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Standing on the shoulders of science

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Abstract

Today's innovations rely on scientific discoveries of the past, yet only some corporate R&D builds directly on scientific output. We analyze U.S. patents to establish three new facts about the relationship between science and the value of inventions. First, we show that patents which build directly on science are on average 26% more valuable than patents in the same technology that are disconnected from science. Patents closer to science are also more likely to be in the tails of the value distribution (i.e., greater risk and greater reward). Based on patent text analysis, we next show that patent novelty predicts their value. Finally, we find that science-intensive patents are more novel. Overall, using science appears to help firms capture more value through relatively novel inventions.

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1 Introduction

Science provides the foundation for modern R&D. The innovation activities in today's corporations would be impossible if not for the technologies and knowledge generated with the formal scientific process. While scientific advances are the bedrock of industrial R&D, only some of those activities build directly on science—translating discoveries from laboratories and scientific publications into novel inventions and commercial products. Other corporate innovation efforts rely only indirectly on science—experimenting, tinkering, optimizing and inventing without the aid (and/or constraints) of "the republic of science," but still using tools and technologies enabled through centuries of scientific advance. Firms' level of engagement in science is an important component of their R&D strategy and a potential source of talent and competitive advantage (Henderson and Cockburn, 1994; Cockburn *et al.*, 2000; Stern, 2004). Yet, surprisingly little is known about the extent to which firms build on scientific knowledge affects the value they *capture* from those innovations.

The canonical anecdotes of technology history are filled with famous private sector inventions that used modern science as a springboard for breakthroughs. Ferdinand Braun and Guglielmo Marconi could not have developed the wireless telegraph before Heinrich Hertz showed the existence of electromagnetic waves. The development of the transistor at the Bell Laboratories would have been difficult to imagine without the scientific understanding of the physics of semiconductors. Similarly, the biotechnology industry was born out of the pioneering scientific work of academic scientists-turned-entrepreneurs like Genentech founder Herbert Boyer.[1] However, technology and management scholars have argued that these cases, while powerful examples, are the exception rather than the rule.[2] Though firms and individual inventors benefit from the cumulative knowledge of scientific progress, this alternative view puts applied industrial engineering and user innovation at the center of

[1] Boyer published some of the the seminal papers on recombinant DNA as a professor at University California San Francisco prior to cofounding Genentech alongside venture capitalist Robert Swanson.

[2] These skeptics assert that inventions are born from other sources outside of formal scientific study (Kline and Rosenberg, 1986; von Hippel, 1988).

the innovation process. Moreover, those that doubt the value of science to corporations have plenty of reason to argue that novel science gets "trapped in the ivory tower," or that knowledge transfer from university to industry does not work efficiently due to frictions in knowledge flows, intellectual property, contracting, and the reliability of academic science (Goozner, 2005; Butler, 2008; Harris, 2011; Osherovich, 2011; Freedman *et al.*, 2015; Bikard, 2018).

Recent trends in the corporate landscape also cast doubt on the relative value of science on private sector innovation. Large firms have retreated from internal scientific research (Arora *et al.*, 2018, 2020), while venture capital investments have moved towards faster experimentation and less capital-intensive software-based business models (Ewens *et al.*, 2018). In the cultural and business zeitgeist, slow-moving research endeavors like PhDs, postdocs and peer review do not fit well into a technology era dominated by the famous Mark Zuckerberg motto "move fast and break things."[3] This shift might reflect a gradual realization that the rewards of translating frontier science into products are not worth their challenges—or at least in comparison to more narrowly focused applied engineering and software development activities. Alternatively, science-based innovation might indeed provide superior expected private value relative to other sources of innovation, in which case the corporate withdrawal from in-house science is merely a symptom of R&D risk aversion or broader trends in the organization of corporate innovation.[4] Quantifying the relative value of inventions across the spectrum of proximity to science is necessary to adjudicate between these differing narratives. Furthermore, the distributions of private value are critical information for R&D leaders choosing how to source innovation and formulate their R&D strategies.

[3]While the product cycles have sped up and R&D teams have adopted "lean" methodologies at technology firms, evidence shows that the organization of academic science has moved in a different direction. Scientific productivity increasingly requires more specialization, larger teams, and more resources in order to overcome the "burden of knowledge" and navigate complex problems (Jones, 2009; Wuchty *et al.*, 2007; Bloom *et al.*, 2020).

[4]For example, the move towards "open innovation" and accessing new innovations through the markets for technology (Chesbrough *et al.*, 2006; Arora *et al.*, 2004; Gans and Stern, 2003; Mowery, 2009; Bhaskarabhatla and Hegde, 2014) has allowed downstream firms in some industries to forgo scientific research under their own roof, while still accessing the technological offspring of those research activities via markets for technology.

In this study, we provide such a quantification by measuring how different degrees of building on science contributes to the private value of patents. Any attempt to measure this contribution is complicated by the fact that science plays a larger role in some technologies than in others (Stephan, 1996). This makes it difficult to distinguish how much of the value of an invention is due to science and how much of it is technology-specific. We solve this challenge with the help of a metric for a patent's level of science-intensity. By comparing the values of more and less science-intensive patents within different technology classes, we can isolate the science component and the technology component of the value of each invention.[5]

To classify patents with respect to their distance to science we build on Ahmadpoor and Jones (2017). When a company files for a patent it has to list all prior art on which the patents build, including scientific articles. This provides a direct link between the patent and the scientific knowledge it makes use of. A patent that directly cites a scientific paper is assigned a distance of one (D=1) to science. A patent that cites a (D=1)-patent but does not cite a scientific article itself has a distance of (D=2), and so on. We match this data with the patent values from Kogan *et al.* (2017), which we will also refer to as KPSS (as shorthand). KPSS derive patent values from excess stock returns of the filing company around the date of the patent publication. Combining these two data sets, we can calculate the average patent value for a given distance to science for 1.2 million U.S. patents filed between 1980 and 2009.

Our empirical analyses describe three key correlations. First, we find that patents directly based on science (D=1) have an average private value that is 26% larger than patents filed in the same technology class and year, but only loosely related to science (D=4). Patents with a distance of two (D=2) or three (D=3) from science have private values of 18% and

[5]Conceptually, we view our analysis as a conservative estimate of the private value of science. Beyond the direct value captured through patents, scientific knowledge may generate private value through a number of additional channels. For example, firms benefit from the productivity enhancing features of working with science-enabled communications technologies and computing systems breakthroughs. Both patented and non-patented inventions rely on knowledge generated by the scientific community, even when the practitioners involved do not formally cite scientific journal articles. For example, firms routinely hire PhD scientists and engineers whose knowledge and techniques are products of their frontier scientific training, even when their subsequent R&D output does not link directly to published research.

7% greater than the (D=4) group, after controlling for technology × year. This propagation of value generated by science to patents that are not directly science-based suggests that scientific progress can be the "remote dynamo of technology innovation" throughout the economy (Stokes, 2011, p.84) with effects beyond the immediately useful applications. Yet, we also show that more science-intensive patents are more risky; i.e., more likely to end up in the tails of the value distribution. In auxiliary results, we show that our main findings are stable when using alternative measures for distance to science based on text similarity and when using measures for patent value based on citations, patent scope, and patent litigation.

As our second finding, we identify a significant link between patent novelty and private sector value. To establish this link, we develop a new measure of patent novelty based on the novelty of words in the text of the patent. For this purpose, we calculate for each patent the probability that a given combination of keywords has been used before. We call a patent "novel" if it contains keyword combinations with low probability. We document that patent novelty predicts the value of patents in a very similar way as patents science-intensity.

Finally, we establish that the content of more science-intensive patents is more novel and that the novelty of the content decreases with distance to science. In addition to the correlation between novelty and distance to science, we find that these characteristics appear to both contribute independently to patent value. Patents both below and above median novelty have average valuations increasing in proximity to science, but novel patents enjoy slightly larger average values at each distance from science.

Our paper contributes to the literature in three main ways. First, it highlights that science-driven R&D is associated with great value in the private sector, not only directly, but also indirectly (i.e., D>1), and it quantifies the respective value contributions in percentage and dollar terms. In intent, this is close to the early surveys of Edwing Mansfield, which showed that in the 1980s and the 1990s around 20 percent of all newly introduced products benefited substantially from recent academic science (Mansfield, 1991, 1995, 1998). The recent literature is primarily focused on patents that are directly science-based and on value

measures such as forward citations and patent renewal payments, which reflect only indirectly and partially the private value of the patents for the owner. Sorenson and Fleming (2004) show that science-based patents have more follow-on citations. Poege *et al.* (2019) find that the quality of cited scientific articles is positively related to various monetary and non-monetary measures of patent value. Ahmadpoor and Jones (2017) document that forward citations decrease with distance to science and that patents close to science are more likely to be renewed. The benefits of academic science and industry seem to flow both ways, as academic-industry collaboration and citation boosts quality and productivity for both sides (Bikard *et al.*, 2019; Bikard and Marx, 2020).

By estimating the private value of science-based patents, our results shed light on firms' incentives to use science in the innovation process. The findings suggest that investments in the firm's ability to build off of science is a source of competitive advantage (Cohen and Levinthal, 1990; Henderson and Cockburn, 1994), and that established firms still capture great value from science-based innovations. Furthermore, our findings support the view that the decline in corporate in-house R&D is more likely due to shifts in organizational boundaries than in the private gains of science-based innovation (Arora *et al.*, 2018).

Second, our results demonstrate a key risk-vs-reward tradeoff in science-based innovation. Our findings show that not only is proximity to science associated with greater *average* private patent values, but it is also associated with more risk—i.e., more likely to end up in extreme outcomes on both ends of the value distribution. That tail-risk suggests that science-based R&D is akin to the exploration arm of classic "explore vs. exploit" models (March, 1991; Manso, 2011; Azoulay *et al.*, 2011; Akcigit and Kerr, 2018). Even if the expected value of a science-based patent exceeds that of innovations more distant from science, risk-aversion or path dependence in the internal R&D decision-making process (Cyert *et al.*, 1963; Argote and Greve, 2007; Hall and Lerner, 2010; Eggers, 2012; Krieger *et al.*, 2021) might lead firms to shy away from science-driven R&D, even when the risk-neutral firm would benefit from greater reliance on science.

Third, our paper takes an important step towards understanding the role of science in patent value by showing that science and the novelty of the innovations protected by the patent go hand in hand. Basic science is frequently credited with stimulating technological innovations. In the context of World War I, Iaria *et al.* (2018) have recently shown that scientists produce more patent-relevant scientific articles if they have access to frontier knowledge. Fleming and Sorenson (2004) argues that science alters inventors' search processes and leads them to useful new knowledge combinations. By linking patent novelty to patent value and science to patent novelty we provide a rationale for why science matters for private sector innovation.[6]

2 Data

Our starting point is a dataset which contains information on the monetary value of 1.8 million patents from 1926 to 2009 (Kogan *et al.*, 2017). The private value of the patent is estimated by studying movements in stock prices following the days that patents were issued to the firm. Specifically, the value is approximated using the abnormal stock market return of the filing company within a narrow window around the grant date of the patent.

We calculate for each of these patents its distance to prior scientific advances using the method of Ahmadpoor and Jones (Ahmadpoor and Jones, 2017). We use information on 2.5 million patents issued by the U.S. Patent and Trademark Office (USPTO) from 1980 to 2010 and information on journal articles indexed by Microsoft Academic (Sinha *et al.*, 2015). We then locate patents that directly cite journal articles; i.e., patents where practical inventions and scientific advances are directly linked (Marx and Fuegi, 2020). A patent that directly

[6]Thus, our study complements the indirect evidence in Fleming and Sorenson (2004), which shows that science increases forward citations in fields in which it is hard to innovate. Recently, Kelly *et al.* (2018) have shown that the value of patents as measured by Kogan *et al.* (2017) is negatively correlated with their text similarity to earlier patents. We add to these findings by demonstrating that patent novelty systematically correlates with the scientific content of a patent, measured both by citation distance and by text similarity between articles and patents. In a new working paper Arora *et al.* (2021) use similar data to evaluate how participation in science and first-mover advantage (in building on science) affects the private value of patents. Different from our analysis, the authors focus on within-firm variation.

cites a scientific paper is assigned a distance of one (D=1) to science. A patent that cites a (D=1)-patent but does not cite a scientific article itself has a distance of two (D=2), and so on (see Figure A.1 in Appendix A.1). The distance for each patent to science is thus defined by the minimum citation distance to the boundary where there is a direct citation link between patent and scientific article.

Combining the information on patent values and citation links, we construct a dataset that contains patent values for 1.1 million U.S. patents filed between 1980 and 2009. 21% of all patents directly cite a scientific article (D=1), 55% are indirectly based on science (D=2 and D=3) and 24% are not based on science (D=4 or larger). The (unadjusted) average value of a patent is $12.9 million in constant 1982 U.S. dollars.

Our primary measure of novelty is built from data on words in patents Arts *et al.* (2018). We calculate how often a given pairwise word combination occurs relative to other patent word combinations, up to a given year. In additional analyses we also use text-based measures of patent similarity to scientific articles cited in the patent, word age, and structural novelty of patented chemicals.

Appendix A.1 gives a detailed description of all the data construction and sources.

3 Context: Science in Patents

If all modern technology is, at least indirectly, indebted to scientific breakthroughs of the past, then how might building directly on scientific research change the types of inventions found in patents? For the purpose of invention, science may serve as a map for technological search—yielding more novel combinations (and recombinations) of knowledge (Fleming and Sorenson, 2004). Under this view, science enables more efficient invention by documenting both promising paths (strong "shoulders" to stand on) and dead-ends to avoid.[7] However, the

[7]At the extreme, scientific articles not only provide a "map" or "foundation" for new inventions, but they also directly produce the invention itself. Patented inventions and scientific projects are sometimes co-produced and co-disclosed as patent-paper pairs (Murray, 2002). These pairs describe the same (or highly similar) discoveries and may be best identified using their overlapping language (Magerman *et al.*, 2015).

"republic of science" often prizes speed, novelty and individual credit over search efficiency (Partha and David, 1994; Stephan, 2012). So even though science offers tools that push the technology frontier to new heights, science also generates (more than) its fair share of irreproducible findings and "shaky shoulders" for both scientists and inventors to build on (Osherovich, 2011; Begley and Ellis, 2012; Begley and Ioannidis, 2015; Freedman *et al.*, 2015; Azoulay *et al.*, 2015). Thus, science's incentive system pushes the methods, ideas, and language of science towards the exploration end of the explore-exploit spectrum (March, 1991; Azoulay *et al.*, 2011; Akcigit and Kerr, 2018). With more novelty comes both more risk and more (potential) reward.

Specific examples are useful for understanding the range of inventions represented in the data. Even among well-cited patents, we see large qualitative differences between patents by their distance from science. Take Coca Cola's 1997 patent titled "Apparatus for icing a package" (5671604). The solo-inventor patent describes a vending machine refrigeration system, featuring a spray nozzle that cools the stored items with a water mist. It has no citations to science, and a distance from science of five (D=5). The patent contains seven figures, all of which are detailed technical drawings of the cooling system and its 80 different enumerated components (e.g., control valves, linear actuator, vortex cooling devices).

In the same technology class as the Coca Cola vending machine patent (G07F, "Coin-freed or like apparatus"), one can also find McKesson Automation's patent number 7010389, "Restocking system using a carousel," intended to aid in the dispensing of medical supplies. The patent's figures bear plenty of similarity to the Coca Cola patent. Both include detailed drawings of a motorized storage system that brings items to a stationary user. Unlike the soda vending machine, the McKesson patent includes a computer, printer, and hand-held wireless device system. Further, the patent cites 15 different scientific articles including articles from journals such as the *International Journal of Bio-Medical Computing* and the

In the words of a patent attorney, such patent applications usually start by "slapping a patent coversheet" on the text of a draft scientific article. On average, patent-paper pairs are associated with more forward citations to the scientific article (Murray and Stern, 2007).

American Journal of Hospital Pharmacy. These articles present evidence on how the implementation of similar database systems improved operations at hospitals, as well as on the health benefits of deploying monitoring systems to prevent toxic multi-drug interactions.

The actual variation in how patents describe their inventions and build off prior art is impossible to properly capture in a small set of illustrative examples. Obvious differences arise across varied patenting areas like medical devices, telecommunications, transportation, computing, machine tools and food processing. Patent metrics can hardly capture all the nuances in these differences, and the full corpus of patents is so large that a counter example is always just a quick Google search away. Thus, in our regression analyses that follow, we emphasize that our methods are useful for describing *average* correlations between groups. Certainly, any given patent may be a glaring exception and the subgroups we investigate themselves have great (within-group) diversity. To minimize apples-to-oranges comparisons, many of our regression specifications use technology class $\times$ year fixed effects to limit comparisons within more comparable subgroups.

Appendix A.2 provides additional examples using patents from CPC class A61L ("Methods or apparatus for sterilising materials"). Across examples, the distinguishing features of science-based patents have more to do with their *process* or R&D than their complexity or sophistication. Patents more proximate to formal science use the tools and language of science to search for a technology solution, identify its novelty, and communicate its value.

Appendix A.2 also describes the patent sample, with summary statistics broken down by distance to science (Tables A.1, A.2 and A.3). Patents closer to science are different across a number of interesting dimensions. Most notably, patents closer to science tend to have more inventors, shorter claims and take longer for the USPTO to process. Their prior art also looks different, as science-based patents tend to build off a larger and broader scope set of backwards citations.

4 Results

In the following, we first map the relation between private sector value and distance to science. We show that patents closer to science have a higher value than patents further away from science. In a second step we show that patents that are more novel are also more valuable. Lastly, we show that patents closer to science are also more novel, highlighting a potential reason why science-based patents are more valuable.

4.1 The private value of patents by their distance to science

Our ***first fact*** documents the relationship between patent values and distance to science. We show that more science-intensive patents are on average more valuable but also riskier; i.e., they are more likely to be in the tails of the value distribution.

[Insert Figure 1 Here]

We start by presenting how relative dollar values of patents differ by distance from science. To estimate relative (%) differences in KPSS values across distance to science groups, we run ordinary least squares (OLS) regressions with (D=4) as the baseline (omitted) distance to science group.[8] We then convert the regression coefficients to percentage differences relative to (D=4) average values. As shown in Panel (a) of Figure 1, a science-based patent that directly cites an academic article (D=1) has an average value that is 82% greater than a patent four degrees removed from science (D=4). This value decreases as the distance to science increases. Patents with a distance of two or three have average values 44% and 14% higher than those in (D=4), respectively. When patents have a distance from science larger than four (D=5, D>5 or "unconnected"), their average values are between 6% and 16% less valuable than those with distance of four. Column (1) of Table 1 presents the same results in regression form.

[8] Distance to science of four as the baseline is an arbitrary choice, but one informed by the data, since the relative value premium begins to flatten after (D=4). Intuitively, the connection to scientific publications is quite tenuous at (D=4), and using this baseline group also ensures that our estimates are somewhat conservative vs. using higher degrees as the baseline.

[Insert Table 1 Here]

Our preferred specifications report patent value differences in relative (%) terms, but to get a sense of the order of magnitude, we present the same results in levels ($USD) in Appendix B.1 (Table A.5).[9] We interpret the dollar magnitudes with caution, adjusting the KPSS values downwards using the most conservative estimate of ex-ante probability of patent grant. Doing so deflates the values by 12%.[10] Thus, we find that a science-based patents that directly cites an academic article (D=1) have an average value of $15.82 million dollars, which is $8.27 million more than the average value of patents with (D=4) and $8.69 million more than those unconnected to science.[11] The average patent values decline to $12.49, $9.90, and $8.69 million for distances of two, three and four, respectively.

The higher average value of science-based patents reflects an upward shift in the value distribution of patents with higher science intensity. Panel (b) of Figure 1 plots the share of science-intensive patents (D=1, D=2 and D=3) and the share of less-science intensive patents (D=4, D=5, D>5 and unconnected) over the percentiles of the value distribution of all patents. If the value distribution of more science-intensive patents were the same as the value distribution of less science-intensive patents, the share of patents at each percentile should be 1%. Figure 1, Panel (b) shows that there are fewer science-intensive patents at the lower end of the value distribution while there are more at the upper end. The pattern for less-science-intensive patents is (mechanically) reversed. They are overrepresented at

[9] To arrive at dollar values for individual patents, (Kogan *et al.*, 2017) makes a number of assumptions about the distribution of firm returns and the (ex-ante) probability of patent grants. While the (Kogan *et al.*, 2017) results appear fairly robust to alternative distributional assumptions (see Footnote 11 in (Kogan *et al.*, 2017)), we focus on percentage differences as our primary results since our interest is in the relative value differences patents of different characteristics. Doing so allows us to apply the consistent quantitative valuation method of (Kogan *et al.*, 2017), without relying too heavily on any assumptions that move the magnitude in any direction.

[10] Carley *et al.* (2015) find acceptance rates vary between 50% and 60% in the 1991–2001 period. We use the low end of that range (50%) instead of the average (56%), which is used in Kogan *et al.* (2017). This adjustment deflates all the patent dollar values by 12%. Conceptually, this adjustment provides a more conservative set of estimates by increasing the amount of market information "surprise" associated with the patent grant. That increased surprise could be a result of more conservative expectations about likelihood of patent issuance, or imperfect information regarding the existence of pending patent applications. Table A.4 in Appendix B.2 shows how different assumptions on patent grant probabilities affect patent valuations.

[11] 7.13/8.69 = 0.82%, the percent difference in value of a science-based patent relative to (D=4) patent mentioned above.

the lower end of the value distribution, while they are significantly underrepresented at the upper end.

We next examine whether this regularity between distance to science and patent value simply reflects differences across technologies, perhaps because science is used predominantly in technologies that are on average more valuable. Stephan (1996) captures the ties between science and particular industries, writing that "to a considerable extent the scientific enterprise evolves in disciplines that from their beginnings have been closely tied to fields of technology." This is why we ask how much of the patent value is technology specific and how much can be attributed to the value of science.

To separate science-related from non-science-related patent value, we need to make assumptions about the data generating process. We assume that the value of a patent is generated by a technological component, a science component, and an idiosyncratic component, and that these components are additively separable. The technological component is assumed to be the same for all patents with the same technology class and the same filing year, independent of their distance to science. The science component is present in patents closely based on science while it is absent in patents unrelated to science. The idiosyncratic component captures the patent value residual after accounting for the science and technological components. We assume that the idiosyncratic component has an expected value of zero.

Under these assumptions, we can isolate the technological component through the value of patents that are distant from science. The value of non-science-related patents is the sum of the technological component and the idiosyncratic component, where by definition the science component is zero. As the technological component is assumed to be the same for all patents in the same technology class and year, we can filter out the idiosyncratic component by taking averages.

Figure 1, Panel (c) and Table 1, Column (2) present the average patent value % premium—within technology (CPC 4-digit) class and filing year—relative to (D=4), by distance to

science. Patents that are directly based on science (D=1) have an average science-value 26% greater than that the average (D=4)-patent of the same technology class-year. Patents indirectly based on science with distances of (D=2) and (D=3) have an implied values of 18% and 7% greater than (D=4) patents, respectively. These values are lower than the raw values presented in Panel (a) of Figure 1—indicating that science-intensive patents are more prevalent in high-value technology classes than in low-value classes. However, the statistically significant within technology-year estimates means that proximity to science has a meaningful relationship with patents' private values.

In Figure 1, Panel (d), we show the distribution of the sum of the science value component and the idiosyncratic component; i.e., the residual in value that is not due to the technology and year, across the percentiles of the value distribution.[12] Less science-intensive patents tend to have values close to the median of the value distribution. Science-intensive patents instead are more likely to have a value that is in the tails of the science value distribution. Relative to a (D≥4)-patent in the same technology and year, more science-intensive patents are more likely to be in the upper and the lower tail of the value distribution.[13] This suggests that the value premium of science over and above the value of the technology comes at the price of an increasing risk of tail outcomes. One potential explanation for this could be the high rate of irreproducible research results which has been said to be as as high as 50 percent (Osherovich, 2011; Freedman *et al.*, 2015). Thus, the science value premium may to some extent be the compensation for the risk that investors associate with science-intensive patents.

[12]We cannot separately identify the science-value from the idiosyncratic value component for a particular patent.

[13]Table A.6 in Appendix B.5 shows that relationship between distance to science and probability of a patent being in the top or bottom 5% of the value distribution. After controlling for technology and filing year, we see that patents closer to science are more likely to be in both extreme ends of the value distribution.

Alternative Measures of Patent Value: Citations, patent scope and litigation

Patent private value is the outcome of interest for profit-maximizing firms; however, other proxies for both value are informative as robustness checks and links to other types of social value (e.g., knowledge flows, spillovers). Columns 3-6 in Table 1 explores three other proxies for patent value: forward citations, patent scope and propensity to be involved in litigation.

The results are broadly consistent with the KPSS value regressions. Column 3 shows the patent forward citation results. Controlling for tech class $\times$ year fixed effects, we find that patents with (D=1) average 99% more forward citations than patents with (D=4). The relative difference is even stronger than the stock market valuation premium—indicating that social returns through knowledge flows may be above and beyond what the inventor firms capture.[14] The citation premium is is 36% and 9% for (D=2) and (D=3), while patents with (D$\geq$5) have significantly fewer citations than the (D=4) group.

Next, we evaluate the relationship between distance from science and patent "scope." Intuitively, patents with greater scope are more valuable by claiming a broader swath of intellectual property space for their assignees, who can then more easily exclude competitors from their technology's domain.[15] We merge our set of patents to the patent scope index from Kuhn and Thompson (2017), and run an ordinary least squares specification, including tech class $\times$ year fixed effects. Column 4 shows that patent scope is increasing in proximity to science. The difference in scope between a (D=1) and (D=4) patent within the same tech-year is equivalent 100% increase over the sample mean.[16]

Columns 5 and 6 repeat the exercise with the binary litigation outcome, both with and without tech class $\times$ year fixed effects . While we can only measure litigation as a binary event, it is a useful signal of patent value. Patent litigation is expensive, so firms will (for

[14]That said, we recognize that patent-to-patent citations are an imperfect measure of knowledge flows (Roach and Cohen, 2013; Marx and Fuegi, 2020; Kuhn *et al.*, 2020), and unlike KPSS they are an ex-post measure of quality, so we cannot easily quantify the gap between private and social value capture.

[15]Kuhn and Thompson (2017) shows that a patent's scope may be reliably measured using the number of words in its first claim.

[16]The sample mean is 0.12 ("Mean Dep." in Column 4 of Table1) and the regression coefficient of (D=1) is 0.12.

the most part) only fight in court for patents that are believed to be valuable.[17] [18] With and without class by year fixed effects, we find that the likelihood of litigation is increasing in proximity to science. Column 5 indicates that patents with (D=1) have a more than double increased likelihood of litigation relative to D=4 patents (10.4 vs. 4.4 per 1,000 patents). Column 6 shows that even within tech class and vintage, patents that build more directly on science are more likely to end up in court. Taken together with the KPSS, citation and scope results, this finding shows patents that build more directly on science are not only valued higher, but firms judge them more worthy of expensive courtroom battles in the years post-grant.

Additional Results and Robustness

Appendix B and C present a number of additional results and robustness checks. Appendix B.3 shows results by broad (1-digit) CPC classes. Appendix B.4 shows how the distance to science measure effectively captures which patents are drawing more directly on the language and ideas of their associated scientific journal articles. Appendix B.5 describes the regressions examining the tails of the value distribution. We show that the main distance to science results hold up across different percentiles of the value distribution in Appendix B.6. Appendix B.7 shows how KPSS values vary by both distance to science and novelty. Appendix C show robustness to alternative method choices—including different distance to science measures (Appendix C.1), using different normalizations and assignee fixed effects (Appendix C.2), and the intensity of citations within the (D=1) group (Appendix C.3).

[17] The American Intellectual Property Lawyer's Association (AIPLA) estimated litigation costs of $250,000 – $950,000 for cases with less than $1 million at risk, and between $2.4 million and $4 million for cases with more at stake (`https://apnews.com/press-release/news-direct-corporation/a5dd5a7d415e7bae6878c87656e90112`)

[18] The dependent variable comes from merging our data to the USPTO's Patent Number and Case Code File dataset, a comprehensive link between patent litigation cases in U.S. district courts and patents between 2003 and 2016. 94% of the court cases are coded as patent infringement suits, with the remaining cases involving disputes around ownership/inventorship, patent validity, royalties, false markings, and other procedural issues involving patents.

4.2 Patent novelty and patent value

Next, we study whether the value of a patent is related to the novelty of its content. If the goal of science is to advance knowledge by making new discoveries, then inventions relying directly on science have the potential to introduce more novel ideas. For these analyses, we construct a new measure of patent novelty. Using this measure, we establish the ***second fact*** of the paper: that patent novelty predicts patent values.

Measuring patent novelty

In the history of technology and innovation, inventions are often conceptualized as the outcome of successfully combining ideas, either by combining new ideas or by combining existing ones in a novel way. In *A History of Mechanical Inventions,* Abbott Payson Usher writes: "Invention finds its distinctive feature in the constructive assimilation of preexisting elements into new syntheses, new patterns, or new configurations of behavior" (Weitzman, 1998). Following this concept of invention as a novel combination of ideas or resources, we develop a new measure for patent novelty that is based on the content of the patent. More specifically, we measure how novel the combinations of words are that are used in a patent. For example, the word "mouse" combined with the word "trap" was used in patents since at least 1870. In contrast, the word "mouse" was combined with the word "display" for the first time in 1981 in the pioneering patents of Xerox.

Our measure of patent novelty is constructed as follows. In a first step, we count how often a particular pairwise combination of different words was used in the abstracts of previous patents up to the filing year. The sets of words for every patent are taken from the dataset of Arts et al. (Arts *et al.*, 2018). We then divide this count with the total number of pairwise word combinations up to the filing year of the patent. We denote this ratio as the probability of a word combination. In a second step, we take the average over the respective probabilities of all pairwise word combinations within a patent to determine the average probability per patent. The smaller the average probability of pairwise word combinations, the more novel

are the pairwise word combinations used in the particular patent. We call patents with a smaller average probability more novel. Appendix C.4 provides similar analyses using alternative definitions of patent novelty such as new words and word age (Figure A.8), as well as chemical novelty (Table A.7). The correlations between these alternative measures and KPSS patent value and distance to science are quite similar to our main measure of novelty.

Novelty and patent value

Figure 2 shows that the novelty of a patent – measured by the average probability of word combinations – predicts the patent value and the likelihood that the value of a patent is in the tails of the distribution. Panel (a) shows that there is a positive relationship between novelty and patent value. The pattern suggests increasing returns to novelty, as the marginal gains from novelty increase as word combinations become more rare. Panel (b) indicates that a higher patent novelty is associated with an upward shift in the patent value distribution. We split all patents into those that have a below average probability of word combinations (i.e., higher novelty) and those that have an above average probability. Panel (b) shows that more novel patents (i.e., patents with a low probability of word combinations) are less likely to be at the lower end of the value distribution and more likely to be at the upper end. The picture is reversed for patents that are less novel.

[Insert Figure 2 Here]

In Panel (c), we plot the relationship between patent novelty and patent value relative to (D=4)-patent values of the same technology and the same year. We also residualize the novelty measure (x-axis), such that x-axis values below (above) zero represent combinations of words that are less (more) common than the average word combinations within technology-year. Again, there is a clear positive relationship between novelty and science value.[19] In

[19]The regression version of this analysis is reported in Columns 1 and 2 of Table 2 (without and with technology × year fixed effects). This specification differs from the one presented in Figure 2, because here

Panel (d), we show the distribution of patent values for patents with below and above average probability of word combinations relative to the probability of a (D=4)-patent in the same technology and year. Highly novel patents are again more likely to be in both tails of the value distribution while patents with a lower novelty are in the middle of the value distribution, relative to its technology and year. Thus, as in the case of distance to science, novelty is associated with a value premium over and above the technology-related value component, but also with higher risk. Kline and Rosenberg (1986) captured the spirit of this relationship in writing, "newness is not, by itself, an economic advantage."

[Insert Table 2 Here]

4.3 Patent novelty and distance to science

As argued above, there are two complementary ways in which science can increase patent novelty. First, science might provide new insights that can be combined with older ideas. This view is akin to how Vannevar Bush described the relation between science and invention in his influential 1945 report *Science: The endless frontier*:

> *Basic science (...) creates the fund from which the practical applications of knowledge must be drawn. New products and new processes do not appear full-grown. They are founded on new principles and new conceptions, which in turn are painstakingly developed by research in the purest realms of science. Today, it is truer than ever that basic research is the pacemaker of technological progress.* (Bush, 1945).

This description is thought to reflect the realities in the large science-intensive corporate laboratories of the post-war period (Smith and Hounshell, 1985; Godin, 2006).

we take the averages over all patents in a technology and year combination and not only over patents with a distance of D=4. The negatively and statistically significant correlations in both specifications indicate that that patent value is decreasing in the likelihood of word combinations.

Second, science can guide the inventor to more fruitful combinations of known elements (Rosenberg *et al.*, 1990; Fleming and Sorenson, 2004). According to mathematician Henri Poincare, "the true work of the inventor consists in choosing among (...) combinations so as to eliminate the useless ones or rather to avoid the trouble of making them" (Weitzman, 1998).

Science can help tell which combinations not to pursue by providing an understanding of why a combination might or might not work. For example, enormous amounts of energy and ingenuity were wasted by alchemists on attempts to transform lead into gold before science demonstrated that nothing short of an atomic reaction could achieve this end. Scientific knowledge also guided the development of the Haber-Bosch method to synthesize ammonia. During the first trial runs, Carl Bosch struggled with the problem that the hydrogen proved to be corrosive for the high-pressure reactor chamber made of steel. Using basic chemistry, he deduced that the problem was due to the carbon contained in the steel walls of the chamber. His solution was to build a double wall reactor chamber with iron on the inside, which contains no carbon, and steel on the outside (Jeffreys, 2008).

In our final set of analyses, we explore the relationship between novel combinations of ideas and proximity to science. The strikingly similar patterns displayed in Figures 1 and 2 suggests that the novelty of patents and their distance to science are related. Consistent with this intuition, we establish as a ***third fact***: patents that are more science-intensive exhibit a higher patent novelty on average.

In Panels (a) and (b) of Figure 3, we show the novelty distributions for relatively more science-intensive patents (D=1, D=2, D=3) and for relatively less science-intensive patents (D=4, D=5, D>5, unconnected). As defined above, the lower the likelihood of a pairwise word combination in a patent is, the more novel is the patent. Panel shows the novelty distribution for the raw data. In Panel (b) of Figure 3, we adjust for differences in technology and year. The novelty distribution for more science-intensive patents has its peak to the left and at a higher density than the novelty distribution for less science-intensive patents, both

in the raw data and when controlling for technologies. This confirms that patents closer to science contain more novel word combinations; i.e., they are more novel (on average). Columns 3 and 4 of Table 2 exhibit this relationship in regression form. In the averages (Column 3) and within technology-year (Column 4), we see that novelty is decreasing with distance to science—i.e., word combinations become, on average, as patents move further away from connections to science.

[Insert Figure 3 Here]

However, we also observe that the relationship is non-linear and asymmetric. While patents more proximate to science are less likely to be in the "less novel" half of the distribution (right tail), they are also less likely to be in the far left tail of the novelty distribution. This asymmetry suggests that connection to science is associated with middle and above average novelty, while the extreme novel patents are more likely to be distant from science. Perhaps, those unconnected to science are less constrained in language (or imagination) than inventions tethered by the norms and formalities of science. In Appendix C.4, we show that these findings are robust to using the emergence of new words, the average age of words, of patent chemical novelty as alternative novelty indicators.

Finally, we combine our measures of distance to science and novelty to assess whether they separately contribute to patent value. The results are presented in Appendix B.7. We interact distance to science with indicators for below and above median novelty, using the same patent novelty measure as Figure 2 (Panels (c) and (d)). Specifically, patents are below (above) median novelty if they have new word combinations that are below (above) median for their CPC (4 digit) class and year. We then generate graphs equivalent to Figure 1 (Panels (a) and (c)) for the below median and above median novelty groups. The results show very similar patterns for both groups. Both with and without adjusting for tech class $\times$ year, we see that relative patent value is increasing in proximity to science. The same is true regardless of whether we look at % differences or average patent dollar values (Panels (c) and (d) of Appendix Figure A.4).

While the relationship between distance to science and relative patent value is quite similar for both novelty groups, Appendix Figure A.4 shows that patent values are consistently higher (shifted upward) for the high novelty sub-groups. Thus, novelty and science appear to both contribute to private value. Since the two characteristics are at least partially co-determined,[20] we cannot quantify their relative influence on patent values. However, since both novelty subgroups have patent values increasing in their proximity to science, novelty is clearly not the sole mechanism behind our main results. Rather, we interpret these patterns as evidence that using science as a tool to explore and express new ideas is a path associated with both greater novelty and value capture.

5 Conclusion

Our study shows that building more directly on science is associated with more novel inventions and capturing greater private value from those inventions. Thus, while scientists since Isaac Newton have been known to see further "by standing on the shoulders of giants," our study suggests that many inventors in the private sector see further by standing on the shoulders of science.

By their nature, our estimates provide an incomplete picture for the private value derived from science. Beyond patented inventions, R&D organizations benefit from applying the tools and training born in the scientific community. These indirect benefits are possible because firms hire scientists and engage with the research frontier (Cohen and Levinthal, 1990; Henderson and Cockburn, 1994; Stern, 2004).

Along with the increased expected rewards from science, our results show that building on science is a relatively risky approach to corporate innovation. We find that patents closer to science and relatively novel patents are both more likely to end up in the tails of the

[20] In addition to the patterns found in Figure 3, Figure A.4 in Appendix B.7 demonstrates the strong correlation between novelty and proximity to science, as the two panels that adjust for technology $\times$ year fixed effects (Panels (b) and (d)) exhibit much bigger differences between the low vs. high novelty subgroups than what we see in the unadjusted raw differences (Panels (a) and (b)).

patent value distribution. This risk-reward trade off helps explain why (risk-averse) firms often favor more certain technological exploitation and acquisitions over novel exploration.

Together, our results suggest science helps firms push the technological frontier by building on more disparate ideas to introduce and combine more novel technologies—many of which fall flat commercially, while others propel their firm's growth. While its value is seemingly available for science-driven firms to capture, science's potential in corporate innovation remains an important area for study. How best to access, engage with and build upon the ever-expanding base of scientific knowledge and methods is an exciting challenge for both R&D managers and scholars.

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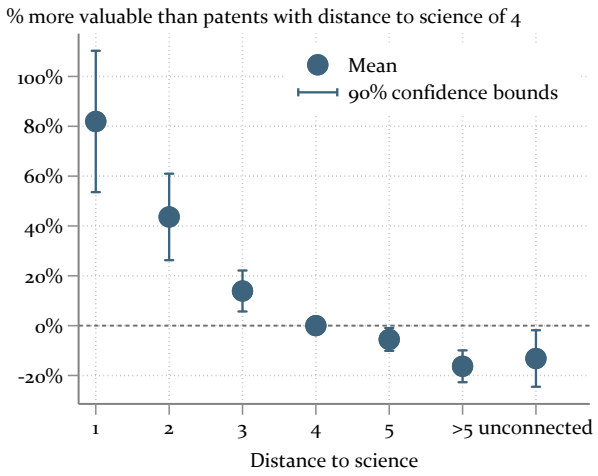
Tables & Figures



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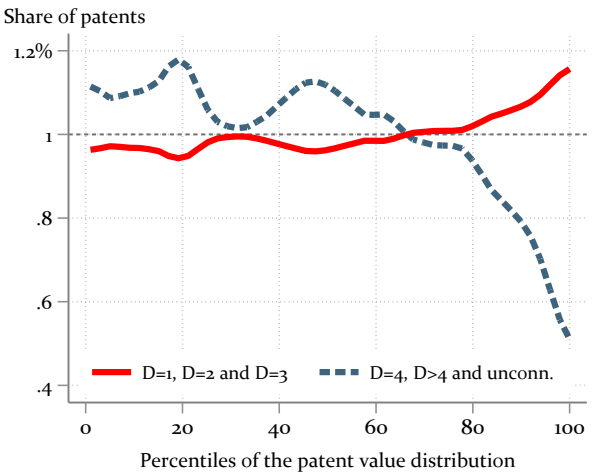

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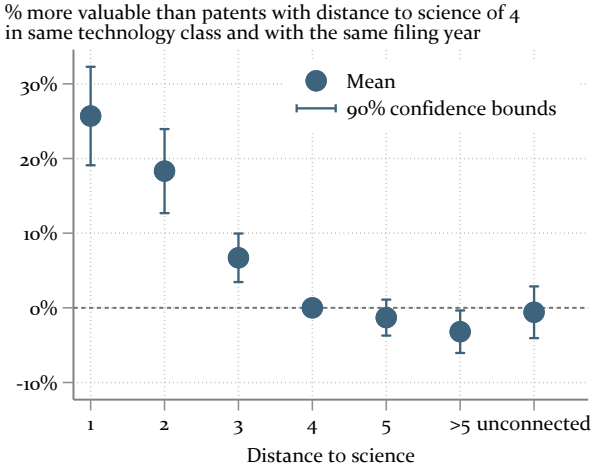

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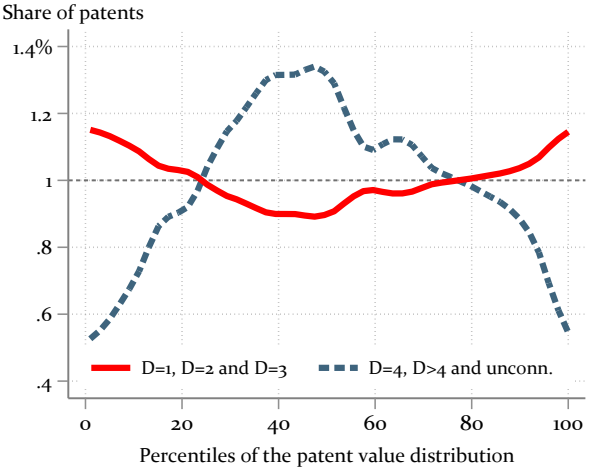
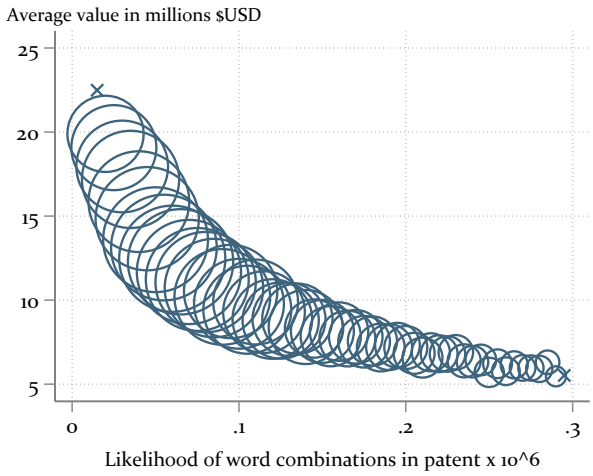


(d) Distribution accounting for technology and year

Figure 1: Distance to science, patent value and risk.

Panel (a) shows the average patent value for all distances to science relative to patents with a distance of four (D=4). The values of U.S. patents are from Kogan *et al.* (2017). The distance to science of U.S. patents is calculated using data from Marx and Fuegi (2020) and the method of Ahmadpoor and Jones (2017). The distance to science is defined by citation links. The values correspond to the coefficients in Table 1, Column 1. Panel (b) shows the distribution of patent values across the percentiles of the value distribution of all patents for more science-intensive patents (D=1, D=2 or D=3; solid red line) and less science-intensive patents (D>3 or unconnected; dashed blue line). The horizontal line at 1% shows the distribution of all patents across the percentiles of the value distribution. In Panel (c), we residualize the patent value by the average value of a patent with the same (four-digit) CPC technology class and filing year and a distance of four, then display relative (%) values indexed to D=4. The values correspond to the coefficients in Table 1, Column 2. In Panel (d), we show the distribution of the patent values normalized by technology and year.



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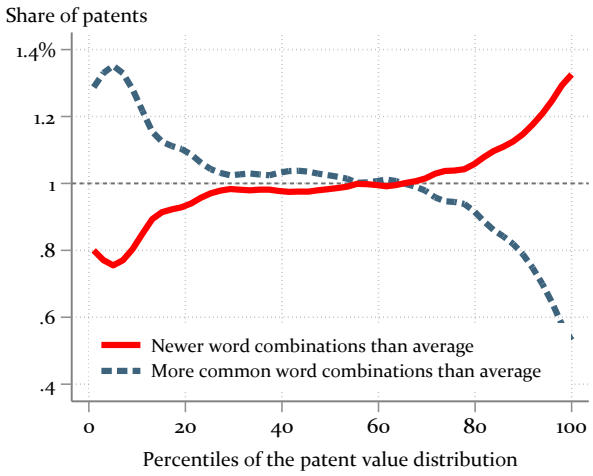

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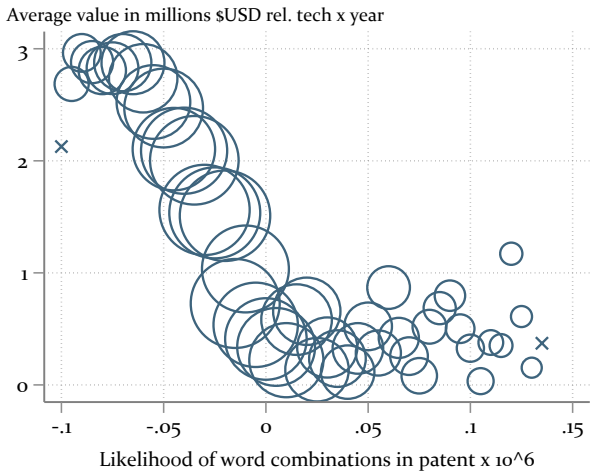
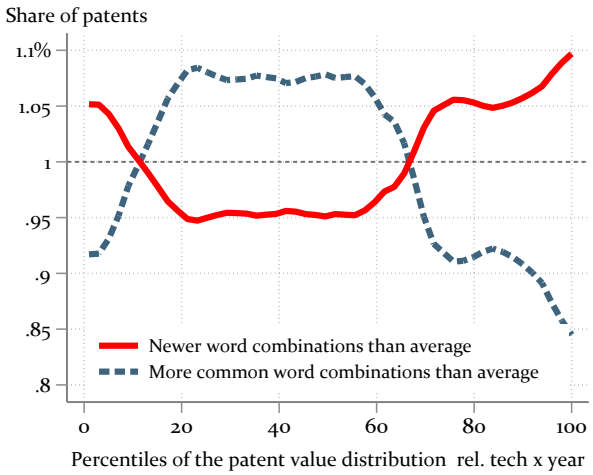


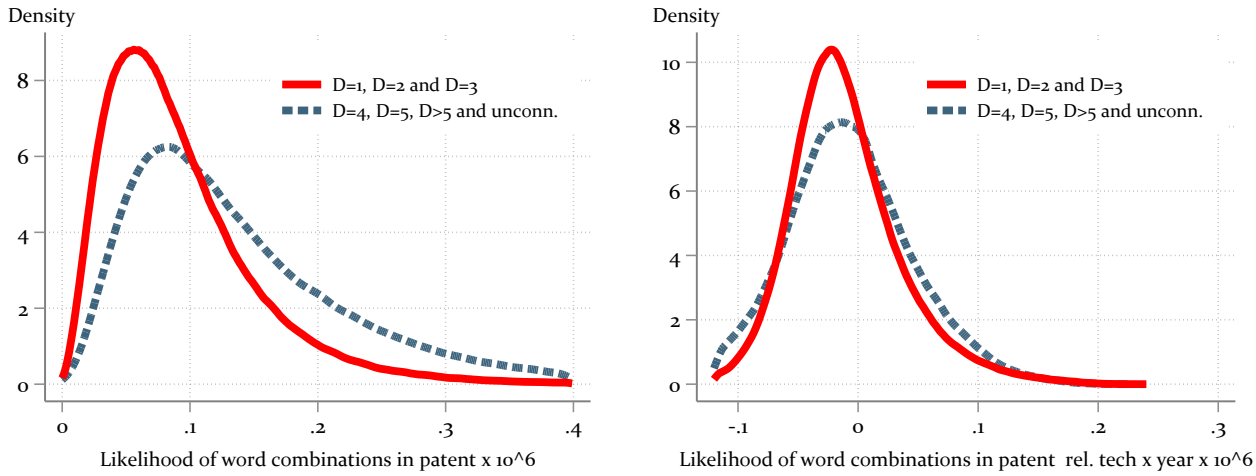
(c) Accounting for technology and year



(d) Distribution accounting for technology and year

Figure 2: Patent novelty, patent value and risk.

Panel (a) shows the average patent value for every likelihood of pairwise combinations of words that occur in a particular patent as an indicator for patent novelty. Smaller probabilities are interpreted as higher novelty. The winsorized values are marked with "X." The size of the bubbles represents the number of patents underlying each point. Panel (b) shows the distribution of patent values across the percentiles of the value distribution of all patents for patents with below average pairwise word combination probability (solid red line) and for above average pairwise word combination probability (dashed blue line). In Panel (c), we plot the average residualized patent value by residualized pairwise word combination probability. We residualize the value and the word combination probability for the interaction of (four-digit) CPC technology class and filing year. Panel (d) shows the distribution of residualized patent values by distance of patents to science across the percentiles of the value distribution of all patents for patents with below average pairwise word combination probability in a technology and year (solid red line) and for above average pairwise word combination probability in a technology and year (dashed blue line).



(a) Novelty distribution by science intensity

(b) Accounting for technology and year

Figure 3: Patent novelty and distance to science.

Panel (a) shows the kernel density plot of the average likelihood of pairwise combinations of words that occur in a particular patent for more science-intensive patents (D=1, D=2 or D=3; red line) and for less science-intensive patents (D>3 or unconnected; dashed blue line). Smaller probabilities are interpreted as a higher novelty. In Panel (b), we residualize the patent value and the likelihood of word combinations by the average value of a patent with the same technology class and filing year and a distance of four.

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Value					
Outcome:	Dollar	Dollar	Citations	Patent Scope	Prob(Litigation) x 1000	
Distance 1	0.82***	0.26***	0.99***	0.12***	10.36***	4.40***
	(0.17)	(0.04)	(0.09)	(0.03)	(1.44)	(0.62)
Distance 2	0.44***	0.18***	0.36***	0.10***	6.77***	1.50***
	(0.11)	(0.03)	(0.04)	(0.02)	(0.60)	(0.42)
Distance 3	0.14***	0.07***	0.09***	0.07***	4.93***	0.16
	(0.05)	(0.02)	(0.02)	(0.01)	(0.38)	(0.34)
Distance 4					4.39***	
					(0.41)	
Distance 5	-0.06**	-0.01	-0.06***	-0.03*	3.88***	-0.52
	(0.03)	(0.01)	(0.01)	(0.02)	(0.40)	(0.43)
Distance >5	-0.16***	-0.03*	-0.14***	-0.05**	3.43***	-0.73*
	(0.04)	(0.02)	(0.02)	(0.02)	(0.30)	(0.40)
Unconnected	-0.13*	-0.01	-0.13***	-0.04	2.49***	-0.57
	(0.07)	(0.02)	(0.03)	(0.08)	(0.26)	(0.41)
Tech x Year FE	No	Yes	Yes	Yes	No	Yes
Mean Dep.	11.56	11.56	29.88	0.12	6.40	6.40
Obs.	1135757	1135757	1135757	231474	1135757	1135757

Table 1: Patent Value Measures

Table 1 reports regression results on how various patent value outcomes with the independent variable of distance to science. The calculation of distance-to-science is based on Ahmadpoor and Jones (2017). Unconnected patents are patents for which we could not find a citation link to any scientific article. Columns 1–3 are generated by ordinary least squares (OLS) specifications, and we report the coefficients in terms of their percentage increases relative to D=4. For example, the coefficient for the first value in Column 1 may be interpreted as an 82% increase relative to (D=4). In Column 1, the outcome is (adjusted) patent values from Kogan *et al.* (2017). In Column 2, we control for (four-digit) CPC technology class × filing year fixed effects such that coefficients represent relative differences within tech-year. In Column 3, the outcome variable is the count of citing families. In Column 4, we use the within art unit patent scope index provided by Kuhn and Thompson (2017) as the outcome variable in an OLS regression. Columns 5 and 6 are both OLS specifications where the outcome variable is an indicator variable for whether or not the focal patent was ever involved in litigation (multiplied by 1000). The litigation outcome variable is based on the data from Marco *et al.* (2017). For all models, the standard errors are clustered on the CPC technology class level. *, ** and *** indicate that the coefficient is significantly different from zero on the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
	Patent value		Patent novelty	
Outcome:	Dollar	Dollar	Probability of word combination	Probability of word combination
Distance 1			7.91***	-1.69***
			(0.36)	(0.18)
Distance 2			9.37***	-0.76***
			(0.28)	(0.11)
Distance 3			10.45***	-0.23***
			(0.17)	(0.07)
Distance 4			11.90***	
			(0.16)	
Distance 5			13.95***	0.30***
			(0.18)	(0.07)
Distance >5			16.58***	0.79***
			(0.20)	(0.13)
Unconnected			16.25***	0.39***
			(0.50)	(0.11)
Probability of word combinations	-43.39***	-10.20***		
	(3.84)	(1.47)		
Tech x Year FE	No	Yes	No	Yes
Mean Dep.	11.56	11.56	10.45	10.45
Obs.	1135669	1135669	1135669	1135669

Table 2: Patent value and text novelty

This table shows OLS regression results on the relation of patent value, patent novelty and distance to science. In Columns 1 and 2, the outcome variable is the adjusted Kogan *et al.* (2017) patent values.The independent variable is the focal patent's probability of word combinations based on the data from Arts *et al.* (2018). In Columns 3 and 4, the outcome variable is the patent's probability of word combinations, and the indepenent variables are the distance-to-science measure based on Ahmadpoor and Jones (2017). Unconnected patents are patents for which we could not find a citation link to any scientific article. In Columns 2, 3, 4 we additionally control for filing year × (four-digit) CPC technology class fixed effects. The standard errors are clustered on the CPC technology class level. *, ** and *** indicate that the coefficient is significantly different from zero on the 10%, 5%, and 1% level.

Appendices

A Data

A.1 Data Sources

For our analysis, we calculate distance to science for each patent following the method of Ahmadpoor and Jones (2017). We then match this data with patent values calculated by Kogan *et al.* (2017) and with patent characteristics from a variety of sources. We use all patents that have a non-missing patent value and in whose technology class and filing year there is at least one patent with a distance to science of four.

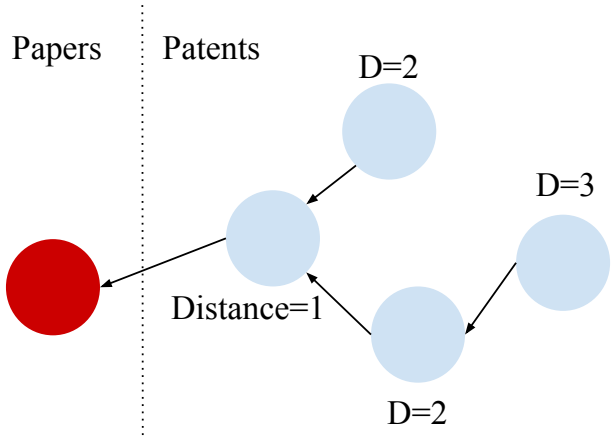


Figure A.1: Distance to science

This figure is adapted from (Ahmadpoor and Jones, 2017). It shows the distance to science for patents based on citation proximity to scientific articles.

Distance to science: Ahmadpoor and Jones (2017) define a patent's distance to science using citation links.[21] A patent that directly cites a scientific paper has a distance to science of one (D=1). Patents cite academic articles or other patents to give credit to prior art on which the technology disclosed in the patent is based. Patent-to-article citations are used in many recent papers to capture the link between science and innovation, e.g. Arora *et al.* (2020) and (Azoulay *et al.*, 2019).[22] A patent that cites a (D=1)-patent but no scientific article has a distance of two (D=2), and so on (Figure A.1). Citing another patent that is

[21] We thank Mohammad Ahmadpoor and Ben Jones for sharing their data.

[22] Roach and Cohen (Roach and Cohen, 2013) suggest that patent-to-article citations reflect knowledge flows from academia to the private sector better than the commonly used patent-to-patent citation.

based on a scientific article provides evidence that the citing patent is also based to some degree on science, but less directly so.

To determine the distance-to-science of individual patents we use data from Marx and Fuegi Marx and Fuegi (2020), which provides a link from academic articles in Microsoft Academic to patents. Then we use data in PATSTAT to obtain patent-to-patent citations. We cross-check the values of our distance-to-science measure based on Marx and Fuegi (2020) with the values calculated by Ahmadpoor and Jones (2017). In cases where Ahmadpoor and Jones (2017) arrive at a smaller distance to science, we substitute their values.

Sources:

https://www.openicpsr.org/openicpsr/project/108362/version/V12/view

https://www.microsoft.com/en-us/research/project/academic/

https://www.epo.org/searching-for-patents/business/patstat.html\#tab-1

Patent value: We match the distance-to-science information with the data on patent values of Kogan *et al.* (2017). Kogan *et al.* (2017) use abnormal stock market returns around the publication date of the patent to infer the value of a patent. Therefore, the data measures the ex-ante expected net present value of the patent for the filing company. This dataset contains patent values for 1.8 million U.S. patents filed between 1926 and 2009.

Source: https://iu.app.box.com/v/patents

Patent novelty: For our novelty measure, we use information on words in patents from Arts *et al.* (2018). Arts *et al.* (2018) tokenize the titles and abstract texts of patents, clean and alphabetically sort the resulting words. The resulting word vector contains on average 37 words per patent and in sum 526,561 words. For the novelty measure, we count how often a particular pairwise word combination occurs in a patent abstract and standardize it with

the total number of pairwise word combinations up to this year. We also calculate for each word how common it is. To do this, we count for each word how often it was used in the past and standardize it with the total number of words used.

Source: *https://dataverse.harvard.edu/dataverse/patenttext*

As an alternative measure of patent novelty, we take the subset of patents which describe chemical compounds and calculate their compound novelty. For any given patent, we calculate the pairwise similarity between each one of its described chemical structures' similarity to all compounds represented in prior patents in the same 3-digit CPC class. One minus the maximum of those pairwise similiarities is a patent's "chemical patent novelty score." To do so, we use the crosswalk of patents-to-compounds from SureChEMBL, which extracts the standardized (SMILES code) chemical structures represented in patents. To calculate the pairwise similarity scores, we use the ChemmineR package (Backman *et al.*, 2011). We describe these analyses in Appendix C.4.

Sources:

http://chembl.blogspot.com/2015/03/the-surechembl-map-file-is-out.html

https://chemminetools.ucr.edu/

https://www.bioconductor.org/packages/devel/bioc/vignettes/ChemmineR/inst/doc/ChemmineR.html

Other patent characteristics:

- **Text similarity**: We calculate the pairwise text similarity between a patent and the articles cited in the patent. Then we take the maximum over all the similarities of a patent to its cited articles to determine the distance to the closest article. To calculate the similarity between the abstracts of the article and of the patent we use

the "term frequency-inverse document frequency" (tf-idf) method. We use the "gensim" implementation in Python for our calculations (https://radimrehurek.com/ gensim/). Article abstracts are from the OpenAcademic Graph (Tang *et al.*, 2008; Sinha *et al.*, 2015) and patent abstracts are from Patstat. For each term used in the abstracts of the patent and the article, tf-idf measures how often this word appears in the abstract and then standardizes this value with the probability that this term appears in general. Using the tf-idf value for each term, we can build a word vector for each of the abstracts. Then we determine the similarity between the abstracts of the patent and the article abstract by calculating the correlation between the two-word vectors. If a patent cites several articles, we take the maximum in similarity.

Source: `https://www.openacademic.ai/oag/` 1

- **Patent scope** is from Kuhn and Thompson (Kuhn and Thompson, 2017). Specifically, we use the z-score within art unit for our results.

  Source: `http://jeffreymkuhn.com/index.php/data/`

- **Patent Litigation** is from the USPTO's Patent Litigation Docket Reports Data (Marco *et al.*, 2017).

  Source: `https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-litigation-docket-reports-data`

- **All other patent characteristics** are from Patstat–including application dates and (four digit patent classes.

  Source: `https://www.epo.org/searching-for-patents/business/patstat.html`

A.2 Patent Characteristics and Distance to Science

The following tables describe characteristics of patents in our data set. All the variables relate to characteristics at the time of patent issuance, rather than subsequent outcomes like stock market reaction, forward citations, and litigation.

20.7% of patents in our data directly cite scientific publications. Among those (D=1) patents, they average 6.1 citations to scientific journal articles, and the average age of those journal articles is 8.04 years prior to the patent's publication. Appendix Tables A.1, A.2 and A.3 present descriptive statistics for patents in our sample, by distance to science. We find that more recent patents are more likely to cite science. In our analysis data, the average patent issuance year of 2001.8 for (D=1) patents, and steadily descends with distance to science all the way to 1989.2 for unconnected patents. Patents closer to science also tend to have larger teams, more patents in their patent "family,"[23] take longer for the patent office to process (from application to publication), and have fewer words in their claims. Appendix Table A.3 shows that these relationships hold even after controlling for patent publication year and CPC (four digit) technology class.

Appendix Table A.2 and Appendix Table A.3 further describe the profile of backward citations, by the focal patent's distance to science. We see that patents closer to science have more backwards citations—indicating that proximity to science involves building off a larger base of prior art. We find that science patents also build off a wider foundation of extant inventions, as the share of same-technology (CPC class) citations is increasing in distance to science. Patents that are most distant to science also cite older prior art. The average age of a cited patent is between 7.38–8.33 years old for (D=1,2,3) patents, while the range grows to 10.9–22.0 year old for (D>3). Finally, we use the patent-to-patent text similarity measure developed by Kuhn and Thompson (2017) to assess how distance to science correlates with similarity between focal patents and their (backwards) cited patents. In both the

[23] A patent family is the set of patents, applied for across different countries, that aim to protect the same invention by the same inventor(s).

raw averages and the year- and technology-adjusted regressions, we see that the maximum cited patent similarity is decreasing in distance from science while the average cited patent similarity is increasing in distance to science. In other words, inventions closer to science cite patents that are more varied in their word similarity to the focal patent. These patterns fit the view that science, as an exploration tool, helps navigate broader patent space. The common language of shared scientific methods enables specific comparisons (i.e., clear performance improvements) to highly similar innovations, while also uncovering new connections and sparking recombination across inventions with disparate product applications.

Additional Examples: U.S. Patent number 6120536 ("Medical devices with long term non-thrombogenic coatings") was published in July 2000 and assigned to Schneider USA Inc. (later purchased by Boston Scientific). It describes a drug-eluting coating applied to a metallic stent in order to prevent blood clots.[24] The patent builds directly on science (D=1), with 8 citations to scientific publications and 35 additional non-patent citations (mostly conference presentations and technical reports). These publications include articles from *The Journal of Biomedical Materials Research*, *The Society of Thoracic Surgeons* and the *American Society for Artificial Internal Organs*. One of the two inventors, Michael Helmus, is an author of four of those non-patent citations, two of which are his own grant applications. The patent's word similarity to its average cited publication and most similar scientific publication are both in the in the top quartile of patents within the CPC technology class (A61L)—meaning that the language employed in the patent is highly similar to its most proximate scientific articles. The application itself is rich in data, presenting eight different figures plotting drug release over time, using different coating conditions and concentrations.

Just as the science-based McKesson restocking system patent shared the same technology class as the scientifically distant Coca Cola vending machine patent (see Section 3 in the main text of the paper), the drug-eluting stent patent above (6120536) shares the same CPC class as many patents that are mostly or totally disconnected from science (D>5). These

[24] As of May 2021, the patent had 566 forward citations.

include materials that prevent oxidation of medical implants (5543471, D=6), a film that shrinks upon contact with excess water (patent number 5641562, D=5), and air filters which contain tea extracts that might deactivate viruses (5747053, D=5). Clearly, all of the above inventions benefit indirectly from the scientific advances of the modern era from physics, chemistry and microbiology. However, as applied engineering efforts, their search process and method for communicating the invention's distinctive features and value is different since they do not relate their work to formal scientific findings.

	Nb. Patents	Year	Family Size	Nb. Inventors	Days Processed	Claim Words App.	Claim Words Filed
Distance 1	234946	2001.8	6.23	2.89	1100.2	110.6	166.3
Distance 2	386061	2001.9	4.13	2.64	1040.9	113.4	164.3
Distance 3	240145	2000.9	3.93	2.54	923.2	122.8	167.1
Distance 4	105705	1997.4	3.77	2.40	795.8	137.6	175.5
Distance 5	60579	1994.0	3.54	2.23	728.4	141.4	181.6
Distance >5	67355	1991.5	3.39	2.07	686.5	146.0	181.8
Unconbected	40966	1989.2	3.51	2.05	701.5	144.0	171.1
Total	1135757	1999.7	4.39	2.57	955.5	118.9	167.2

Table A.1: Patent Characteristics, by Distance to Science

NOTES: Table A.1 presents patent characteristics for patents in the analysis sample, by degree of distance from science.

	Nb. Cites	Share Self-Cites	Share Same-Tech	Age	StdDev. Age	Max. Sim. Cited	Avg. Sim. Cited
Distance 1	13.3	0.14	0.54	8.00	5.27	0.55	0.31
Distance 2	11.8	0.14	0.56	7.38	5.18	0.54	0.32
Distance 3	9.77	0.17	0.56	8.33	6.10	0.52	0.34
Distance 4	9.93	0.18	0.56	10.9	8.11	0.52	0.35
Distance 5	10.7	0.16	0.57	12.9	9.44	0.50	0.35
Distance >5	10.2	0.14	0.60	15.0	10.9	0.48	0.36
Unconnected	8.58	0.13	0.59	22.0	12.7	0.44	0.37
Total	11.2	0.15	0.56	9.18	6.38	0.53	0.33

Table A.2: Backward Citations, by Distance to Science

Table A.2 describes backwards citation characteristics for patents in the analysis sample, by degree of distance from science.

Outcome:	(1) Nb. Inventors	(2) Processing Days	(3) Claim Words	(4) Nb. Backwards Cites	(5) Share Same-Tech	(6) Avg. Age Cites	(7) Max. Sim. Cited	(8) Avg. Sim. Cited
Distance 1	0.329***	101.1***	-13.54***	6.47***	-0.055***	-0.59***	0.054***	-0.037***
	(0.00706)	(10.32)	(0.878)	(0.085)	(0.0013)	(0.024)	(0.00078)	(0.00055)
Distance 2	0.184***	58.03***	-12.82***	3.43***	-0.042***	-1.22***	0.037***	-0.025***
	(0.00647)	(9.445)	(0.800)	(0.078)	(0.0012)	(0.022)	(0.00071)	(0.00050)
Distance 3	0.0796***	-4.608	-9.634***	1.62***	-0.024***	-1.12***	0.0076***	-0.010***
	(0.00657)	(9.598)	(0.787)	(0.079)	(0.0012)	(0.022)	(0.00072)	(0.00051)
Distance 5	-0.0220**	10.47	5.677***	-1.51***	0.014***	1.38***	-0.011***	1.8e-06
	(0.00890)	(13.00)	(1.343)	(0.11)	(0.0016)	(0.030)	(0.00097)	(0.00069)
Distance >5	-0.0494***	16.15	6.206***	-3.74***	0.050***	2.87***	-0.023***	0.0099***
	(0.00887)	(12.96)	(1.746)	(0.11)	(0.0016)	(0.030)	(0.00097)	(0.00069)
Unconnected	-0.0617***	33.51**	1.343	-4.17***	0.055***	9.82***	-0.052***	0.020***
	(0.0106)	(15.47)	(2.352)	(0.13)	(0.0022)	(0.040)	(0.0014)	(0.00097)
Tech x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,135,747	1,135,725	232,049	1,135,747	1,114,025	1,114,025	1,108,568	1,108,568

Table A.3: Patent Characteristics and Backwards Citations, by Distance to Science (Regressions)

Table A.3 presents OLS regression results of distance to science on a a variety of patent characteristics. In each regression, the omitted group is patents where degree is equal to four (D=4). The outcome variable in Column 1 is the number of inventors listed on the patent. In Column 2, the dependent variable is number of days between a patent's first application and issuance. Columns 3 show results for number of words in patents' first claim in the issued patent. Column 4's outcome is the total number of backwards citations to other patents. Column 5 uses the share of each patent's backward citations that go to same (4-digit) CPC technology class as the focal patent. Column 6 reports results for the average age of backwards citations. Column 7 and 8's outcomes are the maximum and average similarity of the focal patent's text to the text of it's cited patents. All models include patent issuance year and technology class (4-digit CPC code) fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

B Additional Regressions and Robustness Results

We further investigate the relationship between patent values and distance to science using additional regression specifications.

B.1 Patent Value Outcomes (in Levels), by Distance to Science and Text Similarity

Columns 1–3 of Appendix Table A.5 are analogous to those Table 1, but with coefficients that correspond to level differences rather than percentage differences. This table generates the patent value magnitudes that we report in Section 4.1. We report the same estimates as Table 1 for Columns 4–6, which show the patent scope and litigation outcomes as alternative measures of value. Appendix Table A.5 also has two additional Columns (7 and 8) which report the text similarity between the focal patent and it's most similar scientific journal articles as described above in Appendix A.1 and B.4.

B.2 Different assumptions for KPSS value estimates

This section shows the sensitivity of our patent value measures to different assumptions about probability of patent grant. Our primary measure of patents' private value is from Kogan *et al.* (2017) [KPSS]. While we primarily use the KPSS values as a measure of *relative* value across distance from science and novelty groups (e.g., see Figure 1 and Table 1), we also report dollar magnitudes adjusted for conservative estimates of patent grant rates (see Section 4.1). An important assumption in the KPSS patent valuation method is choosing the value for a patent's ex-ante probability of success, π. Using a higher probability of patent success mechanically increases all patent values since the method scales all patent values by $(1-\pi)^{-1}$. The intuition is that a big positive stock market response is even more indicative of a valuable patent is the market was already expecting that the patent had a decent chance of approval.

Appendix Table A.4 shows how various adjustments to the KPSS values change the dollar magnitudes of average patent values by distance to science. Columns 1 and 2 of Appendix Table A.4 report the average patent values, by distance to science, based on the adjusted values used throughout the main body of the paper, without and with technology $\times$ year fixed effects. As described in Section 4.1, these "new baseline" estimates deflate all KPSS values by 12% to match the most conservative end of the spectrum for probability of patent grant. In other words, conditional on the market being aware of a patent application, we assume the greatest average market "surprise" for patent publication events. For contrast, Columns 4 and 5 show the same regressiosn using the undadjusted ("old baseline") KPSS values.

Columns 5 and 6 use a more extreme adjustment: assuming that the market had no information about a patent application prior to patent publication. This alternative shows a 40%-50% drop in average patent values with this approach [Column (1) vs. Column (5)], but the general relationship between distance from science and relative value holds. We think this additional analysis is useful for offering a sort of lower-bound, however reality

probably falls in between the "no information benchmark" and the original KPSS patent values. Prior to the American Inventor's Protection Act (AIPA), which was enacted in November 2002, patent applications were not necessarily publicly available prior to grants. Nor was the market totally ignorant of firms' inventions, since firms might still publicly disclose inventions that were "patent pending" through a variety of communication channels, or have publicly disclosed patent documents at non-US patent agencies. Thus, the "no information benchmark" values serve as an extreme lower bound.

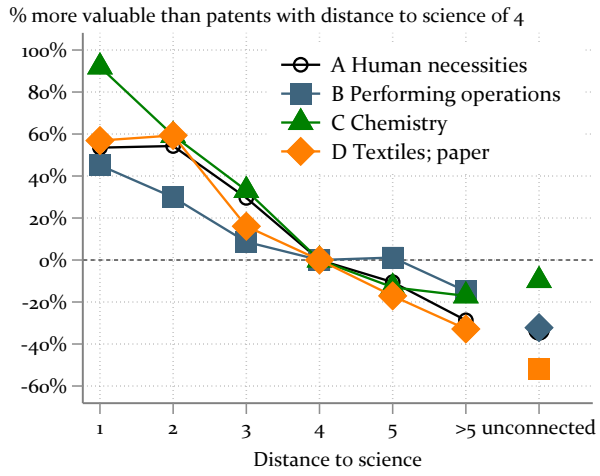
	(1)	(2)	(3)	(4)	(5)	(6)
	New baseline Conservative acceptance rate		Old baseline Original KPSS		No information benchmark	
Outcome:	Dollar	Dollar	Dollar	Dollar	Dollar	Dollar
Distance 1	15.82***	2.64***	17.72***	2.95***	9.73***	1.90***
	(1.56)	(0.36)	(1.75)	(0.40)	(0.97)	(0.21)
Distance 2	12.49***	1.88***	13.98***	2.10***	7.47***	1.31***
	(1.08)	(0.31)	(1.21)	(0.35)	(0.68)	(0.18)
Distance 3	9.90***	0.69***	11.09***	0.77***	5.78***	0.48***
	(0.77)	(0.19)	(0.87)	(0.21)	(0.47)	(0.11)
Distance 4	8.69***		9.74***		4.67***	
	(0.62)		(0.70)		(0.33)	
Distance 5	8.21***	-0.13	9.20***	-0.15	4.25***	-0.04
	(0.46)	(0.15)	(0.51)	(0.17)	(0.24)	(0.08)
Distance >5	7.27***	-0.33*	8.15***	-0.37*	3.69***	-0.12
	(0.33)	(0.18)	(0.37)	(0.20)	(0.17)	(0.09)
Unconnected	7.55***	-0.06	8.45***	-0.07	3.85***	0.04
	(0.64)	(0.22)	(0.71)	(0.24)	(0.34)	(0.12)
Tech x Year FE	No	Yes	No	Yes	No	Yes
Mean Dep.	11.56	11.56	12.95	12.95	6.79	6.79
Obs.	1135757	1134139	1135757	1134139	1135757	1134139

Table A.4: Different assumptions for KPSS calculation

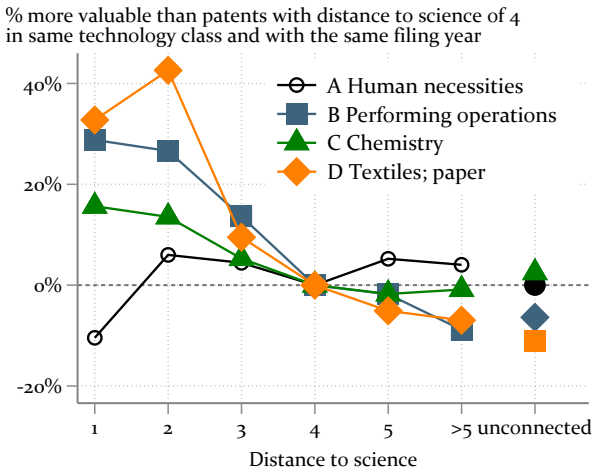
This table shows the results from OLS regressions of distance from science on Kogan *et al.* (2017) patent value estimates. In Columns 1 and 2, we use the same adjusted KPSS values used in the main body of the paper (deflated 12%). Columns 3 and 4 used the original unadjusted KPSS patent value estimates. Columns 5 and 6 use the extreme "no information benchmark" which assumes the stock market had no knowledge of a patent application prior to the patent's ultimate publication. In Columns 2, 4 and 6 we add technology class × filing year fixed effects. The standard errors are clustered on the CPC technology class level. *, ** and *** indicate that the coefficient is significantly different from zero on the 10%, 5%, and 1% level.

B.3 Split by technology

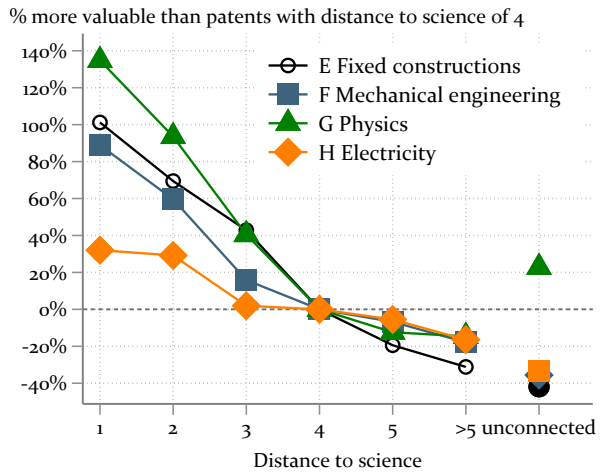
One concern might be that the observed effects are driven by a single technology that benefits particularly from science. This is not the case. In Figure A.2, we show the main graph separately for broad technology categories measured by one-digit CPC classes. Panels (a) and (b) show the raw data. In Panels (c) and (d) we normalize by the average values of patents in the same four-digit CPC technology classification and filing year. For all technologies, there is a decrease in value by distance to science, most pronounced for drugs and chemicals. Results by other technology classifications such as the classification in Hall et al. (Hall *et al.*, 2001) and Schmoch (Schmoch, 2008) are available from the authors on request.



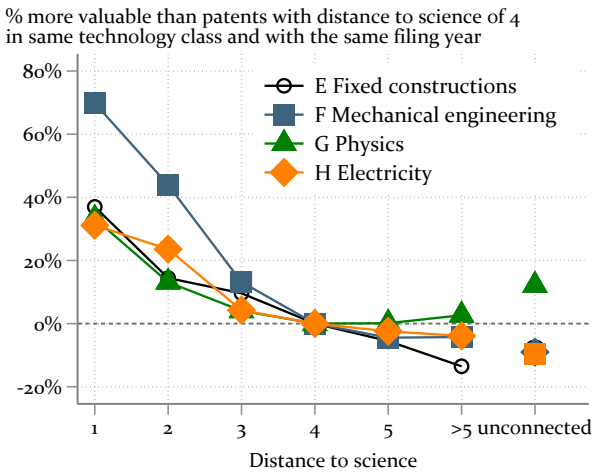
(a) Value by broad patent class A-D



(b) Accounting for technology× year



(c) Value by broad patent class E-G



(d) Accounting for technology × year

Figure A.2: Sample splits by technology

In this figure, we split patents by broad technology fields measured by one-digit CPC classes. In Panels (a) and (c) we show the raw data. In Panels (b) and (d) we normalize by the average patent value of a patent in the same four-digit CPC class and filing year with a distance of four.

B.4 Comparing Patent and Scientific Article Text

One potential concern one might have about our estimation of the science premium of patents is that the distance to science calculated by citations might measure not only how much a patent uses science but also the quality of the inventor. A high-quality inventor might be more aware of scientific research and therefore include more citations, but without actually using science.

To see whether patents close to science make use of its content, we compare the texts of scientific articles and the text of patents. We calculate the pairwise text similarity between a patent and the articles cited in the patent. Then we take the maximum over all the similarities of a patent to its cited articles to determine the distance to the closest article. To calculate the similarity between the abstracts of the article and of the patent we use the "term frequency-inverse document frequency" (tf-idf) method.[25]

The results presented in Column 7 of Table A.5 show that patents with a citation distance of D=1 have a higher text similarity to scientific articles than patents more distant to science. This suggests that citation distance reflects indeed how much a patent is related to science. Consistent with the idea that patents with more scientific content have a higher value, Column 8 shows that the value of a patent increases with its text similarity to scientific articles. This suggests that the relation between citation distance and patent value presented as our main result above is not a result of a spurious correlation driven by third factors that are unrelated to the scientific content of the patent.

B.5 Patent Tail Outcomes

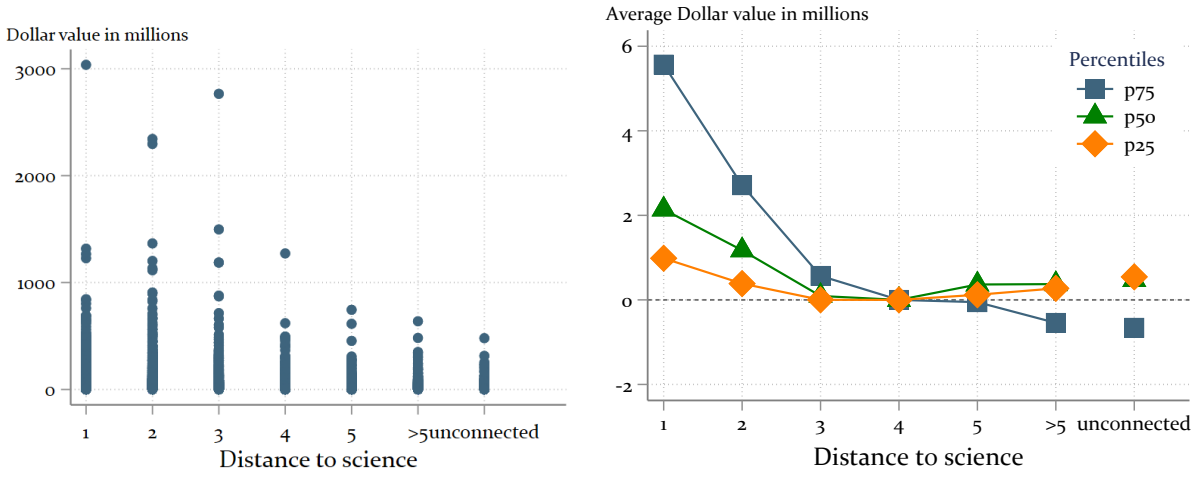
Our primary regression results look at how average patent values vary with distance from science (Table 1). However, as we see in Figure 1 (Panels (b) and (d)) The increase in value due to science also comes with an increased likelihood of tail outcomes accounting

[25] We use the "gensim" implementation in Python for our calculations (see: `https://radimrehurek.com/gensim/`).

for technology and year. In Columns 5 and 6 of Appendix Table A.6, we investigate the likelihood that a patent is in the top 5% or bottom 5% of the distribution of the science component as an outcome. The distribution is taken over all patents. Patents that are closer to science have a higher likelihood to be in the tails of this distribution. So, accounting for the technological component, science-based patents show a larger variance in values.

B.6 Effects over the entire value distribution

The main paper shows that average patent values decrease with distance to science relative to the average value of a patent with the same filing year and the same (four-digit) CPC technology classification with a distance of four. This pattern is already visible in the raw data in Figure A.3a. In Figure A.3b we show the value by distance of science over the 25th, 50th and 75th percentile of the value distribution. We residualize each percentile with the same percentile of patents with D=4.[26] The patent values are falling with distance to science over all percentiles. This confirms that our results are not driven by outliers.



(a) Raw data

(b) Value percentiles residualized with same percentile in D=4

Figure A.3: Effects over the value distribution

Panel (a) shows the raw data for patent values by distance to science data for a 10% sample of patents. The values of U.S. patents are from Kogan et al (Kogan *et al.*, 2017). The distance to science of U.S. patents is calculated with Marx and Fuegi Marx and Fuegi (2020) and Patstat using the method of Ahmadpoor and Jones (Ahmadpoor and Jones, 2017). The distance to science is defined by citation links. A patent that directly cites an academic article has a distance of D=1. A patent that cites a (D=1)-patent but not an academic article has a distance of D=2. Patents are defined as "Unconnected" if there is no citation link to an academic article. In Panel (b), we show the average patent value for all distances to science along with the number of patents in each distance. Panel (b) shows the 25th, 50th and 75th percentiles of the patent value distribution by distance to science normalized by its percentile at a distance of four.

[26]Here, we do not account for technology and year, as for many technology-filing year combinations there are not enough patents to obtain a distribution for every distance to science.

B.7 Patent value by distance to science and novelty

Distance to science and novelty are correlated, however within distance to science group, we still observe variation in novelty of word combinations. This variation allows us to explore how patent value differs if we turn novelty "on" or "off." In Appendix Figure A.4 we compare patent values by both distance to science and novelty. Specifically, we regress patent value on interactions between distance to science and an indicator for whether patents are below or above median novelty. Novelty is measured by the likelihood of pairwise combinations of words that occur in a particular patents after account for technology class and filing year (i.e., the same novelty measure as Figure 2, Panels (c) and (d)). In Appendix Figure A.4, Panels (a) and (b) graph patent values as percentage differences relative to the (D=4), low novelty group, with and without technology $\times$ year fixed effects. Panels (c) and (d) show the equivalent regression results, but reporting coefficients in levels (millions of $USD), rather than percentage differences.

We discuss the results at the end of Section 4.3.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patent Value						Text similarity	
Outcome:	Dollar	Dollar	Cita-tions	Patent Scope	Probability of Litigation x 1000		Text sim.	Dollar
Distance 1	15.82***	2.64***	22.17***	0.12***	10.36***	4.40***	7.13***	
	(1.56)	(0.36)	(1.47)	(0.03)	(1.44)	(0.62)	(0.31)	
Distance 2	12.49***	1.88***	8.07***	0.10***	6.77***	1.50***	4.76***	
	(1.08)	(0.31)	(0.63)	(0.02)	(0.60)	(0.41)	(0.26)	
Distance 3	9.90***	0.69***	2.02***	0.07***	4.93***	0.16	2.46***	
	(0.77)	(0.19)	(0.38)	(0.01)	(0.38)	(0.34)	(0.20)	
Distance 4	8.69***				4.39***			
	(0.62)				(0.41)			
Distance 5	8.21***	-0.13	-1.41***	-0.03*	3.88***	-0.52	0.10	
	(0.46)	(0.15)	(0.27)	(0.02)	(0.40)	(0.43)	(0.09)	
Distance >5	7.27***	-0.33*	-3.10***	-0.05**	3.43***	-0.73*	-0.46***	
	(0.33)	(0.18)	(0.36)	(0.02)	(0.30)	(0.40)	(0.09)	
Unconnected	7.55***	-0.06	-2.94***	-0.04	2.49***	-0.57		
	(0.64)	(0.22)	(0.69)	(0.08)	(0.26)	(0.41)		
Text similarity								3.04***
								(0.87)
Tech x Year FE	No	Yes	Yes	Yes	No	Yes		
Mean Dep.	11.56	11.56	29.88	0.12	6.40	6.40	9.94	11.56
Obs.	1135757	1134139	1134139	231474	1135757	1134139	1134626	1134626

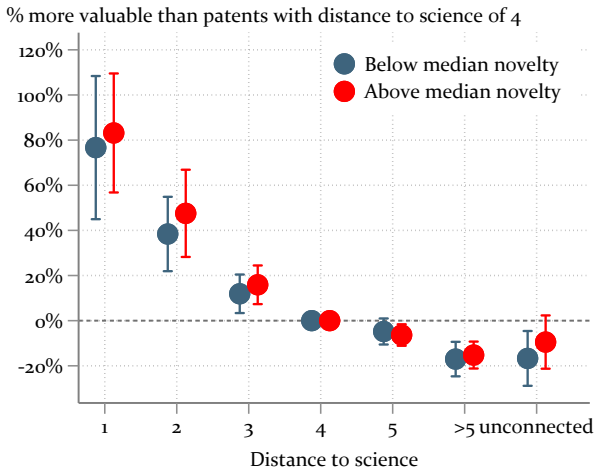
Table A.5: Patent value (in levels) and text similarity, by distance to science

This table shows OLS regression results. In Column 1, we use the patent values of Kogan et al. (Kogan *et al.*, 2017) as outcome variable. The independent variable is the distance to science measured by citation links. The calculation of distance-to-science is based on the method of Ahmadpoor and Jones (Ahmadpoor and Jones, 2017). Unconnected patents are patents for which we could not find a citation link to any scientific article. In Column 2, we control for filing year x (four-digit) CPC technology class fixed effects. We use the distance-to-science of four as a baseline. In Column 3, we use the number of citing patent families as outcome variable. This data is from Patstat. In Column 4, we use the within art unit patent scope index provided by Kuhn and Thompson (2017) as the outcome variable in an OLS regression. Columns 5 and 6 are both OLS specifications where the outcome variable is an indicator variable for whether or not the focal patent was ever involved in litigation (multiplied by 1000). The litigation outcome variable is based on the data from Marco *et al.* (2017). In Column 7, we use the text similarity between the abstract of the scientific article cited and the patent abstract as outcome variable. If there is more than one cited article, we take the maximum of the similarity per patent. In Column 8, we use text similarity as independent variable and KPSS dollar value as the outcome. The standard errors are clustered on the CPC technology class level. *, ** and *** indicate that the coefficient is significantly different from zero on the 10%, 5%, and 1% level.

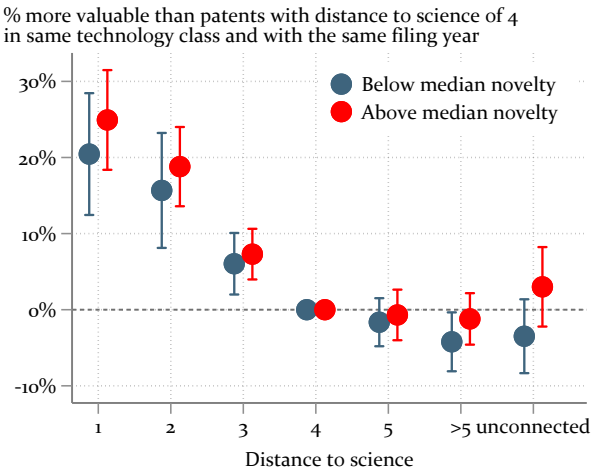
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patent Value				Patent Value relative to D=4 by tech and filing year			
Outcome: Probability of	Top 5%	Bottom 5%	Top 5%	Bottom 5%	Top 5%	Bottom 5%	Top 5%	Bottom 5%
Distance 1	7.8***	3.1***			1.3***	-0.6**		
	(1.1)	(0.5)			(0.2)	(0.2)		
Distance 2	5.5***	4.8***			0.9***	-0.5***		
	(0.6)	(0.5)			(0.2)	(0.2)		
Distance 3	4.1***	6.6***			0.3**	-0.3***		
	(0.4)	(0.6)			(0.1)	(0.1)		
Distance 4	3.3***	6.2***						
	(0.3)	(0.7)						
Distance 5	2.7***	5.6***			-0.0	0.1		
	(0.2)	(0.8)			(0.1)	(0.1)		
Distance >5	2.0***	5.3***			-0.2	0.2**		
	(0.2)	(0.8)			(0.1)	(0.1)		
Unconnected	2.2***	4.0***			0.0	0.3***		
	(0.3)	(0.5)			(0.1)	(0.1)		
Probability of word combinations			-26.7***	25.1***			-4.8***	1.0**
			(2.7)	(4.5)			(0.8)	(0.5)
Mean Dep.	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Obs.	1135757	1135757	1135669	1135669	1135757	1135757	1135669	1135669

Table A.6: Distribution of patent value

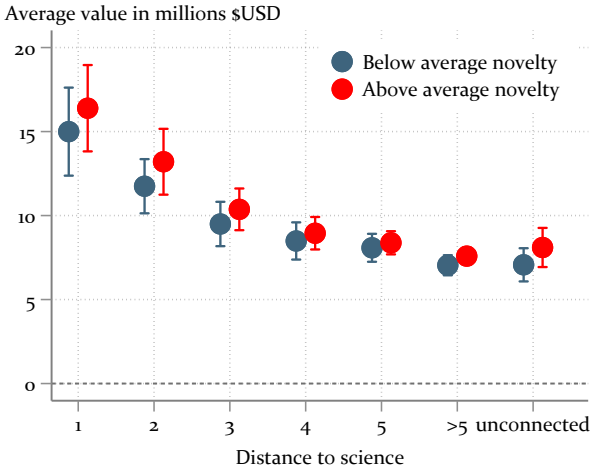
This table shows the distribution of patent values by distance to science and by patent novelty. In columns 1 and 3, we use the patent values of Kogan et al. (Kogan *et al.*, 2017) to assign to each patent an indicator equal to one if its value is in the top 5% of all patent values. In columns 2 and 4, we assign an indicator equal to one if the patent is in the bottom 5% of the patent value distribution. In columns 1 and 2, the independent variable is the distance to science measured by citation links. Unconnected patents are patents for which we could not find a citation link to any scientific article. In columns 3 and 4, we use a novelty indicator - the average probability of 2-tuple word combination of each patent - as an outcome variable. In columns 5 to 8, we use instead of the distribution of all patent values the distribution of the science value component to calculate the top and bottom 5% of the distribution. The science value component is derived by calculating the residual of the patent value and the average patent value of a patent in the same technology and year with a distance of four. The standard errors are clustered on the CPC technology class level. *, ** and *** indicate that the coefficient is significantly different from zero on the 10%, 5%, and 1% level.



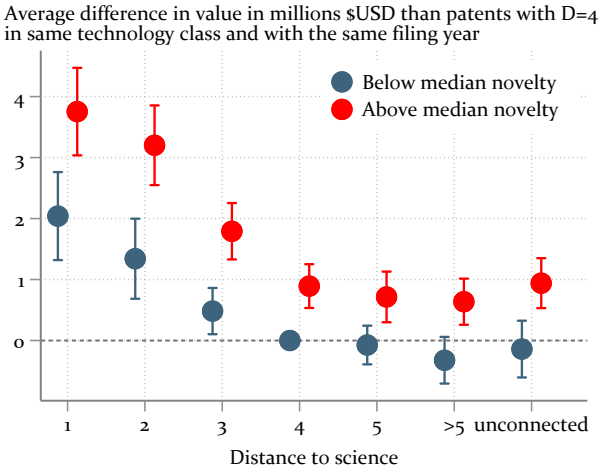
(a) % differences



(b) % difference, accounting for tech and year



(c) Averages ($ levels)



(d) $ level differences, accounting for tech and year

Figure A.4: Patent value by distance from science and novelty

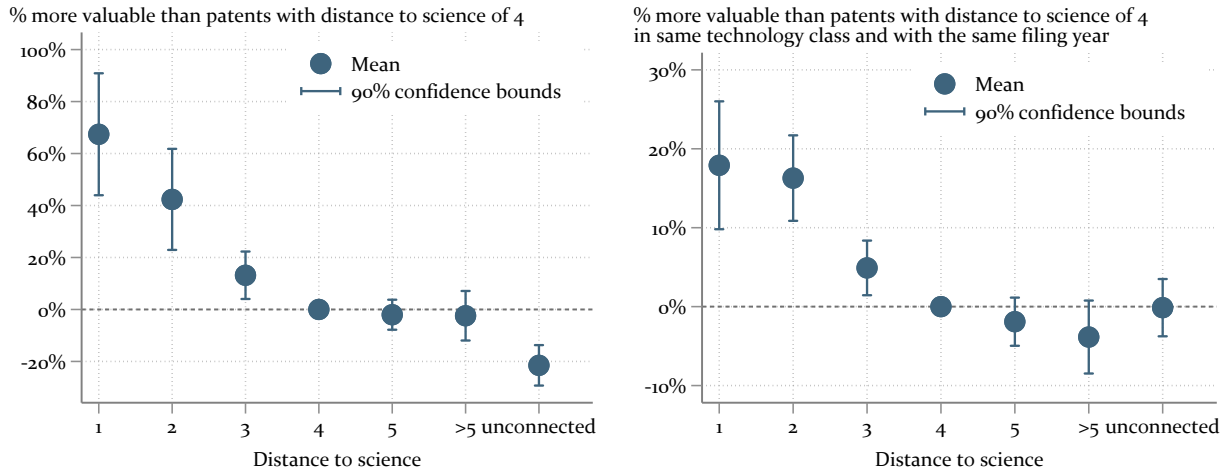
Panel (a) shows the average patent value for all distances to science relative to patents with a distance of (D=4), and separates by patents with above and below median novelty. Novelty is measured by the likelihood of pairwise combinations of words that occur in a particular patents and we account for technology class and filing year. The values of U.S. patents are from Kogan et al. (Kogan *et al.*, 2017). The distance to science of U.S. patents is calculated with Microsoft Academic and Patstat using the method of Ahmadpoor and Jones (Ahmadpoor and Jones, 2017). The distance to science is defined by citation links. The 90% confidence bounds are based on standard errors clustered by (four-digit) CPC technology class. In Panel (b), we residualize the patent value by the average value of a patent with the same (four-digit) CPC technology class and filing year and a distance of four. We again plot seperate values for patents with above and below average novelty. Panel (c) shows the average dollar value of patents in levels for all distances to science for both below and above average novelty patents. Panel (d) residualizes dollar patent values by the average value of a patent with the same (four-digit) CPC technology class and filing year and a distance of four.

C Alternative data and method choices

In this section, we discuss the results using alternative data and methodological choices.

C.1 Using Ahmadpoor and Jones distance values

In Figures A.5a and A.5b, we use the distance-to-science measure based on the data of Ahmadpoor and Jones (Ahmadpoor and Jones, 2017). The data of Ahmadpoor and Jones (Ahmadpoor and Jones, 2017) is based on Web of Science while our measure is based on the data of Microsoft Academic. There are two main differences. First, Ahmadpoor and Jones (Ahmadpoor and Jones, 2017) have many more unconnected patents (165 thousand unconnected patents out of 0.8 million overall patents) than we do (54 thousand unconnected patents out of 1.1 million overall patents). Second, we aggregate the patents with a distance larger than 5 as the number of patents goes down dramatically for larger distances. We find the same overall pattern; i.e., the patent values decrease in percent relative to D=4 with distance to science.



(a) Ahmadpoor and Jones (2017) distance

(b) Controlling for technology and year

Figure A.5: Value of patents by distance to science

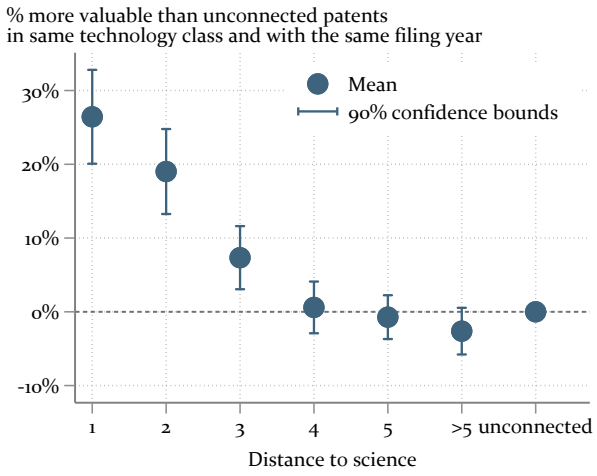
Panel (a) shows the average patent value for all distances to science relative to patents with a distance of 4 (D=4). The values of U.S. patents are from Kogan et al. (2017). The distance to science of U.S. patents is from Ahmadpoor and Jones (2017). In Panel (b), we residualize the patent value by the average value of a patent with the same (four-digit) CPC technology class and filing year and a distance of four, then display relative (%) values indexed to D=4.

C.2 Different normalizations and assignee-fixed effects

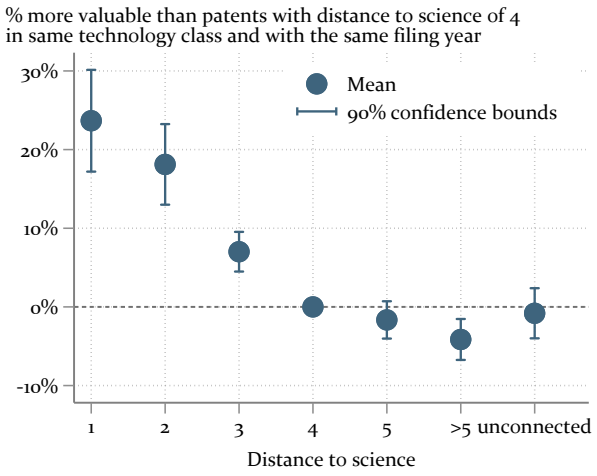
In the main part of the paper, we compare the patent values by the value of patents with a distance of four with the same technology class and filing year. One might ask whether patents with a distance of D=4 are the right comparison group. As a robustness check, we use unconnected patents as a control group and present results in Figure A.6a. The quantitative magnitudes of the effects are similar to our main specification. As a further alternative, we normalize using USPC instead of CPC technology classes and present results in Figure A.6b. The results are the same.

Another concern might be that by comparing patents with a different distance to science we are comparing different company types. Some companies might be closer to science and at the same time produce more valuable patents. If this were the case, our result might be driven by assignee-fixed effects. Comparing patent values within assignee is difficult to do

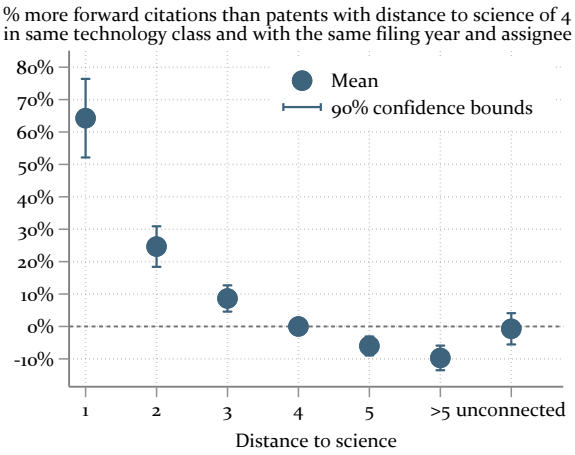
with the Kogan et al. (Kogan *et al.*, 2017) data. The reason is that all patents published by the same assignee at the same date have the same value as their evaluation is based on the same abnormal stock market returns. This is why for this exercise we use forward citations as an outcome variable. In Figure A.6c, we normalize the number of forward citations by each combination of assignee, filing year and technology class. This implies that we look only at citation differences within the same assignee. We find the same pattern as in our main result.



(a) Relative to unconnected



(b) Based on USPC instead of CPC-technology class



(c) Forward citations and assignee fixed effect

Figure A.6: Different normalizations and assignee-fixed effects

Panel (a) shows the average value of patents normalized by the value of patents that were filed in the same year but are unconnected to science. Panel (b) shows results using USPC patent classes instead of CPC patent classes. In Panel (c), we use forward citations instead of patent values as the outcome and adjust for assignee-fixed effects.

C.3 Number of citations to science and value

Our primary measure of distance to science does not account for the intensity of citations to science. A patent that cites one single scientific article and a patent citing dozens of journal articles both end up in the (D=1) group. To investigate whether the number of citations to scientific articles is correlated with patents' private value, we use number of cited articles as an alternative distance to science measure.

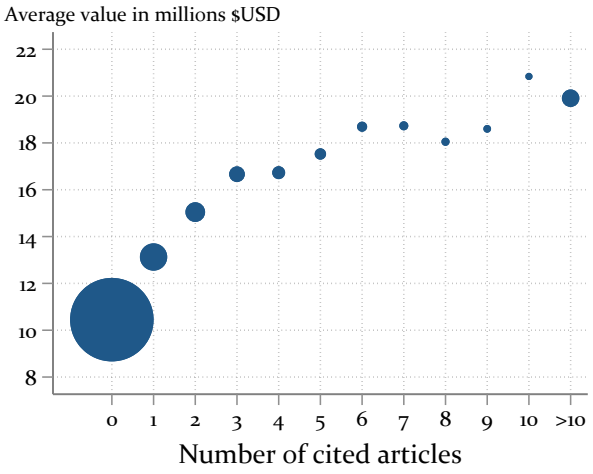
Appendix Figure A.7 shows the results of this analysis. Both panels graph Kogan *et al.* (2017) values for different numbers of citations to scientific articles. The size of each observation circle is proportional to the number of observations for each value of "number of cited articles." The modal patent has no citations to science. Panel (a) displays the raw averages and shoes a fairly steady increase in average value as the number of cited articles increase.

In Panel (b), we residualize values using the average value of patents in the same technology class and filing year. The residualized values show a similar pattern up until seven cited articles, after which the values move more erratically. Notably, patents with more than 10 cited articles have an average value closest to patents with merely one scientific citation.

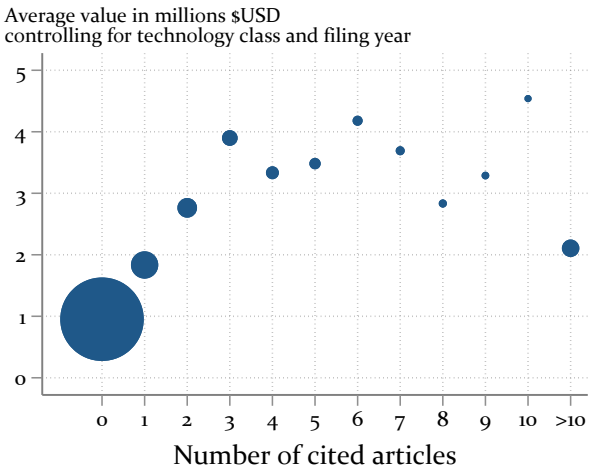
We cannot pinpoint the exact reason for the drop off in residualized values beyond 10 citations, but we can speculate. Within some technology classes, a large number of scientific citations may be indicative of a patent being a more incremental innovation. Relying extensively on a series of past discoveries could mean that the patent is situated in a more mature and crowded technological space. While reliance on science is generally valuable in those technology classes, excessive citations might signal a narrowness or lack of novelty that reduces the patent's private value. Such a pattern is in line with Krieger *et al.* (2021), who find that drug candidates that are highly similar in structure to prior drugs have lower KPSS patent values.

More generally, the number of scientific cites among the (D=1) is a noisy measure of how reliant a paper is on science. Some subfields simply have a norm of more citations Marx and Fuegi (2020). Additional citations in those fields are more likely to be ceremonial in nature.

In such high citation scientific areas, we do not expect more citations to correlate with higher private value, nor relying any more on science than in areas where citing patterns are more selective.



(a) Averages



(b) Averages accounting for technology and year

Figure A.7: Number of articles cited and patent values

Panel (a) shows the average patent value and patents are split by the number of scientific articles cited in the patent. The data on non-patent citations is from Marx and Fuegi (2020). In Panel (b), we residualize the patent value by the average value of a patent with the same (four-digit) CPC technology class and filing year and a distance of four.

C.4 Alternative measures for novelty

New words and word age

In our main specification, we measure how likely or unlikely the word combinations used in a patent are to determine the novelty of a patent. In Figures A.8a and A.8b, we use the data of Arts et al (Arts *et al.*, 2018) to calculate two alternatives measures for novelty. The first measure indicates whether a patent has a new word. A word is new if it was not used in any patent before. Figure A.8a shows that the share of patents with a new word decreases monotonically with its distance to science. The second measure is the average age of words used in a patent. We calculate the age of a word by calculating the difference between the filing year and the filing year of the patent in which it was first used. The average word age is systematically lower for patents that are closer to science (Figure A.8b). If word age is indicative for the age of the ideas they encode, patents closer to science contain more novel ideas.

Both of the alternative novelty measures are positively related to patent value. Figure A.8c compares the patent value for patents with and without new words for each year, controlling for technology $\times$ year fixed effects. From 1980–1998, we see that patents with new words have a positive (average) value premium over those without new words. Then, from 1998–2000, patents with new words are actually less valuable on average. Presumably this period featured a lot of highly valued, but (relatively) low novelty software patents without new words. Firms may have been able to capture value from "jumping on the bandwagon" with software patents in that brief period, but the "bursting" of the dot com bubble in 2000 suggests that many of those software patents were indeed overvalued in the longer run.

Figure A.8d shows the relation between the average age of words of a patent relative to the year and technology class and the residualized patent value. We see a negative relation between patent value and the average age of words.

Chemical Patents and Compound Novelty

A potential shortcoming of measuring novelty with text analysis is that inventors and patent lawyers have many degrees of freedom in choosing words. Word or word combination novelty might reflect the author's preferences or popular tech buzzwords, moreso than innate qualities of the invention. Endogenous language choices might erroneously hide or suggest true novelty (e.g., consider the use and abuse of word combinations involving terms like "crypto" and "artificial intelligence" over time). To avoid the pitfalls of using language to measure novelty, ideally innovation scholars would have standardized and quantifiable measures of technological similarity for all technology classes over time.

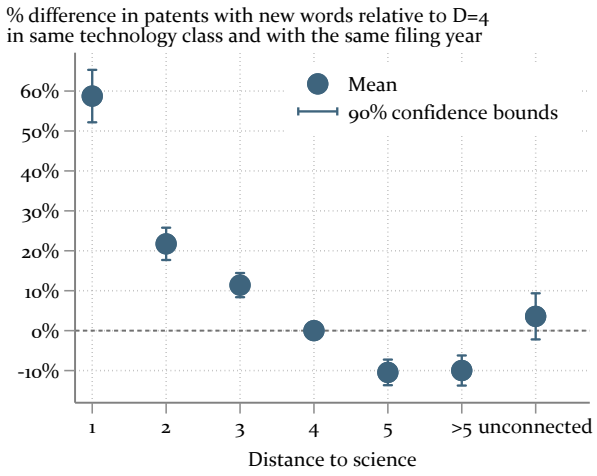
While such standardized novelty measures do not exist for most technologies, chemical patents allow for such structured measures of invention qualities. We use the crosswalk of patents-to-compounds from SureChEMBL, which extracts the standardized (SMILES code) chemical structures represented in patents.[27] Patents often have more than one chemical described in their claims, and these chemicals need not be the central component of the the new invention.

One way that chemists quantify the similarity of two given molecules is to calculate their share of overlapping fragments as a "Tanimoto" (or Jaccard) chemical similarity score from zero (no overlap) to one (total overlap). Using the general approach described in Krieger *et al.* (2021) and with the aid of the ChemmineR package (Backman *et al.*, 2011), we calculate all the maximum pairwise (backwards) similarity between each of the compounds in a given patent and all previously patented chemicals from the same 3-digit CPC class. The average maximum similarity to prior patent chemicals is 0.86 with a median of 1. This general lack of novelty is unsurprising since patents contain multiple compounds and inventive novelty might come from recombination of existing compounds or complementary technologies claimed by the patent. Thus, our chemical similarity measure is a conservative measure of novelty.

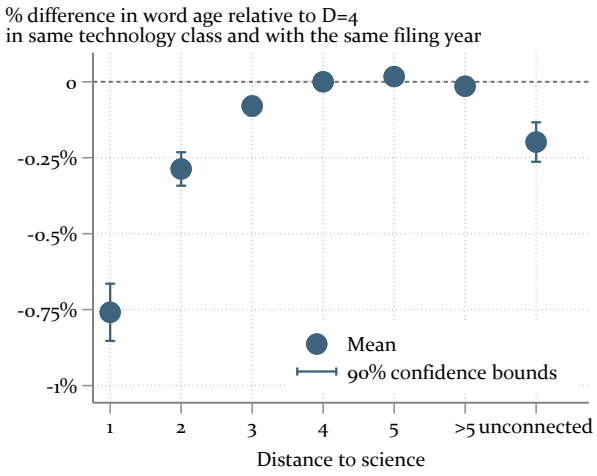
[27] The data includes 187,958,584 patent-compound pairs from 1960–2014. For more information on the data see: `http://chembl.blogspot.com/2015/03/the-surechembl-map-file-is-out.html`.

As a robustness check on our main results, we merge the chemical patent similarity measures to our main analysis data set and evaluate the 58,668 public firm chemical patents in our data. Table A.7 presents the results. Controlling for technology (4-digit CPC) $\times$ year fixed effects, we find that chemical similarity to past patents is negatively associated with KPSS dollar values (Column 1). In Column 2, we show that the most novel compounds (those with backwards similarity < 0.25) have a \$5.35 million higher average KPSS valuation than less novel chemical patents.

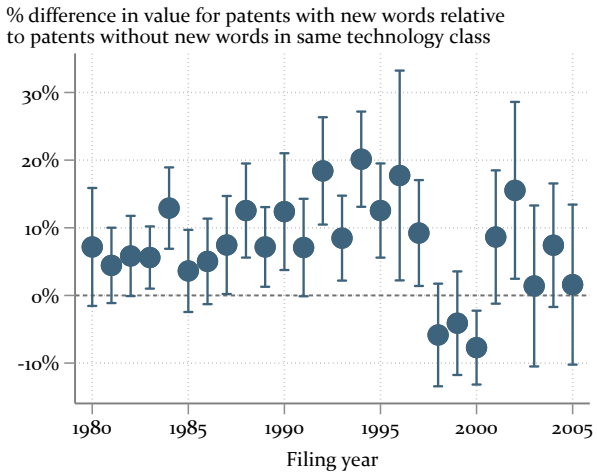
Finally, in Column 3 we evaluate the association between distance to science and chemical patent novelty. Compared to (D=4) patents and controlling for technology (4-digit CPC) $\times$ year fixed effects, (D=1) and (D=2) patents have a significantly lower similarity (more novelty) on average. Interestingly, patents totally unconnected to science also tend to have less similarity to past patented chemicals, while the other distance groups show no difference from (D=4). This pattern mirrors the relationships we find using the new words and word age measures (Figures A.8a and A.8b), where unconnected to science patents also exhibited greater novelty than the (D>3) groups.



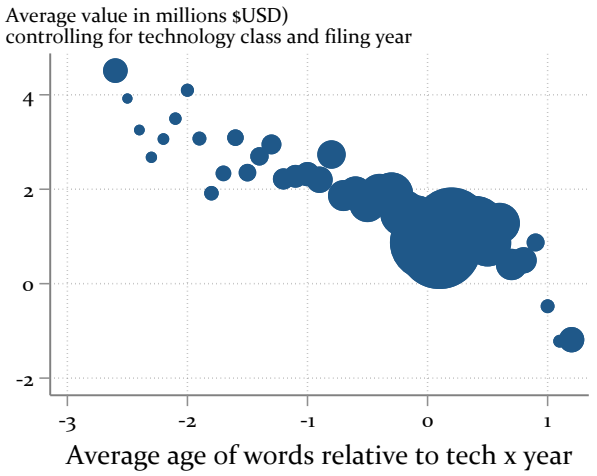
(a) Novelty: New words



(b) Novelty: Average word age



(c) New words and value



(d) Word age and value

Figure A.8: Value and novelty

Panel (a) shows the share of patents that have a new word by distance to science. A new word is a word that has not been mentioned before in a patent according to the data of Arts et al (Arts *et al.*, 2018). In Panel (b), we plot the average word age by distance to science. The age of a word in a patent is the difference between the filing year of the patent and the year the word was first used in a patent. In Panel (c), we plot the average percentage difference in dollar value of a patent with a new word relative to a patent without a new word within the same filing year and (four-digit) CPC technology class over time. In Panel (d), we plot the average word age and the average patent value. The word age is relative to the mean of patents in the same filing year and the same (four-digit) CPC technology class.

Outcome:	(1) Dollars	(2) Dollars	(3) Chemical Similarity
Chemical Similarity	-4.85**		
	(2.36)		
Most Novel Compounds		5.35***	
		(1.99)	
Zero Novelty Compounds		-0.48	
		(0.74)	
Distance 1			-0.037***
			(0.014)
Distance 2			-0.012*
			(0.0069)
Distance 3			-0.00081
			(0.0044)
Distance 5			0.0052
			(0.0058)
Distance >5			-0.0012
			(0.0060)
Unconnected			-0.060***
			(0.020)
Tech x Year FE	Yes	Yes	Yes
Observations	60,009	60,009	60,009

Table A.7: Chemical novelty, patent value and distance to science

NOTES: Table A.7 presents OLS regressions for the subset of patents associated with one or more chemical structure. The patent to chemical crosswalk comes from SureChEMBL (`www.surechembl.org`), and chemical similarity is calculated from zero (no similarity) to one (total structural overlap) based on Tanimoto scores. Most novel compound patents are those with at least one compound with a maximum chemical similarity to previously granted patents of zero or less than 0.25. Zero novelty compounds patents are those which have no compounds with a backwards similarity less than 1. The omitted category is for patents with between 0.25 and 0.99 chemical similarity to prior patents. The dependent variable in Columns 1 and 2 is the (adjusted) KPSS patent dollar value. Column 3 presents the correlations between distance to science and patent maximum chemical similarity to prior patented chemicals. All models have technology (4-digit CPC) $\times$ year fixed effects. *** p<0.01, ** p<0.05, * p<0.1.