficiency	−0.014	−0.120	0.235	0.292	−0.131	0.0228	−0.128	0.197	0.412	1	
Community diversity	0.481	0.447	0.105	0.257	0.457	0.513	0.242	0.099	0.473	−0.292	1

Table 4 DiD estimation results of interfield backward citations

	Model 1 log(#InterBWD + 1)	Model 2 log(#InterBWD + 1)	Model 3 log(#InterBWD + 1)	Model 4 log(#InterBWD + 1)	Model 5 log(#InterBWD + 1)
Treated	0.2822** (0.1246)	0.2114** (0.0941)	0.2888** (0.1195)	0.2286** (0.1099)	0.1615* (0.0871)
log(#TotalBWD + 1)	0.5016*** (0.0475)	0.3617*** (0.0552)	0.4814*** (0.0551)	0.6034*** (0.0568)	0.4298*** (0.0585)
Originality		2.1380*** (0.6213)			2.5134*** (0.5599)
Radicalness		0.1538 (0.2673)			0.3671 (0.2514)
Science		0.0738*** (0.0109)			0.0570*** (0.0091)
degCentNorm			1.4700 (1.4690)		2.4792** (1.2115)
btwnCentNorm			0.0782** (0.0303)		0.0196 (0.0126)
btwnCentLocal			−0.3913 (0.3324)		0.0088 (0.2385)
Community avgcluster				−0.3664* (0.1909)	−0.2741 (0.1712)
Community efficiency				−0.4085** (0.1693)	−0.4131*** (0.1361)
Community diversity				−0.2141 (0.2996)	−0.3363 (0.2051)
Constant	−0.0615 (0.0646)	−0.0653 (0.0546)	−0.0823 (0.0664)	0.0654 (0.0702)	−0.0026 (0.0601)
N	2480	2480	2480	2480	2480
Adj. R^2	0.6973	0.7838	0.7084	0.7261	0.7989
AIC	3700	2900	3700	3500	2700
BIC	3900	3000	3800	3600	2900

Standard errors in parentheses

$^*p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Table 5 DiD estimation results of interfield forward citations

	Model 6 log(#InterFWD + 1)	Model 7 log(#InterFWD + 1)	Model 8 log(#InterFWD + 1)	Model 9 log(#InterFWD + 1)	Model 10 log(#InterFWD + 1)
Treated	0.1283** (0.0807)	0.1086 (0.0818)	0.1544* (0.0805)	0.1788** (0.0771)	0.1456* (0.0785)
log(#TotalFWD + 1)	0.5179*** (0.0361)	0.4099*** (0.0402)	0.5133*** (0.0353)	0.5174*** (0.0357)	0.4323*** (0.0387)
Originality		0.1884 (0.2604)			0.3417 (0.2710)
Radicalness		−0.2016* (0.1132)			0.1569 (0.1100)
Science		0.0394*** (0.0104)			0.0347*** (0.0099)
degCentNorm			−0.5714 (0.9773)		−0.2604 (1.1627)
btwnCentNorm			0.0472 (0.0312)		0.0219 (0.0185)
btwnCentLocal			−0.5373** (0.2624)		−0.2333 (0.2699)
Community avgcluster				−0.1390 (0.1223)	0.0525 (0.1272)
Community efficiency				−0.3269** (0.1309)	−0.2700** (0.1322)
Community diversity				−0.5681*** (0.1493)	−0.5579*** (0.1469)
Constant	−0.0773* (0.0423)	−0.0681 (0.0449)	−0.0479 (0.0426)	−0.0195 (0.0441)	−0.0090 (0.0425)
N	2480	2480	2480	2480	2480
Adj. R^2	0.6619	0.6969	0.6741	0.6794	0.7131
AIC	2400	2200	2300	2300	2000
BIC	2600	2300	2500	2400	2200

Standard errors in parentheses

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Fig. 4 The dynamic impact of enrollment on interfield backward citation counts

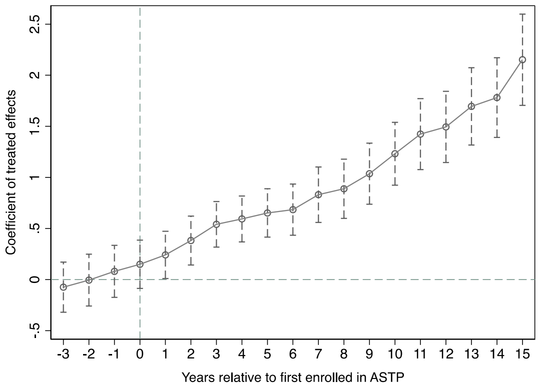
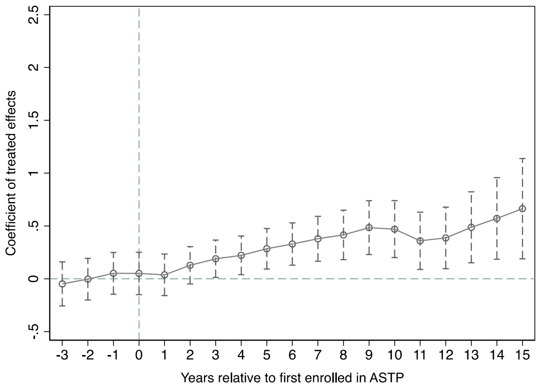


Fig. 5 The dynamic impact of enrollment on interfield forward citation counts



significant positive coefficients in models 2 and 5, indicating that inventors who cite more NPL are more likely to form interfield backward citations. In terms of interfield forward citations, we found that the coefficient of D_{it} is statistically significant in models 6, 8, 9, and 10, but becomes insignificant when patent quality is controlled. Furthermore, the variable science is significant (at the 1% level) and positive, implying that inventors who cite more NPL are more likely to receive interfield forward citations as well. However, community efficiency and diversity show negative coefficients when considering forward citations. This result suggests that living in a diverse community may not be able to attract more forward citations. In sum, we found strong evidence that the program encouraged inventors to engage in multidisciplinary innovation activities, but relatively weak evidence that the program influenced inventors outside the program.

Dynamics of enrollment

In this section, we examine the causality effects of the program by incorporating a series of dummy variables to trace the year-by-year effects of enrollment. This is accomplished by fitting the following regression model:

$$\log\left(1 + Y_{it}\right) = \alpha + \beta_1 D_{it}^{-3} + \beta_1 D_{it}^{-2} + \cdots + \beta_1 D_{it}^{+15} + \mu_i + \lambda_t + \epsilon_{it}, \tag{2}$$

where the dummy variable D^{-j} equals 1 for persons in the jth year before enrollment, whereas D^{+j} equals 1 for persons in the jth year after enrollment; otherwise, the value is 0. We exclude the first year (2000); thus, the dynamic effects of enrollment, the D's, are estimated with respect to the first year. Figures 4 and 5 presented the estimated results and the 95% confidence intervals for interfield backward and forward citations, respectively.

Figure 4 reveals two critical findings. First, the estimated confidence intervals do not deviate significantly from zero in the three years preceding enrollment in ASTP. Hence, we rule out the reverse causality that enrolled inventors already engaged in multidisciplinary research prior to entering the program. Second, the ASTP has a rapid impact, as evidenced by the estimated coefficients and corresponding confidence intervals rapidly shifting from zero. The quick responses are probably driven by the stringent milestone system of the National Advisory Council for Human Genome Research. The strict milestone system has been an effective tool for NHGRI staff to plan and monitor progress, which was also incorporated as a condition of the award. In addition, this award could be attributed to NHGRI's "Mandatory Annual Grantee Meetings," where ASTP inventors were required to report and share their progress regularly.

In contrast, the estimated coefficients for the interfield forward citations in Fig. 5 show no effect in the three years preceding enrollment in ASTP. Even after two years of participation in the program, the coefficients do not significantly differ from zero (confidence intervals contain zero). However, beginning in the third year of enrollment, we can see gradually increasing effects on the number of interfield forward citations (confidence intervals shift from zero). The program's lag effects on the external environment are most likely due to external players needing time to sense and assess the ASTP inventors' work. In addition, the gradual increase in estimated coefficients demonstrated its impact on external multidisciplinary innovation activities. The annual grantee meetings, a distinct and innovative feature of ASTP, could be a critical factor that propels and fosters the process. The meeting was limited to the ASTP inventors and a small group of selected participants during the first few years. However, this was then extended to a large group of people, ranging from representatives of large companies to young scholars and students. The collegial nature of the meetings may facilitate knowledge sharing and serve as a channel for attracting experts from various fields, thereby amplifying their impact on cultivating multidisciplinary collaborations.

Impact of government R&D spending

The ASTP assisted both academic and industrial inventors. The remaining two hypotheses are tested in this section. To test the second hypothesis, we divided our dataset's ASTP inventors into university and industry categories. For testing the third one, we classified the backward and forward citations accrued to the ASTP inventors using the attribute psn_sector provided by PATSTAT.[6]

[6] In PATSATA, each applicant has been assigned to one or more sectors, including individual, company, unknown, government, nonprofit organization, university, and hospital. In our sample, the applicants of backward and forward citations are mainly from the sectors of company, university, and individual. In the following analyses, we will focus on the sectors of company and university and use "industry" as an interchangeable word for company.

Table 6 DiD estimation results for the ASTP university and industry inventors

	Panel A: ASTP university inventors		Panel B: ASTP industrial inventors	
	log(#InterBWD + 1)	log(#InterBWD + 1)	log(#InterBWD + 1)	log(#InterBWD + 1)
Treated	0.4603** (0.2007)	0.1457 (0.1101)	1.0401*** (0.2312)	0.2926** (0.1182)
Constant	0.0813 (0.0793)	−0.0245 (0.0711)	0.1086 (0.0829)	−0.0009 (0.0646)
Control		Yes		Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	1900	1900	1980	1980
Adj-R^2	0.3401	0.7439	0.4287	0.7812
AIC	3700	1900	4100	2200
BIC	3800	2100	4200	2400

Standard errors in parentheses

ASTP Advanced Sequencing Technology Program

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

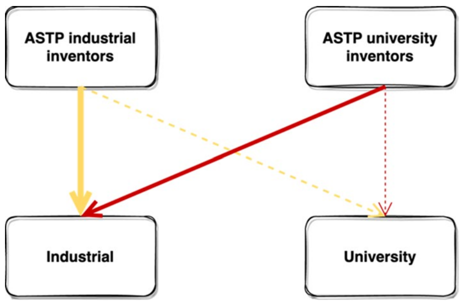


Fig. 6 Channels for inflow knowledge (directions for backward citations)

Direct influences on the internal inventors

To determine the program's heterogeneous impact on enrolled academic and industrial groups, we conducted the DiD estimations on these two groups, respectively, with the year (Year FE) and individual fixed effects (Individual FE). In this case, we are only interested in backward citations because they show how ASTP influenced the behaviors of enrolled inventors. The regression results for the two groups are summarized in Table 6. The coefficients of the treated variable are positive and statistically significant for almost all scenarios, indicating that the program encouraged both parties to develop converging technologies. However, we found that the coefficients for industrial groups are greater than those for academic groups, regardless of the inclusion of controlled variables. This finding suggests that the program has a greater impact on industrial inventors than on university inventors. Therefore, the results support the second hypothesis.

Furthermore, because backward citations depict knowledge flows, we can track the sources of knowledge for these ASTP inventors. In particular, we examine four channels through which knowledge flows to program inventors, denoted by four arrows in Fig. 6. Each arrow's color and line type correspond to the lines in Fig. 8. From Figs. 6 and 8,

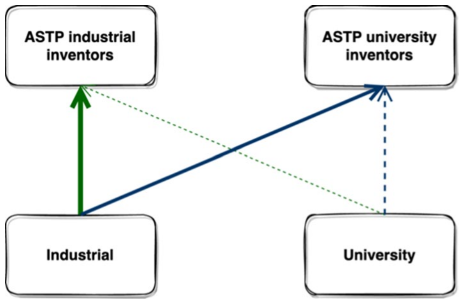


Fig. 7 Channels for outflow knowledge (directions for forward citations)

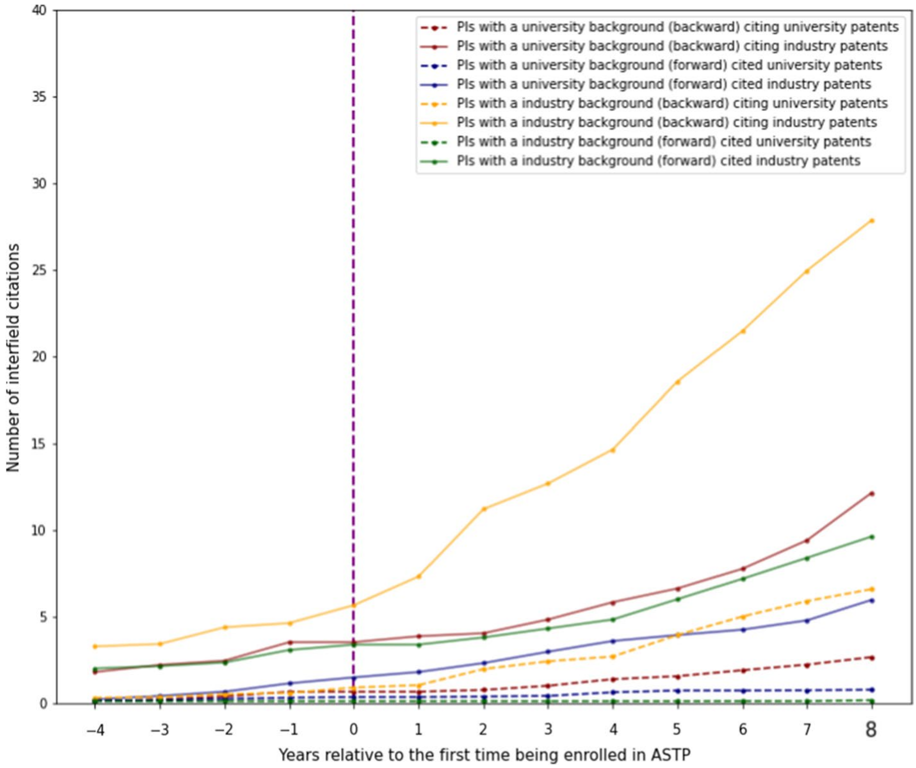


Fig. 8 Decomposition of citation counts

we can observe that the industrial firms cited significantly more interfield citations than university scholars, indicating their dominant roles in leveraging multidisciplinary knowledge. This can be explained by companies shifting resources from near-term product development to innovative early-stage projects after receiving ASTP funding. Figure 8 shows that, despite citing fewer interfield citations than their industrial counterparts, the average number of interfield citations made by ASTP university inventors continues to rise after enrollment. This could be explained by the program's encouragement of academic researchers to reconsider some applied science and technology projects, which were

Table 7 Forward citations made by the external university and industry players

	(a) MeanCitedByUni	(b) MeanCitedByInd	(c) Diff (b) – (a)
RelYear-4	0.1207	1.1034	0.9828
RelYear-3	0.1379	1.2759	1.1379
RelYear-2	0.1724	1.5000	1.3276
RelYear-1	0.2069	2.1034	1.8966**
RelYear 0	0.2241	2.4310	2.2069**
RelYear 1	0.2241	2.5862	2.3621**
RelYear 2	0.2414	3.0517	2.8103***
RelYear 3	0.2586	3.6379	3.3793***
RelYear 4	0.3621	4.2069	3.8448***
RelYear 5	0.4138	4.9655	4.5517***
RelYear 6	0.4211	5.6842	5.2632***
RelYear 7	0.4182	6.6182	6.2000***
RelYear 8	0.4800	7.7200	7.2400***

Standard errors in parentheses

*$p<0.10$, **$p<0.05$, ***$p<0.01$

viewed as non-hypothesis-driven and massive data-gathering exercises and were frequently overlooked in the laboratory (Schloss et al., 2020). Furthermore, when we examined the knowledge sources of the ASTP university inventors, we found that they cited a comparable number of industry patents. This result is somewhat intriguing because the university has always been regarded as one of the industry's primary knowledge sources. The reverse relationship in this case suggests that government intervention can advance technological research. Furthermore, the phenomenon could be interpreted as a result of grantee meetings that facilitated knowledge diffusion between industrial and academic groups. In turn, this case enables university research to perceive knowledge in the industry sector.

Influences on the external inventors

For the third hypothesis, we argue that the program has a more significant impact on attracting external industrial inventors than academic inventors, as evidenced by the ASTP inventors' forward citations. Figure 7 depicts the four channels through which knowledge flows from ASTP inventors to inventors outside the program. The thickness of each arrow is proportional to the forward citation counts shown in Fig. 8. Figures 7 and 8 show that external firms make the majority of forward citations. Because forward citations are a good proxy for tracing the trajectory of knowledge outflows, the results suggest that the external industrial players are the primary audience for the program. Table 7 presents the statistical comparison of the forward citations made by the external university and industry players. The results confirm that forward citation made by external industrial inventors are significantly greater than those of external university inventors on average.

As previously stated, the program's "leverage effects" can be viewed as an attractive force to external inventors. The results suggest that "leverage effects" are more effective for external industrial inventors. This finding suggests that the program can be viewed as a "lever" for attracting other industrial players (e.g., investors), bringing in additional resources for further development and commercialization. By contrast, the limited "leverage effect" is observed for external academic inventors. This can be explained by the fact that academic and industrial players in the national innovation system operate differently: firms have more incentives to respond to market opportunities, whereas universities focus on nurturing basic scientific and technological results (Goto, 2000). Moreover, from the standpoint of TRLs, since the technological complexity of results disclosed at the R&D stage is not exceedingly high, external firms would have opportunities to develop capabilities to catch up (Jeong & Lee, 2015).

Conclusion and discussion

This study investigated the impact of a government funding program (i.e., ASTP) on promoting technological convergence. We hypothesized that a government-supported program would positively promote technological convergence, and that the program would have a greater impact on industrial inventors than university inventors. Furthermore, we conceptualized the program's "leverage effect," which is more effective for external industrial inventors than academic counterparts. We developed a new dataset to investigate this by linking the ASTP grantee information provided by NHGRI with the PATSTAT patent database. Based on this, we developed inventor-level characteristics for propensity score matching, resulting in a control group of inventors comparable to those enrolled in the ASTP. We then used the DiD models to assess the impact of the ASTP on the matched sample. Our results showed that the ASTP encouraged both enrolled and external inventors to engage in multidisciplinary innovation activities. The program's diverse effects on different groups of grantees were then depicted. The results supported our second hypothesis that the program has a more significant impact on industrial inventors than on university inventors. Finally, we demonstrated that the program's "leverage effects" are more effective for external companies than academic institutions.

Some of the results of this study are consistent with previous theoretical and empirical studies (e.g., Karvonen & Kässi, 2013; Hacklin, 2008). The regression table suggested that the number of nonpatent citations is positively related to the formation of interfield backward and forward citations. This idea is consistent with previous research (e.g., Curran & Leker, 2011), which claims that scientific research provides a knowledge foundation for convergence. However, Caviggioli (2016) demonstrated that new convergence is more likely to occur in less anchored fields of scientific research. More research is needed to explore the relationship between scientific knowledge and convergence. Furthermore, in the case of the forward citations, the treatment effects became insignificant when patent quality was controlled, suggesting that future research should include this factor.

Government R&D spending as a driver of convergence

In contrast to a conventionally linear R&D activity, which drives technological advancement by deepening research in a single area, convergence generates novel technologies by combining knowledge from multiple domains. Because of its inherent multidisciplinary nature, convergence necessitates long-term development and is frequently associated with uncertainties and risks, which can deter potential private investors. As innovation and management scholars have discussed, government-supported programs with distinct features help remove barriers, reduce R&D market failures, and ensure the benefits of investments (Jeong & Lee, 2015; Littler & Coombs, 1988; Martin & Scott, 2000). The multidisciplinary configuration, in particular, establishes a knowledge foundation for convergence. Furthermore, the longer-than-usual grant durations enable (1) industrial players to return to guaranteed near-term product development and (2) academic researchers to conduct in-depth research rather than "muddle through" the problem. The program's direct impact, which propels participants to engage in convergence activities, may only cause a few initial sparks in the existing technological space. However, its ripple effects could start a prairie fire, attracting more investors and firms to participate (or even induce social bubbles). The combined force has the potential to change the technological landscape (e.g., converged technologies become mainstream, for example, NGS in this work).

Implications and contributions

Technology convergence is critical for improving firms' overall innovation performance (Curran et al., 2010; Kim et al., 2019a, 2019b); however, the associated uncertainty and risks may deter firms from venturing outside of their technological comfort zones. Jeong (2014) demonstrated that when industrial firms collaborate with public research institutes, they are more likely to develop converging technologies because they gain access to diverse scientific knowledge and a low-cost labor force. Hence, a large-scale convergence-oriented R&D program is needed to explicitly encourage innovation through the channel of technology convergence (Jeong & Lee, 2015). This study empirically demonstrates the underlying mechanism of how a government-funded program affects industrial and academic inventors in such a scenario to better understand how government-supported R&D programs drive technology convergence. The empirical results suggest that industrial inventors participating in such a program are more actively engaged in convergence activities than their academic counterparts. Furthermore, we show that the involvement of industrial firms emphasizes the projects' commercial viability and motivates university scholars to pursue technological research rather than pure scientific exploration. As concerns have been raised about project failures caused by a lack of market-side considerations (Rikkiev & Mäkinen, 2013), this case suggests that policymakers should consider the effects of including industrial entities when designing technology convergence-oriented R&D programs.

In addition, scholars have cast doubts that the impact of such programs (Jeong & Lee, 2015; Metzger & Zare, 1999) may only be marginal. Our research demonstrates that a government R&D program can serve as a channel for disclosing and publicizing internal findings and assuring authorities of emerging and risky convergence concepts, resulting in "leverage effects" that entice outside private investors and industrial players to participate. Such "leverage effects" are, however, limited to academic players. Finally, there is growing concern that the current funding system favors certain and safe research over high-risk/high-gain projects (Wang et al., 2018). With the predictable risk and uncertainty associated with technological convergence, private companies and investors are hesitant to join, whereas academic researchers put these ideas on hold. In this case, an "entrepreneurial" funding program is required to pave the way.

Limitations

The current study has some limitations that we hope to leverage to inspire further research. First, we use the ASTP as an example of how a government-supported R&D program can promote technological convergence; however, whether this can be generalized to other R&D programs remains unclear. To this end, the study encourages validation by other innovation programs. Second, the study mentioned that several program settings and management practices (e.g., U–I cooperation, multidisciplinary setup, and seminar disclosure) may positively contribute to the occurrence of convergence. However, the prominence of these features may require further investigation in future studies. Finally, the present work analyzed technology convergence using patent data; however, the program also discloses paper information that can be used to investigate scientific convergence. This opens the possibility of understanding the relationship between technological and scientific convergence.

Appendix

See Table 8.

Based on their patents in each class, inventor *i*'s characteristic vector is formed, which can be represented by x_i. And then the degree of diversity for a community is given as

$$1 - \frac{1}{n(n-1)}\left[\sum_{i,j} s\left(x_i, x_j\right) - n\right],$$

where function *s* is the cosine similarity. The degree of diversity for the given two examples is 0.059 for community I and 0.251 for community II.

Table 8 Measuring the degree of diversity in a community

Class (IPC Sub-group)	Number of patents in each class			
	Community I			
	Inventor 1	Inventor 2	Inventor 3	Inventor 4
A	3	4	1	3
B	0	0	1	0
C	5	5	6	4
	Number of patents in each class			
	Community II			
Class (IPC Sub-group)	Inventor 5	Inventor 6	Inventor 7	Inventor 8
A	3	2	4	3
B	0	1	2	0
C	5	5	1	1

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Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

References

Aggarwal, V. A., Hsu, D. H., & Wu, A. (2020). Organizing knowledge production teams within firms for innovation. *Strategy Science, 5*(1), 1–16.

Aghion, P., Howitt, P., & García-Peñalosa, C. (1998). *Endogenous growth theory*. MIT Press.

Appio, F. P., Martini, A., & Fantoni, G. (2017). The light and shade of knowledge recombination: Insights from a general-purpose technology. *Technological Forecasting and Social Change, 125*, 154–165.

Arnold, A., Cafer, A., Green, J., Haines, S., Mann, G., & Rosenthal, M. (2021). Perspective: Promoting and fostering multidisciplinary research in universities. *Research Policy, 50*(9), 104334.

Arrow, K. (1962). Economic welfare and the allocation of resources for innovation. In R. R. Nelson (Ed.), *The rate and direction of inventive activity* (pp. 609–625). Princeton University Press.

Bores, C., Saurina, C., & Torres, R. (2003). Technological convergence: A strategic perspective. *Technovation, 23*, 1–13.

Brousseau, E. (1993). *L'economie des contrats*. Presses Universitaires de France.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152.

Collins, F. S., Green, E. D., Guttmacher, A. E., & Guyer, M. S. (2003). A vision for the future of genomics research: A blueprint for the genomic era. *Nature, 422*, 835–847.

Caviggioli, F. (2016). Technology fusion: Identification and analysis of the drivers of technology convergence using patent data. *Technovation, 55*, 22–32.

Curran, C. S., Bröring, S., & Leker, J. (2010). Anticipating converging industries using publicly available data. *Technological Forecasting and Social Change, 77*, 385–395.

Curran, C. S., & Leker, J. (2011). Patent indicators for monitoring convergence—Examples from NFF and ICT. *Technological Forecasting and Social Change, 78*, 256–273.

Dowling, M., Lechner, C., & Thielmann, B. (1998). Convergence—Innovation and change of market structures between television and online services. *Electronic Markets, 8*(4), 31–35.

Eilers, K., Frischkorn, J., Eppinger, E., Waltera, L., & Moehrlea, M. G. (2019). Patent-based semantic measurement of one-way and two-way technology convergence: The case of ultraviolet light emitting diodes (UV-LEDs). *Technological Forecasting and Social Change, 140*, 341–353.

Feldman, M. P., & Kelley, M. R. (2006). The ex ante assessment of knowledge spillovers: Government R&D policy, economic incentives and private firm behavior. *Research Policy, 35*(10), 1509–1521.

Gambardella, A., & Giarratana, M. S. (2013). General technological capabilities, product market fragmentation, and markets for technology. *Research Policy, 42*(2), 315–325.

Gittelman, M., & Kogut, B. (2003). Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. *Management Science, 49*(4), 366–382.
Goto, A. (2000). Japan's national innovation system: Current status and problems. *Oxford Review of Economic Policy, 16*(2), 103–113.
Greenhalgh, C., & Rogers, M. (2010). *Innovation, intellectual property and economic growth*. Princeton University Press.
Hacklin, F. (2008). *Management of convergence in innovation: Strategies and capabilities for value creation beyond blurring industry boundaries*. Physica-Verlag.
Hacklin, F., Battistini, B., & Von Krogh, G. (2013). Strategic choices in converging industries. *MIT Sloan Management Review, 55*(1), 65.
Han, E. J., & Sohn, S. Y. (2016). Technological convergence in standards for information and communication technologies. *Technological Forecasting and Social Change, 106*, 1–10.
Hayden, E. C. (2014). Technology: The $1000 genome. *Nature, 507*, 294–295.
He, C., Shi, F., & Tan, R. (2022). A synthetical analysis method of measuring technology convergence. *Expert Systems with Applications, 209*, 118262.
Jeong, S. (2014). Strategic collaboration of R&D entities for technology convergence: Exploring organizational differences within the triple helix. *Journal of Management and Organization, 20*(2), 227–249.
Jeong, S., Choi, J. Y., & Kim, J. (2011). The determinants of research collaboration modes: Exploring the effects of research and researcher characteristics on coauthorship. *Scientometrics, 89*, 967–983.
Jeong, S., Kim, J. C., & Choi, J. Y. (2015). Technology convergence: What developmental stage are we in? *Scientometrics, 104*(3), 841–871.
Jeong, S., & Lee, S. (2015). What drives technology convergence? Exploring the influence of technological and resource allocation contexts. *Journal of Engineering and Technology Management, 36*, 78–96.
Kani, M., & Motohashi, K. (2020). Technology sourcing in new product development projects: When and how to use external resources? Tezukayama RIEB Discussion Paper Series No. 27.
Karvonen, M., & Kässi, T. (2013). Patent citations as a tool for analysing the early stages of convergence. *Technological Forecasting and Social Change, 80*, 1094–1107.
Katila, R., & Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *The Academy of Management Journal, 45*, 1183–1194.
Kim, D.-H., Lee, H., & Kwak, J. (2017). Standards as a driving force that influences emerging technological trajectories in the converging world of the Internet and things: An investigation of the M2M/IoT patent network. *Research Policy, 46*(7), 1234–1254.
Kim, E., Cho, Y., & Kim, W. (2014). Dynamic patterns of technological convergence in printed electronics technologies: Patent citation network. *Scientometrics, 98*, 975–998.
Kim, J., Kim, S., & Lee, C. (2019a). Anticipating technological convergence: Link prediction using Wikipedia hyperlinks. *Technovation, 79*, 25–34.
Kim, J., & Lee, S. (2017). Forecasting and identifying multi-technology convergence based on patent data: The case of IT and BT industries in 2020. *Scientometrics, 111*, 47–65.
Kim, K., Jung, S., & Hwang, J. (2019b). Technology convergence capability and firm innovation in the manufacturing sector: An approach based on patent network analysis. *R&D Management, 49*(4), 49–606.
Kim, T. S., & Sohn, S. Y. (2020). Machine-learning-based deep semantic analysis approach for forecasting new technology convergence. *Technological Forecasting and Social Change, 157*, 120095.
Klein, J. T., & Falk-Krzesinski, H. J. (2017). Interdisciplinary and collaborative work: Framing promotion and tenure practices and policies. *Research Policy, 46*(6), 1055–1061.
Ko, N., Yoon, J., & Seo, W. (2014). Analyzing interdisciplinarity of technology fusion using knowledge flows of patents. *Expert Systems with Applications, 41*(4), 1955–1963.
Kodama, F. (1992). Technology fusion and the new R&D. *Harvard Business Review, 70*(4), 70–78.
Kodama, F. (1995). *Emerging patterns of innovation: Sources of Japan's technological edge*. Harvard Business School Press.
Kogut, B. (1988). Joint ventures: Theoretical and empirical perspectives. *Strategic Management Journal, 9*(4), 319–332.
Lee, C., Hong, S., & Kim, J. (2020). Anticipating multi-technology convergence: A machine learning approach using patent information. *Scientometrics, 126*, 1867–1896.
Li, D., & Agha, L. (2015). Big names or big ideas: Do peer-review panels select the best science proposals? *Science, 348*, 434–438.
Littler, D., & Coombs, R. (1988). Current and future trends in European technological development: New patterns in the funding of R&D. *European Management Journal, 6*(2), 102–113.
Long, C. (2002). Patent signals. *University of Chicago Law Review, 69*(2), 625–679.
Martin, S., & Scott, J. T. (2000). The nature of innovation market failure and the design of public support for private innovation. *Research Policy, 29*(4/5), 437–448.

Metzger, N., & Zare, R. N. (1999). Science policy—Interdisciplinary research: From belief to reality. *Science, 283*, 642–643.

Meyer, M. (2000). Does science push technology? Patents citing scientific literature. *Research Policy, 29*(3), 409–434.

Mowery, D. C., & Rosenberg, N. (1979). The influence of market demand upon innovation: A critical review of some empirical studies. *Research Policy, 8*, 102–153.

Nordmann, A. (2004). *Converging technologies: Shaping the future of European societies*. Office for Official Publications of the European Communities (EUR 21357).

Nature. (2014). How to get ahead. *Nature, 507*, 273–274.

Park, H., Lee, J., & Kim, B.-C. (2015). Project selection in NIH: A natural experiment from ARRA. *Research Policy, 44*, 1145–1159.

Park, H. S. (2017). Technology convergence, open innovation, and dynamic economy. *Journal of Open Innovation: Technology, Market, and Complexity, 3*, 24.

Passing, F., & Moehrle, M. G. (2015). Measuring technological convergence in the field of smart grids: A semantic patent analysis approach using textual corpora of technologies. In *Proceedings of the international conference on management of engineering and technology (PICMET)*, 2015, Portland (pp. 559–570). IEEE.

Pfirman, S., & Martin, P. (2017). *Facilitating interdisciplinary scholars*. Oxford University Press.

Poyago-Theotoky, J., Beath, J., & Siegel, D. (2002). Universities and fundamental research: Policy implications of the growth of university–industry partnerships. *Oxford Review of Economic Policy, 18*(1), 10–21.

Preschitschek, N., Niemann, H., Leker, J., & Moehrle, M. G. (2013). Anticipating industry convergence: Semantic analyses vs IPC co-classification analyses of patents. *Foresight, 15*(6), 446–464.

Rikkiev, A., & Mäkinen, S. J. (2013). Technology convergence and intercompany R&D collaboration: Across business ecosystems boundaries. *International Journal of Innovation and Technology Management, 10*(4), 1350009.

Roco, M. C., & Bainbridge, W. S. (2002). *Converging technologies for improving human performance*. National Science Foundation.

Roessner, D. (1989). Evaluating government innovation programs: Lessons from the U.S. experience. *Research Policy, 18*(6), 343–359.

Romer, P. (1986). Increasing returns and long run growth. *Journal of Political Economy, 94*, 1002–1037.

Sauermann, H., & Stephan, P. (2013). Conflicting logics? A multidimensional view of industrial and academic science. *Organization Science, 24*(3), 889–909.

Schloss, J. A. (2008). How to get genomes at one ten-thousandth the cost. *Nature, 26*, 1113–1115.

Schloss, J. A., Gibbs, R. A., Makhijani, V. B., & Marziali, A. (2020). Cultivating DNA sequencing technology after the Human Genome Project. *Annual Review of Genomics and Human Genetics, 21*, 117–138.

Schmoch, U., Breiner, S., Cuhls, K., Hinze, S., & Münt, G. (1994). *Interdisciplinary co-operation of research teams in science intensive areas of technology*. Final Report to the Commission of the European Union. Fraunhofer Institute for Systems and Innovation Research.

Schumpeter, J. (1939). *Business cycles*. McGraw-Hill Book Company, Inc.

Schumpeter, J. A. (1934). *The theory of economic development*. Harvard University Press.

Shane, S. (2001). Technological opportunities and new firm creation. *Management Science, 47*, 205–220.

Shendure, J., & Ji, H. (2008). Next-generation DNA sequencing. *Nature, 26*, 1135–1145.

Sick, N., & Bröring, S. (2021). Exploring the research landscape of convergence from a TIM perspective: A review and research agenda. *Technological Forecasting and Social Change, 175*, 121321.

Song, C. H., Elvers, D., & Leker, J. (2017). Anticipation of converging technology areas—A refined approach for the identification of attractive fields of innovation. *Technological Forecasting and Social Change, 116*, 98–115.

Song, M., & Montoya-Weiss, M. M. (2001). The effect of perceived technological uncertainty on Japanese new product development. *Academy of Management Journal, 44*(1), 61–80.

Trajtenberg, M., Henderson, R., & Jaffe, A. (1997). University versus corporate patents: A window on the basicness of invention. *Economics of Innovation and New Technology, 5*(1), 19–50.

Tuncalp, D., & Ercek, M. (2014). Divergence in firms: How technology convergence relate to organizational boundaries. *Academy of Management Proceedings, 2014*(1), 14310.

van Dijk, E. L., Auger, H., Jaszczyszyn, Y., & Thermes, C. (2014). Ten years of next-generation sequencing technology. *Trends in Genetics, 30*(9), 418–426.

Veugelers, R., & Wang, J. (2019). Scientific novelty and technological impact. *Research Policy, 48*(6), 1362–1372.

Wang, J., Lee, Y.-N., & Walsh, J. P. (2018). Funding model and creativity in science: Competitive versus block funding and status contingency effects. *Research Policy, 47*(6), 1070–1083.

Wirsich, A., Kock, A., Strumann, C., & Schultz, C. (2016). Effects of university–industry collaboration on technological newness of firms. *Journal of Product Innovation Management, 33*(6), 708–725.

Zhou, Y., Dong, F., Kong, D., & Liu, Y. (2019). Unfolding the convergence process of scientific knowledge for the early identification of emerging technologies. *Technological Forecasting and Social Change, 144*, 205–220.

Zhu, C., & Motohashi, K. (2022). Identifying the technology convergence using patent text information: A graph convolutional networks (GCN)-based approach. *Technological Forecasting and Social Change, 176*, 121477.