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Government R&D spending as a driving force of technology convergence[1]

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Abstract

This paper investigates the impact of government R&D spending on promoting technology convergence. We test the hypotheses that a government funding program has a positive effect on technology convergence and the effects are heterogenous on different participants (i.e., academic, and industrial inventors). To investigate this, our empirical test applies the Advanced Sequencing Technology Program (ASTP) as one example. We develop a novel dataset by linking the ASTP grantee information with the PATSTAT patent database. Based on this, we create inventor-level characteristics to implement propensity score matching, selecting an appropriate control group of inventors who are comparable to those enrolled in the ASTP. We then employ DiD models to evaluate the impact of the program on the matched sample. The results confirm that the program is a driving force of technology convergence. The findings also indicate that the program is more influential to industry inventors than to their academic counterparts. Additionally, we conceptualize a 'leverage effect' of the program and show it can attract many external industrial inventors. The work contributes to better understanding the role of a government-funded program in encouraging convergence and providing implications for developing convergence-related R&D programs in the future.

Keywords: technology convergence, NIH program, policy analysis
JEL codes: O33, O38

1 This study is conducted as a part of the Project "Research on innovation ecosystem formation processes" undertaken at the Research Institute of Economy, Trade and Industry (RIETI).

1. Introduction

Technology convergence refers to the phenomenon of emerging overlapping trends among at least two technological fields. Following Kodama's (1995) seminal perspective, which states that the combination of existing technologies could spawn novel ones, technology convergence is considered as a source of innovation. Noteworthily, given the complementary nature of contemporary general-purpose technologies (e.g., nanotechnology, information technology, etc.), it is expectable that new technologies will be developed through the form of convergence. Indeed, the concept of innovation-as-combination can be traced back to Schumpeter's notion (1939): '… 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, he metaphorizes firms as human beings that are constantly being born and destined to die. In the case of firms, they die as they are unable to maintain the pace in innovating themselves and then will be eventually overturned by others. For this reason, both policymakers and firm leaders (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 have laid the theoretical foundation for technological convergence and taxonomies (Curran and Leker, 2011; Karvonen and Kässi, 2013), while others contributed to methodological development for either understanding the historical patterns or forecasting the future convergence chances (Preschitschek et al., 2013; Ko et al., 2014; Kim et al., 2014; Passing and Moehrle, 2015; Zhou et al., 2019; Eilers et al., 2019; Kim and Lee, 2017; Kim et al., 2019; Lee et al., 2020; Kim and Sohn, 2020). One of the primary goals of comprehending technology convergence is to help business entities to sense and exploit new opportunities, organize R&D activity, and survive in the present dynamic business environment. On the other hand, as a source of innovation, the convergence processes can give birth to innovation that can either create untapped niche markets or transform people's lives tremendously.

The perceived importance of technology convergence, as well as the academic endeavors to conceptualize and quantify it, may point to a more fundamental and pivotal question of what drives technology convergence (Jeong and Lee, 2015; Sick and Bröring, 2021). Drawing on Curran's four-stage sequential process (science, technology, market, and industry), the growing cross-disciplinary research collaborations will erode the boundary and reduce the distance between science areas, reaching technology convergence (Curran and Leker, 2011). The framework implies that convergence can be driven by both scientific push and market pull. Song et al. (2017) classify convergence drivers into four categories: technological advancement, regulation and policy, market expectation, and social environment change. While these works leave a clue for investigating the drivers of convergence, only a few studies have provided empirical evidence and explanations on what triggers the convergence (Jeong and Lee, 2015, Caviggioli, 2016). Moreover, previous research on this topic has yielded only broad conclusions, stating convergence can be driven by closely related technological fields, a lower technology readiness level, and a longer R&D time horizon. This study aims to contribute to this emerging research field by empirically demonstrating and explaining government R&D spending as one of the drivers of technology convergence, as well as by attempting to understand the underlying mechanism by which a government-funded program can affect the behavior of industrial and academic inventors, who are main pillars engaging in the convergence process.

The program we explore in this study is the Advanced Sequencing Technology Program (ASTP), (or the Advanced Sequencing Technology awards) funded by the US National Human Genome Research Institute (NHGRI). While the program has been credited with its contribution to the success of reducing the costs of genome sequencing, it is also noted as an endeavor that constantly accentuated the multidisciplinary collaborations and steered public-private partnerships (Hayden, 2014). Several of the program’s distinctive features, such as mandatory grantee meetings, also benefit knowledge transfer throughout the sectors and promote information dissemination to external entities. In these respects, ASTP is a better match for our objective of examining the effects of government R&D investment in encouraging technological convergence.

The remainder of this paper is organized as follows: in Section 2 we provide a review of the literature on technology convergence and its drivers, and the hypotheses of the paper; in Section 3 we provide an overview of the programme under study and illustrate the process for constructing the dataset and the models for analyzing the ASTP; Section 4 is dedicated to the illustration the empirical results and analysis of the impact of government R&D spending as well as its implications; finally, we conclude the paper by summing up and discussing our findings in Section 5.

2. Literature review

2.1. Technology convergence and its drivers

While the notion of technology convergence varies according to managerial scope (Hacklin, 2007), we refer to it in this study as the blending of existing technologies. When different technological boundaries erode, spillovers between fields eventually lead to convergence. Unlike the conventional approach, which seeks breakthroughs via a linear R&D pattern, the convergence approach focuses on spawning new technologies by combining distinct ones. Hence, it is more complementary and collaborative in nature (Kodama, 1992). Additionally, Schumpeter (1934) maintained in his seminal work, The Theory of Economic Development, that innovation is a combination of existing resources. Technology convergence could be seen as an instance of the combinatorial process in this context by explicitly emphasizing hybrid technologies. Evidently, the rising exposure of the phenomenon of convergence can be observed in the demise of the adage "one technology, one industry" (Kodama, 1992).

Sick and Bröring (2021) conducted a thorough review of the literature on convergence from the standpoint of technology and innovation management. Among the prior works on technological convergence, great efforts have been made in methodological development to identify historical convergence patterns or anticipate future convergence possibilities through patent analysis (Preschitschek et al., 2013; Karvonen and Kässi, 2013; Ko et al., 2014, Eilers et al., 2019). Surely admitted their great implications to both enterprise and policymakers, it is also necessary to return to the central topic in convergence research, namely, which drivers promote the convergence process. From an evolutionary perspective, Hacklin (2007) conceptualized the convergence process into four phases: knowledge, technological, applicational, and industrial convergence. Curran et al. (2010) subsequently presented a four-stage model, illustrating the chronological order of science, technology, market, and industry convergence. The model implicitly suggests that technological convergence might be fueled by science/technology-push and market-pull, which have been addressed as innovation drivers by Mowery and Rosenberg (1979). Given the numerous factors which can contribute to the convergence, Song et al. (2017) proposed a taxonomy consisting of four groups: technological progress, regulation and policy, market expectation, and social change. In terms of technological progress, the rapid growth of the ICT industry can be viewed as the primary source and driver of convergence, as evidenced by the recent digital transformation (Han and Sohn, 2016).

Besides, other General-Purpose Technologies (GPTs), including information technology and nanotechnology, thanks to the nature of great technological generality (Gambardella and Giarratana, 2013), may serve as a vital knowledge provider to different fields (Appio et al., 2017). In the view of market expectation, it stresses the convergence driven by the demand-side. Dowling et al. (1998) claimed that the purchasing power may create a significant market need for products with integrated functions, which would then motivate firms to adopt and coordinate a variety of technologies. When it comes to social change, convergence is propelled by the challenges and needs that society faces. For example, the recent growth of green technology requires the convergence of different GPTs[1].

2.2. Policy and Technology convergence

The policy can be designed to remove both artificial and technological barriers among different technological fields. For removing the artificial barriers, one example 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. The technological barriers, on the other hand, may refer to the technological distance among distinct domains, and costs for combining them. Discipline-specific vocabulary, theories, and cognitive differences can lead to huge transaction costs associated with achieving convergence in a multidisciplinary setting (Nordmann, 2004). In addition, Jeong et al. (2011) claimed that, in a situation where the level of technology readiness is high, researchers, even within the same organization, are reluctant to work with colleagues with different backgrounds. In this scenario, policy refers to public R&D funding or a multidisciplinary incentive program. According to Littler and Coombs (1988), government-supported programs typically cover a wider range of technical fields than private sector projects but developed with a modest speed. Even if Metzger and Zare (1999) cast doubt on the effectiveness of such programs in fostering technological convergence, Jeong and Lee (2015) empirically showed that government-funded R&D initiatives with a longer timespan or a lower budget had a positive impact on convergence. In addition, Kim et al. (2017) showed that standards can also be a driving force of technology convergence through guiding the technological trajectories.

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

Apart from these two barriers, it is also necessary to mention the uncertainties and costs that usually come along with the convergence. Ambiguity in the market and technological scope are two types of uncertainty that have been often highlighted. Technological uncertainty refers to the incapacity to fathom some facets in technological environments (Song and Montoya-Weiss, 2001) which is common in the context since convergence has the potential to unite previously unrelated fields (Hacklin et al., 2013). On the other hand, market uncertainty raises concern because too innovative products may initially only attract the least lucrative customers (Bores et al., 2003). Besides, the fulfillment of convergence potential requires a considerable initial investment, which may cause enterprises to reallocate their resources to other endeavors (e.g., more promising near-term product development). Companies may then suspend or even kill these initiatives to avoid potential market failure, resulting in under-investment in knowledge creation through convergence. From this perspective, government-supported programs featured with university-industry knowledge exchange help reduce R&D market failures and ensure the benefits of the investments (Martin and Scott, 2000). 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 to success (Metzger and Zare, 1999).

To sum up, the existing literature on the impact of government policy on technology convergence leaves a clue that deregulations and public funding programs can be a potential driver of the convergence. However, we found that the related empirical works on this topic are still rare, which motivated us to devote efforts to this field.

2.3. Hypotheses

The literature review presented in Section 2.2 shows that scholars have investigated the relationship between government funding programs and technology convergence. One of the most critical specificities of technology convergence is multidisciplinary cooperation, which provides a knowledge foundation for convergence. The participation of specialists from a variety of backgrounds may spark novel ideas and inspirations while collaborating. However, a multidisciplinary configuration also implies that developing convergence-related projects would be more hazardous and time-consuming (Schmoch et al., 1994): participants need more time to familiarize themselves with people from diverse backgrounds and more cycles of test and failure to identify suitable solutions. As a result of these uncertainties and risks, both academic and industrial participants are more inclined to shift their focus to short-term and insured undertakings. In this regard, the government funding programs, which offer longer-than-usual grant durations, can enable researchers to conduct in-depth studies rather than seeking quick success. Indeed, since the early decades of the twenty-first century, government-supported initiatives (e.g., held by the National Science Foundation, the National Institutes of Health, etc.), which have incorporated a multidisciplinary setup (with a particular focus on the convergence of nanotechnology, biotechnology, and information technology), usually offered a long-term funding plan (Roco and Bainbridge, 2002).

Besides, since technological convergence is essentially commercially oriented in nature, it also necessitates the commercial potential and feasibility of interdisciplinary knowledge. In this light, the experience can be learned from the U.S. government innovation programs, which fostered the commercial applications and attracted nonfederal investment in R&D through promoting university-industry (U-I) collaborations or directly sponsoring industrial enterprises (Roessner, 1989). The inclusion of industrial entities underlines the commercial viability of developed projects, promoting technological development. In addition, industry-university collaborations enhance academia-industry knowledge diffusion. The influence of this might be bidirectional. On the one hand, firms can stay aware of cutting-edge academic research findings and recruit highly competent and well-matched personnel. On the other hand, academic scholars can get insight into what is happening in the industry sector, understanding potential applications of their work. Moreover, this may allow certain academic workers to shift from pure scientific exploration to technological research. Based on these, we, therefore, propose the following hypothesis:

Hp 1. A government-funded R&D program has a positive impact on promoting technology convergence.

Secondly, university and industry are regarded as two of the most important pillars of technological advancement. Hence, we want to further break down the analysis to investigate the roles of academic and industry inventors in the convergence process, respectively. While government-funded R&D programs are usually accompanied with an explicit goal of knowledge creation, but their management practices (e.g., reciprocal information sharing mechanisms) could also facilitate a mutual learning process across disciplines and sectors, which has the potential to lessen the cognitive distance for both academic and industrial participants. The shortened cognitive distance will enable companies to gain higher absorptive capacity, which then allows them to acquire new value or knowledge and translate it into innovation quickly (Cohen and Levinthal, 1990). In addition, in comparison to science-based knowledge, which is sufficiently codifiable, firm-based knowledge is more implicit, making dissemination more challenging (Kani and Motohashi, 2018; Kogut and Zander, 1992). Also, as opposed to scientific knowledge, which is regarded as a global public good, technological knowledge is often protected by intellectual property laws, which contributes to transmission difficulty as well. In this sense, we anticipate that government-funded R&D programs, which aid in the spread of knowledge, would have a greater policy shock on industry inventors than on university inventors.

On the other hand, the efficacy of reduced cognitive distance to university scholars may be impeded in several ways. Despite several efforts have been made to foster multidisciplinary collaboration in universities, current assessment mechanisms still place a premium on individual accomplishment, which disincentivizes faculty and departments to work across fields (Klein and Falk-Krzesinski, 2017; Pfirman and Martin 2017). As noted by Arnold et al. (2021), compared to a multidisciplinary setting, tenure/promotion committees may assess an academic worker more objectively in a uni-disciplinary context by comparing the productivity and impact of scholarly work to that of colleagues within a discipline. Also, it is risky for an academic researcher to jump into an unfamiliar field. Furthermore, technological convergence inherently bears a commercial purpose. In this sense, researchers inside universities often place a high value on publishing activity, since it carries a higher degree of prestige than commercialization (Sauermann and Stephan, 2013). However, companies typically put a priority on the commercialization potential of technology. And programs that support industry for convergence-related projects would incentivize businesses to move away from short-run projects and toward long-run convergence innovation activities, which are previously less likely to be performed by firms due to the risks and expensive initial expenditure (Feldman and Kelley, 2006). Therefore, firms are more urgent and have more motivation to engage in technology development and patenting activities. This leads to our second hypothesis:

Hp 2. Among the funded inventors, a government-funded R&D program has a greater impact on industrial inventors than university inventors.

The second hypothesis targets delineating the behaviors of the funded inventors. We then want to study how a program may influence the behaviors of inventors outside the program, which can also be divided into university and industry groups. The following three reasons lead us to expect that an R&D program may have a significant impact on attracting external industrial inventors than academic inventors. First, an R&D program that provides funding to not only traditional academic researchers but also companies maintains the commercial feasibility of developed projects. The commercialization relevance has a greater chance of attracting the attention of outside firms. Second, although many naysayers in the private sector may be reluctant to or even go against the convergence ideas initially, new markets and demands created later through converged technologies are very appealing to firms (Park, 2017). In this regard, the scholarly peer-review process inside a program increases the authority of the concepts, which further helps to convince partners for commercialization. Also, the program per se can act as a conduit for the external audience to see and acquire reassurance about associated results and accomplishments, changing their mindset from risk-averse to risk-neutral. We further conceptualize the attractive force to external players as 'leverage effects,' in which the government takes the initiative to invest in convergence ideas and then discloses internal progress and conclusions to grab the attention of externally prospective parties. Given the enormous costs associated with developing technologies through convergence, although the government spending might be only a drop in the bucket, the government can adopt a funding program as a lever to amplify the input force (government R&D spending) to provide a greater output force (potential private investors, industrial and academic participants), thereby achieving the social benefits. Due to the commercial nature of technology convergence, the corresponding leverage effects are expected to be more visible to external industrial inventors than university inventors. Finally, we propose the following hypothesis:

Hp 3. Government spending on R&D has a more significant impact on attracting external industrial inventors than academic inventors. In other words, the leverage effects of a program are more effective/visible to external industrial inventors than university inventors.

2.4. Conceptualization

This section presents the positions of the three hypotheses in Figure 1. While convergence can generate new technologies, it often comes with barriers, uncertainties, and substantial initial investments. In this study, we argue that a government-funded R&D program can be a driver of technology convergence (hypothesis 1). To explain why it is the case, we focus on the program's impact on the behaviors of internal and external participants in the scenario of convergence, which is illustrated by hypotheses 2 and 3. Hypothesis 2 states that the program will encourage academic and industrial inventors to engage in convergence activities, fostering technological development and research. Hypothesis 3, on the other hand, is concerned with the external participants, declaring that the program per se could be a crucial channel for disseminating internal knowledge and assuring authorities of convergence concepts by which motivate external players to take part. As we suspect that its impact will be significant on external industrial players and only limited on external academic researchers, we further conceptualize these as a 'leverage effect' for industry and an 'eye-catching effect' for academia.

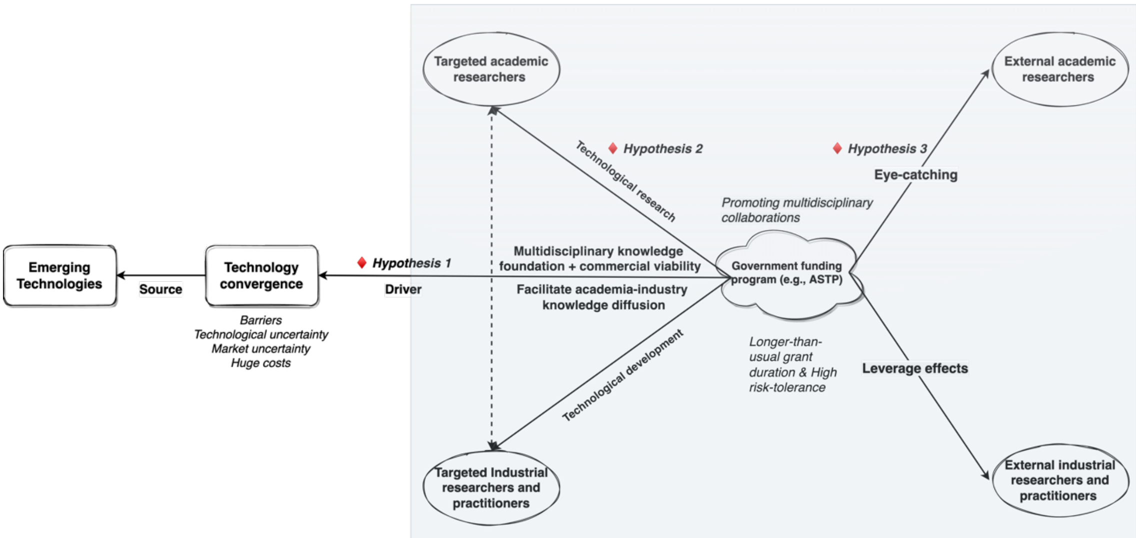

Figure 1. Conceptualization of the role of a government R&D spending in promoting technology convergence and the position of each hypothesis

3. Data source and methodology

Our empirical test relies on the Advanced Sequencing Technology Program (ASTP) at the National Institutes of Health (NIH). In the next section, we first present the context of ASTP that is considered as a potential convergence driver under this study.

3.1. Advanced Sequencing Technology Program from 2004 to 2014

When the Human Genome Project (HGP) was completed in April 2003, the total cost of this project was approximately 3 billion dollars. In the same year, the National Human

Genome Research Institute (NHGRI), an institute of NIH, announced two broad visions for the future genomics research: 'elucidating the structure and function of genomes' and 'translating genome-based knowledge into health benefits,' highlighting the potential of revolutionizing biomedical and clinical practice if the costs of sequencing can be significantly reduced (Collins et al., 2003). For this reason, in 2004, the NHGRI launched a funding program with an explicit goal of reducing costs by two to four orders of magnitude. This program is formally known as the Advanced Sequencing Technology Program (ASTP), which 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]). Even though the explicit goal for the project was to reduce the costs, the NHGRI emphasized that the goal should be achieved through multidisciplinary team collaborations, which can be seen from the three characteristics of the program. First, the ASTP calls for participation by multidisciplinary investigator teams, including biochemistry, chemistry, physics, mathematical modeling, software development, and so on. Second, unlike the traditional funding programs, which are exclusively awarded for academia, the ASTP offers grants to academic, industry, and foreign investigators, which can be seen from most grants were allocated to academia researchers and small companies, and even several research projects inside big companies (e.g., Intel and IBM) can also receive the funds. Finally, annual grantee meetings were held by NHGRI, mandatorily requiring entities sponsored by ASTP to share their findings, which also served as a bridge role in facilitating the knowledge diffusion between academic and industry investigators. Noticeably, the grantee meetings were considered a major feature of the program, and the participators were later extended to people outside the program, including investigators, investors, and so on. In addition, the ASTP also had a high tolerance to accept risky ideas, which were atypical of other NIH grants. Given these exceptional features of the ASTP, we expect this government funding program could be a potential driver of the convergence process.

The Sanger-based sequencing approach (i.e., capillary array electrophoresis (CAE)) was employed for the HGP, which was heavily dependent upon the field of biochemistry and is also referred to as First Generation Sequencing (Schloss, 2008). While the Sanger CAE method achieved high-quality results, the use of electrophoresis only allowed for a limited degree of parallelization, translating into comparably low efficiency and expensive

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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

sequencing costs. Compared to traditional Sanger sequencing, next-generation sequencing (NGS), which employs massively parallel techniques (also known as cyclic-array strategies), enables significantly increased data throughput, scalability, and efficiency (Shendure and Ji, 2008). The success of NGS implementation is dependent on a synergy of biochemistry, information technology, and nanotechnology. For example, information technology is involved in library preparation, which is typically the initial stage in a sequencing operation (van Dijk et al., 2014). Furthermore, the expanding volume of NGS data presents challenges for bioinformatics in areas such as sequence quality assessment, alignment (i.e., re-sequencing), assembly, and data analysis. In this regard, we might refer to the evolution of NGS as a 'convergence age.'

3.2 Data and measures

In studies of technology convergence, patent data, which indicate the knowledge accumulation and development in a specific technical field, are frequently used as a proxy for monitoring the convergence (Karvonen and Kässi, 2013). In this work, the technology convergence is measured by the inter-field citations between information technology (IT) and biotechnology (BT), which are two main technologies used by the Next-Generation Sequencing (NGS). We extract the IT and BT patent data and citation information from the PATSTAT 2020 Autumn version, noting all collected patents are published from the US patent office. To define the boundary of IT and BT patents, we use the concepts of technology classification issued by WIPO. The time window of the data is set from 1996 to 2019 to gather sufficient information for constructing patent indicators. As for the ASTP data, the grant lists are scraped from the NHGRI's websites, which provided detailed records for the ASTP awards from 2004 to 2014. We manually disambiguate the ASTP inventors and then link them to the PATSTAT database. The process for collecting data is visualized in Figure 2.

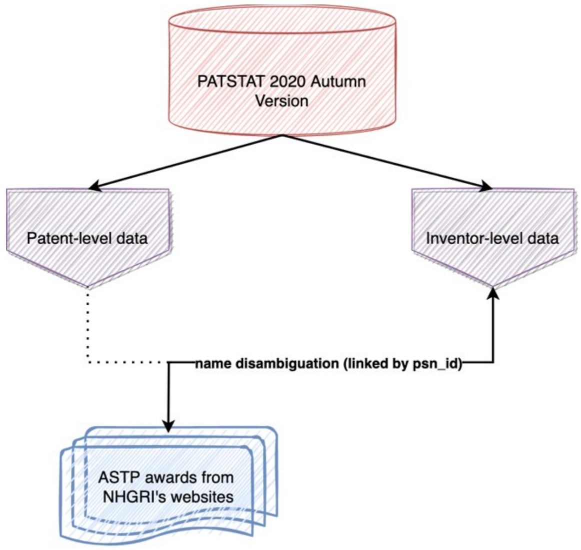

Figure 2. Data collection and processing

3.3. Reduction of selection bias using propensity score matching

Before testing the first hypothesis of the causality effects of government R&D spending on promoting technology convergence, which can be reflected from the inventors enrolled in the program becoming more likely to form inter-field backward citations and receive inter-field forward citations, we need to alleviate the bias induced by the selection process of ASTP review offices. Applicants for the ASTP needed to undergo a peer review process, which was assessed based on five criteria by review panels: *Significance, Approach, Innovation, Investigator, Environment*[4]. The first three criteria are relevant to the project outlined in the RFA, while the rest two tie into the investigator per se (i.e., the experience level) and their surrounding community (i.e., collaborativeness of the surrounding environment). We select and design variables based on these criteria and implement the propensity score matching with the dependent variable *ASTP* (1 to denote if a given individual is enrolled in the program and 0 otherwise). The selected covariates can be categorized into patent portfolio-level, inventor-level, and environment-level. The descriptions for each group of variables are given as follows.

Patent portfolio-level variables are relevant to the first three criteria. For example, in terms of *innovation*, it is asked for 'does the project employ novel concepts, approaches or methods?' and 'are the aims original and innovative?', which are evaluated on the

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

project sketched in the RFA. However, we are not able to rate the quality of the project based on these criteria and the data for the reviewing results are not disclosed either, and more importantly, such information is nonexistent for people who never apply for the program. Therefore, we assume some of the metrics can be reflected in one's past works. For example, we estimate an inventor's innovativeness by aggregating (i.e., average) the innovative scores over 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) designed an indicator to measure the originality of a patent by arguing an invention depending on diverse knowledge sources (i.e., a wide range of technology fields) is more likely to be original. The radicalness index originated from Shane (2001)'s idea, which states that the more radical an innovation is, the more it is based on paradigms that are not the same as the one to which it is applied. For variable *number of coinventors,* we set up a set of ASTP inventors coinventors, and then each person will be measured by the number of coinventors that in that set. The idea is that if a person co-authored with the ASTP inventors' coinventors, he or she may share similar characteristics with the ASTP inventors. And for the variable *number of institutions,* it is similar to coinventors, but in this case, we consider the ASTP inventors' institutions associated with the patent assignee information. Note that these variables will be first examined at the patent-level, and then aggregated to person-level based on one's patent portfolio.

Inventor-level variables are related to the criterion of *Investigator*. In this group, six variables are designed: *experience*, *degree centrality*, *betweenness centrality*, *PageRank*, *local betweenness centrality*, and *local PageRank*. Variable *experience* refers to the number of patents published until the given 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, which are obtained from the global coinventor network. The global coinventor network can further be decomposed into several connected components, which we call local networks or communities. *local betweenness centrality* (role as a bridge within his/her community) and *local PageRank* (importance of an inventor (node) within his/her community) are local network statistics computed from these connected components. The reason for creating both global and local network statistics is to take into account the situation where one may have a relatively small value of *PageRank* (global importance) but actively act as a bridge in his or her community (large value of local betweenness centrality).

Environment-level or community-level variables tied to the criterion of *Environment*. The network statistics in the previous section are calculated with respect to a node. In this section, we create environment-level variables using network statistics with respect to a connected component (community). In this manner, we propose four variables: *diameter* (the size of the community), *average clustering coefficient* (the likeliness that two neighbors of an inventor are also connected within the community), *efficiency* (how efficiently an inventor can reach others within the community), and *community diversity*. The first three are commonly used network statistics. The last one is inspired by Aggarwal et al.'s (2020) work, where they demonstrated a method for measuring within-team knowledge diversity and across-team knowledge diversity. In our case, each inventor in a community would be first represented by a characteristic vector, where each element shows his or her experience in each International Patent Classification (IPC) subgroup. The cosine diversity score is then calculated to measure the degree of diversity for a community (as described in further detail later in the Appendix). As all variables constructed in this group are network-level statistics, inventors within the same community will share the same values.

The matching process will be conducted based on these fourteen variables and implemented for each year separately as the ASTP had multiple application receipt dates. Also, one inventor may receive the ASTP award more than one time, and in this case, we only count the earliest time for each inventor being enrolled in the ASTP. For each year, these fourteen variables will be recomputed based on the information before that timestamp. We carry on an optimal pair matching strategy using the R package 'MatchIt,' where the sum of the pairwise distances in the matched sample will be minimized. Each treated observation would be matched with two control observations. After that, we pool together the matched sample for each year into a whole dataset. The overall flowchart is depicted in Figure 3.

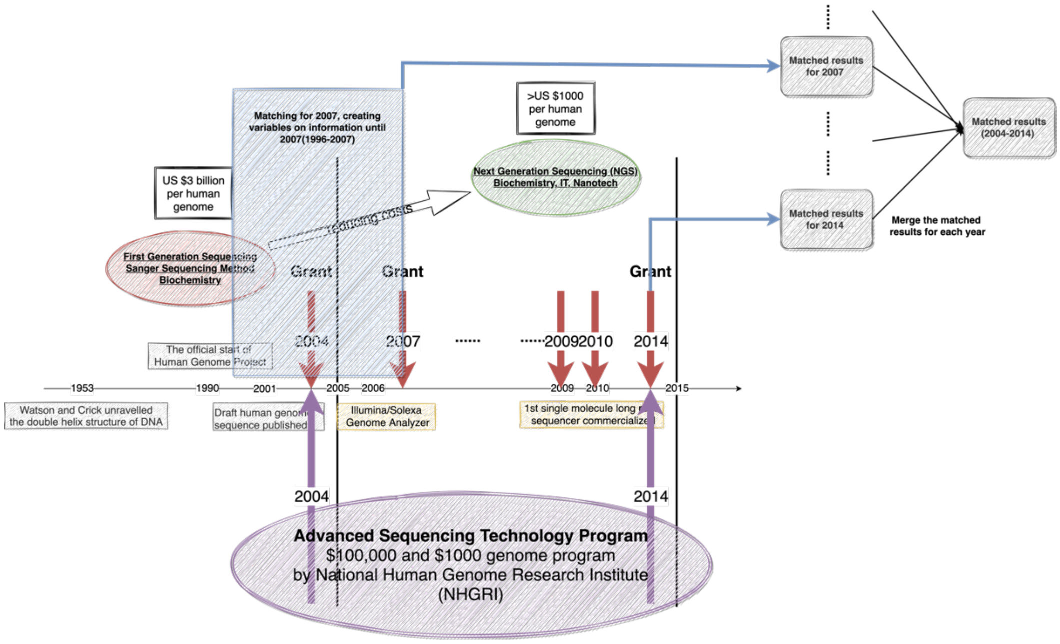

Figure 3. Flowchart of implementation of propensity score matching

3.4. Matching results

After estimating the propensity scores, one treated observation is matched with two control observations for each year. In our sample, there are cases that a non-treated observation is being matched multiple times to treated observations in different years. Hence, in the final combining process, we only keep unique individuals by removing the repeated non-treated observations. Also, there are two special cases where ASTP inventors are matched into control groups before they are enrolled in the program[5]. For these two cases, we simply delete them from the control group. In total, we get 54 observations in the treatment group and 70 observations in the control group. Table 1 reports the results before and after matching for the first year (2004), where propensity scores differ quite substantially between treated and untreated inventors before the matching. After matching, the gap of propensity scores between treated and untreated units is well alleviated, which can also be seen from other variables. Besides, the distribution of propensity scores after matching is presented in Figure 4, which also evidently proves the quality of matching. In particular, the mean values for the treatment

[5] Leamon, John H. and Korlach, Jonas are being matched as untreated units to sample of 2004 and 2005, and both of them later received the grants in 2009 and 2010, respectively. This also somehow proved the quality of selected variables for the matching process.

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. Also, it is noted that 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, the table shows that ASTP inventors are in a more extensive and more diversified community than external inventors on average.

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 avgcluster	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

Table 1. Before and after matching results of the sample in 2004

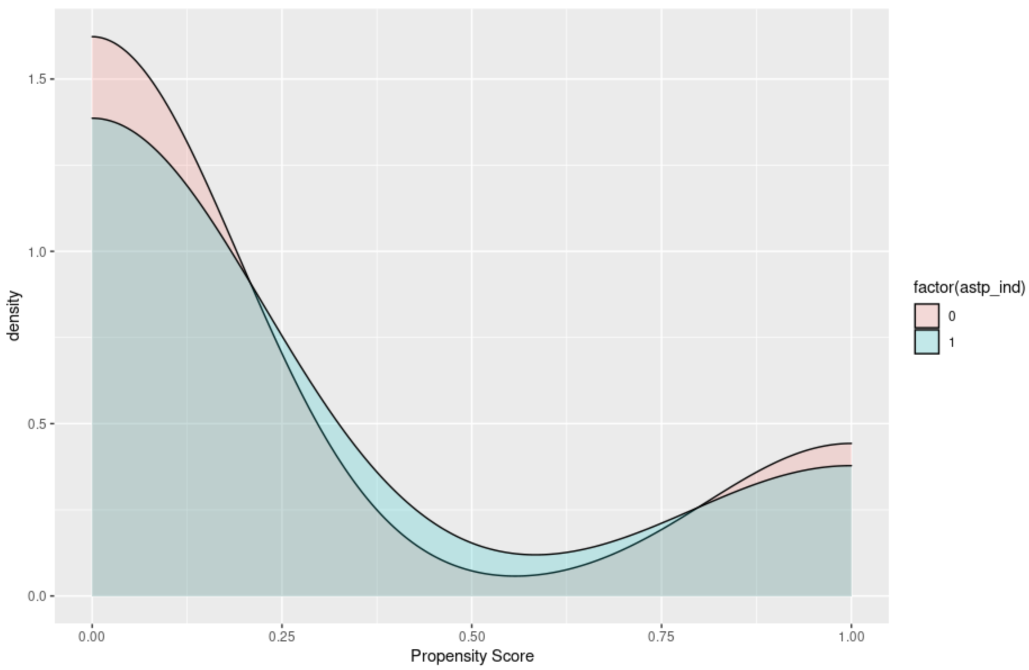

Figure 4. Distribution of propensity scores after matching

3.5. Regression models

We expect that a government R&D program can promote technology convergence, which can be observed from the increasing number of inter-field citations of inventors after being enrolled in the program. We further divide the inter-field citations into backward and forward citations, where the backward citations exhibit the engagement of inter-field innovation activities, and the forward citations manifest their impact on the external environment. As the ASTP had multiple application receipt dates, we adopt a difference-in-differences (DiD) specification with multiple periods to estimate the relation between the ASTP and the inter-field citation counts. The regression set-up is given as follows:

$$\log(1 + Y_{it}) = \alpha + \beta D_{it} + \delta X_{it} + \mu_i + \lambda_t + \epsilon_{it},$$
$$i = 1, \dots, 124; t = 2000, \dots, 2019$$

In the above equation, Y_{it} is a measure of technology convergence of person i in year t, which can be either inter-field backward or forward citation counts. Both backward and forward citations are first counted at the patent level and then aggregated into inventor level by taking the sum over one's patent portfolio. When dealing with the forward citations, we adopt a fixed window patent citation count (count forward citation accrued to the patent of interest from the patent application date to 5 years thereafter). λ_t and μ_i are year and individual fixed effects, ϵ_{it} is the error term. The variable of interest is D_{it}, a dummy variable that equals one in the years after person first being enrolled in the ASTP and zero 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. Control variables are employed to secure a reliable estimate of the impact of ASTP on enrolled inventors. The variables are selected to control three aspects: an inventor's patent quality, an inventor's characteristics in the global and local network, and the characteristics of an inventor's surrounding network. Most of the variables are selected from those being used for matching. In addition, we need to control for the increase in total citation counts. Furthermore, we include variable $science$, which represents the number of backward citations of non-patent literature (NPL), to control for the effects of citing scientific papers. Karvonen and Kässi (2013) suggest the count of NPL evaluates the proximity between technological innovation and scientific research, which can be used to measure the science-technology linkage to some extent. With that being said, Meyer (2000) raises caution that NPL can be added by applicants to intentionally enhance the breadth of patent coverage or due to the standard conduct of examiners.

4. Results

4.1. Empirical results

Our first analysis is to show the effects of a government funding program on promoting technology convergence. Table 2 and 3 report the impact of the ASTP on change of inter-field citations. The model 1-5 show that the coefficients of treated variable D_{it} are statistically significant at the 5% significance level when considering the inter-field backward citations. Thus, we found evidence showing that the enrollment encouraged the inventors to engage in multidisciplinary innovation activities. For model 2 and model 5, variable $science$ has statistically significant positive coefficients, suggesting inventors who tend to cite more NPL are more likely to form inter-field backward citations. As for the inter-field forward citations, we found that the coefficients of D_{it} are statistically significant in terms of model 6, 8, 9 and 10, while it becomes insignificant when we are controlling the patent quality. For variable $science$, it is significant (at the 1% level) and positive again, in this case, indicating inventors who tend to cite more NPL are more likely to receive inter-field forward citations. However, when considering the forward citations, both community efficiency and community diversity show negative coefficients, suggesting locating in a diversified community may not increase the forward citations. In summary, we found strong evidence that the program encouraged inventors to engage in multidisciplinary innovation activities, while relatively weak evidence for its influences on the inventors outside the program.

	Model 1	Model 2	Model 3	Model 4	Model 5
	log(#InterBWD+1)	log(#InterBWD+1)	log(#InterBWD+1)	log(#InterBWD+1)	log(#InterBWD+1)
treated	0.2822**	0.2114**	0.2361**	0.2289**	0.1713**
	(0.1246)	(0.0941)	(0.1109)	(0.1096)	(0.0858)
log(#TotalBWD+1)	0.5016***	0.3617***	0.4992***	0.6031***	0.4357***
	(0.0475)	(0.0552)	(0.0500)	(0.0567)	(0.0552)
originality		2.1380***			2.6407***
		(0.6213)			(0.5364)
radicalness		0.1538			0.3549
		(0.2673)			(0.2357)
science		0.0738***			0.0584***
		(0.0109)			(0.0094)
degCentNorm			0.6346		2.5546
			(3.0947)		(2.1819)
btwnCentNorm			0.0678**		0.0240*
			(0.0300)		(0.0125)
btwnCentLocal			-0.1641		0.0636
			(0.3086)		(0.2476)
pagerank			1.6467		-0.9004
			(5.2970)		(3.6013)
pagerankLocal			-1.3559**		-1.7171
			(0.5704)		(1.1311)
community diameter				0.0009	0.0007
				(0.0053)	(0.0069)
community avgcluster				-0.3793**	-0.5364*
				(0.1803)	(0.3044)
community efficiency				-0.3902**	0.2533
				(0.1588)	(0.4915)
community diversity				-0.2370	-0.2360
				(0.3620)	(0.2551)
constant	-0.0615	-0.0653	-0.0381	0.0639	0.0187
	(0.0646)	(0.0546)	(0.0742)	(0.0714)	(0.0607)
N	2480	2480	2480	2480	2480
adj. R^2	0.6973	0.7838	0.7208	0.7260	0.8023
AIC	3700	2900	3600	3500	2700
BIC	3900	3000	3700	3600	2900

Standard errors in parentheses

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

Table 2. DiD estimation results of backward inter-field citations

	Model 6	Model 7	Model 8	Model 9	Model 10
	log(#InterFWD+1)	log(#InterFWD+1)	log(#InterFWD+1)	log(#InterFWD+1)	log(#InterFWD+1)
treated	0.1283**	0.1086	0.1458*	0.1821**	0.1397**
	(0.0807)	(0.0818)	(0.0807)	(0.0754)	(0.0763)
log(#TotalFWD+1)	0.5179***	0.4099***	0.5064***	0.5092***	0.4298***
	(0.0361)	(0.0402)	(0.0357)	(0.0357)	(0.0389)
originality		0.1884			0.2765
		(0.2604)			(0.2750)
radicalness		-0.2016*			0.1747
		(0.1132)			(0.1105)
science		0.0394***			0.0327***
		(0.0104)			(0.0104)
degCentNorm			-2.2677		-1.1640
			(1.7502)		(1.4680)
btwnCentNorm			0.0461		0.0176
			(0.0305)		(0.0183)
btwnCentLocal			-0.5500**		-0.2127
			(0.2691)		(0.2841)
pagerank			2.8892		2.0277
			(2.6612)		(2.4623)
pagerankLocal			-0.2944		0.4113
			(0.2559)		(0.7421)
community diameter				0.0100**	0.0035
				(0.0048)	(0.0049)
community avgcluster				-0.0036	0.0765
				(0.1080)	(0.1741)
community efficiency				-0.1348	-0.4262
				(0.0993)	(0.3066)
community diversity				-0.8221***	-0.7176***
				(0.2319)	(0.2356)
constant	-0.0773*	-0.0681	-0.0631	-0.0330	-0.0332
	(0.0423)	(0.0449)	(0.0495)	(0.0436)	(0.0453)
N	2480	2480	2480	2480	2480
adj. R^2	0.6619	0.6969	0.6751	0.6847	0.7154
AIC	2400	2200	2300	2300	2000
BIC	2600	2300	2500	2400	2200

Standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3. DiD estimation results of forward inter-field citations

4.2. 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 the enrollment. We do this by fitting the regression model:

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

where the dummy variable D^{-j} equals one for persons in the jth year before enrollment, while D^{+j} equals one for persons in the jth year after enrollment. It equals zero otherwise. We exclude the first year (2000), thus the dynamic effects of enrollment, the D's, are estimated with respect to the first year. Figures 5 and 6 plot the estimated results and the 95% confidence intervals for inter-field backward and forward citations, respectively.

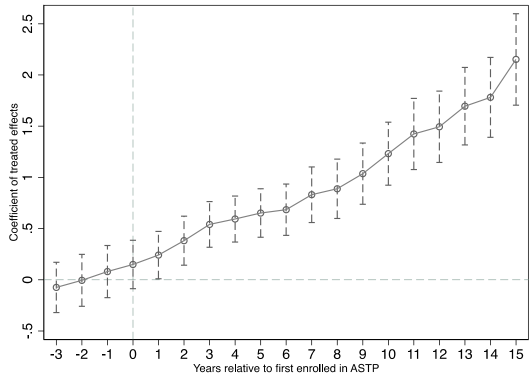

Figure 5. The dynamic impact of enrollment on backward inter-field citation counts.

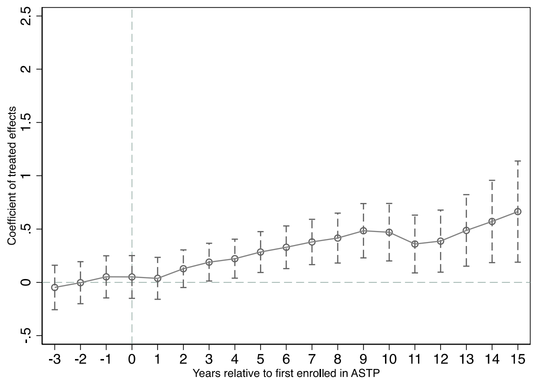

Figure 6. The dynamic impact of enrollment on forward inter-field citation counts.

Figure 5 reveals two important observations. First, the estimated coefficients do not significantly differ from zero in the three years before being enrolled in ASTP, eliminating the concern of reverse causality that the ASTP might have selected multidisciplinary inventors at the beginning. Second, the impact of the ASTP materializes very fast, which can be seen from the estimated coefficients as well as the corresponding confidence intervals quickly shift from zero. The quick responses are probably driven by the stringent milestone system of the National Advisory Council for Human Genome Research. The stringent milestone system has been an effective tool for NHGRI staff to plan and monitor progress, which was also incorporated as a condition of award. In addition, this could be also credited to the 'Mandatory Annual Grantee Meetings' held by NHGRI, where ASTP inventors had to regularly report and share their progress.

On the other hand, for the inter-field backward citations in figure 6, the estimates coefficients show no effects in the three years before being enrolled in ASTP. And even in the first two years after being enrolled in the ASTP, the coefficients still do not significantly differ from zero (confidence intervals contain zero). While starting from the third year after being enrolled, we can see gradually increasing effects on the number of inter-field forward citations (confidence intervals shift from zero). The lagged effects of the program on the external environment are probably due to external players needing time to sense and assess the ASTP inventors' works. Besides, the gradual increase in estimated coefficients proved its impact of promoting external multidisciplinary innovation activities. The annual grantee meetings, which is a distinct and innovative feature of ASTP, could be one of the key factors that impel and foster the process. The meeting had been limited to the ASTP inventors and only a small group of selected participants during the first years of the program, but then extended to a large group of audience from representatives of large companies to young scholars and students. The collegial nature of the meetings facilitates knowledge sharing and forms a channel for attracting experts in different fields, which in turn enhances its impact on nurturing multidisciplinary collaborations.

To sum up, our results confirm what was hypothesized: government R&D spending has a positive impact on promoting technology convergence, which can be seen from the significant positive values of treated variables on both inter-field backward and forward citations. However, the impact might be heterogeneous from different groups of people (i.e., university and industry). Therefore, in the next section, we further break down the analysis to see its impact on the university and industry inventors.

4.3. Impact of government R&D spending

The ASTP supported both academic and industrial inventors. In this section, we test the remaining two hypotheses. To test the second hypothesis, we labeled the ASTP inventors in our dataset into two groups: university and industry. And for testing the third one, we classified the backward and forward citations accrued to the ASTP inventors by using the attribute psn_sector provided by PATSTAT[6]. Explicitly, hypotheses 2 and 3 focus on internal and external inventors, respectively.

4.3.1. Direct influences on the internal inventors

To see the program's heterogeneous impact on enrolled academic and industrial groups, we conduct the DiD estimations on these two groups, respectively. And in this case, we are interested in backward citations only, as backward citations reflected how ASTP shaped the behaviors of inventors who were participants in the program. Table 4 summarizes the regression results on two groups of people. The coefficients of the treated variable are positive and significant for almost all scenarios, indicating the program encouraged both parties to engage in technology convergence activities. However, we found the coefficients for industrial groups are larger than that of academic groups, regardless of inclusion of controlled variables, suggesting the program has greater impact on industrial inventors than university inventors. Therefore, the results support the second hypothesis.

	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**	0.1631	1.0401***	0.2951**
	(0.2007)	(0.1104)	(0.2312)	(0.1162)
Constant	0.0813	-0.0049	0.1086	0.0272
	(0.0793)	(0.0743)	(0.0829)	(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	0.7541	0.4287	0.7852
AIC	3700	1900	4100	2200
BIC	3800	2000	4200	2400

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 4. DiD estimation results for the ASTP university and industry inventors

[6] In PATSATA, each applicant has been assigned to one or more sectors, including individual, company, unknown, government, non-profit 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.

In addition, as the backward citations depicted the knowledge flows in, we can, therefore, also track the source of knowledge of the ASTP inventors. Specifically, we look at four different channels that knowledge flows to inventors inside the program, which are represented by four arrows in figure 7. The thickness of each arrow is proportional to the citation counts shown in figure 9. In figure 7 and 9, the sector of industry plays a dominant role in exploiting multidisciplinary knowledge from outside. This probably can be explained as, by receiving funding from the ASTP, companies can shift from near-term product development and to devote resources to innovative early-stage projects. In figure 9, even the trend of ASTP university inventors is lower than their industrial counterparts, we still can observe a clear growing pattern after being enrolled in the program. This may be explained as the ASTP buttressed regular academic sections to participate in technological development projects, which are generally overlooked in a lab since these are typically just seen as non-hypothesis-driven, and massive data-gathering exercises (Schloss et al., 2020). Additionally, when looking at the knowledge source of the ASTP university inventors, we found they cited a comparable number of patents from the industry. This result is somewhat interesting because the university has always been considered as one of the major knowledge sources for industry. The reverse relationship, in this case, leaves a clue for government intervention can forward technological research. And the phenomenon might also be interpreted as the effects of the grantee meetings, which facilitated the knowledge diffusion between industrial and academic groups, and in turn let university research perceive knowledge in the industry sector.

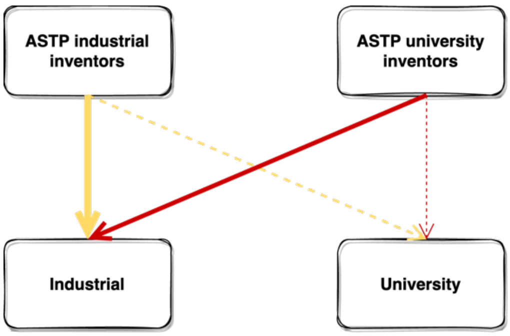

Figure 7. Channels for inflow knowledge (directions for backward citations)

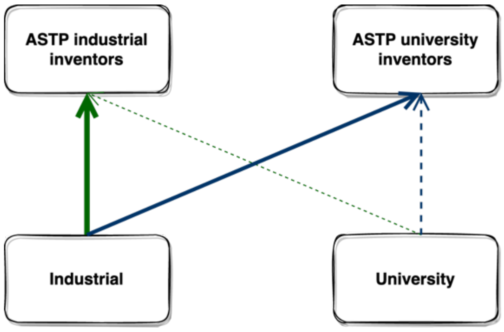

Figure 8. Channels for outflow knowledge (directions for forward citations)

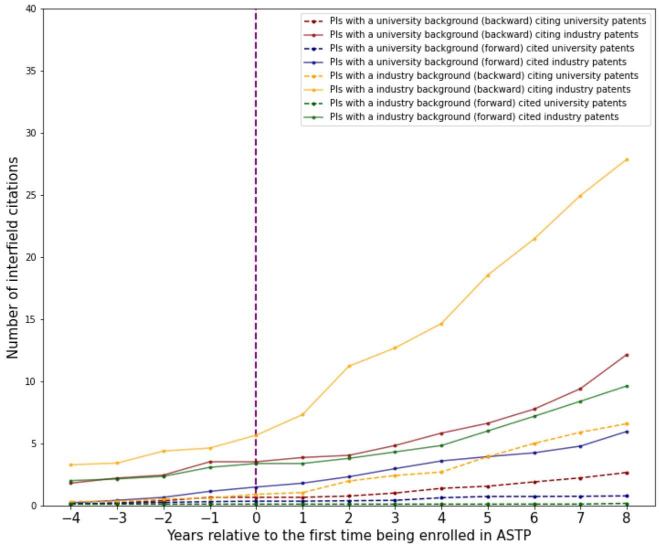

Figure 9. Decomposition of citation counts

4.3.2. 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, which can be traced by the forward citations received by the ASTP inventors. Since the forward citations trace the trajectory of knowledge flows out, it is equivalent to expect that these forward citations are mainly cited by external industrial entities. Figure 8 delineates the four channels that knowledge flows from the ASTP inventors to inventors outside the program, where the thickness of each arrow is proportionate to the forward citation counts shown in figure 9. In figure 8 and 9, the results suggest that the external industrial players are the main audience to program. Table 5 presents the statistical comparison of the forward citations made by the external university and industry players. The results again confirm that forward citations made by external industrial inventors are significantly greater than that of external university inventors on average.

	(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***

Significant level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5. Forward citations made by external university and industry players

As we mentioned earlier, the attractive force to external inventors can also be conceptualized as the 'leverage effects' of the program. The results suggest that the 'leverage effects' are more effective to external industrial inventors, indicating the program per se can be considered as a 'lever' to attract other industrial players (e.g., investors) coming on board, bringing extra resources to the table for further development and commercialization. While for the external academic inventors, the limited 'leverage effect' is observed. And that might be because the costs for developing the related technologies go beyond the affordability of most laboratories. Also, as we explained before, external academic inventors may have less motivation to directly the convergence activities.

5. Conclusion and discussion

This paper has investigated the impact of a government funding program (i.e., ASTP) on promoting technological convergence. We hypothesize that a government-supported program has a positive effect on promoting technology convergence and the program has a greater impact on industrial inventors than university inventors. Also, we conceptualize a 'leverage effect' of the program and hypothesize that it is more effective to external industrial inventors than their academic counterparts. To investigate this, we developed a novel dataset by linking the ASTP grantee information provided by NHGRI with the PATSTAT patent database. Based on this, we created inventor-level characteristics to do propensity score matching, establishing a control group of inventors who are comparable to those enrolled in the ASTP. We then evaluated the impact of the ASTP through DiD models on the matched sample. Our results provided evidence that the ASTP encouraged the enrolled inventors and external inventors to engage in multidisciplinary innovation activities. We then illustrated the program's heterogeneous effects on different groups of grantees. The results confirmed our second hypothesis that it has a greater impact on industrial inventors than university inventors. Finally, we also showed the 'leverage effects' of the program are more effective to external companies than academic institutions.

Some of the results of this work are in line with previous theoretical and empirical studies (e.g., Karvonen and Kässi, 2013; Hacklin, 2007). The regression table suggests that the number of non-patent citations is positively correlated to the forming of both inter-field backward and forward citations. This echoes the previous literature (e.g., Curran and Leker, 2011), which states scientific research provides a knowledge base for convergence. However, Caviggioli (2016) demonstrates that new convergence is more likely to occur among fields that are less anchored in scientific research. This calls for more research to explore the relation of scientific knowledge to convergence. Besides, it is interesting but natural to discover that, in the case of the forward citations, the treatment effects became insignificant when patent quality was controlled, suggesting future research should include this factor.

5.1. Government R&D spending as a convergence driver

Unlike a conventionally linear R&D activity, which impels technological advancement by deepening the investigation within a single area, convergence creates novel technologies through combining knowledge from various domains. The inherent multidisciplinary nature implies that convergence requires a long-run development and is usually associated with uncertainties and risks, which is a major hindrance to daunt potential private investors. In this sense, as innovation and management scholars discussed, government-supported programs with distinct features help remove barriers, reduce R&D market failures, and ensure the benefits of the investments (Littler and Coombs, 1988; Jeong and Lee, 2015; Martin and Scott, 2000). Specifically, the multidisciplinary configuration establishes a knowledge foundation for the convergence, and the longer-than-usual grant durations allow 1) industrial players to shift back from guaranteed near-term product development and 2) academic researchers to conduct in-depth research rather than 'muddle through' the problem. Although the program's direct impact, namely, propelling participants to engage in convergence activities, might only induce a few initial sparks in the existing technological space, its ripple effects could start a prairie fire. First, the program itself could be a route for increasing the exposure of internal discoveries. In addition, the peer-review mechanism ensures scientific credibility and standards, which can help to convince external parties. Moreover, with the involvement of industrial participants, which facilitates the demonstration of commercialization potentials, it may attract more private investors to join in (or even induce social bubbles) and then speed up the development of converged technologies. The joint force may eventually create a significant transformation in the technological space (e.g., converged technologies become mainstream, for example, next generation sequencing in this work).

5.2. Implications

As the ASTP was successful in achieving its goal through fostering multidisciplinary collaboration and facilitating the commercialization of the NGS (Hayden, 2014; Nature 2014), this study contributes to an empirical demonstration of how a government funding program can promote technology convergence. For explicitly promoting innovation through the channel of technology convergence, a large-scale convergence-oriented R&D program is needed (Jeong and Lee, 2015). In this study, the results suggest that industrial inventors under such a program are more actively engaging in convergence activities than academic counterparts. Also, the involvement of industrial participants underscores the commercial viability of the projects, which may motivate universities to take on technological research rather than pure scientific exploration. This gives the suggestion of when designing technology convergence-oriented R&D programs, policymakers should consider the effects of the inclusion of industrial entities. In addition, scholars have raised concerns about the impact of such programs (Metzger and Zare, 1999; Jeong and Lee, 2015) may be only marginal. Our work shows that a government R&D program can serve as a channel for disclosure and propagandize internal findings and assuring authorities of incipient and risky convergence concepts, which may lead to 'leverage effects' enticing outside private investors and industrial players on board. However, such 'leverage effects' are only limited to academic players. In terms of the limitations and future, the paper mentioned that several program settings and management practices may also contribute to the positive impact of convergence; however, the prominence of these features may need to be addressed in future studies.

Appendix

Table A.1. Measuring the degree of diversity for a community

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

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

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

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

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