Relying on recent and temporally dispersed science predicts breakthrough inventions

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Abstract

The development of inventions is theorized as a process of searching and recombining existing knowledge components. Previous studies under this theory have examined myriad characteristics of recombined knowledge and their performance implications. One such feature that has received much attention is technological knowledge age. Yet, little is known about how the age of scientific knowledge influences the impact of inventions, despite the widely known catalyzing role of science in the creation of new technologies. Here we use a large corpus of patents and derive features characterizing how patents temporally search in the scientific space. We find that patents that cite scientific papers have more citations and substantially more likely to become breakthroughs. Conditional on searching in the scientific space, referencing more recent papers increases the impact of patents and the likelihood of being breakthroughs. However, this positive effect can be offset if patents cite papers whose ages exhibit a low variance. These effects are consistent across technological fields.

Keywords: innovation, knowledge recombination, knowledge maturity, breakthrough, non-patent reference

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I. INTRODUCTION

In today’s knowledge-based economy, innovation has been playing an important role in productivity growth and competitive advantage of firms (Ashish et al. 2018, Fleming and Sorenson 2004, Nelson 1982). In the process of the production of innovation, creators—scientists and inventors—face an enormously large space of knowledge from which they can recombine existing knowledge components as input (Fleming 2001, Savino et al. 2017). The questions of how they search in the knowledge landscape and how the search process is linked to the value of resultant innovation have received a considerate amount of attention, with myriad types of searches being theorized and examined, including local search (Rosenkopf and Nerkar 2001), broad search (Katila and Ahuja 2002, Leiponen and Helfat 2010), repeated search (Katila and Ahuja 2002), originality search (Jung and Lee 2016), among many others. In addition, characteristics of recombined components have also been explored, including their locations in technological and geographical spaces (Phene et al. 2006), organizational context (Yang et al. 2010), reuse trajectories (Kok et al. 2019, Wang et al. 2014), etc.

This study concerns about temporal search in the context of inventions: Inventors may recombine prior knowledge that are produced at different points in time, and the extent to which recent versus mature knowledge is recombined may have profound implications for the value of new inventions (Katila 2002). Consequently, the costs and benefits of both recent and mature knowledge have been extensively discussed. On one hand, recent knowledge has been emphasized as valuable, as it may open up avenues for new ideas and practices. The space around recent knowledge provides ample recombinant opportunities, leaving more rooms for explorations of new ideas for valuable inventions (Heeley and Jacobson 2008). Evidence supporting these benefits indicates that firms experimenting with emerging technologies can overcome the “maturity trap” and create breakthrough inventions (Ahuja and Lampert 2001) and combining recent knowledge with knowledge with large time spans is associated with the impact of inventions (Nerkar 2003).

Against this so-called “recency bias”, mature knowledge has also been advocated to be useful to inventions for several reasons. First, it may reduce uncertainty and potential technical errors in applications, making it more reliable than newly created knowledge (Fleming 2001, Petruzzelli and Savino 2014). Second, mature knowledge may reduce its utilization costs due to its compatibility with existing knowledge, making it easy to be integrated into
new applications (Petruzzelli and Savino 2014, Turner et al. 2013). Third, a certain level of
maturity is often needed to make innovation acceptable, as new ideas without connections
to current knowledge can encounter resistance to be recognized (Messeni Petruzzelli et al.
2018). Furthermore, the importance of some types of knowledge can only be appreciated
after sufficient amount of time when discoveries therein are brought to light due to factors
like the advancement of enabling technologies (Cattani 2006, Nerkar 2003). However, the
cost of overly mature knowledge is that it may obsolete and lose its relevance over time.
Moreover, old knowledge may hinder individual and organizational learning (Ahuja and
Lampert 2001, Katila 2002), and inventors who continuously use such knowledge may fall
into “competency traps” (Levitt and March 1988), meaning that they are not able to learn
superior new knowledge and practices and innovation value generated by past knowledge
markedly decreases.

Despite the relevance of temporality to the search process of inventions, the knowledge
space focused in previous discussions has been limited exclusively to the technological space.
Inventions, however, rely on not only technological knowledge but also scientific one, and
the role of science in the development of new technologies has long been substantiated.
Science may alter inventors’ search process towards more useful recombinations (Fleming
and Sorenson 2004); inventions that are closer to science through citation relations are
more impactful and valuable (Ahmadpoor and Jones 2017); the quality of scientific papers
referenced by patents has a strong positive effect on the value of inventions, implying that
good science also leads to good technology (Poege et al. 2019). Moreover, in the private
sector, firms perform less scientific research but instead continuously exploit discoveries
from academia (Ashish et al. 2018, McMillan et al. 2000, Narin et al. 1997). Given these
tight couplings between science and technology and the paucity of inquiry into the hitherto
unknown process of temporal search in the scientific space, here we ask: What is the role
of temporal search in the scientific space in the value of an invention? How does this role
vary across technological fields? And how does it interact with temporal search in the
 technological space?

Temporal search in the scientific space may play a different role in the value of inven-
tive output. On one hand, the commercial potential of scientific knowledge tends to be
uncertain (Bikard 2018). Jensen and Thursby (2001) noted that “when they are licensed,
most university inventions are little more than a ‘proof of concept’”. The application of
newly discovered scientific knowledge in inventive process requires further trials and errors, and the reproducibility of academic studies has raised concerns regarding the usability of findings from academia (Begley and Ellis 2012, Bikard 2018). Moreover, the use of less verified knowledge not only incurs higher likelihood of inventive failures, but also affects third parties’ evaluation of the invention. Zhang et al. (2021) found that lenders are hesitant to collateralize patents associated with prior arts that are too new because of the perceived risk in determining \textit{ex ante} the patent’s full potential. On the other hand, as scientific knowledge functions as public goods, old scientific knowledge may be utilized by multiple firms. Under such circumstances, the value of innovations based on past scientific knowledge is distributed across the firms developing similar technologies (Arora et al. 2023). Furthermore, scientific knowledge is updated rapidly, and failing to stay abreast of these developments may incur reinvention of the wheel. In a nutshell, the uncertainty-appropriation trade-off renders it a challenge to assert that the process of temporal search in the scientific space drives innovation outcome in the same way as in the technological space.

To answer our research questions, we use a dataset of nearly 3.7 million patents granted at the U.S. Patent and Trademark Office (USPTO) in a 34-year period (1976-2009) to study how individual patents temporally search in the scientific space and how this type of search is related to the impact of a patent. We find that scientific search increases patent impact and doubles the odds of becoming hits. The long-established effect of technological search on patent value is dependent on scientific search: While having patent references is associated with higher citations than not having, the difference is much bigger when the patent also has scientific papers as references. Conditional on scientific search, we parameterize temporal search in the scientific space with two statistics: the mean and coefficient of variation (CV) of cited papers’ ages. We find that cited science tends to be older than cited technology but has a lower variation, and there is a recent trend in referencing older science and technology. Patents that reference more recent scientific papers have more forward citations and are more likely to become hits. However, such a positive effect can be offset if patents cite papers whose ages exhibit a low dispersion. Furthermore, we find that there are positive interactions between temporal searches in the scientific and technological spaces, suggesting their mutually beneficial roles. Finally, our findings are consistent across technological fields.
II. LITERATURE REVIEW

A. Typology of search

One pivotal idea in innovation studies is that innovation results from searching and recombining prior knowledge (Nelson 1982, Schumpeter 1939). The literature has proposed various types of searches and examined their performance implications. One widely studied type is local search, defined as search in the neighbor domains of an entity’s current expertise. This mode of search has been shown to be a major strategy adopted by many firms (Helfat 1994, Stuart and Podolny 1996), and it has several advantages. Kaplan and Vakili (2015), for example, found that it is more likely to be associated with patents that initiate new topics. Arts and Vugelers (2015) found that combining familiar knowledge in unprecedented ways is more likely to generate useful inventions, significantly increases the likelihood of breakthroughs, and reduces failure probability. Jung and Lee (2016) refined the concept of local search by emphasizing its interaction with searching original knowledge, demonstrating that originality search, when incorporated into firms’ R&D, makes local search exhibit better performances to produce high-impact breakthroughs than boundary-spanning search.

Implicit in local search is some notions of boundaries between knowledge domains, which have been delineated as technological, organizational, or geographical. Rosenkopf and Nerkar (2001) considered technological and organization boundaries and found that search without spanning organizational boundaries generates lower impact patents. Focusing on the social sciences fields, Schilling and Green (2011) showed that a paper’s impact is associated with drawing atypical connections between different scientific fields. Similarly, Kaplan and Vakili (2015) found that the economic value of a patent is linked to boundary-spanning search from broader technological domains. Kneeland et al. (2020) identified that distant recombination contributes to the generation of outlier patents, those distant from existing inventions. Castaldi et al. (2015) found that US state-level patenting is enhanced by recombining related technologies and unrelated ones stimulate technological breakthroughs. Turning to geographical boundaries, Phene et al. (2006) found that combining domestic knowledge that is technologically distant has a curvilinear effect on breakthrough inventions, while combining international knowledge that is technologically proximate has a positive effect.
B. Temporal search

Apart from search types mentioned above, another stream of literature has focused on search along the temporal dimension, that is, recombining knowledge inputs that are produced at different points in time. This line of studies has emphasized costs and benefits of the search and the use of recent versus old knowledge. Recent knowledge opens avenues for new ideas and practices. Ahuja and Lampert (2001) found supporting evidence that experimentations with emerging technologies help firms overcome the “maturity trap” and create breakthrough inventions. Katila and Ahuja (2002) revealed two aspects of search in robotics firms’ creation of new products: search depth, i.e., the frequency of the use of existing knowledge, and search scope, the width of new knowledge. Nerkar (2003) found that combining recent knowledge and knowledge with large time spans is associated with the impact of patents. In a large-scale study, Mukherjee et al. (2017) explored the relationship between a patent or a paper’s impact and the age distribution of its references, finding that highly cited papers and patents are located in the “hotspot” of low mean age and high age variance. Recent studies have paid attention to moderating effects on the relationship between knowledge maturity and innovation value, pointing out the roles of technological and geographical distances (Capaldo et al. 2017) and the roles of firm age and size (Messeni Petruzzelli et al. 2018).

Old knowledge has also been advocated as useful for knowledge creation. First, old knowledge reduces uncertainty and potential technical errors in applications (Turner et al. 2013), making it more reliable than newly created knowledge (Fleming 2001). Second, old knowledge reduces its utilization costs due to its compatibility with existing knowledge, making it easy to integrate into new applications (Petruzzelli and Savino 2014). Third, a certain level of maturity is often needed to make innovation acceptable (Messeni Petruzzelli et al. 2018), as new ideas without connections to current knowledge can encounter resistance to be recognized. In addition, the importance of some types of knowledge, like papers with delayed recognition (Ke et al. 2015), can only be appreciated after sufficient amount of time when discoveries therein are brought to light due to factors like the advancement of enabling technologies (Cattani 2006, Nerkar 2003).

Aged knowledge, however, may lose its advantage over new knowledge. Old knowledge that has been integrated into the space of existing knowledge quickly becomes common
knowledge, and inventions that embed such knowledge become less valuable (Alnuaimi and George 2016). Moreover, old knowledge hinders individual and organizational learning (Ahuja and Lampert 2001, Katila and Ahuja 2002), and inventors who continuously use such knowledge may fall into “competency traps” (Levitt and March 1988), meaning that they are not able to learn superior new knowledge and practices and innovation value generated by past knowledge markedly decreases. Furthermore, the space of old knowledge lacks recombinant opportunities (Heeley and Jacobson 2008), leaving more room for imitation and similar ideas to competitors but less room for valuable inventions.

As mentioned before, these previous studies on temporal search of inventions are limited to searching in the technological space, leaving temporal search in the scientific space an unexplored topic, which is the focus of the present work.

C. Search in the scientific space

The role of science and technology interaction in the innovation process has long been noted by researchers (Price and Bass 1969, Sherwin and Isenson 1967, Walsh 1973). Although abundant studies have investigated how technological innovations may search and rely on scientific knowledge, the literature has not yet examined temporal search in the scientific space. Just as patent references have been used to represent inventors’ search activity in the technological space, scholars have used non-patent references (NPRs) that refer to scientific papers to capture the reliance of patents on science. The validity of such usage has been guaranteed by surveys. For example, Roach and Cohen (2013) reported that in their survey of R&D lab managers, NPRs better represent knowledge from public research than patent references do.

A series of empirical studies have repeatedly substantiated the reliance of technologies on science. Narin et al. (1997) showed that citations generated by U.S. patents to public science rapidly increased. Ke (2020) similarly found that in biomedicine, patent-to-paper citations have been growing exponentially, doubling every 2.9 years. McMillan et al. (2000) demonstrated that biotechnology firms’ reliance on public research is more apparent than other industries. Ahmadpoor and Jones (2017) devised a measure of citation distance between patents and papers to quantify the reliance of patents on science and found that fields like nanotechnology and computer science are closest to the technological space. Fleming
et al. (2019) revealed that one third of U.S. patents depend on scientific research funded by the federal government.

Another line of inquiry has proved that searching in the scientific space is beneficial to inventive activities. Fleming and Sorenson (2004) argued that the contribution of science to technological advancement is through the alternation of the search process towards more useful combinations and empirically showed that patents referencing non-patent literature receive more and a broader scope of forward patent citations. Ahmadpoor and Jones (2017) revealed that patents that are closer to science through citation relations are more impactful and valuable. Poege et al. (2019) further found that the quality of scientific papers referenced by patents has a strong positive effect on the value of technological inventions, implying that good science also leads to good technology.

Taking nutrients from scientific knowledge not only promotes technological innovations but also facilitates technological breakthroughs and market values. Arts and Fleming (2018) identified that the negative effect of explorative search in the technological inventing process on breakthrough outputs can be mitigated by the reliance on science. Kneeland et al. (2020) found that radical patents cite more NPRs, especially more scientific papers. Finally, Arora et al. (2022) argued that inventions’ reliance on science enhances markets for technology, and empirical evidence indicated that patents with citations to scientific papers are considerably more likely to be traded in intellectual property transactions. Again, despite the heavily emphasized importance of science in technological innovations, surprisingly little theoretical or empirical work has examined how temporal search in the scientific space affects the value of innovations. Below we shall tackle this question.

III. DATA AND METHODS

A. Data

We harvest patent data directly from the USPTO at its Bulk Data Storage System website (https://bulkdata.uspto.gov). We download bibliographic data files for patents granted from 1976 to 2019 and extract bibliographic information and backward citations (i.e., references) of these patents. The unit of our analysis is a patent, and our sample contains 3,693,101 utility patents that are granted between 1976 and 2009, to allow each of
them to have at least 10 years to accumulate forward citations.

We use a patent’s backward citations to reliably capture the knowledge inputs, which is a common practice adopted in the innovation studies literature. Specifically, front-page backward citations to prior patents are used for assessing how patents rely on existing technological knowledge. Similarly, front-page NPRs that refer to scientific papers are used to assess prior scientific knowledge incorporated in the focal patent. One major difference between the two types of backward citations is that for the former, cited patents can be easily identified by patent numbers, but for the latter, only the texts of NPRs are available, without knowing if and which papers they refer to. To get the actual cited paper corresponding to a NPR, we match it with the Web of Science (WoS), a comprehensive bibliographic database for scientific papers, using the algorithm developed in Ke (2018), which has an accuracy of 97%. From the WoS, we retrieve various metadata of a paper, among which the most relevant one is its publication year. Our sample of patents in total made 39,569,667 citations to prior patents and 3,433,070 citations to papers.

B. Regression modeling

At the patent-level, we estimate the effect of scientific search on patent’s impact as

\[ Y_i = \beta_0 + \beta_1 \cdot \text{has\_SNPR}_i + \gamma \cdot \text{controls}_i + \text{year}_i + \text{field}_i + \varepsilon_i , \tag{1} \]

where \( Y_i \) is the impact of patent \( i \), \( \beta_0 \) is the intercept, and \( \beta_1 \) is the coefficient of interest for whether \( i \) has SNPRs. We introduce two measures to quantify impact: (1) the number of citations received by \( i \) within 10 years after granting, \( i.e., \) forward citation count, which is a widely accepted indicator for the value of a patent (Capaldo et al. 2017, Kaplan and Vakili 2015) and has been shown to correlate well with its technical and economic importance (Trajtenberg 1990); (2) a binary variable that indicates whether the focal patent is a hit, defined as its 10-year citations is among the top 5% clustered by granted year and technological field, as operationalized as NEBR Subcategory (Hall et al. 2001). While 10-year forward citations provide a quantitative estimation as the extent of reuse by following-up inventions, a hit patent is extremely frequently reused compared with its peers (Ahuja and Lampert 2001, Jung and Lee 2016, Kaplan and Vakili 2015). To test the robustness, we also consider forward citations until 2019 and use two other thresholds (1% and 10%) to identify
hit patents.

We include several control variables to account for potential confounding factors, and \( \gamma \) in Eq. 1 represents the vector of the coefficients for the controls. First, we consider whether the focal patent has patent references. Second, the broadness of its technological domains, as defined as the number of 4-digit IPC patent classes, is included to account for the tendency that technologically more broad patents may be applicable for more subsequent inventions from diverse domains. Third, we control for the number of inventors in the focal patent, as it has been shown that the size of the inventor team is positively associated with a patent’s forward citations (Capaldo et al. 2017, Mukherjee et al. 2017). Additionally, we create a dummy variable for grant year, as there is a dependence of citations on time, and a dummy variable for technological field to account for differing rates of getting cited due to different extents of research and develop activities across fields.

In a similar fashion, the effect of temporal search in the scientific space on a patent’s impact is estimated as

\[
Y_i = \beta_0 + \beta_1 \cdot \mu_{s,i} + \beta_2 \cdot cv_{s,i} + \gamma \cdot \text{controls}_i + \text{year}_i + \text{field}_i + \varepsilon_i ,
\]

where \( Y_i \) is one of the two impact indicators described above. Following the characterizations of temporal search in the scientific (Mukherjee et al. 2017) and technological spaces (Nerkar 2003), we define the age of a cited paper as the number of years elapsed between its publication year and the granted year of the focal citing patent. We then take the mean and the coefficient of variation (CV) of the ages of all cited papers as the two measures to parametrize how the focal patent temporally searches in the scientific space, denoted as \( \mu_{s,i} \) and \( cv_{s,i} \). While \( \mu_{s,i} \) captures the central tendency of ages, \( cv_{s,i} \) quantifies the dispersion. Thus, \( \beta_1 \) and \( \beta_2 \) are the coefficients of interest.

Control variables in Eq. 2 include mean \( \mu_{t,i} \) and CV \( cv_{t,i} \) of cited patents’ ages, which quantify how the focal patent performs temporal search in the technological domain. The two measures control for the effects brought into play by temporal search in the technological space, as previous studies have shown that such search relates to hit inventions. Here the age of a cited patent is the number of years between its granted year and the year when the focal citing patent is granted, in line with prior works (Mukherjee et al. 2017, Nerkar 2003). Second, we consider the number of patent references, as the number of recombined components is positively associated with the value of an invention (Kelley et al. 2013). Third,
we similarly include the number of cited papers (Poege et al. 2019). Finally, we control for academic quality of cited science, as previous studies have pointed out its role in patent value (Harhoff et al. 2003, Poege et al. 2019). We measure academic quality as the average of logarithm transformed one plus number of citations in 5-years.

Table A1 reports the descriptive statistics of the constructed variables.

IV. RESULTS

A. Search in the scientific space

Before examining how temporal search in the scientific space affects future impact of patents, we first understand whether scientific search is associated with impact. Overall, only a minority (12.5%) of patents have cited scientific papers, although the fraction has been increasing over time (Fig. 1A). By comparison, the vast majority (97.6%) of patents have at least one patent reference. Relating scientific search to impact, we find that patents with SNPRs have larger future impact than those without SNPRs: They consistently collect more forward citations (Fig. 1B) and are more likely to become hit patents (Fig. 1C), as defined as their 10-year forward citations are among the top 5% clustered by granted year and technological subfield (NEBR Subcategory) (Hall et al. 2001).

Further regression analyses that control for confounders confirm the advantage of scientific search in generating future impact (Table I). After controlling for factors like search in the technological space and year and subfield fixed effects, patents with SNPRs have 49% ($e^{0.398} - 1$) more 10-year citations (Column 1 in Table I). Fig. 1D gives the estimated citations (predictive margins) for the four groups of patents based on whether they search in the scientific and technological spaces, indicating that patents with both patent references and SNPRs have the largest number of citations and that, conditional on citing patent reference, patents with SNPRs have more citations than those without SNPRs. We also test whether there is a potential interaction between searches in the two spaces (Column 2 in Table I). The significantly positive interaction term indicates that it is the case. That is, the effect of search in the technological space on forward citations is dependent on whether referencing scientific papers: While having patent references is associated with higher citations than not having patent references, the difference is much bigger when the patent also has scientific
FIG. 1. The positive effect of search in the scientific space on patent impact. (A) Fractions of patents with patent references (PR) and SNPR over time; (B–C) Mean 10-year forward citations (B) and mean hit probabilities (C) for the groups of patents with and without SNPR; (D–E) Estimated 10-year citations based on the negative binomial regression models without (D) and with (E) considering the interaction between searches in the scientific and technological spaces; (F–G) Estimated hit probabilities based on the logistic regression models without (F) and with (G) considering the interaction between the two searches.

paper as reference. This dependence can be readily observed from Fig. 1E, where a steeper increase in estimated citations is apparent for patents with SNPRs. Specifically, without search in the scientific space, the effect of technological search is relatively small (39% increase in citations); by contrast, the effect more than doubles and reaches to a 84% increase when technological search is with the help of scientific search.

Along a similar line, regression modeling of hit patents suggests a 117% \( (e^{0.775} - 1) \) increase in the odds of becoming hits for patents referencing SNPRs, compared to comparable patents granted in the same year and in the same technological subfield but without referencing SNPRs (Column 3 in Table I). For patents without citing prior patents, the estimated probability significantly increases from 2.3% to 4.8% when adding scientific references; for patents with citations to prior patents, the probability increases from 5% to 9.8% when citing papers (Fig. 1F). Including the interaction between searches in the two spaces reveals a boosted effect of citing patent references (Column 4 in Table I); the increase in the estimated
TABLE I. Regression results of patent citations and hit patents.

|                | C10 Hit (5%) | Hit (top 1%) | Hit (top 10%) |
|----------------|--------------|--------------|---------------|
| num_inv        | 0.0695**     | 0.0693**     | 0.122***      |
|                | (0.000402)   | (0.000402)   | (0.00124)     |
| num_ipc        | 0.0623***    | 0.0631***    | 0.151***      |
|                | (0.00162)    | (0.00566)    | (0.00118)     |
| has_pr         | 0.429***     | 0.329***     | 0.736***      |
|                | (0.00422)    | (0.00532)    | (0.0205)      |
| has_snpr       | 0.398***     | 0.128***     | 0.775***      |
|                | (0.00203)    | (0.00848)    | (0.0207)      |
| has_pr×has_snpr| 0.282***     | 0.417***     | 0.653***      |
|                | (0.00860)    | (0.0409)     | (0.00931)     |
| Constant       | 0.0168       | 0.111***     | -4.026***     |
|                | (0.0108)     | (0.0113)     | (0.0410)      |
| lnalpha        | 0.211***     | 0.211***     |               |
|                | (0.000802)   | (0.000802)   |               |

Standard errors in parentheses

- * p < 0.05
- ** p < 0.01
- *** p < 0.001

hit probabilities is more pronounced when the patent also cites papers (Fig. 1G). Specifically, when there is scientific search, the effect of technological search is a 144% increase in hit probability, which is much higher than a 68% increase when there is no scientific search.

We perform several additional tests to ensure the robustness of our results. First, we use two other thresholds, 1% and 10%, to identify hit patents and find that our results are robust: Scientific search remains a significant predictor of hit patents (Columns 5–8 in Table I). Moreover, the effect of scientific search is even more prominent for the most impactful patents (top 1%); there is a 171% increase in the odds of becoming top 1% most highly-cited patents, much larger than the 117% and 96% increases for the top 5% and 10% cases, respectively. The effect of the interaction between the two searches is also stronger as we increase the threshold, suggesting that scientific search is more helpful to
technological search in producing the most influential patents. Second, instead of putting a 10-year window when counting citations, we extend the window to 2019, the last year in our dataset, and find that our results still hold (Table A2). Third, to further explore whether there are cross-field heterogeneities in the effects of scientific search, we repeat our analysis separately for patents belonging to the five categories designated by NBER. These categories are Chemical, Computers & Communications, Drugs & Medical, Electrical & Electronic, and Mechanical (Hall et al. 2001). The results indicate persistent effects of scientific search on patent impact across fields (Tables A3–A7).

B. Temporal search and impact

Having established the positive linkage between patent’s scientific search and future impact, we then examine how such search along the temporal dimension is associated with impact. Here we focus on the subset of patents with scientific references. Figs. 2A–B present patent-level statistical characterizations of temporal searches in the two spaces. We find that, for the focused subset of patents, their cited science has been constantly older than cited technology (Fig. 2A), which is in agreement with the view that it may take a longer time for the translation of scientific discoveries into practical applications. We also observe that, starting from around 2000, there is an upward trend of mean age for both searches, suggesting that recent patents relied on older science and technology. We postulate that this may be related to the rise of modern information technology that makes it easier for inventors to search and retrieve “prior art” that are more distant to the present. Turning to the dispersion of ages, cited patents exhibit a larger variation in their ages than that of cited papers (Fig. 2B), partly due to the fact that there are more references to patents than to papers.

Fig. 2C examines the relationship between temporal search in the scientific space and impact. We partition patents granted in each decade into four categories based on whether their $\mu_s$ and $cv_s$ are below (“L”) or above (“H”) the respective global means over all patents in that decade. We find that first, across all the four groups, patents have probabilities to be hits higher than the background baseline (5%), reinforcing our previous finding that patents with SNPRs are more likely to be hits. Among the four groups, the “LH” one—patents located in the region of low $\mu_s$ and high $cv_s$—enjoys the largest hit probabilities (Fig. 2C).
FIG. 2. Temporal search in the scientific space. (A) Patent-level average of $\mu_s$ and $\mu_t$, mean age of cited papers and cited patents for citing patents granted over time. (B) Patent-level average of $cv_s$ and $cv_t$, coefficient of variation of ages of cited papers and patents; (C) Hit probabilities for the four groups of patents based on whether their $\mu_s$ and $cv_s$ are below or above the respective global means over all patents in the decade.

However, this privilege has been degrading over time. In the 1970s, the hit probability of the LH group is 2.8 times larger than that of the HL group, which decreased to 1.9, 1.7, and 1.5 times larger in the 1980s, 1990s, and 2000s, respectively. Accompanying this decrease is the increasingly higher probabilities of the HH groups, suggesting that search widely along the temporal dimension has become an important factor linked to hit patents.

Regression analyses confirm these results net of controls (Table II). Patents with $\mu_s$ below the average have 14% more citations (Column 1) and 25% higher odds of becoming hit than the counterparts (Column 4); patents with $cv_s$ above the average have 16% more citations (Column 1) and 32% higher odds of being hit (Column 4). Figs. 3A, E plot the estimated citations and hit probabilities for the four groups of patents based on whether $\mu_s$ and $\mu_t$ are below or above average, whereas Figs. 3C, G focus on the estimated impact conditional on $cv_s$ and $cv_t$. In Columns 2 and 5, we test only the interaction between citing recent scientific and technological knowledge, and the results indicate a significantly positive interaction. This effect persists if we examine the roles of recency and dispersion simultaneously. Specifically, Column 3 suggests a positive interaction between the effects of search for recent knowledge in the two spaces, meaning that while relying on recent technological knowledge is associated with higher citations than relying on temporally distant one, the difference is much more prominent when the patent also relies on recent scientific knowledge, which is illustrated in Fig. 3B. A similar conclusion can be drawn when the impact is defined as hit patents (Column 6 and Fig. 3F). Positive interactions are also found for the effects of reliance
TABLE II. Regression modeling of temporal search and impact.

|                | C10          | Hit (5%)     |
|----------------|--------------|--------------|
|                | (1)          | (2)          | (3)          | (4)          | (5)          | (6)          |
| num_inv        | 0.0372***    | 0.0373***    | 0.0371***    | 0.0737***    | 0.0738***    | 0.0735***    |
|                | (0.000964)   | (0.000964)   | (0.000964)   | (0.00251)    | (0.00251)    | (0.00251)    |
| num_ipc        | 0.00851*     | 0.00822*     | 0.00909*     | 0.0321**     | 0.0320**     | 0.0340**     |
|                | (0.00385)    | (0.00385)    | (0.00385)    | (0.0113)     | (0.0113)     | (0.0113)     |
| num_pr         | 0.00675***   | 0.00671***   | 0.00666***   | 0.00652***   | 0.00647***   | 0.00641***   |
|                | (0.0000688)  | (0.0000688)  | (0.0000688)  | (0.000108)   | (0.000108)   | (0.000108)   |
| num_snpr       | 0.00596***   | 0.00589***   | 0.00594***   | 0.0112***    | 0.0111***    | 0.0112***    |
|                | (0.000162)   | (0.000162)   | (0.000162)   | (0.000400)   | (0.000400)   | (0.000400)   |
| snpr_avg_c5    | 0.110***     | 0.111***     | 0.111***     | 0.189***     | 0.190***     | 0.191***     |
|                | (0.00402)    | (0.00402)    | (0.00402)    | (0.0120)     | (0.0120)     | (0.0120)     |
| pr_low_avg     | 0.171***     | 0.118***     | 0.120***     | 0.272***     | 0.165***     | 0.169***     |
|                | (0.00420)    | (0.00628)    | (0.00628)    | (0.0124)     | (0.0196)     | (0.0196)     |
| pr_high_cv     | 0.247***     | 0.249***     | 0.206***     | 0.459***     | 0.462***     | 0.370***     |
|                | (0.00397)    | (0.00397)    | (0.00505)    | (0.0121)     | (0.0121)     | (0.0160)     |
| snpr_low_avg   | 0.133***     | 0.0862***    | 0.0882***    | 0.224***     | 0.136***     | 0.141***     |
|                | (0.00406)    | (0.00582)    | (0.00582)    | (0.0121)     | (0.0173)     | (0.0173)     |
| snpr_high_cv   | 0.149***     | 0.149***     | 0.0938***    | 0.282***     | 0.280***     | 0.152***     |
|                | (0.00427)    | (0.00427)    | (0.00588)    | (0.0123)     | (0.0123)     | (0.0193)     |
| pr_low_avg × snpr_low_avg | 0.0886*** | 0.0864***    | 0.171***     | 0.166***     | (0.00793)    | (0.00793)    |
|                |              |              |              |              | (0.0240)     | (0.0240)     |
| pr_high_cv × snpr_high_cv | 0.103*** | 0.197***     |              |              |              |              |
|                |              |              |              |              |              |              |
| Constant       | 0.259***     | 0.279***     | 0.300***     | -3.462***    | -3.422***    | -3.374***    |
|                | (0.0323)     | (0.0323)     | (0.0323)     | (0.0934)     | (0.0935)     | (0.0937)     |
| lnalpha        | 0.376***     | 0.376***     | 0.376***     |              |              |              |
|                | (0.00218)    | (0.00218)    | (0.00218)    |              |              |              |
| Decade fe      | ✓            | ✓            | ✓            | ✓            | ✓            | ✓            |
| Field fe       | ✓            | ✓            | ✓            | ✓            | ✓            | ✓            |
| N              | 461377       | 461377       | 461377       | 461377       | 461377       | 461377       |
| pseudo R²      | 0.037        | 0.037        | 0.037        | 0.055        | 0.055        | 0.056        |
| BIC            | 3141879      | 3141768      | 3141594      | 254000       | 253962       | 253900       |

Standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001

on temporally dispersed scientific and technological knowledge, for both forward citations (Column 3 and Fig. 3D) and hit patents (Column 6 and Fig. 3H). Finally, changing the threshold for identifying hit patents has no influence in our results (Table A8).
FIG. 3. The effects of temporal search in the scientific space on patent impact. (A–D) Estimated 10-year forward citations based on negative binomial regression models without (A, C) and with (B, D) considering the interaction between temporal searches in the scientific and technological spaces. (E–H) Estimated hit probabilities based on logistic regression models without (E, G) and with (F, H) considering the interaction.

The above analyses use dichotomized versions for the variables of temporal search in the two spaces, we also use the original continuous variables (Table III). The results show that a lower \( \mu_s \) and a higher \( cv_s \) are associated with a larger number of citations (Column 1) and a higher probability to be hits (Column 4), suggesting that high impact patents tend to recombine recent science but at the same time recombine temporally dispersed scientific knowledge. There are positive interactions between searching for recent scientific and technological knowledge as well as between searching for temporally dispersed knowledge sourced from the two spaces (Columns 3 and 6). These results are still robust if we change the threshold for hit patents (Table A9).

Finally, we examine whether there is field heterogeneity in the effects of temporal search in the scientific space. Subsample analyses by technological field reveal that the negative effect of mean age of cited science and the positive effect of the spread of cited science ages are persistent (Tables A10–A14). However, the effect sizes vary by field (Fig. 4). The largest
TABLE III. Regression modeling of temporal search and impact.

|            | C10        | Hit (5%)   |
|------------|------------|------------|
|            | (1)        | (2)        | (3)        | (4)        | (5)        | (6)        |
| num_inv    | 0.0385***  | 0.0385***  | 0.0383***  | 0.0754***  | 0.0754***  | 0.0752***  |
|            | (0.000960) | (0.000960) | (0.000959) | (0.00251)  | (0.00251)  | (0.00251)  |
| num_ipc    | 0.0350***  | 0.0348***  | 0.0357***  | 0.0454***  | 0.0448***  | 0.0462***  |
|            | (0.00395)  | (0.00395)  | (0.00395)  | (0.0116)   | (0.0116)   | (0.0116)   |
| num_pr     | 0.00665*** | 0.00665*** | 0.00658*** | 0.00667*** | 0.00666*** | 0.00660*** |
|            | (0.000670) | (0.000671) | (0.000670) | (0.00109)  | (0.00109)  | (0.00109)  |
| num_snpr   | 0.00547*** | 0.00551*** | 0.00555*** | 0.01018**  | 0.0109**   | 0.0110**   |
|            | (0.000159) | (0.000159) | (0.000159) | (0.000399) | (0.000399) | (0.000400) |
| snpr_avg_c5| 0.118**    | 0.118**    | 0.118**    | 0.184**    | 0.181**    | 0.182**    |
|            | (0.00403)  | (0.00403)  | (0.00403)  | (0.0121)   | (0.0121)   | (0.0121)   |
| pr_age_avg | -0.0142*** | -0.0203*** | -0.0204*** | -0.0284*** | -0.041***  | -0.0411*** |
|            | (0.00341)  | (0.000519) | (0.000519) | (0.00117)  | (0.00178)  | (0.00179)  |
| pr_age_cv  | 0.557***   | 0.564***   | 0.467***   | 0.921***   | 0.935***   | 0.788***   |
|            | (0.00724)  | (0.00726)  | (0.00918)  | (0.0200)   | (0.0200)   | (0.0200)   |
| snpr_age_avg| -0.00851***| -0.0140*** | -0.0140*** | -0.0167*** | -0.0285*** | -0.0283*** |
|            | (0.000263) | (0.000441) | (0.000441) | (0.000907) | (0.00154)  | (0.00154)  |
| snpr_age_cv| 0.327***   | 0.331***   | 0.117***   | 0.621***   | 0.628***   | 0.286***   |
|            | (0.00851)  | (0.00851)  | (0.0150)   | (0.0233)   | (0.0233)   | (0.0455)   |
| pr_age_avg × snpr_age_avg | 0.000470*** | 0.000472*** | 0.00106*** | 0.00104*** | 0.00104*** |
|            | (0.000308) | (0.000308) | (0.000108) | (0.000108) | (0.000108) |
| pr_age_cv × snpr_age_cv | 0.441***    | 0.596***    | 0.0257     | 0.0675     | 0.0675     |
| Constant   | 0.399***   | 0.449***   | 0.486***   | -2.900***  | -2.790***  | -2.732***  |
|            | (0.0436)   | (0.0437)   | (0.0437)   | (0.125)    | (0.125)    | (0.126)    |
| lnalpha    | 0.361***   | 0.360***   | 0.359***   |           |           |           |
|            | (0.00219)  | (0.00219)  | (0.00219)  |           |           |           |
| Year fe    | ✓          | ✓          | ✓          | ✓          | ✓          | ✓          |
| Field fe   | ✓          | ✓          | ✓          | ✓          | ✓          | ✓          |
| N          | 461377     | 461377     | 461377     | 461377     | 461377     | 461377     |
| pseudo R²  | 0.039      | 0.039      | 0.040      | 0.060      | 0.060      | 0.061      |
| BIC        | 3135221    | 3134991    | 3134708    | 253114     | 253042     | 252977     |

Standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001

The effect of citing recent science on patent impact is found for Computers & Communications and Drugs & Medical patents, reflecting the deep reliance on science of both groups of patents and rapid progresses in the fields, whereas the smallest effect is observed for mechanical...
V. DISCUSSION

The vast space of knowledge from which inventors can draw and recombine as input for new inventions has raised the questions of what their search strategies are and the performance implications. While previous inquiry has emphasized the beneficial role of search in the scientific space in technological development, it remains to be seen which and how specific types of scientific searches contribute to new inventions. Here we focus on the temporal dimension of scientific search and examine how inventions rely on prior scientific knowledge that are produced at different points in time.

Using a large-scale sample, we have obtained three sets of results. First, patents involving...
scientific search have roughly 50% more forward citations in 10 years than those without, an effect with the size comparable to the effect size of technological search. The odds of becoming hits for patents with scientific search are more than doubled than comparable patents without such search. Furthermore, there is a strong, positive interaction effect between scientific and technological searches. These results consolidate and further enrich previous studies. For example, Fleming and Sorenson (2004) argued science as a map in technological search, and our results provide empirical evidence for this theoretical argument. Another implication from the positive interaction between searches in the scientific and technological is from the perspective of the science side: Searching technology helps identify science with commercial potential. Second, conditional on search in the scientific space, cited science tends to be older than cited technology but has a lower variation in age, and there is a recent trend in referencing older science and technology. This represents the “distance” from scientific discovery to application, which needs time for commercial trials. Indeed, Jensen and Thursby (2001) reported that about 75% of inventions were no more than a “proof of concept” at the time of licensing, 48% did not have a prototype, and manufacturing feasibility was known for only 8% of inventions. Referencing older science and technology may be attributed to the increasing complexity of technological innovations, as more knowledge elements need to be combined and some of them are from temporally “distant” science. Relating temporal search to patent impact, we find that relying on more recent science but at the same time referencing science with a wider spread in age are associated with more patent citations and higher likelihood of being a hit. This finding is consistent with the conclusion of temporal search in technological space, implying a general rule of knowledge search in the temporal dimension. Furthermore, we find that there are positive interactions between temporal searches in the scientific and technological spaces, suggesting their mutually beneficial roles in patent value. Third, these results are consistent across technological fields, but temporal search in the scientific space has the largest effect for the Computers & Communications and Drugs & Medical fields, reflecting their deep reliance on science.

We discuss the limitations of our study for considerations of future research. First, we have looked at temporal search at the individual patent level. Future work can pay attention to firms and study how they perform temporal search in the scientific space and how it relates to the quantity and quality of their innovative output or other aspects of
performances. Second, we have focused on granted patents, but inventions may take other forms like patent applications. Therefore, the generalizability of our results remains to be tested in other available data of inventive forms. Third, in light of our work and other previous large-scale studies (Mukherjee et al. 2017), the roles of the age structure of prior knowledge—regardless of scientific or technological—in the impact of new knowledge seem universal, raising the questions of what possible channels are for explaining this universality and what moderators are.

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## Appendix

| Variable                                      | Mean   | Std. Dev. | Min  | Max   | N     |
|-----------------------------------------------|--------|-----------|------|-------|-------|
| 10-year forward citations (C10)              | 8.995  | 19.02     | 0    | 3155  | 3693101 |
| Total forward citations until 2019 (C2019)   | 20.095 | 46.339    | 0    | 4543  | 3693101 |
| Number of inventors (num_inv)                 | 2.221  | 1.611     | 1    | 76    | 3693101 |
| Number of IPC patent classes (num_ipc)        | 1.132  | 0.392     | 1    | 11    | 3693101 |
| Has patent reference (has_pr)                 | 0.976  | 0.153     | 0    | 1     | 3693101 |
| Has scientific non-patent reference (has_snpr)| 0.125  | 0.331     | 0    | 1     | 3693101 |
| Number of patent reference (num_pr)           | 10.714 | 20.135    | 0    | 1022  | 3693101 |
| Number of SNPR (num_snpr)                     | 0.93   | 5.474     | 0    | 170   | 3693101 |
| Year                                          | 1996.035 | 9.336     | 1976 | 2009  | 3693101 |
| Mean age of PR (pr_age_avg)                   | 8.899  | 6.287     | 0    | 134   | 461377  |
| CV of PR age (pr_age_cv)                      | 0.453  | 0.299     | 0    | 2.722 | 461377  |
| Mean age of SNPR (snpr_age_avg)               | 11.28  | 7.388     | 0    | 103   | 461377  |
| CV of SNPR age (snpr_age_cv)                  | 0.219  | 0.245     | 0    | 2.037 | 461377  |
| Mean 5-year citations of SNPR in log (snpr_avg_c5) | 1.101  | 0.525     | 0    | 3.86  | 461377  |
### A1. REGRESSION RESULTS OF SCIENTIFIC SEARCH

**TABLE A2.** Regression results of patent citations and hit patents. Citations are counted until 2019, and hit patents are defined accordingly.

|                | C2019 | Hit (5%) | Hit (top 1%) | Hit (top 10%) |
|----------------|-------|----------|--------------|---------------|
| num_inv        | 0.0627*** | 0.0626*** | 0.103***     | 0.123***      |
|                | (0.000407) | (0.000407) | (0.00128)    | (0.00248)     |
| num_ipc        | 0.0582*** | 0.0591*** | 0.132***     | 0.204***      |
|                | (0.00161)  | (0.00161)  | (0.00581)    | (0.0120)      |
| has_pr         | 0.440***   | 0.355***   | 0.779***     | 0.867***      |
|                | (0.00417)  | (0.00526)  | (0.0212)     | (0.0488)      |
| has_snpr       | 0.417***   | 0.187***   | 0.747***     | 0.927***      |
|                | (0.00206)  | (0.00836)  | (0.00687)    | (0.0421)      |
| has_pr×has_snpr| 0.241***   | 0.367***   | 0.440***     | 0.327***      |
|                | (0.00850)  | (0.0423)   |              | (0.0969)      |
| Constant       | 1.303***   | 1.384***   | -4.135***    | -3.966***     |
|                | (0.0106)   | (0.0110)   | (0.0423)     |              |
| lnalpha        | 0.283***   | 0.282***   |              |               |
|                | (0.000718) | (0.000718) |              |               |

|                | ✓     | ✓     | ✓     | ✓     | ✓     | ✓     | ✓     | ✓     |
| Year fe        | ✓     | ✓     | ✓     | ✓     | ✓     | ✓     | ✓     | ✓     |
| Field fe       | ✓     | ✓     | ✓     | ✓     | ✓     | ✓     | ✓     | ✓     |
| N              | 3693101 | 3693101 | 3693101 | 3693101 | 3693101 | 3693101 | 3693101 | 3693101 |
| Pseudo $R^2$   | 0.029 | 0.029 | 0.013 | 0.013 | 0.016 | 0.016 | 0.011 | 0.011 |
| BIC            | 28356534 | 28355754 | 1470450 | 1470390 | 416777 | 416772 | 2414979 | 2414869 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
TABLE A3. Regression results of patent citations and hit patents. Only Chemical patents are included.

|                | C10   | Hit (5%) | Hit (top 1%) | Hit (top 10%) |
|----------------|-------|----------|--------------|---------------|
|                | (1)   | (2)      | (3)          | (4)           | (5)           | (6)           | (7)           | (8)           |
| num_inv        | 0.0533*** | 0.0530*** | 0.0963*** | 0.0961*** | 0.107*** | 0.106*** | 0.0840*** | 0.0838*** |
|                | (0.000945) | (0.000945) | (0.00294) | (0.00294) | (0.00583) | (0.00583) | (0.00226) | (0.00226) |
| num_ipc        | 0.116*** | 0.116*** | 0.235*** | 0.236*** | 0.313*** | 0.314*** | 0.215*** | 0.216*** |
|                | (0.00342) | (0.00342) | (0.0109) | (0.0109) | (0.0222) | (0.0222) | (0.00821) | (0.00821) |
| has_pr         | 0.395*** | 0.313*** | 0.629*** | 0.464*** | 0.680*** | 0.326** | 0.623*** | 0.474*** |
|                | (0.00838) | (0.0107) | (0.0357) | (0.0490) | (0.0791) | (0.109) | (0.0256) | (0.0343) |
| has_snpr       | 0.382*** | 0.181*** | 0.751*** | 0.440*** | 1.050*** | 0.427** | 0.617*** | 0.318*** |
|                | (0.00440) | (0.0165) | (0.0141) | (0.0696) | (0.0291) | (0.155) | (0.0106) | (0.0501) |
| has_pr×has_snpr| 0.215*** | 0.322*** |          | 0.642*** |          | 0.312*** |          |          |
|                | (0.0169) | (0.0707) |          | (0.157) |          | (0.0509) |          |          |
| Constant       | 0.0816*** | 0.158*** | -3.879*** | -3.721*** | -5.879*** | -5.539*** | -3.234*** | -3.091*** |
|                | (0.0157) | (0.0169) | (0.0574) | (0.0657) | (0.128) | (0.146) | (0.0427) | (0.0479) |
| lnalpha        | 0.269*** | 0.268*** |          |          |          |          |          |          |
|                | (0.00210) | (0.00210) |          |          |          |          |          |          |

Year fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
Field fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓

N 610473 610473 610473 610473 610473 610473 610473 610473
Pseudo R² 0.017 0.017 0.018 0.018 0.026 0.026 0.015 0.015
BIC 3417463 3417317 249937 249930 70140 70137 410379 410354

Standard errors in parentheses
*p < 0.05, ** p < 0.01, *** p < 0.001
TABLE A4. Regression results of patent citations and hit patents. Only Computers & Communications patents are included.

|                  | C10  | Hit (5%) | Hit (top 1%) | Hit (top 10%) |
|------------------|------|----------|--------------|---------------|
| num_inv          | 0.0759*** | 0.0759*** | 0.121***     | 0.142***      |
|                  | (0.000899) | (0.000899) | (0.00275)    | (0.00518)     |
| num_ipc          | 0.00637 | 0.00640  | -0.00328     | 0.0616        |
|                  | (0.00430) | (0.00430) | (0.0165)     | (0.0344)      |
| has_pr           | 0.290*** | 0.247*** | 0.619***     | 0.638***      |
|                  | (0.0121) | (0.0132) | (0.0601)     | (0.135)       |
| has_snpr         | 0.387*** | 0.108*** | 0.659***     | 0.108         |
|                  | (0.00419) | (0.0319) | (0.0136)     | (0.0276)      |
| has_pr×has_snpr  | 0.284*** | 0.555*** | 0.776*       | 0.368***      |
|                  | (0.0322) | (0.156)  | (0.351)      | (0.351)       |
| Constant         | 1.069*** | 1.111*** | -3.636***    | -5.364***     |
|                  | (0.0226) | (0.0232) | (0.0895)     | (0.194)       |
| lnalpha          | 0.280*** | 0.280*** | 0.0190      | 0.190         |

Standard errors in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001
TABLE A5. Regression results of patent citations and hit patents. Only Drugs & Medical patents are included.

|        | C10 | Hit (5%) | Hit (top 1%) | Hit (top 10%) |
|--------|-----|----------|--------------|---------------|
|        | (1) | (2)      | (3)          | (4)           |
| num_inv| 0.0400*** | 0.0396*** | 0.0695***   | 0.0794***    |
|        | (0.00122) | (0.00122) | (0.00357)    | (0.00731)    |
| num_ipc| -0.0348*** | -0.0342*** | -0.0619***  | -0.0612***   |
|        | (0.00482) | (0.00482) | (0.0173)     | (0.0368)     |
| has_pr | 0.524*** | 0.378*** | 0.958***     | 0.699***     |
|        | (0.00833) | (0.0143)  | (0.0389)     | (0.0937)     |
| has_snpr| 0.295*** | 0.0909*** | 0.685***     | 0.351***     |
|        | (0.00519) | (0.0168)  | (0.0187)     | (0.0408)     |
| has_pr×has_snpr| 0.222*** | 0.347*** | 0.613***     | 0.281***     |
|        | (0.0173) | (0.0853)  | (0.201)      | (0.0574)     |
| Constant| 0.108*** | 0.238*** | -3.921***    | -3.678***    |
|        | (0.0261) | (0.0281)  | (0.0866)     | (0.103)      |
| lnalpha| 0.442*** | 0.441***  |              |              |
|        | (0.00256) | (0.00256) |              |              |

Year fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
Field fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
N 339053 339053 339053 339053 339053 339053 339053 339053
Pseudo R² 0.038 0.038 0.018 0.018 0.019 0.020 0.016 0.016
BIC 2261245 2261091 136221 136218 39063 39067 222737 222727

Standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001
TABLE A6. Regression results of patent citations and breakthrough patents. Only Electrical &
Electronic patents are included.

|                | C10  | Hit (5%) | Hit (top 1%) | Hit (top 10%) |
|----------------|------|----------|--------------|---------------|
|                | (1)  | (2)      | (3)          | (4)           |
| num_inv        | 0.0641*** | 0.0641*** | 0.111*** | 0.111*** | 0.127*** | 0.127*** | 0.102*** | 0.102*** |
|                | (0.000929) | (0.000929) | (0.00300) | (0.00300) | (0.00596) | (0.00596) | (0.00229) | (0.00229) |
| num_ipc        | 0.0801*** | 0.0802*** | 0.133*** | 0.134*** | 0.153*** | 0.154*** | 0.130*** | 0.130*** |
|                | (0.00423) | (0.00423) | (0.0152) | (0.0152) | (0.0326) | (0.0326) | (0.0112) | (0.0112) |
| has_pr         | 0.329*** | 0.293*** | 0.617*** | 0.513*** | 0.696*** | 0.591*** | 0.609*** | 0.538*** |
|                | (0.0113) | (0.0123) | (0.0555) | (0.0627) | (0.128) | (0.147) | (0.0394) | (0.0445) |
| has_snpr       | 0.424*** | 0.191*** | 0.788*** | 0.386** | 0.855*** | 0.479   | 0.728*** | 0.438*** |
|                | (0.00446) | (0.0300) | (0.0142) | (0.133) | (0.0298) | (0.298) | (0.0108) | (0.0939) |
| has_pr×has_snpr| 0.238*** | 0.407**  | 0.380      | 0.295**     |
|                | (0.0303) | (0.134)  | (0.299)    | (0.0944)    |
| Constant       | 0.591*** | 0.627*** | -3.730*** | -3.628***  | -5.509*** | -5.404*** | -2.874*** | -2.802*** |
|                | (0.0174) | (0.0181) | (0.0730)  | (0.0785)   | (0.165)   | (0.179)   | (0.0519)  | (0.0558)  |
| lnalpha        | 0.189*** | 0.189*** |
|                | (0.00180) | (0.00180) |
| Year fe        | ✓     | ✓        | ✓          | ✓          | ✓         | ✓         | ✓         | ✓         |
| Field fe       | ✓     | ✓        | ✓          | ✓          | ✓         | ✓         | ✓         | ✓         |
| N              | 709139 | 709139   | 709139     | 709139     | 709139    | 709139    | 709139    | 709139    |
| Pseudo R²      | 0.018  | 0.018    | 0.015      | 0.015      | 0.015     | 0.015     | 0.014     | 0.014     |
| BIC            | 4498762 | 4498717  | 287723     | 287727     | 81805     | 81817     | 471014    | 471017    |

Standard errors in parentheses

* \( p < 0.05 \), ** \( p < 0.01 \), *** \( p < 0.001 \)
TABLE A7. Regression results of patent citations and breakthrough patents. Only Mechanical patents are included.

|                  | C10    | Hit (5%) | Hit (top 1%) | Hit (top 10%) |
|------------------|--------|----------|--------------|---------------|
| num_inv          | 0.0875*** | 0.0875*** | 0.152***     | 0.174***      | 0.174***      | 0.138***      | 0.138***      |
|                  | (0.000969) | (0.000969) | (0.00294)    | (0.00555)     | (0.00555)     | (0.00230)     | (0.00230)     |
| num_ipc          | 0.0513*** | 0.0513*** | 0.144***     | 0.185***      | 0.185***      | 0.136***      | 0.136***      |
|                  | (0.00395)  | (0.00395)  | (0.0142)     | (0.0298)      | (0.0298)      | (0.0105)      | (0.0105)      |
| has_pr           | 0.387***  | 0.381***  | 0.733***     | 0.899***      | 0.993***      | 0.617***      | 0.614***      |
|                  | (0.0141)   | (0.0145)   | (0.0746)     | (0.181)       | (0.205)       | (0.0500)      | (0.0524)      |
| has_snpr         | 0.679***  | 0.552***  | 1.189***     | 1.482***      | 1.990***      | 1.032***      | 0.992***      |
|                  | (0.00811)  | (0.0657)   | (0.0224)     | (0.0417)      | (0.434)       | (0.0181)      | (0.175)       |
| has_pr×has_snpr  | 0.128     | 0.112     | -0.511       | 0.0407        |              |              |              |
|                  | (0.0662)   | (0.246)    |              |              |              |              |              |
| Constant         | 0.342***  | 0.348***  | -3.949***    | -3.937***     | -5.911***     | -6.005***     | -3.080***     |
|                  | (0.0176)   | (0.0179)   | (0.0835)     | (0.0872)      | (0.199)       | (0.221)       | (0.0573)      |
| lnalpha          | 0.109***  | 0.109***  |              |              |              |              |              |
|                  | (0.00194)  | (0.00194)  |              |              |              |              |              |

Year fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
Field fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
N 703232 703232 703232 703232 703232 703232 703232 703232
Pseudo $R^2$ 0.019 0.019 0.017 0.017 0.023 0.023 0.014 0.014
BIC 3989690 3989700 289146 289159 81304 81316 476818 476831

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
## A2. REGRESSION RESULTS OF TEMPORAL SEARCH

### TABLE A8. Regression modeling of temporal search and hit patents.

|                | Hit (1%)                  | Hit (10%)                 |
|----------------|---------------------------|----------------------------|
|                | (1)                       | (2)                       | (3)           | (4)           | (5)           | (6)           |
| num_inv        | 0.0832***                 | 0.0832***                 | 0.0828***     | 0.0647***     | 0.0647***     | 0.0646***     |
|                | (0.00451)                 | (0.00451)                 | (0.00451)     | (0.00202)     | (0.00202)     | (0.00202)     |
| num_ipc        | 0.0589**                  | 0.0588**                  | 0.0614**      | 0.0185*       | 0.0184*       | 0.0199*       |
|                | (0.0217)                  | (0.0217)                  | (0.00877)     | (0.00877)     | (0.00877)     |               |
| num_pr         | 0.00484***                | 0.00478***                | 0.00473***    | 0.00732***    | 0.00727**     | 0.00722**     |
|                | (0.000135)                | (0.000136)                | (0.000106)    | (0.000106)    | (0.000106)    |               |
| num_snpr       | 0.0147***                 | 0.0145***                 | 0.0146***     | 0.00985***    | 0.00977***    | 0.00986***    |
|                | (0.000723)                | (0.000724)                | (0.000726)    | (0.000324)    | (0.000324)    | (0.000325)    |
| snpr_avg_c5    | 0.178***                  | 0.180***                  | 0.181***      | 0.178***      | 0.179***      | 0.179***      |
|                | (0.0239)                  | (0.0239)                  | (0.0239)      | (0.00920)     | (0.00921)     | (0.00920)     |
| pr_low_avg     | 0.366***                  | 0.193***                  | 0.199***      | 0.238***      | 0.160***      | 0.163***      |
|                | (0.0246)                  | (0.0390)                  | (0.0390)      | (0.00952)     | (0.0148)      | (0.0148)      |
| pr_high_cv     | 0.520***                  | 0.524***                  | 0.395***      | 0.397***      | 0.399***      | 0.333***      |
|                | (0.0244)                  | (0.0244)                  | (0.0330)      | (0.00921)     | (0.00921)     | (0.0120)      |
| snpr_low_avg   | 0.200***                  | 0.0566                    | 0.0641        | 0.207***      | 0.141***      | 0.145***      |
|                | (0.0239)                  | (0.0345)                  | (0.0345)      | (0.00926)     | (0.0133)      | (0.0133)      |
| snpr_high_cv   | 0.397***                  | 0.394***                  | 0.214***      | 0.256***      | 0.255***      | 0.164***      |
|                | (0.0241)                  | (0.0241)                  | (0.0397)      | (0.00950)     | (0.00950)     | (0.0143)      |
| pr_low_avg × snpr_low_avg | 0.276***                 | 0.269***                  | 0.126***      | 0.122***      |               |               |
|                | (0.0478)                  | (0.0478)                  | (0.0183)      | (0.0183)      |               |               |
| pr_high_cv × snpr_high_cv | 0.263***                 | 0.146***                  |               |               |               |               |
|                | (0.0460)                  | (0.0173)                  |               |               |               |               |
| constant       | -5.403***                 | -5.340***                 | -5.269***     | -2.676***     | -2.646***     | -2.613***     |
|                | (0.200)                   | (0.200)                   | (0.200)       | (0.0715)      | (0.0716)      | (0.0717)      |
| Decade fe      | ✓                         | ✓                         | ✓             | ✓             | ✓             | ✓              |
| Field fe       | ✓                         | ✓                         | ✓             | ✓             | ✓             | ✓              |
| N              | 461377                    | 461377                    | 461377        | 461377        | 461377        | 461377        |
| pseudo R²      | 0.058                     | 0.058                     | 0.059         | 0.050         | 0.050         | 0.050         |
| BIC            | 85872                     | 85852                     | 85832         | 380282        | 380248        | 380189        |

Standard errors in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001
TABLE A9. Regression modeling of temporal search and hit patents.

|        | Hit (1%) | Hit (10%) |
|--------|----------|-----------|
|        | (1)      | (2)       | (3)      | (4)      | (5)      | (6)      |
| num_inv| 0.0857***| 0.0856*** | 0.0854***| 0.0664***| 0.0664***| 0.0663***|
|        | (0.00450)| (0.00450)| (0.00450)| (0.00203)| (0.00203)| (0.00203)|
| num_ipc| 0.0773***| 0.0762*** | 0.0775***| 0.0302***| 0.0296** | 0.0306***|
|        | (0.0223) | (0.0223)  | (0.0223) | (0.00906)| (0.00907)| (0.00907)|
| num_pr | 0.0506***| 0.0504*** | 0.0500***| 0.00738**| 0.00732**| 0.00732**|
|        | (0.00137)| (0.00137)| (0.00137)| (0.000106)| (0.000106)| (0.000106)|
| num_snpr| 0.0146***| 0.0148*** | 0.0149***| 0.00937**| 0.00944***| 0.00953***|
|        | (0.00722)| (0.00722)| (0.00724)| (0.000323)| (0.000323)| (0.000324)|
| snpr_avg_c5| 0.175***| 0.171*** | 0.172*** | 0.176*** | 0.174*** | 0.174*** |
|        | (0.0241) | (0.0241)  | (0.0241) | (0.00930)| (0.00930)| (0.00930)|
| pr_age_avg| -0.0373***| -0.0583***| -0.0582***| -0.0253***| -0.0359***| -0.0360***|
|        | (0.00242)| (0.00345) | (0.00346) | (0.000879)| (0.00135)| (0.00135)|
| pr_age_cv| 1.027*** | 1.052*** | 0.885*** | 0.852*** | 0.865*** | 0.762*** |
|        | (0.0385) | (0.0385)  | (0.0512) | (0.0156) | (0.0156) | (0.0201) |
| snpr_age_avg| -0.0144***| -0.0338***| -0.0336***| -0.0149***| -0.0247***| -0.0246***|
|        | (0.00181)| (0.00290) | (0.00290) | (0.000678)| (0.00115)| (0.00115)|
| snpr_age_cv| 0.838***| 0.851*** | 0.472*** | 0.559*** | 0.565*** | 0.327*** |
|        | (0.0439) | (0.0440)  | (0.0885) | (0.0184) | (0.0184) | (0.0347) |
| pr_age_avg × snpr_age_avg| 0.00172***| 0.00171***| 0.000871***| 0.000862***| 0.000808***| 0.0000810***|
|        | (0.000187)| (0.000188)| (0.0000808)| (0.0000810)| (0.0000810)| (0.0000810)|
| pr_age_cv × snpr_age_cv| 0.624***| 0.435*** | 0.125** | 0.0535| 0.0535| 0.0535| |
|        | (0.260) | (0.261)  | (0.262) | (0.0972) | (0.0976) | (0.0977) |
| constant| -4.763***| -4.582***| -4.512***| -2.215***| -2.122***| -2.082***|
|        | (0.260) | (0.261)  | (0.262) | (0.0972) | (0.0976) | (0.0977) |

Year fe ✓ ✓ ✓ ✓ ✓ ✓
Field fe ✓ ✓ ✓ ✓ ✓ ✓
N 461377 461377 461377 461377 461377 461377
pseudo R² 0.064 0.064 0.065 0.055 0.055 0.055
BIC 85742 85691 85679 378749 378656 378603

Standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001
|                  | C10       | Hit (1%) | Hit (top 5%) | Hit (top 10%) |
|------------------|-----------|----------|--------------|---------------|
| num_inv          | 0.0400*** | 0.0700***| 0.0718***    | 0.0718***     |
|                  | (0.00214) | (0.00967)| (0.00951)    | (0.00518)     |
| num_ipc          | 0.0944*** | 0.164*** | 0.162***     | 0.163***      |
|                  | (0.00809) | (0.0378) | (0.0203)     | (0.0160)      |
| num_pr           | 0.00516***| 0.0150***| 0.00751***   | 0.00747***    |
|                  | (0.000226)| (0.000359)| (0.000306)  | (0.000309)    |
| num_snpr         | 0.00516***| 0.0150***| 0.00751***   | 0.00747***    |
|                  | (0.000226)| (0.000359)| (0.000306)  | (0.000309)    |
| snpr_avg_c5      | 0.197***  | 0.380*** | 0.317***     | 0.311***      |
|                  | (0.00928) | (0.0503) | (0.0255)     | (0.0197)      |
| pr_age_avg       | -0.0150***| -0.0437***| -0.0283***   | -0.0388***    |
|                  | (0.000643)| (0.000504)| (0.000226)  | (0.000309)    |
| pr_age_cv        | 0.616***  | 1.196*** | 0.971***     | 0.896***      |
|                  | (0.0158)  | (0.0747) | (0.0396)     | (0.0197)      |
| snpr_age_avg     | -0.00697***| -0.0313***| -0.0167***   | -0.0267***    |
|                  | (0.000476)| (0.000359)| (0.000226)  | (0.000309)    |
| snpr_age_cv      | 0.325***  | 0.757*** | 0.643***     | 0.453***      |
|                  | (0.0183)  | (0.0853) | (0.0454)     | (0.0359)      |
| pr_age_avg × snpr_age_avg | 0.000490***| 0.01545***| 0.000815***  | 0.000755***   |
|                  | (0.0000502)| (0.000361)| (0.000188)  | (0.000134)    |
| pr_age_cv × snpr_age_cv | 0.156**   | 0.211    | 0.313*       | 0.189         |
|                  | (0.0546)  | (0.0240) | (0.130)      | (0.104)       |
| Constant         | 0.110     | -5.688***| -5.466***    | -3.493***     |
|                  | (0.0596)  | (0.0604) | (0.0407)     | (0.0177)      |
| lalpha           | 0.504***  | 0.503*** | 0.504***     | 0.504***      |
|                  | (0.00490) | (0.00490)| (0.00490)    | (0.00490)     |

Year fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
Field fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
N 104381 104381 104381 104381 104381 104381 104381 104381
pseudo $R^2$ 0.028 0.028 0.060 0.061 0.056 0.056 0.051 0.051
BIC 615490 615407 20527 20535 58439 58439 86320 86310

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
### TABLE A11. Regression modeling of temporal search and impact. Only Computers & Communications patents are included.

|                     | C10       | Hit (1%) | Hit (top 5%) | Hit (top 10%) |
|---------------------|-----------|----------|--------------|---------------|
| num_inv             | 0.0586*** | 0.0585***| 0.110***     | 0.0955***     |
|                     | (0.00211) | (0.00211)| (0.00909)    | (0.00560)     |
| num_ipc             | -0.0333** | -0.0330**| 0.0169       | -0.0572       |
|                     | (0.0110)  | (0.0110) | (0.0683)     | (0.0369)      |
| num_pr              | 0.00703***| 0.00697***| 0.00661***   | 0.00858***    |
|                     | (0.000114)| (0.000114)| (0.000287)  | (0.000210)    |
| num_snpr            | 0.00207*  | 0.00197*  | -0.00813     | -0.00920      |
|                     | (0.000852)| (0.000850)| (0.00439)   | (0.00235)     |
| snpr_avg_c5         | 0.0208**  | 0.0225**  | -0.0336      | 0.0189        |
|                     | (0.00755) | (0.00756) | (0.0497)     | (0.0251)      |
| pr_age_avg          | -0.0314***| -0.0406***| -0.0359***   | -0.0459***    |
|                     | (0.00105) | (0.00173) | (0.00758)    | (0.00391)     |
| pr_age_cv           | 0.208***  | 0.152***  | 0.458***     | 0.397***      |
|                     | (0.0161)  | (0.0189)  | (0.0985)     | (0.0505)      |
| snpr_age_avg        | -0.0102***| -0.0169***| -0.0266***   | -0.0197***    |
|                     | (0.00628) | (0.00121) | (0.00479)    | (0.00236)     |
| snpr_age_cv         | 0.236***  | -0.00158 | 0.972***     | 0.483***      |
|                     | (0.0209)  | (0.0443)  | (0.111)      | (0.0627)      |
| pr_age_avg × snpr_age_avg | 0.000816***| 0.00358***| 0.00291***   | 0.00232***    |
|                     | (0.000125)| (0.000697)| (0.000405)  | (0.000328)    |
| pr_age_cv × snpr_age_cv | 0.453***  | 1.522***  | 0.802***     | 0.512***      |
|                     | (0.0737)  | (0.367)   | (0.213)      | (0.168)       |
| Constant            | 1.785***  | 1.863***  | -3.464***    | -3.173***     |
|                     | (0.117)   | (0.117)   | (0.524)      | (0.526)       |
| lnalpha             | 0.187***  | 0.187***  |              |               |
|                     | (0.00450) | (0.00450) |              |               |

Year fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓  
Field fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓  
N 92545 92545 92422 92422 92545 92545 92545 92545  
pseudo $R^2$ 0.017 0.017 0.051 0.053 0.052 0.053 0.049 0.050  
BIC 741750 741689 18159 18146 51638 51641 77725 77693  

Standard errors in parentheses  
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
TABLE A12. Regression modeling of temporal search and impact. Only Drugs & Medical patents are included.

|                    | C10     | Hit (1%)  | Hit (top 5%) | Hit (top 10%) |
|--------------------|---------|-----------|--------------|---------------|
|                    | (1)     | (2)       | (3)          | (4)           |
| num_inv            | 0.0247*** | 0.0245*** | 0.0652***    | 0.0652***     |
|                    | (0.00162) | (0.00162) | (0.00907)    | (0.00907)     |
| num_ipc            | 0.0209**  | 0.0200**  | 0.0720       | 0.0713        |
|                    | (0.00642) | (0.00642) | (0.01419)    | (0.01419)     |
| num_pr             | 0.00832*** | 0.00824*** | 0.00614***   | 0.00609***    |
|                    | (0.000153) | (0.000154) | (0.000351)   | (0.000353)    |
| num_snpr           | 0.00478*** | 0.00483*** | 0.0151***    | 0.0152***     |
|                    | (0.000210) | (0.000210) | (0.00106)    | (0.00106)     |
| snpr_avg_c5        | 0.143***  | 0.142***  | 0.210***     | 0.207***      |
|                    | (0.00847) | (0.00847) | (0.0558)     | (0.0558)      |
| pr_age_avg         | -0.00620*** | -0.00993*** | -0.0316***   | -0.0412***    |
|                    | (0.000623) | (0.00105) | (0.00498)    | (0.00921)     |
| pr_age_cv          | 0.699***  | 0.607***  | 1.432***     | 1.389***      |
|                    | (0.0136)  | (0.0196)  | (0.0758)     | (0.116)       |
| snpr_age_avg       | -0.00909*** | -0.0124*** | -0.0204***   | -0.0289***    |
|                    | (0.000600) | (0.000952) | (0.00472)    | (0.00834)     |
| snpr_age_cv        | 0.300***  | 0.174***  | 0.827***     | 0.745***      |
|                    | (0.0152)  | (0.0239)  | (0.0919)     | (0.167)       |
| pr_age_avg × snpr_age_avg | 0.000313*** | 0.000848 | 0.000778*** | 0.000768***  |
|                    | (0.0000704) | (0.000674) | (0.000289)   | (0.000199)    |
| pr_age_cv × snpr_age_cv | 0.310***  | 0.143     | 0.410***     | 0.261***      |
|                    | (0.0452)  | (0.236)   | (0.121)      | (0.121)       |
| Constant           | 0.642***  | 0.709***  | -4.805***    | -4.700***     |
|                    | (0.0815)  | (0.0820)  | (0.465)      | (0.470)       |
| lalpha             | 0.497***  | 0.497***  |             |               |
|                    | (0.00393) | (0.00393) |             |               |

Year fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
Field fe ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
N 153197 153197 153197 153197 153197 153197 153197 153197
pseudo $R^2$ 0.048 0.048 0.065 0.065 0.063 0.064 0.056 0.057
BIC 975700 975657 21473 21494 69424 69428 109224 109226

Standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001
### TABLE A13. Regression modeling of temporal search and impact. Only Electrical & Electronic patents are included.

|                  | C10          | Hit (1%)     | Hit (top 5%)  | Hit (top 10%) |
|------------------|--------------|--------------|---------------|---------------|
|                  | (1)          | (2)          | (3)           | (4)           |
| num_inv          | 0.0473***    | 0.0475***    | 0.103***      | 0.103***      |
|                  | (0.00249)    | (0.00249)    | (0.0130)      | (0.0130)      |
| num_ipc          | 0.0292*      | 0.0291*      | 0.0597        | 0.0603        |
|                  | (0.0130)     | (0.0130)     | (0.0773)      | (0.0774)      |
| num_pr           | 0.00390***   | 0.00386***   | 0.00227***    | 0.00222***    |
|                  | (0.000157)   | (0.000157)   | (0.000354)    | (0.000355)    |
| num_snpr         | 0.0114***    | 0.0113***    | 0.0247***     | 0.0247***     |
|                  | (0.000805)   | (0.000804)   | (0.00263)     | (0.00264)     |
| snpr_avg_c5      | 0.153***     | 0.152***     | 0.167**       | 0.163**       |
|                  | (0.00852)    | (0.00852)    | (0.0558)      | (0.0558)      |
| pr_age_avg       | -0.0215***   | -0.0290***   | -0.0330***    | -0.0549***    |
|                  | (0.000918)   | (0.00139)    | (0.00646)     | (0.00942)     |
| pr_age_cv        | 0.451***     | 0.422***     | 0.912***      | 0.853***      |
|                  | (0.0163)     | (0.0194)     | (0.0941)      | (0.120)       |
| snpr_age_avg     | -0.00697***  | -0.0139***   | -0.0131**     | -0.0331**     |
|                  | (0.000619)   | (0.00114)    | (0.00467)     | (0.00784)     |
| snpr_age_cv      | 0.481***     | 0.350***     | 0.995***      | 0.791***      |
|                  | (0.0209)     | (0.0436)     | (0.105)       | (0.231)       |
| pr_age_avg × snpr_age_avg | 0.000653*** | 0.00199***   | 0.00114***    | 0.00102***    |
|                  | (0.0000921)  | (0.000582)   | (0.000332)    | (0.000246)    |
| pr_age_cv × snpr_age_cv | 0.241***    | 0.348        | 0.217         | -0.123        |
|                  | (0.0681)     | (0.327)      | (0.174)       | (0.141)       |
| Constant         | 1.035***     | 1.105***     | -3.784***     | -3.596***     |
|                  | (0.0916)     | (0.0919)     | (0.438)       | (0.442)       |
| lnalpha          | 0.177***     | 0.176***     | -3.596***     | -2.547***     |
|                  | (0.00516)    | (0.00516)    | (0.442)       | (0.253)       |
| Year fe          | ✓            | ✓            | ✓             | ✓             |
| Field fe         | ✓            | ✓            | ✓             | ✓             |
| N                | 76290        | 76290        | 76290         | 76290         |
| Pseudo $R^2$     | 0.021        | 0.021        | 0.043         | 0.043         |
| BIC              | 548691       | 548648       | 15295         | 15307         |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
|                      | C10 (1) | Hit (1%) (2) | Hit (top 5%) (3) | Hit (top 10%) (4) | Hit (top 20%) (5) | Hit (top 30%) (6) | Hit (top 50%) (7) | Hit (top 70%) (8) |
|----------------------|---------|--------------|------------------|-------------------|------------------|------------------|------------------|------------------|
| num_inv              | 0.0300  | 0.0310       | 0.0700***        | 0.0702***         | 0.0534***        | 0.0536***        | 0.0683***        | 0.0686***        |
|                      | (0.00487) | (0.00487) | (0.0184)         | (0.0184)          | (0.0115)         | (0.0115)         | (0.00976)        | (0.00977)        |
| num_ipc              | 0.0290  | 0.0292       | -0.102           | -0.103            | 0.0162           | 0.0169           | 0.0263           | 0.0269           |
|                      | (0.0185) | (0.0185) | (0.0834)         | (0.0834)          | (0.0463)         | (0.0463)         | (0.0385)         | (0.0385)         |
| num_pr               | 0.00696*** | 0.00698*** | 0.00495***       | 0.00494***        | 0.00595***       | 0.00599***       | 0.00588***       | 0.00595***       |
|                      | (0.00209) | (0.00209) | (0.000409)       | (0.000409)        | (0.000374)       | (0.000376)       | (0.000375)       | (0.000376)       |
| num_snpr             | 0.0116*** | 0.0115*** | 0.0213***        | 0.0219***         | 0.0228***        | 0.0226***        | 0.0198***        | 0.0195***        |
|                      | (0.00179) | (0.00179) | (0.00536)        | (0.00538)         | (0.00388)        | (0.00389)        | (0.00368)        | (0.00368)        |
| snpr_avg.c5          | 0.127*** | 0.126***    | 0.191*           | 0.190*            | 0.148**          | 0.145**          | 0.119**          | 0.116**          |
|                      | (0.0180)  | (0.0180)    | (0.0848)         | (0.0849)          | (0.0468)         | (0.0469)         | (0.0383)         | (0.0384)         |
| pr_age_avg           | -0.0204*** | -0.0236*** | -0.0436***       | -0.0558***        | -0.0418***       | -0.0474***       | -0.0365***       | -0.0443***       |
|                      | (0.00131) | (0.00195)   | (0.000411)       | (0.000611)        | (0.000324)       | (0.000475)       |                   |                   |
| pr_age_cv            | 0.431*** | 0.450***    | 1.035***         | 0.902***          | 0.918***         | 0.993***         | 0.790***         | 0.883***         |
|                      | (0.0317)  | (0.0371)    | (0.138)          | (0.169)           | (0.0793)         | (0.0948)         | (0.0656)         | (0.0779)         |
| snpr_age_avg         | -0.00497*** | -0.00861*** | -0.0109          | -0.0250*          | -0.00663*        | -0.0125*         | -0.00569*        | -0.0139*         |
|                      | (0.00108) | (0.00194)   | (0.00104)        | (0.00411)         | (0.00305)        | (0.00582)        | (0.00244)        | (0.00449)         |
| snpr_age_cv          | 0.308*** | 0.378***    | 0.771***         | 0.210             | 0.618***         | 0.900***         | 0.620***         | 0.964***         |
|                      | (0.0422)  | (0.0924)    | (0.165)          | (0.411)           | (0.0983)         | (0.228)          | (0.0839)         | (0.189)          |
| pr_age_avg × snpr_age_avg | 0.000271*   | 0.00111     | 0.000478         | 0.000647*         |                   |                   |                   |                   |
|                      | (0.000122) | (0.000667)  | (0.000389)       | (0.000287)        |                   |                   |                   |                   |
| pr_age_cv × snpr_age_cv | -0.113    | 0.829       | -0.430           | -0.538*           |                   |                   |                   |                   |
|                      | (0.138)   | (0.541)     | (0.319)          | (0.270)           |                   |                   |                   |                   |
| Constant             | 1.220*** | 1.238***    | -3.419***        | -3.215***         | -1.700***        | -1.692***        | -1.350***        | -1.329***        |
|                      | (0.122)   | (0.123)     | (0.497)          | (0.505)           | (0.261)          | (0.266)          | (0.235)          | (0.239)          |
| lnalpha              | 0.190*** | 0.190***    |                 |                  |                   |                   |                   |                   |
|                      | (0.0103)  | (0.0103)    |                 |                  |                   |                   |                   |                   |

| Year fe               | ✓        | ✓          | ✓               | ✓                | ✓                | ✓               | ✓                | ✓                |
| Field fe              | ✓        | ✓          | ✓               | ✓                | ✓                | ✓               | ✓                | ✓                |
| N                     | 19447    | 19447      | 19447           | 19447            | 19447           | 19447           | 19447           | 19447           |
| pseudo $R^2$          | 0.033    | 0.033      | 0.077           | 0.078            | 0.069           | 0.069           | 0.058           | 0.059           |
| BIC                   | 137041   | 137055     | 6444            | 6459             | 15426           | 15442           | 20689           | 20700           |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$