Harnessing Academic Science for Corporate Technology: The Role of Interpersonal Networks and Absorptive Capacity[1]

Sam Arts
Department of Management, Strategy and Innovation
Faculty of Economics and Business
KU Leuven
sam.arts@kuleuven.be

Lee Fleming
Management of Organizations, Haas School of Business
Industrial Engineering and Operations Research, College of Engineering
UC Berkeley
lfleming@berkeley.edu

Elena Veretennik
Department of Management, Strategy and Innovation
Faculty of Economics and Business
KU Leuven
elena.veretennik@kuleuven.be

ABSTRACT

If firms conduct less scientific research internally and yet increasingly rely on science for innovation, how do they gain access to external scientific knowledge? To examine the role of interpersonal networks among corporate inventors and academic scientists in facilitating scientific knowledge transfer from academia to industry, we construct the social network encompassing nearly the entire population of life science academic scientists and corporate inventors listed on U.S. patents. To isolate the influence of interpersonal connections from the inherent characteristics and commercial potential of scientific discoveries, we leverage paper twins—scientific papers with nearly identical findings published around the same time by independent academic teams—and analyze their citations in corporate patents. Although academic science is often viewed as a public good, our findings highlight the critical role of interpersonal connections—within two degrees of separation—in harnessing academic science for corporate innovation. Moreover, the ability of corporate inventors to leverage their connections to academic scientists depends upon their own active engagement in scientific research as well as the alignment of their scientific expertise with the academic knowledge they seek to integrate.

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1. Introduction

Scientific research has long been recognized as a key driver of technological progress in industry (Bush 1945, Mokyr 2002). The "scientification" of corporate technology is particularly evident in industries such as biotechnology and semiconductors, where firms increasingly rely on scientific research for innovation (Henrekson and Rosenberg 2001). Despite this growing reliance, firms—particularly large ones—have scaled back internal investments in scientific research, opting instead to increasingly rely on external scientific knowledge from academia (Arora et al. 2018, Fleming et al. 2019). Although extensive research demonstrates that relying on academic science enhances corporate innovation and financial performance, the specific mechanisms that enable firms to identify, access, and integrate external scientific knowledge remain less well understood (Cockburn and Henderson 1998, Zucker et al. 2002, Fleming and Sorenson 2004). While prior research has extensively examined the transfer of academic knowledge to industry through formal market mechanisms such as licensing, contracting, and the creation of academic startups (Jensen and Thursby 2001, Shane 2004, Agrawal 2006), other work suggests that such knowledge transfers are inherently social processes, occurring primarily through interpersonal connections rather than being exclusively governed by market transactions (Liebeskind et al. 1996, Murray 2004, Perkmann et al. 2013, Perkmann et al. 2021).

Accessing and leveraging external academic science poses several challenges. The rapid expansion and dispersion of scientific knowledge—millions of new papers annually—makes it difficult for firms to search and filter relevant scientific advancements. Moreover, much of this scientific knowledge is complex and tacit—residing partially in the minds of the academic scientists who produce it—complicating its transfer through publications alone (Collins 1974, Zucker et al. 2002, Roche 2023). The ability of corporate inventors to access and integrate these scientific insights may therefore depend on their interpersonal connections with the academic scientists responsible for the scientific discoveries (Murray 2004, Agrawal 2006). Connections alone may not suffice, however; corporate inventors might also require personal absorptive capacity—that is, the relevant scientific training and expertise needed to recognize, assimilate, and apply external academic knowledge in the development of corporate technologies (Cohen and Levinthal 1990, Pavitt 1991, Cockburn and Henderson 1998, Cavallo et al. 2025).

This paper explores how the combination of interpersonal networks between corporate inventors and academic scientists, and inventors' personal absorptive capacity, shapes firms' ability to integrate academic science. We use corporate patent citations to academic papers as an indicator of knowledge integration (Fleming and Sorenson 2004, Arora et al. 2018) and construct a large-scale collaboration network linking over 9 million PubMed authors—covering the near-entire population of academics in life sciences—and 2.5 million U.S. patent inventors. This new dataset includes a unique crosswalk that, for the

first time, enables the measurement of social proximity between any academic scientist in life sciences and any corporate inventor (Smalheiser and Torvik 2009). While prior work has focused on direct collaborations—typically captured through co-authorships between academic scientists and corporate inventors (e.g., Liebeskind et al. 1996, Cockburn and Henderson 1998)—we leverage the new dataset to adopt a broader, network-based perspective. Specifically, we examine the full structure of interpersonal networks, including indirect connections, that facilitate firms' access to and integration of scientific knowledge. We also examine how network position and personal absorptive capacity jointly shape the integration of academic science. Specifically, we test whether corporate inventors are more likely to leverage social proximity to academic scientists when they are themselves active in scientific research and publishing, and when their scientific expertise aligns with the focal academic research.

To isolate the influence of network connections from the intrinsic characteristics and commercial potential of scientific discoveries, we employ academic paper twins—nearly identical scientific findings published around the same time by independent academic teams (Merton 1957, Bikard et al. 2019). We then identify corporate patents that cite only a subset of the twin papers, using the uncited twin as a counterfactual to estimate the effect of interpersonal ties on knowledge transfer (Bikard 2018). Applying conditional logit models, we estimate the effect of social proximity—measured as the shortest path between corporate inventors and academic scientists—on the likelihood of citation, while controlling for unobserved heterogeneity in the scientific discovery, patented technology, and the patenting firm and team of corporate inventors.

While academic science is generally viewed as a public good—freely accessible and beneficial to all without exclusion or competition (Nelson 1959)—our findings suggest that interpersonal ties to academic scientists remain critical for firms to effectively tap into external scientific knowledge. The probability of knowledge transfer declines significantly and monotonically as social distance within the network increases. Indirect connections can still facilitate knowledge transfer, though their effect becomes negligible beyond two degrees of separation—that is, when a corporate inventor is linked to the academic scientist who made the scientific discovery only via a common collaborator. Importantly, interaction effects show that the ability of corporate inventors to leverage these interpersonal ties depends on both their own active engagement in scientific research as well as the alignment of their scientific expertise with the academic knowledge they seek to apply (Rosenberg 1990, Cohen and Levinthal 1990). Finally, replicating our design using paper-to-paper instead of patent-to-paper citations to the same twin papers, we find that interpersonal proximity also shapes science-to-science knowledge transfer, but significantly less so. This contrast suggests that close interpersonal connections matter most when scientific knowledge is translated into corporate technology.

Our findings hold across both large public firms and smaller firms, including startups, and remain robust to a range of checks, including alternative measures of social distance. To address concerns that our results may be driven by endogenous tie formation for knowledge transfer, we demonstrate robustness by excluding observations in which academic scientists and corporate inventors have direct connections, as these cases are most likely to reflect intentional tie formation. In addition, our results remain consistent when social distance is measured solely based on co-authorship links established prior to the publication of the academic twin papers, thereby eliminating ties that may have (intentionally) formed after the discovery specifically to facilitate knowledge transfer and commercialization.

Our study makes two main contributions. First, we ground our work in the micro-foundations literature, which emphasizes that firm-level constructs such as network advantages and absorptive capacity ultimately emerge from the actions and interactions of individuals (Felin et al. 2012). Building on this perspective, we demonstrate how individual inventors—through their ties to academic scientists and their own absorptive capacity—shape their firms' capability to access and integrate external scientific knowledge. In doing so, we advance research on the value of academic science for firms (e.g., Fleming and Sorenson 2004, Simeth and Cincera 2016) by shifting attention from the outcomes of using science to the mechanisms that enable firms to source and absorb it (Bikard et al. 2019). To our knowledge, this is the first empirical evidence showing that interpersonal networks—including both direct and indirect ties up to two degrees—between academic scientists and corporate inventors play a critical role in firms' ability to access and integrate academic knowledge. Whereas prior research has focused on direct interpersonal collaboration (e.g., Cockburn and Henderson 1998, Zucker et al. 2002), we adopt a network-based perspective and show that a greater number of knowledge transfers from academia to industry occur through indirect connections, consistent with network theory on the value of indirect ties in providing access to novel, non-redundant, and distributed information (Granovetter 1973, Cowan et al. 2007). Moreover, while prior work shows that interpersonal networks shape the diffusion of scientific knowledge among academic scientists (Mohnen 2022) and technological knowledge among corporate inventors (Singh 2005, Paruchuri and Awate 2017, Moreira et al. 2018), we leverage an integrated network linking academic scientists and corporate inventors to show how interpersonal connections between them facilitate the transfer of scientific knowledge into corporate technology.

Second, we contribute to classic work on boundary spanning (Allen 1977, Tushman 1977, Tushman and Scanlan 1981) and individual absorptive capacity (Cohen and Levinthal 1990) by theorizing and demonstrating that corporate inventors benefit from active engagement in both scientific research and technology development to most effectively leverage interpersonal ties to academia. These dual-engaged inventors are uniquely positioned to recognize, assimilate, and apply external scientific insights from socially connected academics—especially when their scientific expertise closely aligns with the academic

work they seek to integrate (Scharfmann et al. 2025). While prior work has shown that corporate inventors involved in scientific research contribute to firm innovation (Cockburn and Henderson 1998, Zucker et al. 2002, Gittelman and Kogut 2003, Arts and Veugelers 2020), our study identifies an interaction mechanism underpinning this performance advantage—namely, interpersonal ties that provide social access to academic knowledge, combined with personal absorptive capacity that enables its interpretation and application in corporate technology.

2. Theory and Hypotheses

Firms increasingly rely on academic science to fuel technological innovation, particularly as they scale back internal investments in scientific research (Arora et al. 2018, Fleming et al. 2019). Yet despite the growing importance of external scientific knowledge, integrating academic science into corporate technology remains challenging. Prior work has mostly examined formal market mechanisms for transferring academic knowledge to industry, such as licensing, sponsored research contracts, and university spinoffs (Jensen and Thursby 2001, Shane 2004). However, a growing body of work suggests that knowledge exchange between academia and industry is fundamentally a social process, facilitated by interpersonal connections and interactions rather than mediated exclusively through market transactions (Liebeskind et al. 1996, Owen-Smith and Powell 2004). While ongoing collaborations between academic scientists and corporate inventors likely provide the strongest conduit for knowledge transfer, prior collaborative ties often remain effective channels for continued knowledge flow (Cowan et al. 2007, Fleming et al. 2007).

Interpersonal networks between academic scientists and corporate inventors play a critical role in bridging academia and industry. Social proximity to academic scientists fosters knowledge exchange in several ways. First, interpersonal networks help corporate inventors become aware of relevant scientific insights (Cockburn and Henderson 1998, Murray 2004). Given the overwhelming volume of external academic research, such network ties also reduce search costs by filtering and directing attention to relevant and high-quality scientific findings. Second, interpersonal ties improve access to tacit knowledge—the know-how, techniques, and insights that are not fully codified in publications but are often critical for developing technological applications (Collins 1974, Zucker et al. 2002, Agrawal 2006). An inventor connected to the academic who made the scientific discovery, or to their students or collaborators, may obtain informal insights or practical guidance not captured in the published work. Third, interpersonal contact builds trust and credibility, making corporate inventors more confident in the validity and importance of academic findings and increasing academics' willingness to share novel insights that might otherwise have been withheld across institutional boundaries (Owen-Smith and Powell 2004).

Both direct and indirect ties contribute to these processes. Direct ties foster mutual awareness and are particularly effective for transferring complex and tacit scientific knowledge (Collins 1974, Hansen 1999, Zucker et al. 2002). Indirect ties—such as those formed through mutual collaborators—can also facilitate knowledge diffusion and may provide access to more diverse and novel information than direct connections (Granovetter 1973, Cowan et al. 2007). A corporate inventor may not have collaborated personally with a given academic but may be linked through a shared collaborator. Such second- and higher-degree connections can still enable informal exchanges of research insights through various interaction channels and professional networks where mutual contacts bridge otherwise distant actors. Crucially, such knowledge flows do not necessarily require direct interaction: a mutual collaborator may flag a new scientific finding, circulate a paper, or contextualize its relevance for an ongoing technological problem. Even brief encounters or indirect referrals of this kind can raise awareness of relevant scientific discoveries and offer contextual information about their potential commercial application. Such indirect channels can, in turn, serve as a catalyst for deeper engagement—for instance, prompting subsequent informal advice exchanges or targeted problem-solving discussions—through which scientific insights are ultimately integrated into technological development. Moreover, while each indirect tie is individually less likely to facilitate knowledge transfer than a direct tie, there are often many more indirect than direct ties, and in aggregate they may transmit a greater volume of information.

Despite their aggregate importance, the effectiveness of indirect ties diminishes as network distance increases (Singh 2005). Distant ties may suffer from lower interaction frequency, reduced trust, or fewer opportunities to communicate substantive knowledge. Thus, we expect direct ties between academic scientists and corporate inventors to have the strongest influence on the incorporation of academic science into corporate technology. Indirect ties will also have a positive influence on the likelihood of building upon academic science. However, this influence will wane as the number of intermediaries—that is, the social distance between inventors and academic scientists—increases.

Hypothesis 1: Corporate technology is more likely to build on academic science as corporate inventors are more closely connected to the academic scientists who produced that science.

Social proximity alone may not guarantee successful application of academic science to corporate invention—mere exposure to external scientific knowledge may not suffice to enable its effective transfer. Moreover, corporate inventors likely vary in their ability to recognize, assimilate, and apply academic science. We therefore propose two interaction hypotheses, suggesting that personal absorptive capacity moderates the effect of social proximity on the use of academic science. Specifically, and consistent with absorptive capacity theory, we distinguish two dimensions of personal absorptive capacity: first, active

engagement in scientific research at the time of corporate invention; and second, alignment between an inventor's scientific expertise and the focal academic research.

Active engagement in scientific research enables corporate inventors to develop and maintain greater personal absorptive capacity—that is, the ability to recognize the value of new external scientific knowledge, assimilate it, and apply it in the development of commercial technology (Cohen and Levinthal 1990). Such inventors are more likely to notice new academic findings and understand their implications for the firm's innovation projects. In contrast, inventors without active scientific engagement may not immediately grasp an academic discovery, even if an academic colleague draws attention to it. Even with interpersonal connections, they remain handicapped—by their limited personal absorptive capacity—to make sense of what they learn through those connections (Tushman and Scanlan 1981).

If these arguments are correct, corporate inventors' active involvement in scientific research should amplify the benefits of network ties, above and beyond the value of network connections alone (Operti and Carnabuci 2014). A corporate inventor who actively conducts scientific research is more effectively bilingual in the languages of academia and industry, and science and technology (Cockburn and Henderson 1998). They can read academic papers and translate new scientific insights for themselves and for corporate colleagues who are not actively engaged in scientific research. In essence, corporate inventors who straddle both worlds act as boundary spanners or gatekeepers, translating and importing external knowledge from academia into the firm (Allen 1977, Tushman 1977).

Moreover, active scientific engagement embeds corporate inventors in the academic community to some degree, increasing their visibility and credibility (Rosenberg 1990). This can make academics more willing to share information or collaborate, further strengthening knowledge flows. At the organizational level, prior work shows that firms with such boundary-spanning scientist-inventors generate more innovation (Cockburn and Henderson 1998, Zucker et al. 2002, Arts and Veugelers 2020). We posit that one reason is their ability to exploit social ties to academia more effectively. For these reasons, the positive effect of social proximity to academic scientists should be stronger for corporate inventors who actively engage in scientific research.

Hypothesis 2: The increased likelihood that corporate inventors with social proximity will build on academic science will be greater when inventors are actively engaged in scientific research.

Independent of the benefits of active engagement in scientific research, corporate inventors' ability to leverage social networks may also depend on how closely their scientific expertise aligns with the academic knowledge they seek to integrate. Scientific knowledge is often highly specialized, complex, and domain-specific (Collins 1974), making it difficult to identify, absorb, and apply in commercial technology development without the particularly appropriate background and expertise (Ellis 1965). Prior

work suggests that absorptive capacity of individuals is stronger when it is domain-specific—individuals are better able to recognize, assimilate, and apply new external knowledge when it relates closely to their prior experience and expertise (Cohen and Levinthal 1990, Lane and Lubatkin 1998).

Corporate inventors with directly relevant scientific expertise are more likely to recognize valuable academic insights, grasp their technological implications, and be able to translate them into commercial applications. Crucially, the effectiveness of social proximity to academic scientists in facilitating knowledge transfer hinges on this alignment: when corporate inventors possess scientific expertise closely related to the focal academic domain, their interpersonal ties to academic scientists are more likely to result in meaningful knowledge exchange. Conversely, when corporate inventors lack relevant scientific expertise, even close interpersonal connections may be insufficient to enable effective knowledge integration.

Hypothesis 3: The increased likelihood that corporate inventors with social proximity will build on academic science will be greater when inventors' scientific expertise is closely related to the focal academic science.

Together, these arguments imply two related but distinct interaction effects that reflect key dimensions of individual absorptive capacity: active scientific engagement and domain-specific scientific expertise each strengthen the impact of social proximity on the integration of academic science.

3. Data and Empirical Strategy

3.1 Collaboration network spanning PubMed authors and U.S. patent inventors

To construct the collaboration network linking all PubMed authors and U.S. patent inventors, we use disambiguated author and inventor data from Torvik and Smalheiser (2009, 2018), Smalheiser and Torvik (2009), and Torvik (2018), covering records through 2009. The PubMed author disambiguation dataset is widely used in prior research (e.g., Azoulay et al. 2017) and includes linked files identifying both PubMed authors and U.S. patent inventors, allowing us to assign unique person identifiers and reconstruct each individual's co-authored papers and patents.

First, we construct a bipartite graph consisting of instances (papers and patents) and individuals (their authors and inventors). Each co-authored paper or patent creates a link between the individuals involved from the year of publication or patent filing onward (e.g., Breschi and Catalini 2010). We treat the publication or filing year as the establishment date of a co-authorship tie (e.g., Singh 2005). We then project this bipartite graph into a unimodal network in which nodes represent individuals and edges indicate prior co-authorship at a given point in time. Each new co-authored paper or patent may thus create collaboration links between previously unconnected individuals.

To capture the dynamic nature of the network, we construct a separate network for each year from 1975 to 2009, based on all co-authorship ties formed up to and including that year. The final 2009 network includes 11.6 million individuals—8.99 million authors, 2.34 million inventors, and 0.3 million inventor-authors—and 80.2 million direct collaboration links, constructed from 18.6 million papers and 3.9 million patents. Using this network, we identify interpersonal ties and social proximity between any corporate inventor and academic scientist at a given point in time. Following prior research, we measure social proximity using shortest path length, defined as the minimum number of edges required for knowledge to flow between two individuals (Wasserman and Faust 1994). This measure captures whether two individuals are socially connected and, if so, how many steps separate them. In robustness checks, we show that our results hold when using an alternative measure of social distance that accounts for tie decay over time.

3.2 Academic paper twins to strengthen identification

To separate the influence of interpersonal networks on bridging academic science and corporate technology from the influence of the content and commercial potential of the scientific discoveries themselves, we leverage instances of simultaneous academic discoveries. This identification approach involves identifying cases of "paper twins" where nearly identical findings are published around the same time by independent academic teams as described by Merton in 1961 and previously used in empirical research as an identification strategy (Bikard 2018, Bikard et al. 2019, Bikard and Marx 2020, Marx and Hsu 2022). We use an open-access dataset of paper twins from Bikard (2020), which identifies pairs of PubMed papers published between 1960 and 2018 that 1) are in the top 10 of most similar papers according to PubMed's most similar article list, 2) do not have any common authors, 3) are not published more than one year apart, (4) received at least five citations each and the Jaccard index based on the overlap in the citing papers is at least 50%, i.e. the papers are mostly cited together by the same papers, 5) and finally at least three co-citing articles must be available in open access for credit allocation check, i.e. to check whether they are cited adjacently or within the same parentheses. The co-citation reflects that the scientific community gives equal credit to twin papers by citing them together (Merton 1957). Below, we illustrate the robustness of our findings in case we use stricter criteria to identify paper twins.

Starting from the full sample of potential paper twins from Bikard (2020), we retain only those in which all authors are affiliated with universities or public research institutions, excluding any paper co-authored by individuals with corporate affiliations.[2] Following the identification approach of prior studies, we keep the subset of paper twins where a company patent is only citing a subset of the twin papers

[2] Affiliation data was collected and verified across three sources: Web of Science, PubMed, and the "MapAffil" dataset by Torvik (2021).

(Bikard 2018, Bikard and Marx 2020, Marx and Hsu 2022).[3] These criteria resulted in a sample of 247 simultaneous discoveries comprising 501 academic papers published between 1975 and 2007. Some papers were paired with multiple others, forming seven triplets.[4] The twin papers in our dataset are most often affiliated with universities such as Harvard, MIT, UC San Diego, and UC San Francisco, and are mostly published in top journals like *Nature*, *PNAS*, *Cell*, and *Science* (see Appendix Table A.1). The twin papers in our sample are highly similar, with a median publication gap of 2.5 months (average: 2.49) and a median PubMed rank difference of 3.5 (average: 6.27). Using SPECTER embeddings, we find a median cosine similarity of 0.92 (average: 0.89), confirming almost identical scientific content (Cohan et al. 2020). The median Jaccard index of shared citations is 0.55 (average: 0.57), and 81% (average: 76%) of citing papers mention both twins adjacently. Notably, 90 of the 247 twin papers were published back-to-back in the same journal issue, a common signal of simultaneous discovery.

Figure A.1 in the Appendix shows an example of a paper twin from our data. In 1998, two independent teams of academic scientists simultaneously discovered that the CD40 signal can activate killer immune cells independently of helper cells (Bennett et al. 1998, Schoenberger et al. 1998). Published back-to-back in *Nature*, these twin papers are ranked first in PubMed's list of most similar papers, with a cosine similarity of 0.97, indicating virtually identical content. Each paper has received over a thousand citations, and a 77% adjacent co-citation rate, reflecting equal credit allocation. This simultaneous scientific discovery was a breakthrough that paved the way for developing new vaccines and treatments for those with weakened immune systems, such as AIDS patients, and has potential applications in cancer treatment. The substantial commercial value is reflected in over 250 patents that cite these scientific publications. Among them, approximately 20% cite only the Schoenberger paper, 15% cite only the Bennet paper, and the remaining patents cite both.

3.3 Variables and estimation method

We identify all patent citations to twin papers from U.S. utility patents filed by firms between 1975 and 2009 (Marx and Fuegi 2020). Following our identification strategy, we include only cases in which a patent cites one (or a subset, in the case of triplets) of the twin papers. This design allows us to use the uncited twin paper to construct a counterfactual or "pseudo-citation" and estimate whether social distance between inventors and authors influences citation likelihood using conditional logit models. Because twin papers report essentially the same scientific discovery, inventors could, in principle, have cited either or both. U.S. patent law requires disclosure of all relevant prior art, and non-disclosure risks rejection or

[3] However, as we demonstrate later, our results remain consistent even when using the full sample, which includes company patents citing all papers from the same twin discovery.
[4] Triplets refer to a unique grouping of three papers conducted by independent research teams.

invalidation of the patent. It is therefore unlikely that inventors were aware of the uncited twin paper but deliberately chose not to cite it. Supporting this interpretation, Bikard and Marx (2020) conducted 21 interviews with inventors citing paper twins and found that inventors themselves—rather than patent attorneys or examiners—were usually responsible for adding references to scientific literature. The inventors emphasized that citations are driven more by their familiarity with specific papers than by legal necessity or an intention to cite all relevant prior art. Nevertheless, our results remain robust when we extend the analysis to include cases in which corporate patents cite all papers from the same twin discovery.

Our unit of analysis is a paper–patent dyad, encompassing both cited paper-patent dyads (real patent-to-paper citations) and uncited paper-patent dyads (counterfactual or pseudo patent-to-paper citations). Our final sample includes 247 academic paper twins, 501 papers, and 1,951 citing company patents. This results in 4,169 paper-patent dyads, of which 2,070 cited paper-patent dyads and 2,099 uncited paper-patent dyads. The academic twin papers are most frequently cited in patents from companies such as Genentech, Millennium Pharmaceuticals, Zymogenetics, and BASF Plant Science (see Table A.2 in the Appendix).

To study whether interpersonal networks bridge academic science and corporate technology, we follow the approach of Bikard (2018) and estimate the following conditional logit model with paper twin-patent level fixed effects:

$$cited_{ijk} = \alpha_0 + \alpha_1 * social_dist_{ik} + \alpha_2 * X_{ik} + \alpha_3 * Y_i + \gamma_{jk} + \varepsilon_{ijk}$$

In this model, $cited_{ijk}$ is a binary outcome variable equal to 1 in case paper *i* from paper twin *j* is cited by patent *k* and 0 in case patent *k* is not citing paper *i* but another paper of the same twin *j*. Our main explanatory variable is a count measure of $social_dist_{ik}$ which captures the shortest path, i.e. the minimum number of edges in the collaboration network, between any of the academic authors of paper *i* and any of the company inventors of patent *k.* In a small percentage of the paper-patent dyads (1.7%), there is no connection between any of the inventors and authors and $social_dist_{ik}$ has a missing value. In these cases, we assign a value of 9 as 8 is the maximum observed value in our dataset. Nevertheless, we find consistent results dropping observations with missing values from the analysis. To avoid imposing a linear functional-form assumption, we also use a series of binary indicators to capture social distance. For instance, *social_dist_0* is a binary indicator equal to 1 if the shortest path is 0, i.e. an author of paper *i* is the same person as an inventor of patent *k*. As another example, *social_dist_1* is a binary indicator equal to 1 if the shortest path is 1, i.e. an author of paper *i* is a direct prior collaborator of an inventor of patent *k*.

To test the interaction effect outlined in *Hypotheses 2*, we first assess whether corporate inventors listed on a patent are actively engaged in scientific research at the time of patent filing. We define a binary variable, *active_inventor_author*, which equals one if any co-inventor of a patent has published a

scientific paper in the year preceding the patent's filing.[5] As discussed below, we control for the team's overall prior patenting and publishing to ensure that the *active_inventor_author* variable captures simultaneous engagement in scientific research during corporate technology development. To examine how corporate inventors' active engagement in scientific research enables them to leverage interpersonal connections with academic scientists, we introduce an interaction term between *social_dist* and *active_inventor_author* in our model.

To examine the interaction effect proposed in *Hypothesis 3*, we measure the degree to which corporate inventors' scientific expertise aligns with the academic research they build upon. To quantify this alignment, we compute SPECTER embeddings for each paper based on its title and abstract and calculate the cosine similarity between corporate inventors' prior publications and the academic twin papers. At the twin-patent level, we take the maximum of these pairwise similarity scores as a proxy for inventors' familiarity with the academic twin discovery. We then define a binary variable, *close_paper*, set to one if this similarity measure exceeds the median value in our dataset.[6] Finally, to evaluate whether closely related scientific expertise enhances corporate inventors' ability to leverage interpersonal connections with academic scientists, we incorporate an interaction term between *social_dist* and *close_paper* in our model.[7]

Turning to control variables, we note that although twin papers capture nearly identical scientific findings, they remain distinct publications authored by different teams. The characteristics at both the paper and team levels may affect the likelihood of a paper being cited by a corporate patent. To account for this, Y_i in the model above represents a vector of paper-level control variables that might influence the likelihood that paper *i* is cited by patent *k*. We include *no. authors* (number of authors on the paper), *degree3_size* (number of individuals within 3 degrees of separation of the paper's authors up to the year of patent filing, i.e. to control for the size of the authors' social network), *author-inventor team* (binary indicator equal to 1 if at least one of the paper's authors is an author-inventor at the patent filing year), *publication stock* (number of unique PubMed papers published by any of the paper's authors up to the

[5] We find consistent results when defining *active_inventor_author* as equal to one if any co-inventor of a patent has published a scientific paper within the two years preceding the patent's filing. However, the results lose significance when we define *active_inventor_author* based on any prior publication, regardless of timing. This supports the notion that corporate inventors must be actively engaged in scientific research at the time of patenting to benefit from network ties to academic scientists. As illustrated later, we also find consistent results when using the count measure of prior publications instead of a binary indicator.
[6] For ease of interpretation, our main specification uses a binary indicator. As illustrated later, we find consistent results when using the raw similarity measure between any of the corporate inventors' prior scientific papers and each of the twin papers, instead of a binary indicator.
[7] Alternatively, one might argue that the effect of social distance varies with the substantive relevance of the cited paper to the patent. To assess this, we computed embedding vectors for every patent and twin paper and calculated the cosine similarity between them. We then split the sample at the median similarity and re-estimated our main model separately for patents that are more versus less similar to the twin papers. Consistent with the idea that interpersonal ties matter more when the scientific prior art is more peripheral, the estimated effect of social distance is larger in the low-similarity subsample, although the difference is not statistically significant at conventional levels.

patent filing year), *patent stock* (number of unique patents by any of the paper's authors up to the patent filing), *institutional prestige* (number of unique PubMed papers linked to individuals with the same affiliations as the authors on the focal paper up to the year of patent filing), *U.S. based* (binary indicator equal to 1 if any affiliation of the authors on the focal paper is in the U.S.), *journal impact factor* (journal impact factor of the paper in year of publication), *journal commercial impact factor* (journal commercial impact factor of the paper in year of publication, available from Bikard and Marx (2020)), *paper citations* (number of times the focal paper is cited by other papers up to the year before patent filing), *patent citations* (number of times the focal paper is cited by patents up to the year before patent filing), and *published first* (binary indicator equal to 1 if the focal paper is published earlier or on the same day as the twin paper(s)). Prior work illustrates that scientific papers with more details and clarity are more likely cited in corporate patents (Bikard 2018). Therefore, we control for both *text length* (number of words in title and abstract) and *readability* (Gunning-Fog Index, calculated by considering the average number of words per sentence and the proportion of complex words with three or more syllables) (Hengel 2022). The control variable *patent citations* captures citations received by the focal paper from prior patents and as such could perhaps control for any remaining unobserved paper-level heterogeneity that affect the likelihood that the paper is cited in a patent.[8]

In addition to paper-level control variables, X_{ik} represents a vector of control variables at the paper-patent dyad level. We control for *time lag* as the number of days between the publication date of the paper and the filing date of patent, and for *min geographic distance* as the minimum distance in miles between any of the author(s) of the paper and any of the inventor(s) of the patent.

Finally, γ_{jk} accounts for fixed effects at the paper twin-patent level, effectively controlling for any unobserved heterogeneity present either at the level of the paper twin or the patent. This inclusion is crucial as it controls for several factors, including the nature and commercial potential of the scientific discovery, the specifics of the patented technology, as well as the characteristics of the company and the team of inventors behind the patent. Table 1 presents a detailed overview and definitions of all the variables.

'Insert Table 1'

To illustrate our empirical approach, consider the case of the CD40 academic twin discovery, which uncovered how CD40 signaling activates the immune system—a critical scientific insight that enabled the development of vaccines and immunotherapies targeting immune deficiencies. Building on this scientific discovery, Pfizer and Abgenix patented antibodies designed to activate CD40 to enhance immune responses (see US7288251, titled "Antibodies to CD40"). Nevertheless, the patent cites only

[8] Nevertheless, all findings remain consistent if we estimate the regressions without controlling for *paper citations* and *patent citations* (results available from the authors).

Bennett et al. (1998) and not Schoenberger et al. (1998), who made essentially the same scientific discovery at the same time.

'Insert Figure 1'

Figure 1 visualizes the social network connecting the corporate inventors named on the patent with the academic authors of both the cited and uncited twin papers. Each node represents an individual: red triangles indicate those who only publish, yellow dots those who only patent, and green squares those who do both. Corporate inventors on the citing patent are denoted by black light bulb icons; academic authors of the cited paper are marked with checked drawing board symbols, while academic authors of the uncited paper are marked with unchecked drawing board symbols. Edges represent co-authorship and/or co-inventorship ties up to 2002, the year the patent was filed. As shown in the figure, Ronald P. Gladue, a corporate inventor at Pfizer, had a prior co-authorship with Richard A. Flavell, an immunologist at Yale University and co-author of the cited Bennett et al. paper. This direct interpersonal tie (a shortest path of one) likely facilitated the transfer of knowledge from academia into corporate innovation. In contrast, the authors of the uncited twin paper by Schoenberger et al. (1998) were only indirectly connected to the corporate inventors, with a shortest path of two. Given that both papers reported essentially the same scientific discovery, the fact that only Bennett et al. (1998) was cited suggests that social proximity—rather than differences in content or commercial potential—may have influenced whether corporate inventors became aware of and built on a particular academic discovery.

4. Results

4.1 Summary statistics

Table 2 presents descriptive statistics comparing academic papers cited by company patents with their uncited twin counterparts. The analysis reveals no significant differences in team characteristics. The only notable exception is that cited papers tend to have authors with more prior patents, suggesting corporate inventors may pay more attention to research from academic scientists with stronger patenting track records. Similarly, cited and uncited papers do not differ significantly in paper characteristics.

'Insert Table 2'

Table 3 presents descriptive statistics at the paper-patent dyad level, comparing cited and uncited dyads. As expected, corporate inventors are socially closer to the academic authors of cited papers than to those of uncited ones: the average social distance is 2.75 for cited dyads versus 2.83 for uncited. Cited dyads are significantly more likely to have a shortest path of 0 or 1, indicating a direct or former direct collaboration tie. Notably, 2.8% of cited dyads exhibit a social distance of 0, in stark contrast to only 0.4% in uncited dyads. A zero-distance link reflects a direct connection where at least one corporate inventor is also an author of the cited academic paper. This overlap likely results from career mobility, as many PhD-

trained academic scientists in life sciences transition into industry (Sauermann and Roach 2012), especially given the average twelve-year gap between paper publication and patent filing. Alternatively, these individuals may retain academic positions while contributing to industrial R&D through consulting, contract research, or part-time roles. An additional 6.3% of cited dyads involve a prior co-authorship (distance = 1), versus 4.3% of uncited dyads—a pattern illustrated in Figure 1 by the connection between Ron Gladue (Pfizer) and Richard Flavell (Yale). In contrast, uncited dyads are more often connected at a distance of two or greater, though these differences are not always statistically significant. Overall, these findings suggest that closer interpersonal ties between corporate inventors and academic scientists increase the likelihood of knowledge transfer from academia to industry.

While prior research has primarily focused on direct collaborations between corporate inventors and academic scientists, these cited paper–patent dyads indicate that current or former direct collaboration ties (i.e., social distance of 0 or 1) account for only a small share of citations, approximately 3% and 6%, respectively. In contrast, indirect ties are far more common: 26% of citations occur at a social distance of 2, and 53% at a distance of 3. While we cannot assess the magnitude of influence (i.e., whether direct collaborators facilitate greater amounts of total knowledge transfer), these findings suggest that academic knowledge transfer to industry primarily occurs through indirect interpersonal ties, which may expose corporate inventors to a broader and more diverse set of academic insights beyond the naturally restricted set of scientific findings produced by current or former collaborators. We confirm the external validity of this finding using a random sample of corporate patent-to-academic paper citations for non-twin papers.[9]

'Insert Table 3'

4.2 Main effect of interpersonal connections

Table 4 presents our main results using binary indicators for social distance, with *social_dist_0* as the reference category. Model 4-1 includes controls only and Model 4-2 tests our main hypothesis. Consistent with *Hypothesis 1*, we find that corporate technology is significantly more likely to build on academic science when inventors are more closely connected to the academic authors through shorter interpersonal ties. The social distance indicators are jointly significant at $p<0.01$ (chi2(5)=36.10).

'Insert Table 4'

To quantify effect sizes, we calculate the predicted probability of citation at varying levels of social distance using the method of King et al. (2000). Figure 2 shows the results. When social distance is 0—i.e., an inventor is also a co-author of the cited paper—the predicted probability of citation is 68%.

[9] We selected a random sample of 10,000 patent-to-paper citations from Marx and Fuegi (2022). As in our main analysis, we calculated *soc_dist* as the shortest path between any inventor on the citing corporate patent and any academic author of the cited paper. The distribution of *soc_dist* in this random sample is similar the one based on corporate patent-to-academic twin paper citations. Once again, direct and former direct connections (*soc_dist* = 0 and 1) account for only a small fraction of all citations—3% and 6%, respectively, similar to our sample. In contrast, indirect connections play a significantly larger role: *soc_dist* = 2 represent 22% of all citations, while those at a distance of 3 constitute 43% of all citations

This predicted probability falls to 52% (a 24% relative decrease) at a social distance of 1 (prior collaborator), and to 43% (a 37% relative decrease) at a distance of 2 (indirect link). At social distances of 3, 4, and 5 or more, the probability of citation further declines to 38%, 38%, and 34% (relative decreases of 44%, 44% and 50%), respectively. These results reveal a clear and monotonic decline in citation probability as social distance increases, underscoring the importance of close interpersonal ties in enabling knowledge transfer from academia to industry.

'Insert Figure 2'

Furthermore, the binary indicators for social distances of 0, 1, and 2 (*social_dist_0*, *social_dist_1*, and *social_dist_2*) are each statistically distinct from one another and from all higher-distance indicators (*social_dist_3*, *social_dist_4*, and *social_dist_5_or_more*). In contrast, the indicators for social distances of 3, 4, and 5 or more do not differ significantly from one another. These results point to a clear threshold in the effectiveness of interpersonal networks: while indirect ties up to two degrees of separation facilitate knowledge transfer, their influence becomes insignificant beyond that point.

'Insert Table 5'

Table 5 replicates Table 4 but replaces the binary indicators for social distance with a count measure (*social_dist*). Across all models, *social_dist* is statistically significant at $p<0.01$. A one-unit decrease in social distance—representing one fewer intermediary between academic authors and corporate inventors—is associated with a substantial increase in the average probability of citation of 8% to 13% (models 5-2 to 5-8). Given a baseline citation probability of roughly 50%, these effects correspond to a relative increase of approximately 16% to 26%.

Table A.3 in the Appendix presents results by firm type. Patents are categorized by assignee, including U.S. public firms, startups (3, 5, or 10 years old or younger at the time of patent filing), and firms with above- or below-median patent stocks (median = 560). Across all firm types, *social_dist* remains statistically significant at $p<0.01$, with no substantial variation in effect size.[10] However, the effect appears somewhat stronger for startups compared to older firms. Science-based startups often originate in academia, with many—especially in biotechnology and pharmaceuticals—founded by former university scientists or emerging directly from academic laboratories (Zucker et al. 1998). These startups typically rely heavily on external scientific knowledge from academia, making interpersonal networks particularly critical for accessing and integrating frontier knowledge that would be difficult to generate internally.[11]

[10] In some smaller subsamples, the limited number of observations where certain binary indicators for social distance (specifically *social_dist_0*, *social_dist_1,* and *social_dist_5_or_more*) equal one reduces the precision of estimates. To address this, we use a count-based measure of social distance as the main specification.

[11] We also examined whether the effect of social proximity changed over time by interacting social distance with year dummies or five-year windows. Across all specifications, none of the interaction terms were statistically significant, suggesting no meaningful temporal change in the effect of social proximity over our observation window.

4.3 Endogenous formation of interpersonal connections

In line with prior work, we do not model the endogenous formation of co-author teams on papers or patents, treating the resulting interpersonal network ties as exogenous (e.g., Singh 2005, Bikard et al. 2019, Marx and Hsu 2022).[12] This assumption could lead to an overestimation of causal effects, if corporate inventors and academics formed interpersonal ties with the expectation of knowledge transfer. However, in our data, the average social distance in patent-to-paper citations is three degrees, meaning corporate inventors typically cite an academic collaborator of their collaborator's collaborator. If ties were endogenously formed to enable knowledge transfer, we would expect much shorter average social distances—that is, inventors would form direct or very close indirect ties specifically to gain access to knowledge. This interpretation is further supported by our finding that a social distance of three does not significantly influence knowledge transfer. In addition, the average patent in our sample cites 87 academic papers authored by 325 unique academic scientists and is co-invented by only four individuals, making it highly unlikely that all citations result from intentional tie formation with these academic scientists.

Nevertheless, to empirically test whether our results are driven by the endogenous formation of ties to enable knowledge transfer, we exclude observations where academic scientists and corporate inventors have direct or former direct connections, as these are more likely to reflect deliberate efforts to establish such ties. First, we omit observations with direct collaborations (*soc_dist* = 0).[13] Reassuringly, results remain consistent (Table 4, Model 4-3; Table 5, Model 5-3). The findings also hold when excluding both direct and prior direct ties (*social_dist* = 0 or 1; Table 4, Model 4-4; Table 5, Model 5-4). As expected, the effect size of *social_dist* decreases but remains large and statistically significant ($p<0.01$). A one-unit decrease in social distance increases the probability of citation by approximately 13% in the full model, by 12% when excluding social distance = 0, and by 8% when excluding social distances 0 and 1.

As an additional check, we recalculate social distance using only co-authorship ties formed *before* the publication of the twin papers, excluding all ties created during the 12-year average lag between paper and patent. This approach, by design, eliminates interpersonal ties formed after the academic twin discovery—ties that might have been intended to facilitate knowledge transfer and support the commercial exploitation of the academic discovery. The effect remains strong and significant at $p<0.01$ and similar in magnitude (Table 5, Model 5-6), with a one-unit decrease in *social_dist* increasing citation probability by

[12] Please note that other streams of research have modeled the formation of collaborative teams (Boudreau et al. 2017, Vakili et al. 2022).

[13] Collecting data on patent–paper pairs from Marx and Scharfmann (2024), we find that fewer than 1% of all paper–patent dyads in our sample represent such pairs. All findings remain consistent after excluding these observations from the analysis (results available upon request from the authors).

11% compared to a 13% increase using the standard social distance measure incorporating interpersonal ties up to patent filing. Due to the 12-year average lag between paper publication and patent filing, 30% of paper–patent dyads involve inventors or authors with no publications or patents prior to the twin papers' publication, and hence result in missing values for *social_dist* in this subsample.[14] The limited number of non-zero observations for certain binary indicators of social distance makes precise estimation difficult. To address this, we use the count-based measure of *social_dist* as the primary specification (Table 5, Model 5-6). As shown in Table 4, Model 4-6, our results remain robust when using binary indicators for social distance, with the exception that *social_dist_1* is no longer statistically distinguishable from *social_dist_2* and *social_dist_3* at conventional levels—unsurprising given the small number of dyads at distance 1 when restricting to co-authorship links formed before the twin papers' publication.

As a final check for endogenous tie formation, we manually identify and exclude twin papers that acknowledge any form of corporate support or funding, including direct financial support, provision of research materials or tools, or acknowledged support from individuals with a corporate affiliation. The results remain unchanged (Table 4, Model 4-7; Table 5, Model 5-7). Together, these checks suggest that our findings are unlikely to be driven by the intentional formation of interpersonal ties to enable knowledge transfer from academia to industry.

4.4 Corporate inventors' scientific expertise and active engagement in scientific research

Having established the role of social proximity in enabling corporate inventors to build on academic science, we next examine whether inventors' personal absorptive capacity conditions this effect. Specifically, we test whether active engagement in scientific research and alignment of scientific expertise strengthen the impact of social proximity on the use of academic science.

To test *Hypothesis 2*, we extend Model 5-2 by including an interaction term (*social_dist* × *active_inventor_author*). Note that the main effect of *active_inventor_author* is absorbed by the patent-level fixed effects and cannot be separately estimated. As shown in Table 7, Model 7-2, the interaction term is highly significant ($p<0.01$), while the main effect of *social_dist* becomes insignificant and drops sharply (from –0.957 to –0.068). For corporate teams without inventors active in scientific research, a one-unit decrease in *social_dist* yields a statistically insignificant 1% increase in the probability of citation. In contrast, for teams with active inventor-authors, the same one-unit decrease in *social_dist* increases the probability of citation by 15%, an effect significant at $p<0.01$. Table A.4 in the appendix replicates all robustness checks from Table 5, confirming the stability of the interaction effect between *social_dist* and

[14] Consistent with our approach to handling missing values, we impute these as the maximum observed social distance plus one (i.e., 9). Reassuringly, when excluding these observations entirely from the analysis, the findings are nearly identical: a one-unit decrease in *social_dist* is associated with a 12.72% increase in the probability of citation when imputing, compared to 12.63% when dropping the observations from the analysis.

active_inventor_author.[15] As an additional robustness check, column 11 in Table A.4 uses a more granular count measure rather than a binary indicator, calculating *active_inventor_author* as the number of unique scientific papers published by any co-inventor of a patent in the year preceding the patent's filing. Together, these findings indicate that corporate inventors are better able to leverage interpersonal ties to academic scientists when they are actively engaged in scientific research. Absent such active engagement, social connections are unlikely to translate into effective integration of academic insights into corporate technology.

'Insert Table 7'

To test whether closely related scientific expertise enables corporate inventors to more effectively leverage interpersonal connections with academic scientists (*Hypothesis 3*), we introduce an interaction term (*social_dist* × *close_paper*) in Model 7-3 of Table 7. While the main effect of *close_paper* is absorbed by the patent-level fixed effects, its interaction with *social_dist* is highly significant ($p<0.01$). Including this interaction substantially reduces the magnitude of the *social_dist* coefficient (from -0.957 to -0.376). Among inventor teams lacking closely related scientific expertise (*close_paper* = 0), a one-unit decrease in social distance increases the probability of citation by 5%. In contrast, for teams with closely related expertise (*close_paper* = 1), the same decrease results in a 17% increase in probability of citation. Table A.5 replicates all robustness checks from Table 5, confirming the stability of this interaction effect. As an additional check, column 11 in Table A.5 uses a more granular continuous measure rather than a binary indicator, calculating *close_paper* as the maximum cosine similarity between any of inventors' papers published before the patent filing year and any of the twin papers. These findings underscore that the ability to absorb external academic knowledge through interpersonal connections is strongly shaped by the inventors' own scientific expertise and background knowledge.

In Model 7-4, which includes both interaction terms, both remain statistically significant ($p<0.01$ and $p<0.05$), while the main effect of *social_dist* becomes insignificant. The three terms are jointly significant at $p<0.01$. Taken together, these results indicate that both active engagement in science and having closely related scientific expertise are critical for corporate inventors to fully benefit from their interpersonal ties to academia, enhancing their ability to access and integrate external scientific knowledge into technology development.

4.5 Robustness checks

Our findings are robust for the subsample of patent to paper citations that appear in the body text of the patent, excluding those citations only listed on the front page (Table 4, Model 4-8; Table 5, Model 5-8).

[15] The only exception is that the interaction effect *social_dist_time* × *active_inventor_author* is observed at p = 0.104 in Column 10, falling slightly outside conventional significance thresholds.

In-text citations are more likely included by the inventors themselves, perhaps providing a more accurate insight into academic knowledge transfers to corporate inventors (Bryan et al. 2020). Our findings also remain robust when we expand the sample to include all instances where a corporate patent cites every paper from the same twin discovery, rather than only a subset as in our previous analysis (Table 4, Model 4-9; Table 5, Model 5-9).

While our measure of social distance does not account for tie decay, one could argue that more recent interpersonal ties facilitate knowledge transfer more effectively than older ones (Hansen 1999). To address this, we introduce a time-weighted measure of social distance, *soc_distance_time*, which prioritizes the shortest paths between academic authors and company inventors while incorporating the recency of their collaborations (Wasserman and Faust 1994). This approach ensures that more recent collaborations contribute less to the overall path length compared to older ties, thereby emphasizing the temporal relevance of connections. The exact calculation is detailed in Table 1. As shown in model 5-10 of Table 5, our findings remain robust. A unit decrease in *soc_distance_time*—indicating a more recent tie and/or a shorter path between academic scientists and corporate inventors—increases the probability of citation by 3%. Figure A.2 displays the predicted probability of citations for different values of *soc_distance_time.*

'Insert Table 6'

Table 6 presents additional robustness checks related to the criteria used to identify paper twins and the sample of corporate patents included in the analysis. In certain smaller subsamples, the small number of observations where some binary indicators for social distance equal one makes obtaining accurate estimates challenging. Consequently, we utilize the count measure for social distance as our main specification. Nevertheless, we find qualitatively similar results using binary indicators for social distance as shown in Table A.6.[16] Model 6-1 excludes observations linked to higher order twins, i.e. triplets. Model 6-2 is confined to twin papers published within a three-month instead of a one-year window. Model 6-3 includes only twin papers with a very high degree of content similarity, defined as having a cosine similarity score above 0.9. In Model 6-4, we focus on twin papers that each rank first on PubMed's list of most similar papers to one another. Model 6-5 runs the analysis based on the subset of twin papers that are published back-to-back in the same journal, volume and issue. Model 6-6 selects twin papers cited adjacently 100% of the time, indicating they are always mentioned together in the references of other papers. Model 6-7 excludes papers authored by large teams, specifically those with more than five authors. Model 6-8 removes papers that were highly cited before the patent filing, specifically those with over 1,000 citations. Model 6-9 disregards observations linked to the two companies most frequently

[16] Please notice that estimations for the subsamples of twins with PubMed rank order=1 or published back-to-back did not converge because of insufficient observations for some of the different binary categories of social distance.

listed as patent assignees in our dataset, Genentech and Millennium Pharmaceuticals. Despite the very large differences in the composition of the different subsamples, we find consistent results: *social_dist* is always statistically significant at $p<0.01$, and the probability of citation increases between 12% and 17% with each unit decrease in social distance.

4.6 Characterizing corporate inventors with ties to academia

Our empirical identification strategy estimates the effect of social proximity while controlling for unobserved heterogeneity at the patent level. The inclusion of patent fixed effects absorbs any time-invariant characteristics of the patented technology, the firm, and the team of corporate inventors. Even so, better understanding who the corporate inventors are that most directly bridge academic science and corporate technology remains important. Building on the above results, we therefore examine the characteristics and career trajectories of two groups of inventors: (i) those on corporate patents who hold the closest interpersonal ties to the academic authors of the cited paper, and (ii) those who actively engaged in scientific research (active inventor–authors). Using the full publication and patent histories of all corporate inventors,[17] we reconstruct prior affiliations, scientific and inventive output, and broader career trajectories for each inventor.

Table A.7 in the Appendix reveals clear differences between inventors with the shortest interpersonal ties to cited academic authors and other inventors on the same corporate patents without shortest ties. Socially proximate inventors are substantially more likely to have past and recent affiliations with universities or public research institutes, including shared affiliations with the authors of the cited papers. They also exhibit stronger scientific engagement: they began publishing earlier, have larger cumulative publication records, and remain more active in recent scientific publishing, and show higher recent patenting activity. Finally, they have a more extensive collaboration network, with a substantially larger number of inventors, authors, and inventor–authors within three degrees of separation. Taken together, these patterns indicate that socially proximate inventors are those with more recent and overlapping academic affiliations, longer scientific publishing experience, greater recent scientific and inventive activity, and markedly larger collaboration networks—features that position them especially well to bridge academic science and corporate technology.

[17] Affiliation data from publications and patents are imperfect and may contain noise or omissions, especially for older records. In scientific publications, such errors are more common because papers often involve many co-authors with multiple affiliations, and automated parsing can incorrectly assign institutional affiliations to specific authors. One alternative would be to use LinkedIn to trace inventors' career histories, but this source is incomplete for our study period. In a manual check of 20 randomly selected inventors, 30% had no LinkedIn profile, and 35% of those with a profile omitted key prior affiliations or positions that we could verify through other sources. As a result, LinkedIn does not provide sufficiently comprehensive or reliable coverage for our purposes. Our findings should therefore be interpreted with appropriate caution regarding likely measurement noise in affiliation histories.

In parallel, Table A.8 in the Appendix compares corporate inventors who were actively publishing in the year before patent filing with those who were not. Actively publishing inventors display a distinct profile: they are substantially more likely to have recent and past affiliations with universities or public research institutes—including shared affiliations with the cited academic authors—and they exhibit markedly higher scientific and inventive output. They also tend to have significantly larger collaboration networks. Taken together, these patterns indicate that inventors who continue to publish while working in industry remain more academically embedded and have broader collaborative reach.

4.7 Comparing the effect of interpersonal connections on science-to-science versus science-to-technology knowledge transfer

As theorized and empirically demonstrated in this paper, accessing and integrating scientific findings into corporate technology depends on close interpersonal connections between corporate inventors and the academic scientists who produced those scientific discoveries. A remaining question, however, is whether interpersonal proximity operates differently for science-to-technology knowledge transfer (our focal context) than for science-to-science knowledge transfer (Balsmeier et al. 2025). To examine this, we replicate our empirical strategy using paper-to-paper rather than patent-to-paper citations to the same set of twin papers. We construct a dataset of PubMed articles published between 1975 and 2009 that cite exactly one (but not all) of the papers in a twin. Following the same identification approach as in the patent-to-paper analysis, each citing paper is paired with both the cited and the uncited twin paper, yielding a matched set of cited and uncited paper–paper dyads. For each dyad, we compute the shortest path between the authors of the citing paper and the authors of respectively the cited and uncited twin paper using the same integrated author–inventor collaboration network as before. The resulting dataset contains 221 paper twins (448 twin papers), 21,571 citing papers, and 44,220 paper–paper dyads, including 22,069 cited dyads and 22,151 uncited dyads.

Table A.9 presents descriptive statistics at the paper–paper dyad level, comparing cited and uncited dyads, parallel to the descriptive statistics for patent-paper dyads in Table 3. Consistent with the patent-to-paper patterns, authors of citing papers are socially closer to the authors of the cited twin paper than to the authors of the uncited one, indicating that interpersonal proximity also shapes science-to-science knowledge transfer. As expected, authors of citing papers are typically more closely connected to the authors of the cited paper than citing corporate inventors are to the cited authors. In the paper-to-paper data, 59.2% of dyads have a social distance of two or less, whereas in the patent-to-paper setting only 34.8% of dyads fall within the same range. This difference underscores that interpersonal proximity is naturally stronger within the academic community than across the boundary between academia and industry.

Table A.10 replicates our conditional logit analysis using paper-to-paper citations in line with the analysis for patent-to-paper citations in Table 5. Across all models, *social_dist* is statistically significant at $p<0.01$. A one-unit decrease in social distance—representing one fewer intermediary in the interpersonal network—is associated with an increase in the probability of a paper-to-paper citation of 9% (Table A.10 column 2) while a one-unit decrease in social distance was associated with an increase in the probability of a patent-to-paper citation by 13% (Table 5 column 2). A formal test of coefficient differences confirms that the effect of *social_dist* is statistically stronger for patent-to-paper than for paper-to-paper citations ($z = -3.08$, $p = 0.002$). Moreover, the pseudo-R^2 is much smaller for paper-to-paper citations (0.112 for Table A.10 column 2 versus 0.396 for Table 5 column 2), suggesting that interpersonal proximity explains substantially less variation in science-to-science knowledge transfers.

Together, these results show that translating scientific discoveries into technological inventions is more sensitive to interpersonal proximity than science-to-science knowledge transfer. This aligns with our theoretical argument that science-to-technology transfer requires bridging significant cognitive and institutional boundaries, making close interpersonal ties disproportionately important for recognizing, interpreting, and applying academic insights in the development of corporate technology. Overall, while interpersonal networks facilitate knowledge diffusion in both domains, they matter more for science-to-technology transfer, underscoring the distinctive challenges firms face in accessing and integrating academic knowledge.

5. Discussion and Conclusion

Scientific research fuels technological progress in industry, yet essential scientific knowledge increasingly originates from outside the firm, in universities and public research labs. This shift raises a critical question: how can firms effectively identify and utilize external academic knowledge that is often complex, tacit, and dispersed? Our study highlights the combination of interpersonal networks between corporate inventors and academic scientists and personal absorptive capacity of inventors in facilitating this transfer. By leveraging nearly identical scientific discoveries published by separate academic teams and examining how they are incorporated into corporate technology, we isolate the influence of interpersonal connections from the content and commercial potential of scientific discoveries.

Our findings indicate that while firms employ both direct and indirect connections to access scientific insights from academics, and more direct ties are more effective at transferring insights, a greater number of knowledge transfers occur through the greater volume of indirect ties. Consistent with network theory, we also observe sharp limits to the reach of these networks. Beyond a social distance of two degrees—between a corporate inventor and an academic linked through a mutual collaborator—the network effect dissipates. Moreover, aligning with theory on individual-level absorptive capacity, the

ability of inventors to leverage their social proximity to academics hinges on their personal involvement in scientific research and the alignment of their scientific expertise to the academic knowledge they aim to integrate. Replicating our design using paper (rather than patent) citations to the same twin papers, we find that interpersonal proximity also shapes science-to-science knowledge transfer, but significantly less so—underscoring that close ties are most consequential when scientific knowledge is translated into corporate technology.

Our study faces several limitations. First, relying on patent citations to academic papers captures only a subset of the scientific knowledge relevant for technological development. Yet, surveys suggest such citations correlate with managers' reports of leveraging academic research (Roach and Cohen 2013) and reflect inventors' awareness of the papers (Bikard and Marx 2020). Unlike patent references, most citations to scientific papers are added by inventors rather than examiners, making them more reliable indicators of knowledge transfer (Marx and Fuegi 2020). Moreover, paper twins represent only a non-random subset of academic work. Also, we construct interpersonal networks using co-authorship links and advance this line of research by leveraging a new dataset that captures all co-authorships on both patents and papers from PubMed and U.S. patents, while also providing a structured crosswalk between the two. However, our approach potentially does not capture interpersonal ties formed through other channels, such as conferences, workshops, or industry meetings (Baruffaldi and Poege 2025).

Relatedly, while our analysis documents a strong association between interpersonal proximity and the transfer of scientific knowledge, our large-scale data cannot capture the micro-level processes through which such ties operate—such as informal conversations, advice seeking, or collaborative problem-solving. We conceptualize interpersonal networks not as direct conduits of knowledge transmission but as enablers of complementary processes: they raise awareness of relevant scientific advances, build trust in their validity, facilitate their interpretation and translation into a corporate context, and bridge institutional and cognitive boundaries. Our findings should therefore be interpreted as capturing the enabling role of interpersonal connections within a broader, multifaceted process of knowledge transfer, rather than as evidence of a single, straightforward causal pathway. Future research that complements our large-scale quantitative approach with qualitative or survey evidence could help unpack these micro-level dynamics in greater depth.

Furthermore, our study focuses on the life sciences, where science–industry linkages are particularly strong. The extent to which our findings generalize to other fields therefore remains an open question. We expect interpersonal proximity to matter most when scientific knowledge is tacit, complex, or rapidly evolving, when academic research is a key input to technological development, and when cross-sector mobility and collaboration are common. These conditions characterize the life sciences but are less typical in domains such as mechanical engineering, where R&D is more internally oriented and science–

technology linkages are weaker (Cohen et al. 2002). The role of interpersonal networks should diminish in settings where scientific knowledge is highly codified, standardized, or embedded in more mature technologies. At the same time, the life sciences account for roughly one-third of global scientific output (National Science Board 2023) and a disproportionately large share of science-to-technology flows, underscoring the relevance and value of our setting. Future comparisons across fields could further refine these boundary conditions.

Also, corporate inventors who possess greater skills or better recognize the potential benefits are perhaps more likely to form interpersonal ties that allow them to occupy valuable network positions and act as cross-institutional boundary-spanners within the social network (Lee 2010). Yet, our analysis controls for any unobserved heterogeneity at the patent level and thus for the corporate inventors on the patent. For academic scientists, our estimations control for various characteristics that might confound the influence of interpersonal connections on knowledge transfer, such as their stock of prior patents and papers, the size of their social network, and the prestige of their academic institution.

Finally, we lack exogenous variation in social proximity, corporate inventors' engagement in scientific research, and their scientific expertise. Several robustness checks—such as excluding direct or prior collaborations and measuring social proximity before the scientific discovery—suggest that endogenous tie formation is unlikely to drive our results. Nonetheless, as with any observational design, we cannot fully rule out all alternative explanations, and our findings should therefore be interpreted with this uncertainty in mind.

Within these limitations, our study advances theory and offers implications for practice. Adopting a micro-foundations perspective, we conceptualize firms' ability to benefit from academic science as an emergent outcome of individual inventors' social connections, active scientific engagement, and domain-specific scientific expertise. Building on this view, we contribute to the literature on how firms benefit from academic science by illuminating the social dimension of absorptive capacity—showing how interpersonal ties to academics enable corporate inventors to more effectively leverage external scientific knowledge. In doing so, we bridge network theory, which highlights the role of interpersonal connections—especially indirect ties—in accessing novel, tacit, and distributed knowledge, with absorptive capacity theory, which emphasizes how active scientific engagement and prior domain-specific scientific expertise enable individuals to recognize, assimilate, and apply external academic insights within corporate innovation.

While prior research has largely focused on direct interpersonal collaborations between firms and academia (Liebeskind et al. 1996, Cockburn and Henderson 1998, Zucker et al. 2002, Agrawal 2006), our study adopts a broader network perspective by analyzing the full interpersonal network structure that links corporate R&D staff to the academic community. Our findings highlight social proximity—up to two

degrees of separation—as a key mechanism enabling the transfer of academic knowledge to industry. Notably, direct collaboration ties to academic scientists represent the most effective conduit for knowledge transfer, yet account for only a small fraction—approximately 9%—of all observed transfers. In contrast, indirect ties at a social distance of two, where corporate inventors are connected to the academic scientist who made the scientific discovery only via a common collaborator, still significantly support knowledge transfer and account for nearly 26% of all observed transfers. These results resonate with network theory on the value of indirect or weak ties in accessing non-redundant, novel, and distributed knowledge not available through one's immediate circle (Granovetter 1973, Cowan et al. 2007). At the same time, our finding that indirect ties beyond two degrees of separation do not facilitate knowledge transfer aligns with Hansen's (1999) insight that weak ties may lack the relational strength or informational bandwidth required to transmit complex or tacit scientific knowledge. Future work should go beyond citations as a measure of knowledge transfer—for example, using text-based analyses to estimate finer-grained measures of knowledge flow—and thereby enable more precise comparisons of the volume of knowledge transferred through direct versus indirect ties.

Our work also extends prior research showing that interpersonal networks among academic scientists shape the transfer of scientific knowledge within academia (Mohnen 2022), as well as studies demonstrating how networks of corporate inventors facilitate the transfer of technical knowledge within and across firms (Singh 2005, Paruchuri and Awate 2017, Moreira et al. 2018). In contrast, we examine the transfer of scientific knowledge across the boundary between academia and industry, focusing on patent-to-paper citations as an outcome and using an integrated collaboration network that spans both academic scientists and corporate inventors. Whereas Singh (2005) found that even very distant indirect ties (four degrees or more) can facilitate technical knowledge diffusion between firms, we find that scientific knowledge transfer from academia to industry drops off sharply beyond two degrees—highlighting that translating academic knowledge into corporate innovation is perhaps more complex and demanding, relying on closer interpersonal ties. Our research also extends prior work that mapped collaboration networks linking academic scientists and corporate inventors (Balconi et al. 2004, Breschi and Catalini 2010, Lissoni 2010) by providing empirical evidence that these network configurations indeed enable the transfer of scientific knowledge from academia to industry.

Our findings also contribute to classic work on boundary-spanning individuals—those who serve as organizational gatekeepers by acquiring, translating, and integrating external knowledge (Allen 1977, Tushman 1977, Tushman and Scanlan 1981). In our context, corporate inventors who are simultaneously engaged in scientific research and commercial technology development fulfill this role. Prior research has shown that these dual-role inventors enhance firm innovation outcomes (Cockburn and Henderson 1998, Zucker et al. 2002, Gittelman and Kogut 2003), yet the mechanisms behind this effect remain

underexplored. Our study provides micro-level evidence that these individuals leverage their scientific expertise and academic ties to bridge the gap between scientific discovery and technological application. In line with theories of individual absorptive capacity (Ellis 1965, Cohen and Levinthal 1990) and boundary-spanning (Tushman and Scanlan, 1981), we find that only those inventors with active engagement in scientific research and closely aligned scientific expertise are able to effectively draw on interpersonal connections to absorb and apply academic knowledge. This dual requirement—scientific proximity and social proximity—appears essential to translate external academic discoveries into corporate innovation.

For managers and policymakers, our findings carry several implications. One is the importance of cultivating human bridges to academia, not just through direct collaborations but also indirect ties. Firms should recruit and develop R&D personnel who are fluent in the language of science—for example, PhD-trained researchers who continue to publish or collaborate with universities. These individuals not only bring their own scientific expertise, but also come with professional networks that can alert the firm to important scientific discoveries. The firm's culture should support their continued engagement with the scientific community (e.g. attending conferences, publishing) that builds connections, credibility, and absorptive capacity. Given the documented decline in firms' internal investments in scientific research and their reduced publication output (Arora et al. 2018), our findings underscore the risks of this trend. While reduced investment in scientific research may limit knowledge spillovers to competitors, it may inadvertently erode absorptive capacity, weaken interpersonal networks, and isolate the firm from the upstream scientific knowledge generation (Cockburn and Henderson 1998, Arora et al. 2021).

Second, our research challenges the notion of academic science as a purely public good that any firm can exploit equally without any restrictions or competition (Nelson 1959). In theory, once academic research is published, it's available. In practice, we find that firms with close social ties to the academics who made that scientific discovery gain a disproportionate advantage in using that research. This implies a form of natural exclusion—firms lacking those social connections may be left behind in leveraging science, which can lead to underutilization of academic science in industrial R&D. For managers, this underscores the value of investing in relationship-building with universities and participating in knowledge networks (e.g., industry consortia, research alliances, sponsoring conferences). For policymakers and university administrators, it suggests that simply publishing research is not enough to ensure broad dissemination (Mumtaz 2025). Facilitating industry–academia interactions (through joint workshops, researcher exchanges, or industry liaison programs) is vital so that valuable academic knowledge does not languish unused. Encouraging informal social networks, such as alumni networks and conference communities, can pay dividends by spreading know-how to where it can be applied. Our study focused on co-authorship ties as a measurable subset of relationships, but the benefits we observe likely

extend to other forms of professional connections and social capital (Baruffaldi and Poege 2025). Policies that encourage scientists to engage with industry (for instance, by valuing applied collaborations in academic promotion, or providing grants that require industry partners) could enhance these knowledge flows.

Lastly, our findings re-emphasize the importance of geographical proximity and cluster-based innovation policy in a new light. It has long been argued that colocation of firms near universities boosts knowledge spillovers (Zucker et al. 1998, Alcácer and Chung 2007). Our results provide a micro-mechanism for this: physical proximity fosters interpersonal ties between academics and corporate inventors—through chance meetings, local networks, repeated interactions—that in turn facilitate the transfer of the often tacit and complex scientific knowledge to industry. Thus, geographic clusters create fertile ground for the very social networks between academia and industry we find so critical. At the same time, social connections themselves may also shape where individuals and organizations choose to locate, suggesting a mutually reinforcing dynamic between geographic and social proximity. For both firms and policymakers, this means that investments in regional innovation hubs (incubators, science parks, joint research centers) are not just about infrastructure or formal partnerships, but about enabling the dense web of social connections through which knowledge truly flows.

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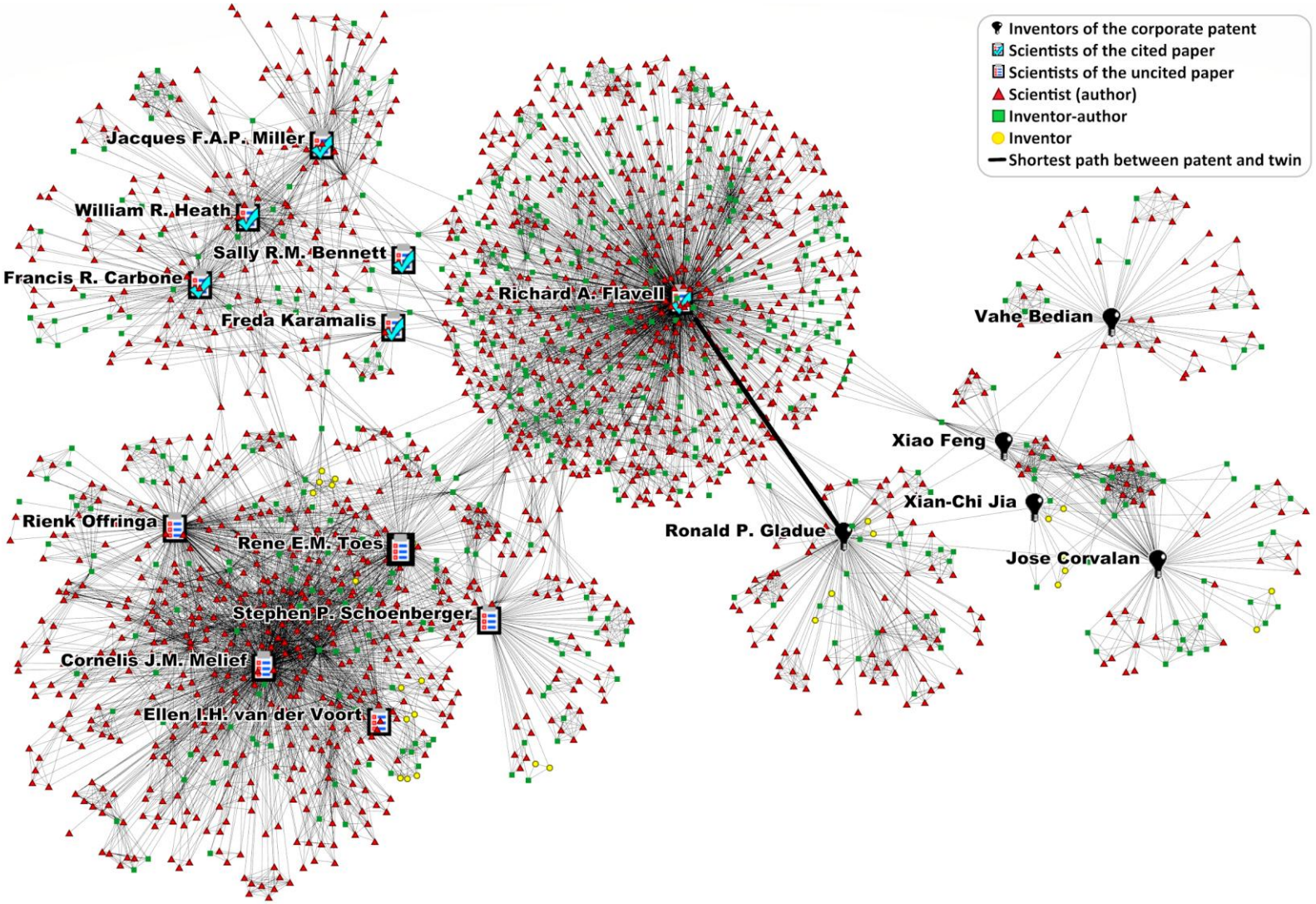
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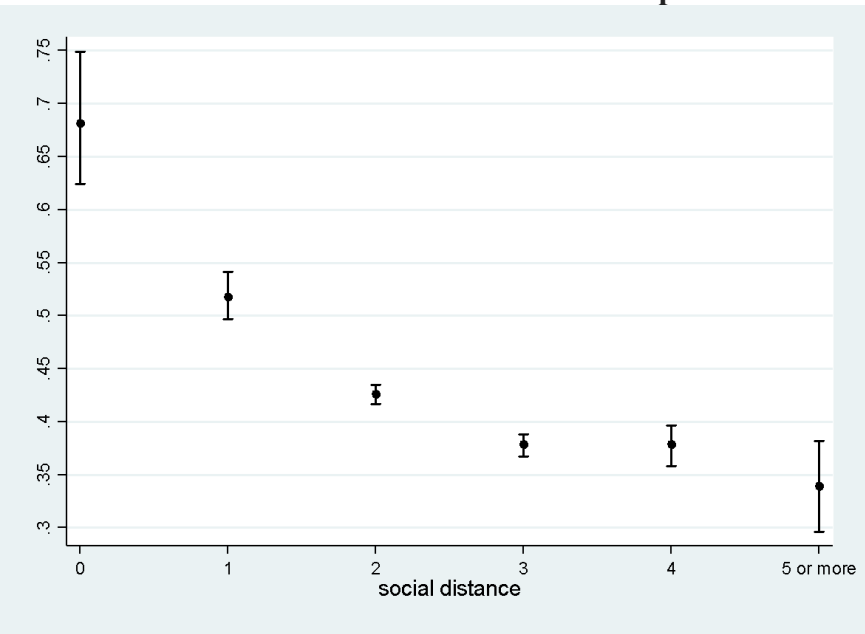
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Figure 1. Shortest interpersonal paths between corporate inventors on a citing patent and academic scientists on cited and uncited twin papers



Notes: The graph depicts all direct collaborators of the corporate inventors of patent US7288251 (titled "Antibodies to CD40") assigned to Abgenix and Pfizer, as well as all direct collaborators of the academic authors of the cited paper by Bennett et al. (1998) titled "Help for cytotoxic-T-cell responses is mediated by CD40 signalling," and all direct collaborators of the academic authors of the uncited twin paper by Schoenberger et al. (1998) titled "T-cell help for cytotoxic T lymphocytes is mediated by CD40–CD40L interactions." Each node represents an individual: red triangles indicate individuals who exclusively publish, yellow dots indicate individuals who only patent, and green squares indicate individuals who both publish and patent. Corporate inventors of the citing patent are represented by black light bulbs, academic authors of the cited paper are shown as checked drawing boards, and authors of the uncited twin paper are depicted as unchecked drawing boards. The edges (lines connecting two nodes) represent co-authorship/co-inventorship ties up to 2002, the patent filing year. To improve visibility, ties established before 1989 are removed. The length of the ties is arbitrary. The shortest path between the corporate inventors of the citing patent and the academic scientists of the cited paper has a length of 1 and is highlighted as a bold line. The shortest path between the corporate inventors of the citing patent and the academic scientists of the uncited twin paper has a length of 2 but is not displayed.

Figure 2. Predicted probability of corporate patent citations to academic papers across different levels of social distance between academic authors and corporate inventors



Notes: Figure 2 depicts the predicted probability of citation along with the 95% confidence interval across different levels of social distance between academic authors and corporate inventors in paper-patent dyads. This analysis employs the simulation methodology proposed by King et al. (2000). Detailed regression results are presented in column (2) of Table 4.

Table 1. Main variables and definitions

Variable	Definition
cited	Dummy equal to 1 if paper is cited by patent.
social_dist	Shortest path between any of the author(s) of the paper and any of the inventor(s) of the patent at the patent filing year *t*. Unreachable is imputed with value 9, i.e. one more than the maximum distance observed in our data, i.e. distance 8.
social_dist_0	Dummy equal to 1 if shortest path is 0, i.e. an author of the paper is inventor of the patent.
social_dist_1	Dummy equal to 1 if shortest path is 1, i.e. an author of the paper is a past collaborator of an inventor of the patent.
social_dist_2	Dummy equal to 1 if shortest path is 2, an author of the paper and an inventor of the patent have a common collaborator.
social_dist_3	Dummy equal to 1 if shortest path is 3.
social_dist_4	Dummy equal to 1 if shortest path is 4.
social_dist_5_or_more	Dummy equal to 1 if shortest path is 5 or more, including unreachable.
soc_distance_time	Weighted shortest path length (P^*) between any author of paper *a* and any inventor of patent *b*. The path consists of 1 to k connections, where each connection (edge) is weighted based on the time since the most recent collaboration between the individuals in the path. The weight is 1 plus the difference between the patent filing year (*t*) and the last collaboration year. If no path exists, the length is set to 30, one more than the maximum observed distance (29). If an author of the paper is also an inventor of the patent, the distance is 0. The shortest path is computed using Dijkstra's algorithm from the R igraph library. $$soc_distance_time_{ab} = min_{P^* \in P(a,b)} \sum_{i=1}^{k} (weight(a_{i-1}, a_i) + 1)$$
degree1_size	Number of collaborators (those within 1 degree of separation) of the paper's authors up to the year of patent filing (year *t*).
degree2_size	Number of connections within 2 degree of separation of the paper's authors up to the year of patent filing (year *t*).
degree3_size	Number of connections within 3 degree of separation of the paper's authors up to the year of patent filing (year *t*).
no. authors	Number of authors on the paper.
author-inventor team	Dummy equal to 1 if at least one of the paper's authors is an author-inventor at the patent filing year *t*.
publication stock	Number of unique PubMed papers published by any of the paper's authors up to the patent filing year *t*
patent stock	Number of unique granted patents by any of the paper's authors up to the patent filing year *t*.
institutional prestige	Count of unique PubMed papers linked to individuals with the same affiliations as the authors on the focal paper up to the year of patent filing (year *t*).
U.S. based	Dummy equal to 1 if any affiliation of the authors on the focal paper is in the US.
min geographic distance	Minimum geographic distance in miles between any of the author(s) of the paper and any of the inventor(s) of the patent.
journal impact factor	Journal impact factor of the paper in year of publication
journal commercial impact factor	Journal commercial impact factor of the paper in year of publication based on patent citations to papers from the same journal as the focal paper (see Bikard and Marx (2020)).
paper citations	Number of times the focal paper is cited by other papers up to the year before patent filing (t-1).
patent citations	Number of times the focal paper is cited by patents up to the year before patent filing (t-1).
time lag	Number of days between publication date of paper and filing date of patent.
published first	Dummy equal to 1 if the focal paper is published earlier or on the same day as the twin paper(s).
text length	Number of words in title and abstract of paper.
readability	The Gunning Fog index, a measure of readability, is calculated by considering the average number of words per sentence and the proportion of complex words (defined as words with three or more syllables) This calculation uses both the title and abstract of a paper, applying the formula: 0.4×(average sentence length+100×(complex words/total words)) (Hengel 2022).
active_inventor_author	Dummy equal to 1 if at least one of the patent's inventors published a paper in the year before the patent filing year *t*.
close_paper	We compute the SPECTER embedding of each paper using its title and abstract, and measure the cosine similarity between each prior paper of the corporate inventors on the patent published before the patent filing year and the twin papers (Cohan et al. 2020). Next, we calculate the maximum of these pairwise paper similarities at the twin-patent level as a measure of how close and familiar the corporate inventors are to the academic twin discovery. We then create a binary indicator, close_paper, which equals one when this value exceeds the median in our dataset.

Notes: The unit of observation is a paper-patent dyad, which includes both cited paper-patent dyads and uncited paper-patent dyads. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values. We do not apply the logarithmic transformation to *social_dist* to maintain ease of interpretation.

Table 2. Summary statistics at the paper level

	All		Cited		Not Cited		T test
	Mean	SD	Mean	SD	Mean	SD	p value
degree1_size	5.532	1.070	5.579	1.100	5.486	1.039	0.289
degree2_size	9.448	1.286	9.501	1.320	9.395	1.252	0.321
degree3_size	12.822	1.129	12.861	1.152	12.784	1.106	0.411
no. authors	1.535	0.590	1.571	0.569	1.499	0.609	0.143
author-inventor team	0.642	0.480	0.670	0.471	0.614	0.488	0.153
publication stock	5.011	0.990	5.052	1.025	4.970	0.952	0.314
patent stock	1.109	1.091	1.202	1.119	1.017	1.056	0.039**
institutional prestige	9.535	1.438	9.593	1.395	9.478	1.480	0.334
U.S. based	0.637	0.481	0.646	0.479	0.627	0.484	0.630
journal impact factor	1.817	0.677	1.833	0.679	1.802	0.677	0.577
journal commercial impact factor	0.110	0.113	0.114	0.118	0.107	0.108	0.448
paper citations	3.175	1.893	3.221	1.877	3.129	1.912	0.558
patent citations	0.625	0.864	0.615	0.828	0.635	0.900	0.786
published first	0.699	0.459	0.714	0.453	0.685	0.465	0.435
text length	5.169	0.420	5.171	0.421	5.168	0.421	0.923
readability	2.740	0.184	2.738	0.177	2.742	0.191	0.784

Notes: The unit of observation is a paper (n=501) from 247 paper twins (7 are triplets), including cited papers (n=294) and uncited twin papers (n=295). The large majority of the papers (413, or 82%) maintain a consistent status as either cited or uncited throughout the dataset. However, 88 papers (18%) appear both as cited and uncited paper due to multiple patent citations to different papers of the same twin. Excluding these dual-role papers from the analysis does not significantly alter the summary statistics or T-test results. We consider the first observation year of each paper in our dataset, whether cited or uncited. T test considers not equal variances. *, **, and *** denotes significance at the 10%, 5%, and 1% level. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values.

Table 3. Summary statistics at the paper-patent dyad level

	All		Cited		Not Cited		T test
	Mean	SD	Mean	SD	Mean	SD	p value
cited	0.497	0.500	1.000	0.000	0.000	0.000	
social_dist	2.789	1.145	2.751	1.195	2.827	1.091	0.034**
social_dist_0	0.016	0.124	0.028	0.164	0.004	0.062	0.000***
social_dist_1	0.053	0.224	0.063	0.243	0.043	0.204	0.005***
social_dist_2	0.271	0.445	0.257	0.437	0.285	0.452	0.036**
social_dist_3	0.538	0.499	0.527	0.499	0.548	0.498	0.168
social_dist_4	0.100	0.300	0.104	0.305	0.096	0.294	0.383
social_dist_5_or_more	0.023	0.149	0.022	0.147	0.023	0.151	0.808
soc_distance_time	5.912	3.848	5.979	3.811	5.847	3.884	0.269
min geographic distance	6.416	2.328	7.027	1.938	5.813	2.516	0.000***
time lag	8.063	1.169	8.077	1.122	8.050	1.213	0.451

Notes: The unit of observation is a paper-patent dyad (n=4,169), including cited paper-patent dyads (n=2,070) and uncited paper-patent dyads (n=2,099). The sample includes 247 paper twins (7 are triplets), 501 papers, and 1,951 citing patents. T test considers not equal variances. *, **, and *** denotes significance at the 10%, 5%, and 1% level. Min geographic distance and time lag are logarithmically transformed after adding one.

Table 4. Influence of social distance between academic scientists and corporate inventors on company patent citation to academic paper: Binary indicators for social distance

	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Linear probability
	Only controls		Exclude social distance 0	Exclude social distance 0 or 1	Exclude social unreachable	Social distance measured before academic paper twin	Exclude corporate funding	Exclude front page citations	
	(4-1)	(4-2)	(4-3)	(4-4)	(4-5)	(4-6)	(4-7)	(4-8)	(4-9)
social_dist_1		-2.571***			-2.588***	-2.822***	-2.644***	-2.744***	-0.348***
		(0.653)			(0.649)	(0.622)	(0.769)	(0.768)	(0.088)
social_dist_2		-4.101***	-1.775***		-4.121***	-2.756***	-4.206***	-4.386***	-0.660***
		(0.974)	(0.495)		(0.968)	(0.737)	(1.189)	(1.123)	(0.138)
social_dist_3		-4.910***	-2.625***	-0.852***	-4.914***	-3.631***	-5.040***	-5.294***	-0.836***
		(1.068)	(0.631)	(0.254)	(1.059)	(0.785)	(1.316)	(1.265)	(0.158)
social_dist_4		-4.906***	-2.706***	-0.966**	-4.893***	-4.295***	-5.222***	-5.257***	-0.812***
		(1.149)	(0.722)	(0.388)	(1.139)	(1.021)	(1.375)	(1.434)	(0.195)
social_dist_5_or_more		-5.585***	-3.448***	-1.759***	-5.522***	-5.098***	-5.876***	-5.127***	-1.096***
		(1.111)	(0.745)	(0.607)	(1.113)	(1.095)	(1.338)	(1.503)	(0.200)
N of observations (paper-patent dyads)	4,169	4,169	4,039	3,706	4,099	4,169	3,591	3,422	5,745
N of twin-patent dyads	2,068	2,068	2,003	1,837	2,033	2,068	1,782	1,698	2,850
N of citing patents	1,951	1,951	1,886	1,732	1,920	1,951	1,704	1,603	2,641
N of papers	501	501	493	462	491	501	405	362	634
N of twins	247	247	243	228	242	247	200	178	312
Log-Likelihood	-945.8	-847.4	-821.5	-724.6	-834.0	-874.3	-713.4	-666.5	
R2	0.346	0.414	0.414	0.437	0.414	0.396	0.428	0.439	0.393

Notes: The unit of observation is a paper-patent dyad (n=4,169), including cited paper-patent dyads (n=2,070) and uncited paper-patent dyads (n=2,099). The sample includes 247 paper twins (7 are triplets), 501 papers, and 1,951 citing patents. We identify all cases where a patent cites only one (or a subset) of the twin papers. The binary outcome variable *cited* is equal to 1 in case the paper is cited by the patent, and 0 in case of an uncited twin paper patent dyad, i.e. the uncited twin paper matched to the same patent. The table reports coefficient estimates from conditional logit models with fixed effects at the twin patent-level, social_dist_0 is the excluded category in columns 2, 5, 6, 7, 8, 9 and social_dist_1 is the excluded category in column 3, social_dist_2 is the excluded category in column 4. Column 4-9 also includes cases where a patent cites all twin papers, estimated using a linear probability model with twin patent-level fixed effects. This extended sample includes 312 paper twins, 634 papers, and 2,641 citing patents. All models include control variables: *degree3_size, no. authors, author-inventor team, publication stock, patent stock, institutional prestige, U.S. based, min geographic distance, journal impact factor, journal commercial impact factor, paper citations, patent citations, time lag, published first, text length and readability*. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values. Robust standard errors clustered at the twin level and reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level.

Table 5. Influence of social distance between academic scientists and corporate inventors on company patent citation to academic paper: Count measure for social distance

	Conditional logit	Conditional logit	Conditional logit Exclude social distance 0	Conditional logit Exclude social distance 0 or 1	Conditional logit Exclude social unreachable	Conditional logit Social distance measured before academic paper twin	Conditional logit Exclude corporate funding	Conditional logit Exclude front page citations	Linear probability	Conditional logit Social distance time (shortest path weighted by recency of ties)
	(5-1)	(5-2)	(5-3)	(5-4)	(5-5)	(5-6)	(5-7)	(5-8)	(5-9)	(5-10)
social_dist		-0.957***	-0.897***	-0.632***	-0.947***	-0.815***	-1.020***	-1.021***	-0.196***	-0.214***
		(0.205)	(0.208)	(0.190)	(0.204)	(0.207)	(0.226)	(0.246)	(0.041)	(0.062)
N of observations (paper-patent dyads)	4,169	4,169	4,039	3,706	4,099	4,169	3,591	3,422	5,745	4,169
N of twin-patent dyads	2,068	2,068	2,003	1,837	2,033	2,068	1,782	1,698	2,850	2,068
N of citing patents	1,951	1,951	1,886	1,732	1,920	1,951	1,704	1,603	2,641	1,951
N of papers	501	501	493	462	491	501	405	362	634	501
N of twins	247	247	243	228	242	247	200	178	312	247
Log-Likelihood	-945.8	-873.8	-839.1	-729.7	-861.1	-887.7	-731.3	-690.7		-927.4
R2	0.346	0.396	0.401	0.433	0.395	0.386	0.413	0.418	0.384	0.359

Notes: The unit of observation is a paper-patent dyad (n=4,169), including cited paper-patent dyads (n=2,070) and uncited paper-patent dyads (n=2,099). The sample includes 247 paper twins (7 are triplets), 501 papers, and 1,951 citing patents. We identify all cases where a patent cites only one (or a subset) of the twin papers. The binary outcome variable *cited* is equal to 1 in case the paper is cited by the patent, and 0 in case of an uncited twin paper patent dyad, i.e. the uncited twin paper matched to the same patent. The table reports coefficient estimates from conditional logit models with fixed effects at the twin patent-level. Column 5-9 also includes cases where a patent cites all twin papers, estimated using a linear probability model with twin patent-level fixed effects. All models include control variables: *degree3_size, no. authors, author-inventor team, publication stock, patent stock, institutional prestige, U.S. based, min geographic distance, journal impact factor, journal commercial impact factor, paper citations, patent citations, time lag, published first, text length and readability*. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values. Robust standard errors clustered at the twin level and reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level.

Table 6. Robustness checks

	Exclude higher order twins	Exclude twins published > 3 months apart	Exclude twins text similarity <0.90	Twins with Pubmed rank order=1	Twins with back-to-back papers	Twins with share of adjacent citations =100%	Exclude twins with papers from large teams (>5)	Exclude twins with top cited papers	Exclude patents of Genentech & Millennium Pharmaceuticals
	(6-1)	(6-2)	(6-3)	(6-4)	(6-5)	(6-6)	(6-7)	(6-8)	(6-9)
social_dist	-0.976***	-1.066***	-1.132***	-1.627***	-1.260***	-0.893***	-1.310***	-0.983***	-0.873***
	(0.209)	(0.234)	(0.217)	(0.155)	(0.282)	(0.199)	(0.193)	(0.210)	(0.185)
N of observations (paper-patent dyads)	3,996	3,368	3,310	2,010	2,301	935	2,953	4,007	3,417
N of twin-patent dyads	1,998	1,668	1,642	1,005	1,150	467	1,464	1,987	1,692
N of citing patents	1,888	1,583	1,587	980	1,114	450	1,410	1,870	1,584
N of papers	480	354	308	130	181	103	246	493	493
N of twins	240	174	152	65	90	51	121	243	243
Log-Likelihood	-836.6	-678.2	-663.2	-333.1	-431.2	-196.7	-537.9	-821.1	-803.8
R2	0.396	0.420	0.423	0.522	0.459	0.393	0.475	0.410	0.322

Notes: The unit of observation is a paper-patent dyad (n=4,169), including cited paper-patent dyads (n=2,070) and uncited paper-patent dyads (n=2,099). The sample includes 247 paper twins (7 are triplets), 501 papers, and 1,951 citing patents. We identify all cases where a patent cites only one (or a subset) of the twin papers. The binary outcome variable *cited* is equal to 1 in case the paper is cited by the patent, and 0 in case of an uncited twin paper patent dyad, i.e. the uncited twin paper matched to the same patent. The table reports coefficient estimates from conditional logit models with fixed effects at the twin patent-level. All models include control variables: *degree3_size, no. authors, author-inventor team, publication stock, patent stock, institutional prestige, U.S. based, min geographic distance, journal impact factor, journal commercial impact factor, paper citations, patent citations, time lag, published first, text length and readability*. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values. Robust standard errors clustered at the twin level and reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level.

Table 7. Mechanisms: Company inventors active in scientific research as boundary-spanners

	Conditional logit (7-1)	Conditional logit (7-2)	Conditional logit (7-3)	Conditional logit (7-4)
social_dist	-0.957***	-0.068	-0.376***	0.105
	(0.205)	(0.187)	(0.140)	(0.213)
social_dist*active_inventor_author		-1.081***		-0.744***
		(0.289)		(0.216)
social_dist*close_paper			-0.920***	-0.728**
			(0.325)	(0.321)
N of observations (paper-patent dyads)	4,169	4,169	4,115	4,115
N of twin-patent dyads	2,068	2,068	2,041	2,041
N of citing patents	1,951	1,951	1,924	1,924
N of papers	501	501	493	493
N of twins	247	247	243	243
Log-Likelihood	-873.8	-859.0	-848.4	-842.1
R2	0.396	0.406	0.406	0.410

Notes: The unit of observation is a paper-patent dyad (n=4,169), including cited paper-patent dyads (n=2,070) and uncited paper-patent dyads (n=2,099). The sample includes 247 paper twins (7 are triplets), 501 papers, and 1,951 citing patents. We identify all cases where a patent cites only one (or a subset) of the twin papers. The binary outcome variable *cited* is equal to 1 in case the paper is cited by the patent, and 0 in case of an uncited twin paper patent dyad, i.e. the uncited twin paper matched to the same patent. The table reports coefficient estimates from conditional logit models with fixed effects at the twin patent-level. All models include control variables: *degree3_size, no. authors, author-inventor team, publication stock, patent stock, institutional prestige, U.S. based, min geographic distance, journal impact factor, journal commercial impact factor, paper citations, patent citations, time lag, published first, text length and readability*. *Active_inventor_author* is a dummy equal to 1 if any of patent's inventors have at least 1 PubMed paper published in the year before patent filing. *Close_paper* is a dummy equal to 1, if the max similarity between inventors' prior papers (published before the patent filing year) and the twin papers (cited or not cited) is higher than sample median. Paper-patent dyads where inventors have 0 prior papers have a value of 0 for cosine similarity. Paper-patent dyads for which cosine similarity could not be calculated due to due missing text data are dropped in models 7-3, 7-4. We tested alternative models where patent-twin dyads with 0 prior papers were also put to missing observations, the effect size and significance hold. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values. Robust standard errors clustered at the twin level and reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level.

Online Appendix

Figure A.1 Example of twin papers



letters to nature

Help for cytotoxic-T-cell responses is mediated by CD40 signalling

Sally R. M. Bennett*†, Francis R. Carbone‡, Freda Karamalis*†, Richard A. Flavell§, Jacques F. A. P. Miller* & William R. Heath*

* Immunology Division, The Walter and Eliza Hall Institute of Medical Research, PO The Royal Melbourne Hosital, Melbourne, Victoria 3050, Australia
† The Cooperative Research Centre for Vaccine Technology at the Queensland Institute of Medical Research, PO The Royal Brisbane Hospital, Herston, Queensland 4029, Australia
‡ The Monash Medical School, Commercial Road, Prahran, Victoria 3181, Australia
§ The Section of Immunology and Howard Hughes Medical Institute, Yale University, 310 Cedar Street, FMB 412, PO Box 208011, New Haven, Connecticut 06520-8011, USA

Cytotoxic T lymphocytes (CTLs) which carry the CD8 antigen recognize antigens that are presented on target cells by the class I major histocompatibility complex. CTLs are responsible for the killing of antigen-bearing target cells, such as virus-infected cells. Although CTL effectors can act alone when killing target cells, their differentiation from naive CD8-positive T cells is often dependent on 'help' from CD4-positive helper T (T_H) cells[1–4].

Furthermore, for effective CTL priming, this help must be provided in a cognate manner, such that both the T_H cell and the CTL recognize antigen on the same antigen-presenting cell[5,6]. One explanation for this requirement is that T_H cells are needed to convert the antigen-presenting cell into a cell that is fully competent to prime CTL[3]. Here we show that signalling through CD40 on the antigen-presenting cells can replace the requirement for T_H cells, indicating that T-cell 'help', at least for generation of CTLs by cross-priming, is mediated by signalling through CD40 on the antigen-presenting cell.

CD8-positive CTLs are responsible for the lysis of antigen-bearing target cells. These CTLs recognize peptide antigens presented by class I molecules encoded within the major histocompatibility complex (MHC). Generation of effective CTL responses often requires help from a second subset of T lymphocytes, the CD4-positive helper T (T_H) cells[1–4], but this is not always the case[6,7]. In response to the soluble protein ovalbumin (OVA), both T_H-cell-dependent and T_H-cell-independent CTL immunity can be induced[3,8]. When the K^b-restricted OVA peptide determinant spanning residues λ57 to 264 (OVAp) was emulsified in complete Freund's adjuvant (CFA) and injected subcutaneously, CTLs could be generated in mice lacking CD4-positive T cells (Fig. 1a)[4]. In contrast, priming by intravenous injection of irradiated spleen cells loaded with OVA by osmotic shock (OVA-loaded spleen cells) required the presence of CD4-positive T cells (Fig. 1b). This latter form of immunization occurs by cross-priming[6,9], requiring representation of antigen by host bone-marrow-derived antigen-presenting cells (APCs). Dissection of the cellular interactions involved in this response[5] revealed that, like the induction of CTLs that are specific for the Qa1 antigen[7], the T_H and CTL populations must recognize OVA on the same APC for effective CTL priming. This could be explained in two ways: either the T_H cells need to closely associate with the CTL to deliver short-range signals such as interleukin(IL)-2 (ref. 1), or they are required to modify the APC, converting it into a stimulatory cell for CTL priming[3].

There is evidence that CD40 and CD40 ligand (CD154) are important in both the humoral and cellular immune responses (reviewed in refs 10, 11). These molecules have been implicated in the generation of CTL responses to adenovirus[12] and in the estab-

Figure 1 OVA-specific CTLs can be generated in CD4-independent and CD4-dependent ways. Normal B6 mice (filled circles) or B6 mice depleted of CD4-positive T cells by twice-weekly intraperitoneal injection of 100 μl GK1.5 ascites* (open circles) were injected either **a**, subcutaneously with 20 μg OVAp in 200 μl CFA, or **b**, intravenously with irradiated B6 OVA-loaded spleen cells as described*. After 8 days, spleen cells from each mouse were restimulated for 6 days *in vitro* as described*. On the day of assay, effector cells were examined for their ability to lyse ^{51}Cr-labelled EL4 targets that were or were not pulsed with OVAp. Non-specific EL4 lysis was <10%.

Figure 2 Treatment with a monoclonal antibody against CD40 replaces CD4-positive T-cell help in generating OVA-specific CTLs. Normal B6 mice (circles) and H-2A^b-deficient B6 mice (squares), were injected intravenously with irradiated, OVA-loaded bm1 spleen cells*. They were then left untreated (circles), or were injected intravenously daily for 4 days with either 0.1 mg of a CD40-specific monoclonal antibody, FGK45 (ref. 17) (open squares) or an IgG2a isotype control, KT50, specific for Vα8 (filled squares). Eight days after priming, the spleen cells from each mouse were restimulated *in vitro* for six days. We then examined their ability to lyse ^{51}Cr-labelled EL4 targets that were or were not pulsed with OVAp. Nonspecific EL4 lysis was <7%.

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provide inflammatory signals that activate APCs directly, circumventing their need for activation through CD40. Perhaps the requirement for CD40 signalling depends on whether the professional APC is directly infected or presents antigen indirectly by cross-presentation. Alternatively, there may be other inherent properties of some viruses that allow CD40-independent activation of APCs.

The ability to replace T_H cells with an antibody against CD40 may provide an opportunity for vaccination under circumstances that were previously difficult, either because of a lack of available class II-restricted antigenic determinants (as may occur with some tumour antigens) or because of a deficiency in CD4-positive T_H cells (as occurs in AIDS patients). Further dissection of the molecular interactions involved in the generation of immunogenic CTL responses may help in vaccine design and function. □

Methods

Generation of CTL responses. CTL responses to OVA were generated as described*. Briefly, mice were primed with 25×10^6 OVA-loaded spleen cells. Seven to eight days later, we restimulated spleen cells from primed mice *in vitro* for six days with irradiated (1,500 centiGray) OVA-loaded B6 spleen cells or irradiated (20,000 centiGray) E.G7 tumour cells. We then examined the ability of the primed spleen cells to lyse ^{51}Cr-labelled EL4 target cells, pulsed or unpulsed with OVAp as described*. The percentage of OVA-specific lysis was then calculated as the percentage of OVAp-pulsed EL4 lysis minus the percentage of EL4 lysis. To generate CTLs in CD154-deficient[18] or CD40-deficient[19] mice, we modified the *in vitro* culture conditions slightly to avoid responses to mouse strain 129 minor histocompatibility antigens. Seven days after immunization with OVA-loaded bm1 spleen cells, we removed 'responder' spleens and irradiated half the cells from each spleen (1,500 centiGray). We then loaded these irradiated cells with OVA with OVA by osmotic shock and used these cells as *in vitro* stimulators for the remaining splenocytes. We combined unirradiated 'responder' spleen cells (3×10^6 cells ml^{-1}) with irradiated OVA-loaded cells from the same animal (3×10^5 cells ml^{-1}) and cultured them *in vitro* for six days in several 2-ml cultures. On day 6, we pooled effector cells from each mouse and used them in a chromium-release assay as described*.

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Correspondence and requests for materials should be addressed to W.R.H. (e-mail: Heath@wehi.edu.au) or to F.R.C. (e-mail: carbone@cobra.path. monash.edu.au).

T-cell help for cytotoxic T lymphocytes is mediated by CD40–CD40L interactions

Stephen P. Schoenberger*†‡, Rene E. M. Toes*†, Eilen I. H. van der Voort*, Rienk Offringa* & Cornelis J. M. Melief*

* Department of Immunohematology and Blood Bank, University Hospital Leiden, PO Box 9600, 2333 AZ, Leiden, The Netherlands
† These authors contributed equally to this work.

Although *in vivo* priming of CD8$^+$ cytotoxic T lymphocytes (CTLs) generally requires the participation of CD4$^+$ T-helper lymphocytes[1,2], the nature of the 'help' provided to CTLs is unknown[3]. One widely held view is that help for CTLs is mediated by cytokines produced by T-helper cells activated in proximity to the CTL precursor at the surface of an antigen-presenting cell (APC)[4]. An alternative theory is that, rather than being directly supplied to the CTL by the helper cell, help is delivered through activation of the APC, which can then prime the CTL directly[5]. CD40 and its ligand, CD40L, may activate the APC to allow CTL priming. CD40L is expressed on the surface of activated CD4$^+$ T-helper cells and is involved in their activation and in the development of their effector functions[6,7]. Ligation of CD40 on the surface of APCs such as dendritic cells, macrophages and B cells greatly increases their antigen-presentation and co-stimulatory capacity[8–11]. Here we report that signalling through CD40 can replace CD4$^+$ T-helper cells in priming of helper-dependent CD8$^+$ CTL responses. Blockade of CD40L inhibits CTL priming; this inhibition is overcome by signalling through CD40. CD40–CD40L interactions are therefore vital in the delivery of T-cell help for CTL priming.

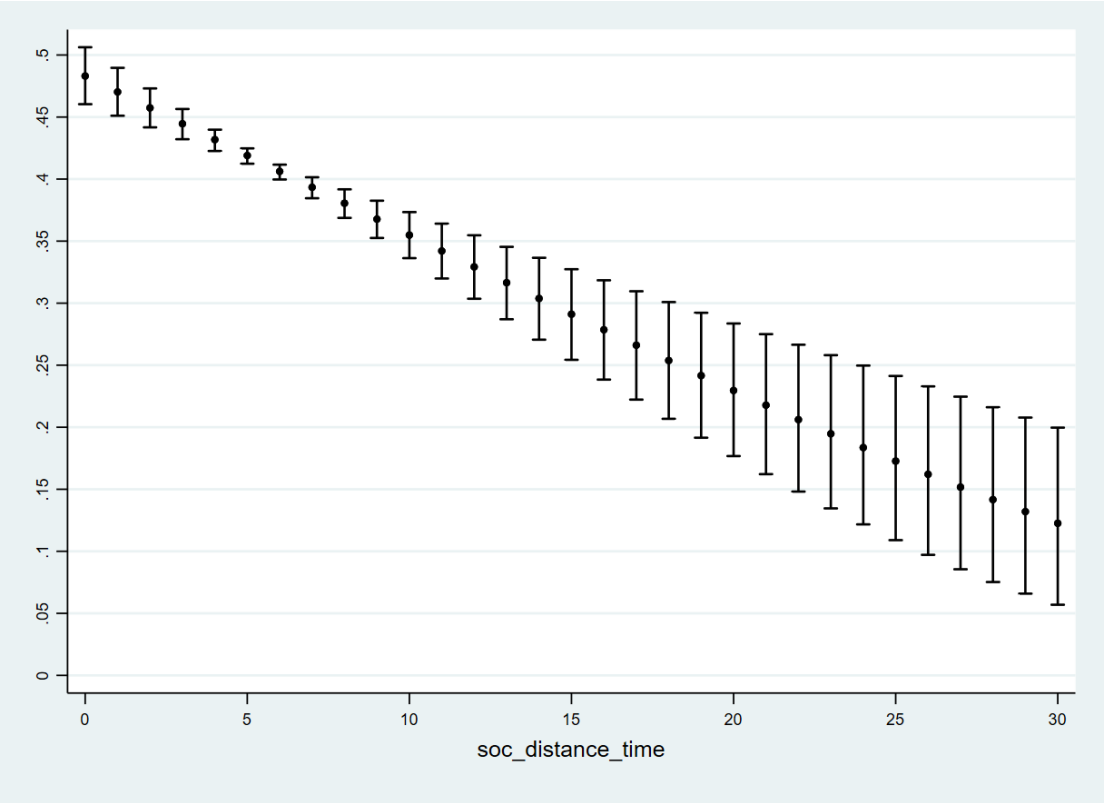
The dependence on 'help' mediated by CD4$^+$ T cells for the priming of antigen-specific CD8$^+$ CTL responses has been well documented[1–4]. Despite this, the mechanism through which help is

‡ Present address: Division of Immune Regulation, La Jolla Institute for Allergy and Immunology, San Diego, California 92121, USA.

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Notes: Example of twin papers published back-to-back in *Nature*. Paper on the left: Bennett S, Carbone F, Karamalis F, Flavell R, Miller J, Heath W (1998) Help for cytotoxic-T-cell responses is mediated by CD40 signalling. Nature 393(6684):478–480. Paper on the right: Schoenberger S, Toes R, van der Voort E, Offringa R, Melief,C (1998) T-cell help for cytotoxic T lymphocytes is mediated by CD40–CD40L interactions. Nature 393(6684):480–483.

Figure A2. Predicted probability of corporate patent citations to academic papers across different levels of soc_distance_time between academic authors and corporate inventors



Notes: Figure A2 depicts the predicted probability of citation along with the 95% confidence interval across different levels of soc_distance_time (shortest path weighted by recency of ties) between academic authors and corporate inventors in paper-patent dyads. This analysis employs the simulation methodology proposed by King et al. (2000). Detailed regression results are presented in column (10) of Table 5.

Table A.1 Universities and academic institutions most commonly listed as affiliation on twin papers

	N. (1)	Share (2)
Harvard University	35	0.070
Massachusetts Institute of Technology	15	0.030
University of California, San Diego	15	0.030
University of California, San Francisco	13	0.026
Yale University	13	0.026
Johns Hopkins University	11	0.022
National Cancer Institute	11	0.022
University of Toronto	10	0.020
Cold Spring Harbor Laboratory	10	0.020
Massachusetts General Hospital	10	0.020
University of Washington	10	0.020
CNRS	10	0.020
University of California at Berkeley	10	0.020
Stanford University	9	0.018
European Molecular Biology Laboratory	9	0.018
Dana Farber Cancer Institute	9	0.018
University of Chicago	8	0.016
University of Michigan	8	0.016
Baylor College of Medicine	8	0.016
California Institute of Technology	7	0.014

Notes: Top 20 universities and institutions most commonly listed as affiliation on twin papers. The number in column 1 refers to the number of papers and the share in column 2 is computed based on the total number of twin papers in our sample (n=501). Papers with multiple affiliations can appear in multiple rows.

Table A.2 Companies most commonly listed as assignee on citing patents

	N. (1)	Share (2)
Genentech	219	0.112
Millennium Pharmaceuticals	209	0.107
ZymoGenetics	59	0.030
BASF Plant Science	45	0.023
BASF AG	35	0.018
CuraGen Corporation	34	0.017
Eli Lilly & Company	32	0.016
Kyowa Hakko Kogyo Co.	26	0.013
Amgen	25	0.013
Kyowa Hakko Kirin Co.	24	0.012
Schering Corporation	23	0.012
Virogenetics Corporation	23	0.012
Abbott Laboratories	22	0.011
Agrinomics	22	0.011
Biogen IDEC	20	0.010
Human Genome Sciences	19	0.010
Bio Merieux	17	0.009
Bristol-Myers Squibb Company	18	0.009
Pioneer Hi-Bred International	16	0.008
Geron Corporation	15	0.008

Notes: Top 20 companies most commonly listed as assignee on citing patents. The number in column 1 refers to the number of patents and the share in column 2 is computed based on the total number of citing patents in our sample (n=1,951). Patents with multiple assignees can appear in multiple rows.

Table A.3 Results by company type

	Main effect	U.S. public firms	Firm age <=3 years	Firm age <=5 years	Firm age <=10 years	Firm patent count<p50	Firm patent count>=p50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
social_dist	-0.957***	-0.813***	-0.952*	-0.656*	-0.661***	-0.948***	-1.011***
	(0.205)	(0.151)	(0.526)	(0.342)	(0.221)	(0.320)	(0.225)
N of observations (paper-patent dyads)	4,169	2,124	237	405	841	765	1,288
N of twin-patent dyads	2,068	1,050	115	198	411	370	644
N of citing patents	1,951	1,011	103	181	387	353	626
N of papers	501	245	92	130	202	175	124
N of twins	247	121	44	63	99	86	71
Log-Likelihood	-873.8	-366.0	-45.5	-72.3	-162.2	-147.4	-155.1
R2	0.396	0.504	0.449	0.487	0.446	0.447	0.653

Notes: The unit of observation is a paper-patent dyad (n=4,169), including cited paper-patent dyads (n=2,070) and uncited paper-patent dyads (n=2,099). The sample includes 247 paper twins (7 are triplets), 501 papers, and 1,951 citing patents. We identify all cases where a patent cites only one (or a subset) of the twin papers. The binary outcome variable *cited* is equal to 1 in case the paper is cited by the patent, and 0 in case of an uncited twin paper patent dyad, i.e. the uncited twin paper matched to the same patent. The table reports coefficient estimates from conditional logit models with fixed effects at the twin patent-level. All models include control variables: *degree3_size, no. authors, author-inventor team, publication stock, patent stock, institutional prestige, U.S. based, min geographic distance, journal impact factor, journal commercial impact factor, paper citations, patent citations, time lag, published first, text length and readability*. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values. Robust standard errors clustered at the twin level and reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level.

Table A.4 Robustness checks: Company inventors active in scientific research as cross-institutional boundary-spanners

	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Linear probability	Conditional logit	Conditional logit
			Exclude social distance 0	Exclude social distance 0 or 1	Exclude social unreachable	Social distance measured before academic twin	Exclude corporate funding	Exclude front page citations		Social distance time (shortest path weighted by recency of ties)	Count measure for *active_inventor_author*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
social_dist		-0.068	-0.061	-0.001	-0.067	-0.189	-0.162	0.003	-0.009	-0.027	-0.764***
		(0.187)	(0.195)	(0.229)	(0.185)	(0.253)	(0.165)	(0.233)	(0.040)	(0.098)	(0.173)
social_dist*active_inventor_author		-1.081***	-1.032***	-0.849**	-1.072***	-0.718**	-1.018***	-1.185***	-0.223***	-0.218	-0.034**
		(0.289)	(0.299)	(0.356)	(0.287)	(0.295)	(0.318)	(0.326)	(0.056)	(0.134)	(0.014)
N of observations (paper-patent dyads)	4,169	4,169	4,039	3,706	4,099	4,169	3,591	3,422	5,745	4,169	4,169
N of twin-patent dyads	2,068	2,068	2,003	1,837	2,033	2,068	1,782	1,698	2,850	2,068	2,068
N of citing patents	1,951	1,951	1,886	1,732	1,920	1,951	1,704	1,603	2,641	1,951	1,951
N of papers	501	501	493	462	491	501	405	362	634	501	501
N of twins	247	247	243	228	242	247	200	178	312	247	247
Log-Likelihood	-945.8	-859.0	-826.9	-722.9	-846.6	-882.4	-721.1	-679.6		-924.6	-868.0
R2	0.346	0.406	0.410	0.438	0.405	0.390	0.421	0.428	0.390	0.361	0.400

Notes: The unit of observation is a paper-patent dyad (n=4,169), including cited paper-patent dyads (n=2,070) and uncited paper-patent dyads (n=2,099). The sample includes 247 paper twins (7 are triplets), 501 papers, and 1,951 citing patents. We identify all cases where a patent cites only one (or a subset) of the twin papers. The binary outcome variable *cited* is equal to 1 in case the paper is cited by the patent, and 0 in case of an uncited twin paper patent dyad, i.e. the uncited twin paper matched to the same patent. The table reports coefficient estimates from conditional logit models with fixed effects at the twin patent-level. *Active_inventor_author* is a dummy equal to 1 if any of the patent's inventors have at least 1 PubMed paper published in the year before patent filing. In column 11, *Active_inventor_author* is a total count of PubMed indexed papers authored by patent's inventors in the year before patent filing. All models include control variables: *degree3_size, no. authors, author-inventor team, publication stock, patent stock, institutional prestige, U.S. based, min geographic distance, journal impact factor, journal commercial impact factor, paper citations, patent citations, time lag, published first, text length and readability*. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values. Robust standard errors clustered at the twin level and reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level.

Table A.5 Robustness checks: Company inventors with closely related scientific expertise as cross-institutional boundary-spanners

	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Conditional logit	Linear probability	Conditional logit	Conditional logit
			Exclude social distance 0	Exclude social distance 0 or 1	Exclude social unreachable	Social distance measured before academic twin	Exclude corporate funding	Exclude front page citations		Social distance time (shortest path weighted by recency of ties)	Continuous measure for *close_paper*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
social_dist		-0.376***	-0.382***	-0.250	-0.367***	-0.206	-0.398***	-0.311*	-0.084**	0.093	0.573
		(0.140)	(0.141)	(0.187)	(0.140)	(0.207)	(0.153)	(0.164)	(0.033)	(0.069)	(0.556)
social_dist*close_paper		-0.920***	-0.915***	-0.880*	-0.922***	-0.894*	-0.935**	-1.101***	-0.165**	-0.476***	-1.948**
		(0.325)	(0.328)	(0.455)	(0.322)	(0.490)	(0.368)	(0.322)	(0.075)	(0.116)	(0.805)
N of observations (paper-patent dyads)	4,169	4,115	3,985	3,652	4,053	4,115	3,551	3,380	5,675	4,115	4,115
N of twin-patent dyads	2,068	2,041	1,976	1,810	2,010	2,041	1,762	1,677	2,815	2,041	2,041
N of citing patents	1,951	1,924	1,859	1,705	1,897	1,924	1,684	1,582	2,606	1,924	1,924
N of papers	501	493	485	454	485	493	401	356	628	493	493
N of twins	247	243	239	224	239	243	198	175	309	243	243
Log-Likelihood	-945.8	-848.4	-815.4	-712.0	-836.4	-864.5	-711.9	-666.3		-895.3	-856.7
R2	0.346	0.406	0.410	0.438	0.405	0.395	0.422	0.432	0.387	0.373	0.400

Notes: The unit of observation is a paper-patent dyad (n=4,169), including cited paper-patent dyads (n=2,070) and uncited paper-patent dyads (n=2,099). The sample includes 247 paper twins (7 are triplets), 501 papers, and 1,951 citing patents. We identify all cases where a patent cites only one (or a subset) of the twin papers. The binary outcome variable *cited* is equal to 1 in case the paper is cited by the patent, and 0 in case of an uncited twin paper patent dyad, i.e. the uncited twin paper matched to the same patent. The table reports coefficient estimates from conditional logit models with fixed effects at the twin patent-level. *Close_paper* is a dummy equal to 1, if the max similarity between inventors' prior papers (published before the patent filing year) and the twin papers (cited or not cited) is higher than sample median (0.772). In column 11, *Close_paper* is a continuous measure, i.e. max cosine similarity between inventors' prior papers (published before the patent filing year) and the twin papers (cited or not cited). Paper-patent dyads where inventors have 0 prior papers have a value of 0 for cosine similarity. Paper-patent dyads for which cosine similarity could not be calculated due to due missing text data are dropped in all models. We tested alternative models where patent-twin dyads with 0 prior papers were also put to missing observations, the effect size and significance hold. All models include control variables: *degree3_size, no. authors, author-inventor team, publication stock, patent stock, institutional prestige, U.S. based, min geographic distance, journal impact factor, journal commercial impact factor, paper citations, patent citations, time lag, published first, text length and readability*. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values. Robust standard errors clustered at the twin level and reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level.

Table A.6 Robustness checks: Binary indicators for social distance

	Exclude higher order twins	Exclude twins published > 3 months apart	Exclude twins text similarity <0.90	Twins with share of adjacent citations =100%	Exclude twins with papers from large teams (>5)	Exclude twins with top cited papers	Exclude patents of Genentech & Millennium Pharmaceuticals
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
social_dist_1	-2.568***	-2.494**	-3.331***	-1.742**	-3.138***	-2.532***	-2.277***
	(0.665)	(1.031)	(0.717)	(0.686)	(0.604)	(0.691)	(0.626)
social_dist_2	-4.104***	-4.089***	-5.232***	-3.510***	-5.655***	-3.985***	-3.631***
	(0.992)	(1.307)	(1.053)	(0.744)	(0.866)	(1.053)	(0.853)
social_dist_3	-4.953***	-5.152***	-6.152***	-4.234***	-6.687***	-4.884***	-4.423***
	(1.075)	(1.433)	(1.188)	(0.668)	(0.981)	(1.130)	(0.895)
social_dist_4	-4.918***	-5.309***	-6.109***	-3.701***	-6.861***	-4.944***	-4.395***
	(1.182)	(1.515)	(1.327)	(0.839)	(1.095)	(1.204)	(0.963)
social_dist_5_or_more	-5.741***	-6.160***	-6.836***	9.905***	-7.183***	-5.676***	-5.042***
	(1.134)	(1.293)	(1.153)	(1.823)	(1.102)	(1.145)	(1.058)
N of observations (paper-patent dyads)	3,996	3,368	3,310	935	2,953	4,007	3,417
N of twin-patent dyads	1,998	1,668	1,642	467	1,464	1,987	1,692
N of citing patents	1,888	1,583	1,587	450	1,410	1,870	1,584
N of papers	480	354	308	103	246	493	493
N of twins	240	174	152	51	121	243	243
Log-Likelihood	-810.2	-663.5	-632.8	-187.5	-512.4	-799.5	-783.7
R2	0.415	0.433	0.449	0.422	0.500	0.425	0.339

Notes: The unit of observation is a paper-patent dyad (n=4,169), including cited paper-patent dyads (n=2,070) and uncited paper-patent dyads (n=2,099). The sample includes 247 paper twins (7 are triplets), 501 papers, and 1,951 citing patents. We identify all cases where a patent cites only one (or a subset) of the twin papers. The binary outcome variable *cited* is equal to 1 in case the paper is cited by the patent, and 0 in case of an uncited twin paper patent dyad, i.e. the uncited twin paper matched to the same patent. The table reports coefficient estimates from conditional logit models with fixed effects at the twin patent-level. Distance 0 is excluded category in all models. All models include control variables: *degree3_size, no. authors, author-inventor team, publication stock, patent stock, institutional prestige, U.S. based, min geographic distance, journal impact factor, journal commercial impact factor, paper citations, patent citations, time lag, published first, text length and readability*. Please notice that estimations for the subsample of twins with PubMed rank order=1 or published back-to-back did not converge because of insufficient observations for some of the different binary categories of social distance. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values. Robust standard errors clustered at the twin level and reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level.

Table A.7 Descriptive Statistics Comparing Corporate Inventors With and Without a Shortest-Path Connection to Cited Academic Scientists

	Corporate inventor with shortest path		Corporate inventor without shortest path		T test
	Mean	SD	Mean	SD	p value
Years since first patent/paper with same firm	4.302	4.647	3.260	4.296	0.000***
Recent public research affiliation	0.728	0.445	0.539	0.499	0.000***
Past public research affiliation	0.874	0.332	0.725	0.446	0.000***
Shared recent public research affiliation	0.251	0.434	0.150	0.357	0.000***
Shared past public research affiliation	0.373	0.484	0.200	0.400	0.000***
Number of prior patents	16.922	31.539	16.236	39.499	0.396
Number of prior patents in t-1	1.911	3.864	1.563	3.997	0.000***
Patent experience (years)	6.731	5.979	4.665	5.488	0.000***
Number of prior publications	36.733	60.572	11.189	24.820	0.000***
Number of prior publications in t-1	2.599	4.232	0.919	2.046	0.000***
Publication experience (years)	14.275	9.669	9.641	8.893	0.000***
Total network size (up to 3 degrees, log)	11.626	1.767	10.506	1.658	0.000***
Inventor network size (up to 3 degrees, log)	7.141	1.597	6.112	1.619	0.000***
Author network size (up to 3 degrees, log)	11.450	1.813	10.291	1.710	0.000***
Inventor-author network size (up to 3 degrees, log)	9.657	1.549	8.702	1.513	0.000***

Notes: The unit of observation is a corporate inventor at the time of patent filing linked to a cited twin paper. *Corporate inventor with shortest path* indicates the inventor has the shortest social distance to the authors of the cited twin paper, while *without shortest path* refers to other inventors on the same patent. *Recent public research affiliation* equals 1 if the inventor has a non-corporate (university, hospital, government, or other public research) affiliation on a paper or patent in the previous five years (t–5 to t–1); *past public research affiliation* refers to such affiliations held more than five years before filing (t–6 or earlier). *Shared recent (past) public research affiliation* equals 1 if the inventor and any author of the cited paper were affiliated with the same non-corporate organization within the recent (past) period. *Network size* variables measure the logarithm of the number of unique individuals within three degrees of separation at the time of patent filing: *total* includes all individuals, while *inventor*, *author*, and *inventor–author* network sizes restrict the network to inventors only, authors only, or those active in both domains. p-values from unequal-variance t-tests; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.8 Descriptive Statistics Comparing Corporate Inventors With and Without Recent Scientific Publications

	Inventors with recent publications		Inventors without recent publications		T test
	Mean	SD	Mean	SD	p value
Years since first patent/paper with same firm	4.371	4.560	3.239	4.387	0.000***
Recent public research affiliation	0.810	0.393	0.446	0.497	0.000***
Past public research affiliation	0.885	0.320	0.719	0.450	0.000***
Shared recent public research affiliation	0.287	0.453	0.109	0.312	0.000***
Shared past public research affiliation	0.361	0.480	0.227	0.419	0.000***
Number of prior patents	20.800	43.528	12.657	25.831	0.000***
Number of prior patents in t-1	1.864	3.148	1.621	4.542	0.005***
Patent experience (years)	6.484	5.968	4.983	5.609	0.000***
Number of prior publications	42.360	62.579	7.042	15.154	0.000***
Number of prior publications in t-1	3.664	4.189	0.000	0.000	0.000***
Publication experience (years)	14.122	9.687	9.765	8.936	0.000***
Total network size (up to 3 degrees, log)	11.932	1.144	10.270	1.930	0.000***
Inventor network size (up to 3 degrees, log)	7.352	1.351	5.959	1.694	0.000***
Author network size (up to 3 degrees, log)	11.768	1.171	10.044	1.985	0.000***
Inventor-author network size (up to 3 degrees, log)	9.903	1.028	8.515	1.748	0.000***

Notes: The unit of observation is a corporate inventor at the time of patent filing linked to a cited twin paper. *Corporate inventor with recent publications* indicates the inventor has at least one scientific publication in the year before patent filing (t-1), while *without recent publications* refers to inventors without recently published papers. *Recent public research affiliation* equals 1 if the inventor has a non-corporate (university, hospital, government, or other public research) affiliation on a paper or patent in the previous five years (t–5 to t–1); *past public research affiliation* refers to such affiliations held more than five years before filing (t–6 or earlier). *Shared recent (past) public research affiliation* equals 1 if the inventor and any author of the cited paper were affiliated with the same non-corporate organization within the recent (past) period. *Network size* variables measure the logarithm of the number of unique individuals within three degrees of separation at the time of patent filing: *total* includes all individuals, while *inventor*, *author*, and *inventor–author* network sizes restrict the network to inventors only, authors only, or those active in both domains. p-values from unequal-variance t-tests; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.9 Summary statistics at the paper-paper dyad level

	All		Cited		Not Cited		T test
	Mean	SD	Mean	SD	Mean	SD	p value
cited	0.499	0.500	1.000	0.000	0.000	0.000	
social_dist	2.325	1.051	2.212	1.120	2.438	0.965	0.000***
social_dist_0	0.047	0.212	0.079	0.270	0.015	0.123	0.000***
social_dist_1	0.124	0.330	0.138	0.345	0.110	0.313	0.000***
social_dist_2	0.392	0.488	0.375	0.484	0.410	0.492	0.000***
social_dist_3	0.358	0.479	0.335	0.472	0.380	0.485	0.000***
social_dist_4	0.067	0.250	0.062	0.242	0.072	0.258	0.000***
social_dist_5_or_more	0.012	0.107	0.011	0.103	0.013	0.111	0.069*
min geographic distance	6.641	2.284	6.348	2.509	6.933	1.994	0.000***
time lag	7.417	1.110	7.433	1.053	7.401	1.164	0.002**

Notes: The unit of observation is a paper–paper dyad (n = 44,220), including cited dyads (n = 22,069) and uncited dyads (n = 22,151). The sample comprises 221 paper twins, 448 twin papers, and 21,571 citing papers. We identify all PubMed papers published between 1975 and 2009 that cite at least one of the twin papers in our sample. Following the patent-to-paper identification strategy, we retain only cases where a citing paper references one (or a subset, in the case of triplets) of the twin papers, using the uncited twin paper matched to the same citing paper as a counterfactual or "pseudo-citation." Minimum geographic distance and time lag are logarithmically transformed after adding one. T-tests assume unequal variances. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.10 Influence of social distance on paper-to-paper citation

	Conditional logit	Conditional logit	Conditional logit Exclude social distance 0	Conditional logit Exclude social distance 0 or 1	Conditional logit Exclude social unreachable
	(1)	(2)	(3)	(4)	(5)
social_dist		-0.406***	-0.298***	-0.153***	-0.407***
		(0.026)	(0.027)	(0.032)	(0.026)
N of observations (paper-paper dyads)	44,220	44,220	40,058	32,030	44,032
N of twin-citing paper dyads	22,005	22,005	19,939	15,945	21,911
N of citing papers	21,571	21,571	19,562	15,703	21,479
N of twin papers	448	448	448	448	448
N of twins	221	221	221	221	221
Log-Likelihood	-13891.6	-13620.1	-12699.6	-10241.8	-13560.6
R2	0.094	0.112	0.086	0.078	0.112

Notes: The unit of observation is a paper–paper dyad (n = 44,220), including cited (n = 22,069) and uncited (n = 22,151) dyads. The sample includes 221 paper twins, 448 twin papers, and 21,571 citing papers. We identify all cases where a citing paper references only one (or a subset, in the case of triplets) of the twin papers. The binary outcome variable *cited* equals 1 when the cited paper is referenced by the citing paper and 0 for the uncited twin paper matched to the same citing paper. The table reports coefficient estimates from conditional logit models with fixed effects at the twin–citing-paper level. All models include the same control variables as in the patent-to-paper analysis:: *degree3_size, no. authors, author-inventor team, publication stock, patent stock, institutional prestige, U.S. based, min geographic distance, journal impact factor, journal commercial impact factor, paper citations, patent citations, time lag, published first, text length and readability*. All control variables measured in counts are logarithmically transformed after adding one to variables with zero values. Robust standard errors clustered at the twin level and reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level.