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An empirical test for general purpose technology: an examination of the Cohen–Boyer rDNA technology

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General purpose technologies (GPTs) provide fundamental breakthroughs that transform industries and provide a platform for increased productivity. While a large theoretical literature describes GPT characteristics there has been little empirical work that measures the attributes of GPTs. Our analysis focuses on patents associated with the Cohen–Boyer rDNA patents, a credible GPT candidate. We empirically test our predictions about technological complementarity, applicability and discontinuity against a control group of patents with similar origins. Our results suggest that the characteristics of GPTs may be discernable through the analysis of patent data.

JEL classification: L65, L29, O31, O33.

1. Introduction

The introduction, diffusion, and adaptation of new technologies provide the basis for economic growth. Certain discoveries, called general purpose technologies (GPTs), provide fundamental breakthroughs that transform industrial activity and provide a platform for increased productivity throughout the economy. Historical examples such as the steam engine, electricity, and computers share attributes that are particularly salient for long-running economic growth (Helpman, 1998; Crafts, 2004; Rosenberg and Trajtenberg, 2004; Lipsey *et al.*, 2005). GPTs represent new knowledge that is complementary with existing technologies and applicable to a broad

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range of existing industrial sectors while providing opportunity for the creation of entirely new industries.

A fundamental question is how to discern which new technologies have the potential to become transformative GPTs. Major technological innovation is inherently disruptive and involves discontinuities and disequilibrium, making it difficult to model (Youtie et al., 2008). While there is a rich theoretical literature on GPTs, there are unfortunately relatively few empirical studies (Thoma, 2009). Most empirical academic work deals with incremental innovations, which are easier to model (Helpman, 1998: 2, 3). As a result, while many nations, regions, and places invest resources in technology-based economic development, we have only a rudimentary understanding of the types of inventions that generate transformative economic growth.

Our objective is to define a set of theoretical predictions about the characteristics of GPTs and to empirically test these predictions. We focus on the Cohen–Boyer patented invention for recombinant DNA (rDNA, the purposeful recombination of genetic material). We use patent citations, augmented with company and inventor characteristics, to explore whether this technique, invented by Stanley Cohen of Stanford University and Herbert Boyer of the University of California, San Francisco, exhibits characteristics that the literature associates with GPTs. Specifically, we derive empirical measures of technological complementarity, technological applicability, and technological discontinuity. We then empirically test these attributes against a control group of similar patents.

Our results support the assertion that the Cohen–Boyer patents exhibit characteristics of a GPT (Ruttan, 1999: 54). First, the Cohen–Boyer patents exhibit high technological complementarity: patents that cite Cohen–Boyer also cite prior art from a greater number of industrial sectors compared to the control group. Second, the patents that cite the Cohen–Boyer invention demonstrate wider applicability by representing a broader range of technology classes than the patents citing the control group. Finally, we found evidence of technological discontinuity through a pronounced tendency for subsequent inventors to be located in the same region as the inventors of the GPT. The proximity of subsequent inventions suggests that the ability to extend a technology benefits from geographically mediated knowledge spillovers, and suggest that a GPT's implications are difficult to codify, making proximity an important factor in obtaining and extending its technology to new inventions.

This article has five sections. Section 2 examines the theoretical background and motivates a set of hypotheses that define a GPT. Section 3 describes the Cohen–Boyer patents and the construction of the set of patents that cite these patents. Section 4 presents our empirical results. Section 5 discusses those results and concludes with suggestions for future research.

2. Defining GPT

Academics, since Schumpeter (1911), have explored the origins of new industries and the impacts of technological breakthroughs and entrepreneurial activities on economic growth. Schumpeter identified long cycles of economic growth attributable to basic inventions that, when their economic potential was revealed, created surges of investment. The result was a temporal burst of economic growth as the invention diffused widely across the economy. These "gales of creative destruction," as Schumpeter labeled them, alter technological and economic advantages both within and between countries. In Schumpeter's conceptualization, technological change is endogenously determined and is the most important factor for creating economic growth.

The concept that major revolutionary discoveries drive economic growth has persisted in a variety of conceptualizations. Nelson and Winter (1982: 257) called technological regimes "the frontier of achievable capabilities along a complementary set of research trajectories" and the primary drivers of economic growth. Freeman and Perez (1998) defined platforms that create opportunity for profitable investment in a large set of innovations, called carrier branches.

Scholars expanding these ideas more recently have focused on the concept of GPTs (Helpman, 1998; Lipsey *et al.*, 2005). The criteria for defining a GPT are not yet standardized. According to Lipsey *et al.* (2005: 96), a GPT is "a single technology, recognizable as such over its whole lifetime that initially has much scope for improvement and eventually comes to be widely used, to have many uses, and to have many spillover effects." For example, Lipsey *et al.* (2005: 99) have argued that gunpowder is not a GPT because, despite its tremendous social and economic impact, it had limited adaptability across industrial sectors. Meanwhile, computers and microprocessors could be considered a GPT because they have been used widely and in a variety of ways (Lipsey *et al.*, 2005: 94). Moser and Nicholas (2004) embraced the four characteristics enumerated by Lipsey *et al.* (1998): a wide scope for improvement and elaboration; applicability across a broad range of uses; potential for use in a wide variety of products and processes; and strong complementarities with existing or potential new technologies. Their empirical results concluded that electricity could not be considered a GPT, a finding that contradicts historical productivity growth (David, 1990) and raises questions about the methodology (Lipsey *et al.*, 2005: 108, 9). Alternatively, Hall and Trajtenberg (2004) relied on the criteria provided by Helpman and Trajtenberg (1998a): pervasiveness in terms of use across multiple sectors of the economy; continuous related technical advances; and complementarity in terms of investment in downstream sectors. Hall and Trajtenberg used patent data to define four operational measures of a GPT: number of patent citations from outside the original patent class; a pattern of cumulative innovation within its technology area; a burst of activity as complementary goods are developed; and longer than average citation patterns reflecting the length of time required for a

GPT to pervade the economy. They used these criteria to examine all US patents from 1967 to 1999 and found that only a small number of patents were credible candidates for GPTs. This may reflect several artifacts. First, while radical breakthrough technologies often have long time lags, it is not clear exactly how much time should be allowed for the complementary expertise associated with a GPT to develop. Certainly, the length of time required to capitalize on a GPT will be a function of factors such as general economic conditions, industry structure, and firm strategy. Second, a GPT may be the product of sets of complementary patents rather than a single patent. A patent family that encompasses different applications may qualify as a GPT although no single patent created sufficient impact. Finally, because technology class is a categorical assignment, the distribution of citations among technology classes is heterogeneous (Hall *et al.*, 2001: 12, 13). Analyses of the universe of patents should account for this heterogeneity with fixed effects or by making comparisons within a technology class.

As there is limited agreement about the measurable characteristics of a GPT, the next section endeavors to define a consensus set of characteristics that will guide our empirical analysis. The literature suggests three GPT characteristics that might be measured empirically with patent data: complementarity, applicability, and discontinuity.

2.1 Technological complementarity

There is general agreement that a GPT can be integrated with a wide range of industrial applications in order to realize productivity gains (Helpman, 1998; Rosenberg and Trajtenberg, 2004; Lipsey *et al.*, 2005). GPTs are radical innovations that motivate subsequent incremental innovations in a broad array of established industrial sectors. Thus a GPT will be punctuated by a follow-on set of more incremental innovation that adapts the breakthrough technologies across a range of existing industrial sectors (Bresnahan and Gambardella, 1998). Specifically, we would expect other economic sectors to conduct R&D in order to combine the GPT invention with sector-specific expertise, thus creating new, complementary inventions leading to economic growth (Helpman and Trajtenberg, 1998b).

Technologies are complementary when two or more technologies are combined to create a novel and unique new technology, or "when the decisions of the initiating agents with respect to their own technologies affect the value of the receiving agents' existing technologies and/or their opportunities for making further technological changes" (Carlaw and Lipsey, 2002: 1310). Thus, we would expect to see a GPT integrated into follow-on inventions across a broader array of industries. This suggests the following prediction:

> *Hypothesis 1: Follow-on inventions using GPT will be combined with complementary applications in a broader number of technology sectors when compared to other inventions.*

We use the term *technological complementarity* to indicate a GPT's potential to induce R&D investment in a broad number of downstream industries. Specifically, we would expect a GPT to be cited in combination with prior art from a larger variety of industrial sectors in first-generation patents when compared to the control patents.

2.2 Technological applicability

The second generally accepted characteristic of a GPT is its ability to be incorporated into a wide variety of different industrial applications (Bresnahan and Gambardella, 1998). Lipsey *et al.* (2005) argue that this characteristic is often discussed in one of two ways: either as vertical applicability, in which the GPT is used widely in the subsectors of one industry sector, or as horizontal applicability, in which the GPT is applicable across a variety of diverse industry sectors. Bresnahan and Gambardella (1998) emphasize that horizontal usage is the key attribute if economic growth is to be realized, arguing that a wide scope of applicability is what makes a technology general, in that it can be used for a variety of purposes in different industries. These authors argue that "the extent of the market for a GPT is not only the volume of production in the one sector that applied it, but also the number of distinct application sectors that apply it" (p. 255). A GPT provides knowledge that can be incorporated into subsequent follow-on inventions in diverse industries in order to realize its economic growth potential. Thus,

> *Hypothesis 2: Follow-on inventions built on a GPT will be applied to a wider range of industries than other inventions*

Specifically, inventions that cite a GPT are likely to be assigned to a wider range of industry sectors than those citing incremental innovations. This is similar to the concepts of "patent scope" as introduced by Lerner (1994) and "generality" as introduced by Hall *et al.* (2001) to measure the technology diversity of follow-on inventions. Following Hall and Trajtenberg (2004), we developed a generality measure to capture the broad application of a GPT in subsequent second-generation inventions. The generality measure is the proportion of total forward citations accrued in patent classes outside the GPT's original patent class.

2.3 Technological discontinuity

Finally, a GPT introduces discontinuity in the sense that it represents a radical break with existing practice (Helpman, 1998; Rosenberg and Trajtenberg, 2004; Lipsey *et al.* 2005). In contrast to incremental innovations that provide enhancements or improvements to existing means of production, GPTs represent radical departures from existing knowledge. There are two relevant empirical aspects of this discontinuity. The first relates to the geographic locus of inventive activity and the second relates to the time lag associated with technology diffusion.

The geographic extent of knowledge spillovers and the importance of proximity is expected to be different between radical and incremental technologies. It may be relatively easy for incremental discoveries to diffuse widely: for instance, an expert trained in one field could read about an incremental discovery in another field and incorporate it into his or her own work. However, as a GPT is new and relatively unfamiliar to researchers trained with existing technology, the technological significance, and mechanics of an innovation would be more difficult to communicate. Face-to-face conversations would become critical to the exchange of meaningful ideas, to ascertaining the opportunities a new technology presents, and to capturing a tacit understanding of how to advance the technology (Audrestch and Feldman, 1996). Thus, we would expect to see more complementary inventive activities initially in geographic proximity to inventors familiar with that GPT:

> *Hypothesis 3: Relative to an incremental technology, a GPT will spur greater technological complementarity and applicability in the geographic area where it originated.*

We believe that innovation has a strong local component (Feldman and Kogler, 2010). As the GPT matures it becomes codified and diffuses more rapidly. However, the ways a GPT is refined and adapted is expected to have a decided geographic component as knowledge is recombined with existing expertise in a region, leading to geographic concentrations of specific industries and applications. Co-location of groups of inventors with an existing expertise is expected to yield differentiated adaptation of the discovery. Over time, as new discoveries are incorporated into existing expertise, we would expect technological trajectories to develop that reflect unique regional expertise.

In conclusion, the GPT literature posits the importance of three associated empirical regularities: technological complementarity, technological applicability, and technological discontinuity. The next section will consider one example widely classified as a GPT: the Cohen–Boyer patents.

3. Overview of the Cohen–Boyer's rDNA technology

On December 2, 1980, Stanford University was granted a patent for rDNA methods developed by Dr Stanley Cohen of Stanford and Dr Herbert Boyer of the University of California, San Francisco. The patent, entitled *Process for Producing Biologically Functional Chimeras* (US 4237224), and its claims indicate that the Cohen–Boyer method for recombining genetic material represented a fundamental scientific discovery. The Cohen–Boyer patent application claimed both the process of making rDNA and any products enabled by that process.

The Cohen–Boyer patent application was filed in 1974 and was subject to 6 years of debate and three continuations until it was granted in 1980. Two factors contributed to the delay. First, university patents were rather unusual at the time and ownership of discoveries funded under federal grants was not automatically assigned to universities. It is notable that these patents were part of the debate that culminated in the December 12, 1980, passage of P.L. 96-517, The Patent and Trademark Law Amendments Act, commonly known as the Bayh–Dole Act (Fredrickson, 2001). Second, rDNA was highly controversial because it unleashed the potential to genetically modify organisms. The scientific community agreed to a voluntary moratorium on rDNA research until its safety could be investigated and established (Smith Hughes, 2001). The Supreme Court decision, *Diamond v. Chakrabarty* 447 US 303, decided in June 1980, established the patentability of living organisms, which validated the Cohen–Boyer claims.

The US Patent and Trade Office (USPTO) initially denied the Cohen–Boyer product claims. Stanford then divided the claims into two divisional product applications: one that claimed rDNA products produced in prokaryotic cells,[1] and one that claimed rDNA products produced in eukaryotic cells.[2] Although the Cohen–Boyer patents referred to "process" and "product" patents, the "product" claims cover compositions of matter (rDNA plasmids), which were then used to make proteins and are a basic component of the production method. Thus, although three patents were granted, Stanford University licensed them as a single technology (Feldman *et al.*, 2008).

Ruttan (1999) has argued that biotechnology will be the most important GPT of the first half of the 21st century. In addition to rDNA, two other techniques associated with biotech are fermentation and monoclonal antibodies. Fermentation is an established technique with a long history of incremental innovation. Monoclonal antibodies, discovered by Georges Kohler, Cesar Milstein, and Niels Kaj Jerne in 1975, were not patented.[3]

As a GPT, we would expect to find both a spatial and temporal discontinuity, which can be examined by considering the time lag and geographical concentration of follow-on inventive activities. The Cohen–Boyer technology has been cited 362 times. Patents that cite Cohen–Boyer are concentrated in California, specifically around the San Francisco Bay area where Cohen and Boyer worked. The industry

[1]A prokaryotic cell is one without a contained nucleus. The prokaryotic patent is US 4468464, issued on August 28, 1984.

[2]A eukaryotic cell has a contained nucleus. The eukaryotic patent is US 4740470, issued on April 26, 1988.

[3]Another potential candidate for a GPT is the technique for making polymerase chain reactions (PCR). This foundational piece of biotechnology intellectual property is contained in two US patents, 4,683,195 and 4,683,202, filed in 1985 and issued to Cetus Corporation on July 28, 1987. Invented by Kary B. Mullis and developed by Cetus, the technology was sold to Roche for $300m in 1991 and aggressively licensed. The patents had received 2228 citations as of February 6, 2011. We thank an anonymous referee for pointing this out.

developed on the East Coast as well, but there were notably fewer patent citations there. These results are hardly conclusive given that we lack data on the universe of inventors who might have potentially cited the patent. Nevertheless, the pronounced concentration of inventive activity in the Bay area supports the notion that the technology community building on the Cohen–Boyer patents was geographically concentrated.

To identify the technology sectors where inventive activity took place, we constructed location quotients using the location of inventions citing the Cohen–Boyer patents by industry sectors based on the Derwent World Patent Index (DWPI) in Table 1.[4] For each of the most prevalent sub-technologies associated with biotechnology, we calculated the proportion of patents in the region that cited Cohen–Boyer, by sector, and divided it by the proportion of patents that cited Cohen–Boyer in the sector. If a region's technology had a location quotient >1, the proportion of technology patents citing Cohen–Boyer in that sector was greater than the national average.

Including the San Francisco Bay area, where rDNA technology originated, there are 17 unique metropolitan statistical areas (MSAs) with location quotients >1. For example, the Boston area applied Cohen–Boyer technology to scientific instruments (location quotient = 2.06), St Louis innovations concentrated around plant genetics (location quotient = 13.12), and Houston inventors were most active in animal care (location quotient = 26.67). The San Francisco area had the largest number of technology classes with a location quotient higher than one. Moreover, the number of classes with a location quotient >1, indicating specialization, increased over time in San Francisco. The well-represented technology classes in the San Francisco area in the first period (1981–1988) were natural products and polymers, and fermentation. In the second period (1988–2004), concentrated sectors emerged in diagnosis, surgery, other foodstuffs, and treatment.

The fact that Cohen–Boyer's rDNA technology was incorporated in different applications in different locations suggests that existing capability within a place was a factor in adapting the new technology. This may be the basis for regional technological specialization as GPTs are incorporated and adapted to existing expertise. The table also indicates that activity in the San Francisco area benefited from spatial proximity—that locating in the place where Cohen–Boyer's rDNA technology originated encouraged its application to a greater number of technology classes.

Next, we addressed the lag of follow-on inventive activities. Hall and Trajtenberg (2004) found that citations to GPT had a longer time lag than the average patent. Figure 1 provides the timing of forward citations to Cohen–Boyer. There are two peaks in forward citations. The first peak was 4 years after the patent was granted, and the second peak was from Years 17 to 19. The second peak of forward citations

[4]Technology sectors by Derwent World Patent Index system is used rather than Standard Industrial Classification (SIC) in order to cross check the significance of the analysis.

Table 1 Geographic technological trajectories of patents citing Cohen–Boyer's patents

MSAs	Major technology class	Location Quotient (LQ)		
		Over all	1981–1987	1988–2004
Albany–Schenectady–Troy, NY MSA	B04 Natural products and polymers	1.18	1.11	1.38
	D16 Fermentation industry	1.20	1.03	1.50
Boston–Worcester–Lawrence, MA–NH–ME–CT CMSA	S03 Scientific instrumentation	2.06	1.23	6.03
	B04 Natural products and polymers	1.15	1.62	1.38
Chicago–Gary–Kenosha, IL–IN–WI CMSA	S03 Scientific instrumentation	2.27	0.00	3.83
Des Moines, IA MSA	C03 Other organic and inorganic compounds	12.63	0.00	10.02
Houston–Galveston–Brazoria, TX CMSA	P14 Animal care	26.57	23.39	0.00
Indianapolis, IN MSA	D16 Fermentation industry	1.41	2.06	1.50
Kalamazoo–Battle Creek, MI MSA	C03 Other organic and inorganic compounds	5.41	0.00	4.30
Los Angeles–Riverside–Orange County, CA	S03 Scientific instrumentation	5.68	9.57	0.00
Minneapolis–St Paul, MN–WI MSA	C03 Other organic and inorganic compounds	4.21	0.00	3.34
	B04 Natural products and polymers	1.23	0.00	1.23
New York–Northern New Jersey–Long Island, NY–NJ CMSA	S03 Scientific instrumentation	1.68	3.06	1.53
	C03 Other organic and inorganic compounds	2.10	0.00	3.11
	D16 Fermentation industry	1.10	1.65	1.15
Philadelphia–Wilmington–Atlantic City	S03 Scientific instrumentation	4.55	0.00	5.11
San Diego–Carlsbad–San Marcos, CA	B04 Natural products and polymers	1.03	1.58	1.07
	J04 Chemical/physical processes/apparatus	5.68	6.58	7.52
San Francisco–Oakland–San Jose, CA CMSA	B04 Natural products and polymers	1.03	2.11	0.00
	D16 Fermentation industry	1.01	1.96	0.00
	D13 Other foodstuffs and treatment	3.36	0.00	2.96
	P31 Diagnosis, surgery	3.36	0.00	2.96
Seattle–Tacoma–Bremerton, WA CMSA	B04 Natural products and polymers	1.38	2.22	1.34
	D16 Fermentation industry	1.40	2.06	1.50
St Louis, MO–IL MSA	C06 Plant genetics and veterinary vaccine	13.12	0.00	9.25
Upstate NY (Rochester, Ithaca)	D16 Fermentation industry	1.21	1.38	0.00
Washington–Baltimore, DC–MD–VA CMSA	D16 Fermentation industry	1.08	1.13	1.40

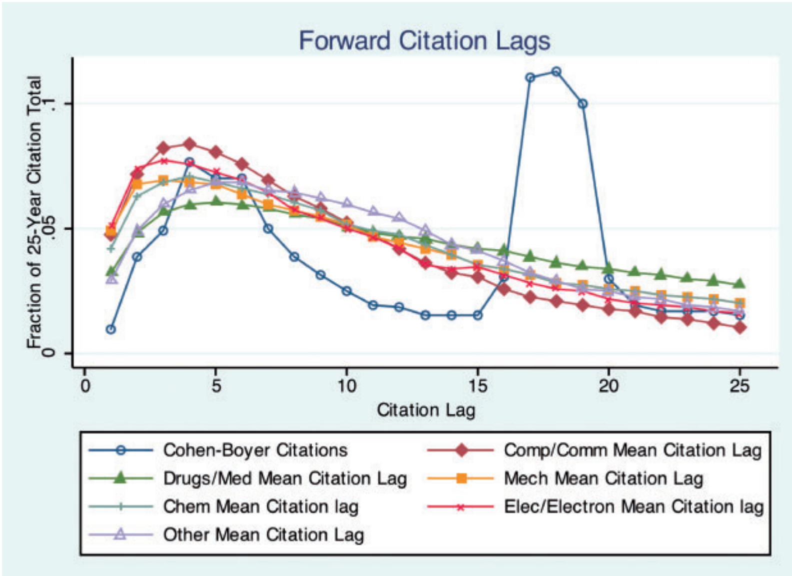

Figure 1 Forward citation lag to Cohen–Boyer compared to other patents. *Source*: Authors' calculations for Cohen–Boyer. Mean citations lag to other industry sectors are from Hall *et al.* (2001) adjusted from a 35-year share to a 25-year share to be comparable to the calculations for the Cohen–Boyer patent.

was due largely to patents for nucleic acid tests, used as diagnostics for a variety of human diseases. Given that the Cohen–Boyer invention took 6 years to issue from the date of its original application, the citation time lag was 23–25 years after the date of discovery and longer than the 17 year duration of the patent. For comparison, Hall and Trajtenberg, (2004) and Hall *et al.* (2001) found that, on average, patent citations peak at 6 years and argue that a technology becomes obsolete after 6 years. The Cohen–Boyer technology was so radical that it had significant impact on the follow-up inventions for three times longer than citation lag of the average invention.

4. Data and methodology

To test the hypothesis that the Cohen–Boyer technology is a GPT, we constructed a novel data set of patents that cited the Cohen–Boyer patents and estimated their characteristics against a group of patents that cited a control group of similar patents. Initially, we used five criteria to construct our control group: technology class, the year a patent was issued, the numbers of backward and forward citations, and assignee type. A control group should also represent classes developed around similar technologies and in a similar time period. Patel (2003) suggests that the patent classes of genetic engineering (424), biosensors (514), and biological materials for therapeutic applications (530) or with genetic applications (536) were similar to the Cohen–Boyer rDNA discovery. From these, we selected patents issued in 1976–1980.

There were 5725 US patents granted in the four control patent groups in 1976–1980. From these, we selected patents with no domestic backward citation and at least 50 forward citations. Patents with no backward patent citations do not reference prior patent art and are expected to be more radical in terms of their technological contribution (Jaffe *et al.*, 1993). Forward citations are another measure of a patent's importance: Hall and Trajtenberg (2004) estimate that only 0.01% of US patents receive more than 100 forward citations. Among applications filed in 1976–1980, the average number of forward citations was less than seven (Hall *et al.*, 2001). In our 5725 biotechnology patents applied for between 1976 and 1980, only five patents received more than 50 forward citations, and no other biomedical patent was cited as often as the Cohen–Boyer technology. Finally, Cohen–Boyer was a university patent, and university patents are generally more basic in nature and more likely to become a GPT (Mokyr, 1990). Therefore, our fifth criterion for control patents was assignment to a university.

Two patents that satisfied all five criteria for the control were US4164559, assigned to Cornell University, and US4201770, assigned to Ohio State University. These patents had 50 and 55 unique forward citations, respectively, excluding reissued patents. The product technologies they covered are summarized in Table 2. We also included a patent granted to Stanford University (US394907) that covers a process technology in the field of biotechnology. This patent is included because of the 127 forward citations received even though it referenced prior art.[5] This patent provides an additional control for the effect of an invention originating at Stanford University.

The three patents in our control group were widely cited. The average forward citation for the 5725 patents in biotechnology is 5.7. Hence, the effect of applicability and complementarity of the Cohen–Boyer's technology is conservatively analyzed, compared to the situation where we included all the patents in biotechnology as the control group.

Our unit of observation is second-generation patents that cite either the Cohen–Boyer patents or the control group patents: both the Cohen–Boyer and control group serve as prior art

We have a total of 594 observations: 362 observations that cite the Cohen–Boyer technology, and 232 observations that cite the three control patents.

We examined all prior art included with each second-generation patent to determine the technological origin for each new invention. The fact that these patents were combined with our focal patents suggests they provide complementary

[5]It was not possible to identify whether the examiner added the reference to prior art.

Table 2 Control patents used in the analysis

Patent number	Assignee	Title	Number of forward citations
US4164559	Cornell	Collagen drug delivery device: chemically modified collagen membrane prepared at physiologic pH and soluble thereat provides a carrier for ophthalmic medication leaving no removable material after drug release.	50
US4201770	Ohio State University	Antigenic modification of polypeptides: modified hormones or fragments of hormones are useful in producing antibodies when administered to an animal. These modified hormones or fragments may be administered to animals for the purpose of contraception, abortion, or treatment of hormone-related disease states and disorders.	55
US3949073	Stanford	Process for augmenting connective mammalian tissue with *in situ* polymerizable native collagen solution: a method for augmenting hard or soft connective tissue, such as skin, tendon, cartilage, bone, or interstitium, in a living mammal.	127

technology. There are 1645 patent classes cited as prior art for the second-generation patents that cite Cohen–Boyer's invention, ranging from 1944 to 2001,[6] a range of 57 years. On the other hand, three other control patents are cited along with 394 instances of prior art that were applied between 1942 and 2000, a range of 58 years.

4.1 Dependent variables

To test Hypothesis 1, *technological complementarity*, we constructed a variable that measures the number of unique industry sectors associated with the patents that are combined with the primary patent, with Cohen–Boyer or the controls, to create a new follow-up invention, patent i in year j. These patents are the first-generation inventions that are cited by the second-generation patents. We constructed this variable by matching each citing, or first-generation, patent to the Standard Industrial Classification (SIC)-concordance table provided by the USPTO. There

[6]Note that we excluded reissued patents and patents in the same patent family from the count of unique patents because the original patents were already counted.

are over 100,000 subclasses and each application is evaluated to assess novelty and the relationship to prior art. Patent examiners assign an application to one or more subclasses. Lerner (1994: 320, 1) notes that examiners have incentive to classify patents carefully because the patent becomes prior art for subsequent searches. Also, to ensure accuracy and maintain consistency, each classification is subject to review and oversight. There can be multiple patent classes associated with each patent, and hence, a patent can be associated with multiple industry sectors. Thus, when a patent had a class that matched at least one industry sector, we counted that industry as associated with the patent. We only counted those industries that were different from the primary patent. For example, Cohen–Boyer was associated with Drugs and Medicines (SIC 283) and Industrial Organic Chemicals (SIC 286). When a second-generation patent cited prior art in Drugs and Medicines (SIC 283), the number of complementary industry sectors is zero. Alternatively, if a second-generation patent cited prior art in Drugs and Medicines (SIC 283), Industrial Organic Chemicals (SIC 286), and Agricultural Chemicals (SIC 287), then the number of complementary sectors is one. The variable *technological complementarity* measures the total number of unique industries citing the primary patents as prior art, and ranged from 0 to 17.

To test Hypothesis 2, *technological applicability,* we used the procedure outlined above to construct a variable that measures the number of unique industries associated with each second-generation patent that cited either Cohen–Boyer or the control patents, using the USPTO patent class-SIC concordance table to assign patent classes to industry sectors.

4.2 Independent variables

To test for technological discontinuity, Hypothesis 3, the locations of inventors are included. Following the logic that patent citations are more likely to be in the same metropolitan area, (Jaffe *et al*., 1993), we constructed a dummy variable equal to one if all the inventors listed on a patent had an address in the San Francisco Bay MSA, the location of Stanley Cohen (Stanford University), and Herbert Boyer (University of California, San Francisco) while developing their rDNA discovery.

A discovery is expected to incorporate more unique types of knowledge when more inventors are involved. We controlled for the *number of inventors* by counting the number of inventors listed on the patent. Similarly, the *number of assignees* may also be important, as novel technologies can be developed by interaction among different organizations (Rosenkopf and Nerker, 2001)

We also used the *number of backward citations* and the *number of claims* to control for the effect of the absolute number of backward citations and the number of claims on the number of different ways a technology can be used or applied (Lerner, 1994). Patents with a large number of backward citations and claims are more likely to span

Table 3 Descriptive statistics

Variables	*n*	Mean (Std. Dev.)	Min	Max
Dependent variables				
Complementarity	594	2.33 (3.55)	0	17
Applicability	594	1.03 (0.79)	0	4
Independent variables				
Number of claims	594	19.75 (19.93)	1	140
Number of backward references	594	16.02 (22.87)	2	187
Number of inventors	594	2.56 (1.49)	1	11
Number of assignees	594	1.06 (0.27)	1	4
Organization type				
Biotechnology firms	594	0.48 (0.5)	0	1
University	594	0.18 (0.39)	0	1
Citing Cohen–Boyer	594	0.73 (0.45)	0	1
All inventors located in the Bay area	594	0.09 (0.28)	0	1

multiple technologies. This variable controls for the effect of a patent with backward citations and claims in the same or fewer different industries.

We also controlled for patent assignees of different organizational types. Different organizations have different technological capabilities that will affect the number of different technologies in the backward citations. For example, small start-up firms will focus more narrowly while larger corporations will have operations in diverse application sectors. We constructed three dummy variables for different organizational types: biotechnology firms, universities, and other types of firms. There are 15 patents associated with more than one organizational type: the dummy variables of the organizational types are not mutually exclusive.

We used a dummy variable to identify the effect of Cohen–Boyer patents. This variable is equal to 1, if Cohen–Boyer was the primary patent and equal to 0, if the primary patent was one of the control patents.

Finally, we controlled for yearly variation because the number of different technologies in backward citations can change based on unobservable factors driven by the patent application year. Table 3 provides descriptive statistics. Table 4 provides the correlation matrix.

5. Cohen–Boyer's patent as a GPT: empirical analysis

Table 5 provides a set of regressions on the dependent variable testing technological complementarity. We used the negative binomial count data model (NB) because the

Table 4 Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Complementarity	1.00									
(2) Applicability	0.09	1.00								
(3) Number of claims	0.06	0.22	1.00							
(4) Backward reference count	0.56	0.28	0.16	1.00						
(5) Number of inventors	0.05	0.04	−0.03	0.04	1.00					
(6) Number of assignees	0.02	−0.04	−0.03	0.02	0.15	1.00				
(7) Biotechnology firm	0.26	0.28	0.14	0.48	0.02	−0.08	1.00			
(8) University	−0.14	−0.21	−0.07	−0.28	−0.17	−0.02	−0.43	1.00		
(9) Cohen–Boyer citation control	0.16	0.32	0.10	−0.11	0.06	−0.02	0.16	−0.20	1.00	
(10) All inventors located in the Bay area	0.40	0.17	−0.07	0.31	0.07	−0.07	0.34	−0.14	0.12	1.00

dependent variable technological complementarity is count data, a non-negative integer value. We ran a Poisson count data model to check for consistent estimation results. The Poisson model's alpha value is significantly different from zero, indicating that the Poisson distribution is not appropriate. Model (1) provides the Negative Binomial model, while Model (2) includes an interaction term of the Cohen–Boyer dummy variable and all inventors located in the Bay area for *technological complementarity*. The marginal effects of the covariates of Model (2) evaluated at the mean are also provided.

Model (1) indicates that complementarity is greater for patents citing Cohen–Boyer than for patents citing other primary patents (0.28, $P < 0.000$). This suggests that patents that cite Cohen–Boyer draw knowledge from a greater number of industry sectors. Moreover, examining the interaction effect between Cohen–Boyer citations and all inventors located in the Bay area in Model (2), the effect on complementarity gets stronger when inventors are located in the Bay area. Thus, greater *complementarity* was realized when inventors were co-located with inventors of the GPT: the effect is significant (0.93, $P < 0.000$). The marginal effect on complementarity of citing Cohen–Boyer technology with all inventors located in the Bay area was 3.27. Evaluating this at the mean value of the independent variables, a patent citing Cohen–Boyer technology cited 0.43 more first-generation patents from different industry sectors than the control patents. [d(complementarity)/d(Cohen–Boyer) $= 0.14 + 3.27 \times 0.09$].

The effect of the number of domestic backward references on complementarity was positive and significant, while the number of claims was weakly significant. The number of inventors did not have a significant effect on technological complementarity. On the other hand, the number of assignees had a positive and significant

Table 5 Empirical results

Independent variables	Technological complementarity						Technological applicability					
	Model (1)		Model (2)				Model (3)		Model (4)			
	Coef.	Sig.	Coef.	Sig.	dy/dx	Sig.	Coef.	Sig.	Coef.	Sig.	dy/dx	Sig.
Constant	−1.53		−1.6				0.2		0.21			
	−0.47	***	−0.45	***			−0.27		−0.3	***		
Ln (No. of claims)	0.04		0.06	*	0.13	*	0.01		0.02		0.01	
	−0.03		−0.03		−0.07		−0.05		−0.05		−2.14	
Ln (No. of backward citations)	0.54		0.56		1.27		0.11		0.07		0.05	
	−0.03	***	−0.03	***	−0.07	***	−0.06	*	−0.06	*	−7.93	
No. of inventors	−0.01		−0.01		−0.02		0		0		0	
	−0.02		−0.02		−0.03		−0.03		−0.03		−0.05	
No. of assignees	0.22		0.21		0.47		−0.02		−0.02		−0.01	
	−0.08	**	−0.08	***	−0.18	***	−0.15		−0.15		−1.86	
Biotech firm	−0.11		−0.24		−0.54		0		0.1		0.06	
	−0.07		−0.07	**	−0.16	**	−0.11		−0.12		−0.09	
University	−0.09		−0.2		−0.43		−0.19		−0.16		−0.1	
	−0.11		−0.1		−0.2		−0.16		−0.16		−0.11	
Cohen–Boyer	0.28		0.06		0.14		1.11		1.26		0.78	
	−0.07	***	−0.07		−0.17		−0.13	***	−0.16	***	−0.09	***
All inventors located in the Bay area	0.43		−0.01		−0.02		0.25		0.8		0.69	
	−0.07	***	−0.09		−0.21	***	−0.12	**	−0.21	***	−0.22	***
Cohen–Boyer*			0.93		3.27				−0.89		−0.41	
All inventors in Bay area			−0.13	***	−0.67				−0.77		−0.68	
Year dummies	Included		Included		Included		Included		Included			
Log likelihood	−1087.54		−1065.36				−623.54		−630.67			

Sig.: ***1%, **5%, *10%.

effect on technological complementarity, which implies that a GPT is more likely when multiple firms are involved in developing an invention. At the same time, inventions by biotechnology firms had less complementarity than inventions developed by other organizations, suggesting that inventions by biotechnology firms are more likely to be applied narrowly than to a broad array of industry sectors. This implies that biotechnology firms may be focused on relatively more specialized projects that can be profitable in the near future. This issue merits examination with more detailed information about biotechnology firms' research targets.

Further descriptive analysis of the technological complementarity associated with Cohen–Boyer indicates that there were 35 industry sectors at the three-digit SIC level and 13 two-digit industry sectors that were complementary to Cohen–Boyer.[7] Cohen–Boyer was most likely to be combined with industries in chemicals (SIC 28), where the overall share was ~58.5%. The complementarity between Cohen–Boyer technology and chemicals declined over time as combinations with other sectors increased. In particular, in the first 3 years >50% of patents citing Cohen–Boyer were from the fields of chemicals and allied products (SIC 28), especially drug and medicines (SIC 283). However, combinations of the Cohen–Boyer patents with other sectors, such as industrial machinery and equipment (SIC 35) and instruments and allied products (SIC 38), became increasingly more common over time. This is consistent with theory that predicts the GPT diffusion should become broader over time (Bresnahan and Trajtenberg, 1995; Lipsey *et al.*, 2005).

Model (3) provides the results for technological applicability. The negative binomial model was used because the dependent variable is a non-negative, over dispersed count variable. Model (4) includes the interaction term of citing the Cohen–Boyer patent and all inventors located in the Bay area, along with the estimates of the marginal effects estimated at the mean of the covariates. We hypothesized (H2) that a patent citing Cohen–Boyer would be associated with a wider variety of industries when compared to patents citing the primary control patents. This captures the horizontal application of a GPT (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998b; Lipsey, 2005). The positive and statistically significant coefficient indicates that Cohen–Boyer patents yielded greater technological applicability in the second generation of innovation.

In Model (3), applicability is greater for patents citing Cohen–Boyer than for patents citing the three control technologies (1.11, $P < 0.000$). This means that patents citing Cohen–Boyer generated innovation in a greater number of industry sectors than patents citing the three control patents. Moreover, examining the interaction effect between citing Cohen–Boyer technology and all the inventors being located in the Bay area, the effect of Cohen–Boyer on applicability became weaker as the number of inventors in the Bay area increased. The overall effect of citing

[7]Details are available from the authors.

Cohen–Boyer technology and the inventors being located in the Bay area is positive and significant on the applicability, respectively (1.26, $P < 0.000$; 0.80, $P < 0.000$). This suggests that the Bay area was not the only region that applied Cohen–Boyer technology in a variety of industry sectors.

Evaluating this at the mean value of the independent variables, a patent citing Cohen–Boyer technology cited 0.74 more first-generation patents from different industry sectors than those patents citing other primary technologies. [d(complementarity)/d(Cohen–Boyer) $= 0.78 + (-0.41) \times 0.09$]. In summary, our empirical results imply that patents citing Cohen–Boyer were likely to originate in more unique industries than patents citing the three control technologies.

Cross-checking the applicability descriptively, the patents that cite Cohen–Boyer were distributed across 15 industry sectors (based on the USPTO SIC concordance table). The second-generation patents initially appeared in the field of Drug and Medicines (SIC 283). However, as time passed, Cohen–Boyer was applied in other sectors, notably instruments and allied products (SIC 38) and industrial machinery and equipment (SIC 35).

Location in the Bay area and using Cohen–Boyer's technology had a positive and significant effect on technological complementarity (0.93, $P < 0.000$), but no effect on technological applicability. This implies that technologies with wide applications may be invented away from a GPT's origin, although proximity matters for combining different technologies with the GPT. This result suggests that the breadth of innovative capabilities in the region where the GPT-applied technologies are adopted determine the incorporation of GPTs to a variety of industry sectors.

5.1 Robustness check on geographic discontinuity

We tested whether patents citing Cohen–Boyer technology were more likely than the control group technologies to be in regions with geographically specialized industry sectors. We constructed location quotients for patents associated with the control patents and tested the difference between the average location quotients of each technology. (See the Appendix Table A1–A5 for the location quotients of control group technologies). We conducted a two-sample *t*-test with difference variances for the average location quotients between Cohen–Boyer technology and the control patents. The test results indicate that the Cohen–Boyer technology was more regionally specialized than other GPT candidates.

Next, we estimated a survival analysis to examine the extent to which an inventor located in a GPT's location of origin was more likely to cite that GPT—the discontinuity associated with H3. We used Kaplan and Meier's (1958) non-parametric product limit estimation to compare Bay area inventors to inventors that used Cohen–Boyer technology in another location. The Kaplan–Meier method provides a descriptive view of the overall survival functions, allowing us to unconditionally compare to what extent patents with all inventors in the Bay area and patents with inventors outside the Bay area cite Cohen–Boyer's technology over time (thus serving as a summary statistic). The result indicates that inventors in the Bay area cited Cohen–Boyer's technology more often than inventors in other areas, a result that is consistent with our technological discontinuity hypothesis.

5.2 Robustness check on examiner added citations

Thus, far our analyses have included examiner-added citations. One might argue that these citations would lead us to overestimate complementarity and applicability. In this section, we offer analyses that exclude examiner-added citations to check the robustness of our original analyses.

Examiner-added citations can be identified for patents issued since 2001. These citations are marked with an asterisk at the end of the patent number in the citation section of original patent documents issued since 2001. We considered only those patents in the original sample issued in 2001 or later because patents issued before 2001 offer no way to determine which citations were added by examiners. This left us with a sample of 159 patents.

Among those 159 patents, which we call the second-generation patents, 9 had platform patents as examiner-added citations. We excluded those 9 patents, leaving 150 patents for the analyses. We re-constructed the applicability measure using those 150 patents. We also re-constructed the complementarity measure by examiner-added prior art.

Table 6 presents empirical results for the negative binomial model, excluding examiner-added citations where the dependent variables are the measures of applicability and complementarity and with the same covariates from the original analyses.

The empirical results show that our initial analyses of applicability, complementarity, and discontinuity remain even when examiner-added citations are removed.

6. Conclusion

This article empirically demonstrates that the Cohen–Boyer innovations are a GPT in terms of technological complementarity and broad technological applicability. This empirical result supports the anecdotal argument that the Cohen–Boyer rDNA technique created important new opportunities for systematically searching large protein molecules, triggering the emergence of the biotechnology industry.

Moreover, inventors located in the Bay area had a positive effect on the Cohen–Boyer technology by combining it with other technology components in the application sectors. This supports the notion that knowledge spillovers have a strong local component and reinforces the idea that proximity is important to the development of useful applications for new technologies. Proximity may facilitate the intense interaction required to understand the implications of an invention and its potential

Table 6 Empirical results excluding examiner-added citations

Dependent variable:	Applicability		Complementarity	
Independent variables	Coef.	Sig.	Coef.	Sig.
Constant	−0.51 (0.54)		−1.03 (0.46)	**
Ln (No. of claims)	−0.12 (0.06)	**	0.04 (0.06)	
Ln (No. of backward citations)	0.11 (0.08)		0.56 (0.06)	***
No. of inventors	0.04 (0.05)		−0.05 (0.03)	
No. of assignees	0.09 (0.12)		0.20 (0.13)	
Biotech firm	−0.13 (0.19)		−0.27 (0.14)	*
University	−0.19 (0.20)		−0.31 (0.19)	
Cohen–Boyer	0.86 (0.24)	***	0.75 (0.14)	***
All inventors in the Bay area	0.37 (0.19)	*	0.41 (0.14)	**
Year dummies	Included		Included	
Log likelihood	−157.61		−327.74	
	Obs. = 150		Obs. = 150	

Sig.: ***1%, **5%, *10%.

applications. Certainly, the Bay area was the locus of creative activity in genetic engineering at the earliest stages of the industry.

The Bay area effect may be a result of characteristics particular to Silicon Valley rather than pure geographic proximity. Silicon Valley is well known as a locus of innovative activity, with significant resources directed toward the exploration of new ideas. For example, Koo (2006) found that the state of California generates the largest count of patents. Kenney and Berg (1999) have argued that Silicon Valley may best be described as a system for creating innovation. While Stanford University's pursuit of the Cohen–Boyer patents was controversial at the time (Feldman *et al.*, 2008), the university's location in the heart of Silicon Valley undoubtedly contributed to an environment that encouraged the commercialization of the discovery. The potential endogeneity of the discovery is an open question, and follow-on work should examine these effects in greater detail. The testable hypothesis would be that GPTs are more likely to arise from a geographic concentration of inventors than from locations on the periphery of innovative communities. Of course, identifying these technologies is the first step.

The limited boundaries for the Cohen–Boyer technology proved an advantage for our exploratory analysis. This is certainly the first step in a research agenda, and we hope future research will build on the work begun in this article. While we focus on the Cohen–Boyer rDNA patents as a GPT, it is important to consider that technological discoveries are most appropriately considered on a continuum, with incremental discoveries on the lower end, and GPT as the highest and most significant form of discovery. Cohen–Boyer certainly has some of the attributes of a GPT, but additional innovation is usually required for a biotechnology or any GPT to reach its potential, and there are certainly no guarantees in terms of the pace and direction of future development. Lipsey *et al.* (1998: 50) sum up our sentiments:

> ... [C]an we identify future GPTs that are emerging on the current technological horizon? As we have suggested, a consideration of the characteristics of new technologies often allow us to identify potential GPTs. A consideration of their current evolutionary trajectory then allows us to assess whether or not they are currently fulfilling their potential .... Biotechnology is an obvious future GPT, although it is not yet widely used in producing economic value. Many diverse possible uses have already been established and more are being discovered at a rapid pace. Many of the practical applications, however, await further reductions in costs and an assessment of their side effects.

In summary, patent citations are a useful tool for identifying technologies with the potential for economic growth. Realizing that potential requires additional resources and planning.

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Appendix A

Table A1 Location quotients for US4164559

MSA	A96 medical, dental	B04 natural products	B07 general	D16 fermentation	D22 sterilizing	P31 diagnosis	P32 dentistry	P34 sterilizing
Washington–Baltimore DC–MD–VA–WV CMSA	0.34	**1.67**	0.52	0.00	0.00	0.00	0.00	0.00
Boston–Worcester–Lawrence, MA–NH–ME–CT CMSA	0.34	0.00	0.00	0.00	0.00	**2.78**	**1.39**	0.00
San Francisco–Oakland–San Jose, CA CMSA	0.28	0.31	0.36	0.46	0.36	0.00	0.13	0.29
Los Angeles–Riverside–Orange County, CA	0.26	0.00	0.39	0.00	0.39	0.00	0.52	0.30
New York–Northern New Jersey–Long Island, NY–NJ CMSA	0.51	0.00	0.78	0.00	0.00	0.00	0.00	0.00
Seattle–Tacoma–Bellevue, WA MSA	0.31	0.50	0.31	0.00	0.47	0.00	0.00	0.24
Minneapolis–St Paul, MN–WI MSA	0.28	**2.50**	0.00	0.00	**1.17**	**6.25**	0.00	0.00
Skillman, NJ	0.26	0.00	0.39	0.00	0.39	0.00	**1.04**	0.00
Stamford–Norwalk, CT	0.34	0.00	0.00	0.00	0.52	0.00	0.00	0.79
Wayne, PA	0.51	0.00	0.78	0.00	0.00	0.00	0.00	0.00

LQs for the control patents are presented below. An LQ ≥ 1, bold indicates above average specialization in a sector.

Table A2 Location quotients for US4201770

MSA	B04 Natural products	C03 Other organics compounds	C06 Biotechnology	D16 Fermentation	S03 Scientific Instruments
Washington–Baltimore DC–MD–VA–WV CMSA	0.94	0.00	0.00	0.61	0.00
Boston–Worcester–Lawrence, MA–NH–ME–CT CMSA	0.56	0.00	0.00	**1.83**	0.00
San Diego–Carlsbad–San Marcos MSA	0.56	0.00	0.00	0.28	0.28
Sacramento–Yolo, CA CMSA	0.79	0.00	**2.75**	0.73	0.00
Columbus, OH	0.67	0.56	**1.02**	0.95	0.00
Delanson, NY	**1.12**	0.00	0.00	0.00	0.00
Fort Collins, CO	0.52	**2.33**	0.00	0.24	0.00

Note: Location quotients (LQs) greater than 1 are marked bold. A region having a sector with LQs greater than 1 means that the sector is specialized in that region, while other sectors with LQs less than 1 are not.

Table A3 Location quotients for US3949073

MSA and others	A96 Medical, dental	B04 Natural products and polymers	B07 General	D16 Fermentation	D22 Sterilizing, bandages, dressing and skin-protection agents	P31 Diagnosis, surgery	P32 Dentistry, bandages, veterinary, prosthesis	P34 Sterilizing, syringes, electrotherapy
Acton, MA	0.37	0.00	0.00	0.00	0.34	0.00	0.41	0.29
Austin–San Marcos, TX	0.00	0.26	0.47	0.00	0.35	0.00	0.22	0.45
Boston–Worcester–Lawrence, MA–NH–ME–CT CMSA	0.27	0.39	0.17	0.56	0.21	0.13	0.24	0.17
Canton, MA	0.68	0.00	0.00	0.00	0.62	0.00	0.00	0.00
Charlotte–Gastonia–Rock Hill, NC MSA	0.34	0.46	0.00	**1.76**	0.00	0.00	0.00	0.39
Eatontown, NJ	0.25	0.17	0.30	0.64	0.22	0.00	0.27	0.29
Elkridge, MD	0.34	0.00	0.81	0.00	0.31	0.00	0.00	0.39
Exton, PA	0.00	0.37	0.00	**1.41**	0.25	**1.95**	0.30	0.00
Fort Collins–Loveland, CO	0.31	0.06	0.74	0.00	0.08	0.00	0.34	0.35
Knoxville, TN	0.00	0.92	0.00	**3.53**	0.00	0.00	0.00	0.00
San Diego–Carlsbad–San Marcos MSA	0.39	0.26	0.47	**1.01**	0.00	0.00	0.22	0.22
San Francisco–Oakland–San Jose CMSA	0.34	0.26	0.50	0.05	0.27	0.08	0.34	0.29
Milford, NH	0.46	0.00	**1.09**	0.00	0.00	0.00	0.00	0.52
Murray Hill, NJ	0.34	0.00	0.00	0.00	0.62	0.00	0.00	0.39
New York–Northern New Jersey–Long Island, NY–NJ CMSA	0.29	0.26	0.00	0.00	0.26	0.00	0.32	0.34
Newark, DE	0.28	0.00	0.15	0.00	0.25	0.00	0.45	0.39
Norfolk, VA	0.00	**1.10**	0.00	**1.41**	0.25	0.00	0.00	0.00
North Bend, WA	0.39	0.26	0.93	0.00	0.35	0.00	0.00	0.00
Stamford–Norwalk, CT	0.34	0.00	0.81	0.00	0.31	0.00	0.00	0.39
San Francisco–Oakland–San Jose CMSA	0.28	0.26	0.35	0.06	0.26	0.08	0.27	0.22
Philadelphia–Wilmington–Atlantic City	0.00	0.61	0.00	0.00	0.00	0.00	0.50	0.52
Minneapolis–St Paul, MN–WI MSA	0.37	0.33	0.00	0.00	0.34	**2.66**	0.00	0.00
Somerville, NJ	0.68	0.00	0.00	0.00	0.62	0.00	0.00	0.00
Tampa, FL	0.00	0.92	0.00	**3.53**	0.00	0.00	0.00	0.00
Tucson, AZ	0.34	0.46	0.00	**1.76**	0.31	0.00	0.00	0.00
West Orange, NJ	0.00	0.61	0.00	**1.18**	0.21	0.00	0.25	0.26

Table A4 Descriptive statistics of the GPT candidates

GPT candidates	Average of the LQs	Std. Dev. of the LQs	Observations by technology sectors and locations
Cohen–Boyer	1.96	10.01	184
US4164559	0.37	0.74	112
US4201770	0.61	1.78	65
US3949073	0.29	0.50	248

Table A5 *T*-test for difference between the Cohen–Boyer's and control patents location quotients

Ha: (Cohen–Boyer)—(other GPT candidates) > 0	*t*-stat.	*P*-value
Ha: (Cohen–Boyer)—(US4164559) > 0	2.16	0.016
Ha: (Cohen–Boyer)—(US4201770) > 0	1.75	0.041
Ha: (Cohen–Boyer)—(US3949073) > 0	2.26	0.013