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OLD AND CONNECTED VERSUS YOUNG AND CREATIVE: NETWORKS AND THE DIFFUSION OF NEW SCIENTIFIC IDEAS

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ABSTRACT

The adoption of new ideas is critical for realizing their full potential and for advancing the knowledge frontier but it involves analyzing innovators, potential adopters, and the networks that connect them. This paper applies natural language processing, network analysis, and a novel fixed effects strategy to study how the aging of the biomedical research workforce affects idea adoption. We show that the relationship between adoption and innovator career age varies with network distance. Specifically, at short distances, young innovators' ideas are adopted the most, while at greater network distances, mid-career innovators' ideas have the highest adoption. The main reason for this contrast is that young innovators are close to young potential adopters who are more open to new ideas, but mid-career innovators are more central in networks. Overall adoption is hump-shaped in the career age of innovators. Simulations show that the aging of innovators and of potential adopters have comparable effects on the adoption of important new ideas.

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1 Introduction

Major discoveries rarely appear in readily usable form. Rather they require ongoing elaboration, refinement, and application by the research community. Thus, whether and how rapidly an important discovery realizes its potential depends on the community's use of that idea which, in turn, depends on the characteristics and networks of innovators and potential adopters. Unfortunately, far more work has focused on the glamorous introduction of new ideas leaving a gap in our understanding of adoption, but adoption generates interesting challenges and, as we show below, can be highly consequential. Moreover, from a policy perspective, it seems conceivable that making fuller and more rapid use of the important new ideas that have been introduced may be less expensive and less risky than producing more new ideas, which is often the focus of science policy.

This paper applies natural language processing and network analysis to a comprehensive corpus of biomedical research articles to identify important new ideas introduced over nearly three decades and tracks their diffusion through collaboration networks. We apply our methods to study how the aging of the research community influences the adoption[3] of important new ideas. This application is important given that the research community is aging rapidly - indeed, former NIH Director, Elias Zerhouni, identified this as, "the number-one issue in American science (quoted in Kaiser, 2008)"! It also highlights the importance of a novel, "two-sided" network approach to adoption that accounts for changes in the age composition of both potential adopters and innovators, which age together by construction.

[3] In principle, one might distinguish the first use of an idea by a researcher from subsequent uses, but that is challenging in a number of ways. First, our publication data are effectively at the annual level, making it hard to sequence articles within a year. It is hard to know who introduces an idea in a paper when there are multiple coauthors. Thus, our use of "adoption" can be thought of as a combination of taking up an idea and using it in future publications.

To see the novelty of our two-sided network approach, consider the 150-year-old, multi-disciplinary literature on the relationship between age and the production of innovations. Work in this vein often (but not always) finds that innovation declines with age. These estimates can be used to impute the effect of aging on innovation using a "one-sided" analysis - essentially reweighting the estimated probabilities that innovators at different ages produce important innovations by changing the age distribution of innovators.

There is a smaller and more closely related literature on the adoption of ideas, which is often framed in terms of "Planck's principle".[4] Here a one-sided reweighting could be applied to impute the effects of aging on the adoption of ideas. Because younger scientists have been shown to be more willing to embrace new ideas (Packalen and Bhattacharya, 2019), the aging of the research workforce should reduce the adoption of new ideas.

Yet a thorough understanding of how the aging of the research workforce (or other changes in it) affects the adoption of new ideas requires a "two-sided" approach that accounts for the aging of both innovators and potential adopters and for the networks connect them. To see how networks mediate the flow of ideas between innovators and potential adopters, consider our three main results.

First, the relationship between age and idea adoption varies markedly by network distance. Ideas introduced by young innovators are adopted more than those introduced by older innovators at short network distances but that relationship changes as network distance increases, with mid-career innovators ideas having higher adoption rates at greater network distances. These findings suggest that middle-aged innovators' ideas have greater spread. Because, even for well-connected innovators, there are considerably more potential adopters

[4] Max Planck wrote, "A new scientific truth does not triumph by convincing its opponents and making them see the light, but rather because its opponents eventually die and a new generation grows up that is familiar with it. (Planck, 1950, p. 33).

at larger distances than nearby, overall adoption is dominated by adoption at large network distances, favoring more established researchers.

Second, and in keeping with the literature, young researchers are more likely to adopt new ideas. Moreover, they disproportionately tend to adopt new ideas introduced by the youngest innovators in proximate networks and networks tend to exhibit homophily with young innovators being better connected to young potential adopters. Decomposition analysis reveals that a higher adoption rate among young potential adopters is the main reason for the higher adoption rate of young innovators' ideas at short network distances.

Third, to account for differences in researcher prominence and journal visibility among young and old innovators, we conduct several subgroup analyses. The findings indicate that new ideas first published in (relatively) less prominent journals or by innovators with lower status (fewer publications or less central in networks) are relatively more recognized by young potential adopters in nearby networks. This finding suggests the importance of young researchers in identifying important ideas that might otherwise be underused.

While we believe that these micro results are important additions to our understanding of the diffusion of innovations in their own right, they are also inputs into a series of two-sided simulations to investigate how the aging of the scientific workforce will affect the diffusion and utilization of new ideas. We show that the aging of innovators is harmful for the diffusion of new ideas primarily because it lowers the quality of ideas being introduced. However, if we hold constant the quality of new ideas, the aging of innovators has only a slight negative impact because an increase in the share of middle-aged innovators, who tend to be prominent and well-connected, raises adoption. Nevertheless, the benefits of better connections are more than offset by the lower adoption rate of older innovators' ideas, especially when the relatively lower quality of new ideas introduced by older innovators is taken into account. If we assume that the entire scientific workforce (i.e., both potential adopters and innovators) continue to age at the same rate as between 2000 and 2010, in 20 years, the overall adoption of new ideas will be approximately 14% lower. Moreover, the effect of the aging via potential adopters is quantitatively comparable to the effect via the reduction in the quality of ideas. That is to say, focusing on only one side of the adoption (either innovator or potential adopters) will likely underestimate the negative impact of aging by half.

This paper contributes to two literatures. First, we contribute to the literature on innovation and especially to work on knowledge spillovers. At a substantive level, the innovation literature has tended to emphasize the production of new innovations. By contrast, we focus on the use of new ideas.[5] Focusing on idea flows leads us to introduce a two-sided network approach that studies the characteristics and networks of innovators and potential adopters and how they interact. Studying flows of knowledge puts our work squarely in the active body of work on knowledge spillovers. While the most natural way of measuring knowledge spillovers would be to trace knowledge flows, work on knowledge spillovers has typically sought to quantify knowledge spillovers using productivity in part due to the challenges of measuring knowledge flows directly.[6] We contribute to this literature by using natural language processing to directly track the introduction and flows of specific, important ideas - some of the most consequential

[5] Notable exceptions are Packalen and Bhattacharya (2019), which also studies aging, and a companion piece to the present piece, which shows that the ideas introduced by women and racial and ethnic minorities are adopted less than those introduced by men and non-Hispanic whites, but does not account for changes in the distribution of potential adopters (Cheng and Weinberg, 2023).

[6] Prominent pieces on knowledge spillovers that seek to infer spillovers from productivity include Azoulay et al. (2010), Waldinger (2010, 2012), Borjas and Doran (2012, 2015). When the literature has sought to measure knowledge flows, it has tended to rely on citation patterns (Jaffe et al., 1993), which were valuable when text data was not as readily available and easy to analyze, but they have drawbacks (Fong and Wilhite, 2017). Much of the motivation for such work stems from research showing that knowledge spillovers have important consequences for growth, trade, and urban agglomerations (Romer, 1990; Lucas, 1988; Krugman, 1991; and Glaeser et al., 1992).

ideas of the 20th century, including advances in molecular biology and understanding and treating HIV / AIDS.[7]

A major issue in the literature on knowledge spillovers has been controlling for selection into networks. We implement a new identification strategy for network data, which can be applied in other contexts. Specifically, focusing on the shortest network paths between potential adopters and innovators, we can employ multi-way fixed effects to control for the "quality" of ideas, which we allow to vary over time, and the adoption propensity of authors. Our approach allows us to identify specific ideas, the innovators who introduce those ideas, and the adoption of those ideas as a function of the characteristics of the innovators and potential adopters. Our findings imply that an inclusive collaboration network that is open to early-career researchers is especially beneficial for the diffusion of a new idea.

The second literature into which our work falls is on understanding the impact of age on innovation**.** As indicated, most work on age and innovation has focused on the productivity of individual researchers although a smaller literature studies the effects of researcher aging on receptivity to new ideas. Our work expands our lens by thinking about the implications of the aging of the entire research workforce - innovators and potential adopters alike. Moreover, estimates from our novel fixed-effect regressions allow us to sequentially and separately simulate how future changes in each of these factors (innovator age, potential adopter age, network proximity, and idea quality) would affect the diffusion of new ideas. Empirically, we show that the effect of aging on the receptivity to new ideas is comparable in magnitude to that of the effects of aging on the production of ideas. Our findings help us to better understand how and in what way the aging of the scientific workforce would affect the structure of knowledge production.

[7] Moreover, we believe that we are able to address the presence of synonyms convincingly using the Unified Medical Language System (UMLS) thesaurus.

The rest of the paper is structured as follows: Section 2 reviews the related literature. Section 3 describes the data and the sample construction. Empirical analysis is conducted in Section 4. Section 5 provides various decomposition and simulation analysis. Section 6 presents robustness checks. Finally, Section 7 concludes.

2 Related literature

Our piece falls within a broader literature on the economics / science of science and innovation. Within that broader literature, our work relates most closely to work on knowledge spillovers and on age and innovation. Here we survey those literatures and situate our work within them.

2.1 Collaboration networks and knowledge spillovers

Knowledge spillovers have been a consistent focus in the economics of science and innovation. Knowledge spillovers are central to economists' understanding of growth, trade, and urban agglomerations for over thirty years (Romer, 1990; Lucas, 1988; Krugman, 1991; and Glaeser et al., 1992).

Empirical micro evidence on knowledge spillovers typically focuses on indirect proxies of spillovers such as productivity. Recognizing that the people that innovators are linked to are unlikely to be random, much of the work in this space has sought to identify quasi-random variations in the quantity and/or quality of knowledge spillovers. Thus, Azoulay et al. (2010) study shocks in peer quality generated by deaths of star biomedical researchers. Like us, Mohnen (2021) studies the role of coauthorship networks, but uses deaths as shocks. Waldinger (2010, 2012) studies the effects of the dismissal of Jewish scientists from Nazi Germany on peer scientists and students. Borjas and Doran (2012, 2015) study the effects of the outflow of Jewish mathematicians from the Soviet Union on American mathematicians and mathematicians who remained in the Soviet Union. Catalini (2018) uses the relocation of scientists during asbestos abatement to study collaborations. The primary outcomes in all of these articles are measures of productivity or collaboration, while studies that directly track the spread of scientific ideas are scarce.

Jaffe et al. (1993) use citations to infer knowledge flows. (See a critique by Thompson and Fox-Kean, 2005). Despite the advantages offered by the citation-based method, it suffers from some well-recognized issues[8] and cannot follow the diffusion of specific ideas. Text analysis offers a more direct, objective and powerful alternative method to capture knowledge flows.

There is also a growing literature looking at how collaboration networks impact the production and diffusion of knowledge and ideas (Wuchty et al., 2007). Collaboration networks can serve as conduits for tangible and intangible resources, such as information, knowledge, grants, laboratorial capacity, reciprocal trust, etc. Many studies have shown that collaboration networks are closely related to scientists' productivity and creativity (Azoulay et al., 2010; Freeman and Huang, 2014; Ductor, 2015).

More relevant to the research question of this paper, there are also studies examining the role of networks in idea diffusion. Singh (2005) indicates that network proximity is associated with an elevated probability of knowledge flow, and its role even surpasses that of geographic distance. Sorenson et al. (2006) demonstrate that knowledge diffusion through networks depends crucially on the complexity of the knowledge at hand, and that knowledge of moderate complexity diffuses along networks to a greater extent.

There are also studies showing that the features of networks, as well as the functions of networks, vary substantially for scientists in different demographic groups. Female scientists'

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[8] There are a variety of other motives for citation than knowledge flows (see Gilbert, 1977; Moed, 2005; Moed and Garfield, 2004; Collins, 2004; Woolgar, 1991; Fong and Wilhite, 2017). Alcácer and Gittelman (2006) show that more than half of the citations on a patent are added by patent examiners, and thus may not represent knowledge flows.

networks tend to be smaller, with a larger proportion of women, and often with the same group of collaborators (van der Wal et al., 2021). Cheng and Weinberg (2023) finds that new ideas introduced by female innovators are less recognized by the scientific community, partly due to less network connections. However, how networks differ for scientists at different career stages is less known.

2.2 Age and innovation

Our work also relates to research on the relationship between age and innovation. We first discuss work on age and productivity and then discuss the relationship between age and the adoption of new ideas.

2.2.1 Age and productivity

Research has studied how innovativeness varies over the life cycle for at least 150 years back to Beard (1874) and the topic has received attention from psychologists and sociologists (Lehman, 1953; Zuckerman and Merton, 1973; Simonton, 1988) and economists (Diamond, 1984; Jones, 2009; Kaltenberg et al., 2023). It is commonly, but not universally (Sinatra et al., 2016), believed that scientist's productivity and creativity reaches its peak fairly early in the career and then declines gradually with age. The peak productivity is also believed to vary across fields and change over time (e.g., Simonton, 1988; Jones and Weinberg, 2011). Such findings have been found in cross-sectional and longitudinal data using various methodologies, though they differ in terms of the explanation for this age pattern. There are also a range of measures of the quantity and quality of output, such as publications and patents, citation patterns, awards, major achievements and discoveries (Gringas et al., 2008; Jones et al., 2014).

Not surprisingly, economists have applied the human capital model to understand age dynamics in scientific output. For instance, Levin and Stephan (1991) explain the age-productivity relationship assuming that individuals optimally allocate time to research activities that bring about future financial rewards. Given the finite time horizon, the investment motive implies a decline in research productivity over the career.[9]

Many have argued that life-cycle productivity exhibits a curvilinear pattern, yet how well this canonical trajectory represents individual researchers is the subject of increased attention. Way et al. (2017) suggest that the conventional narrative is misleading for the whole scientific workforce, which exhibits considerable heterogeneity.[10] The average trajectory only reflects the life-cycle pattern of one-fifth of faculty. Similarly, Győrffy et al. (2020) and Sunahara et al. (2023) also find more heterogeneous productivity trajectories by analyzing data from a wide range of disciplines.

One significant confounder when studying life-cycle productivity is selective attrition. Thus, the aging pattern observed in the data may be driven by a compositional change of the active scientific workforce. Gingras et al. (2009) suggest that a growing fraction of professors are less active or stop publishing as they age, while the active professors' productivity remains at its peak until retirement. The timing of retirement and the length of the academic career are also affected by research productivity. Productive researchers choose to retire later and have longer publishing careers (Kim, 2003; Yu et al., 2023). Cole (1979) attributes this selective attrition to the operation of the reward system in most universities, which discourages researchers whose work is not favorably received and causes outflows from academic research.

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[9] Levin and Stephan (1991)'s model incorporates both the investment and consumption motives, but their results align more with the investment motive.

[10] Feichtinger et al. (2019) develop a theoretical model that underpins the different patterns found in Way et al. (2017). Like Levin and Stephan (1991), Feichtinger et al. (2019) also use a dynamic life-cycle model with investment and finite horizon. But the difference is that Feichtinger et al. (2019) consider not only investment in knowledge/human capital, but also in reputation through networking activities. Both knowledge and reputation have positive effects on a researcher's output. Investment motive does not decline for all even given a finite time horizon because scientists have different valuations for reputation achieved by the end of their scientific lifetime.

Stephan (1996) considers the extreme inequality in science as the result of the winner-take-all nature of scientific contests (Matthew effect in science).

Work also studies differences across disciplines in the relationship between age and the production of important scientific advances and how that relationship changes over time / cohorts.[11] Zuckerman and Merton (1973) introduced the codification hypothesis, which highlights the differential level of consolidation of empirical knowledge in cohesive and interdependent theoretical formulations across various sciences and specialties. More codified disciplines (such as physics) provide the young more opportunities for making significant contributions early in their careers, leading to a relatively younger peak-productivity age. Falagas et al. (2008), for instance, find a relatively early peak in biomedicine, our context, followed by a modest downward trend. The codification hypothesis has received mixed support (Oromaner, 1977; Cole, 1979). Jones and Weinberg (2011) show that the frequency of great achievement at young ages is more a function of time and research approach than field. They found that the dynamics in the prevalence of theoretical contributions over time in a given field parallels its shifts to younger ages at great achievement.

Additionally, the expansion of foundational knowledge in a field may increase educational requirements, which make training durations longer (NRC, 1990; Jones, 2010). Jones (2009) introduces a model that explains the "burden of knowledge" mechanism, which suggests that as knowledge accumulates and technology advances, successive generations of innovators face an increasing educational burden to reach the knowledge frontier.

Finally, there are a range of other potential explanations for the life-cycle productivity / creativity pattern, including changes in cognition (Kaltenberg et al., 2023) and physical health (Dietrich and Srinivasan, 2007), family responsibilities (especially for women), tenure

[11] The literature also notes the challenge of disentangling age and cohort effects (Lillard and Weiss, 1978; Hall et al., 2005).

(Franzoni et al., 2017), increasing administrative or other research-unrelated demands, depreciation and obsolescence of knowledge, and shifts in demand[12]. While each of these may play some limited role, it is unlikely to be the main driver of the whole career trajectory.

2.2.2 Age and receptivity to new ideas

In addition to the relationship between age and productivity, there is work on the impact of age on receptivity to new ideas, which is often framed in terms of Planck's principle (Kuhn, 1970). Here, young scientists are believed to have more flexible minds, less attachment to existing theories, and more exposure to recent advances in their education.

However, empirical studies looking at Planck's principle find mixed evidence. Hull et al. (1978) may well be the first to test this principle empirically. They found that age played a statistically significant but minor role in the reception of Darwin's evolution of species theory. Diamond (1980) provides similar findings in the case of the adoption of cliometrics. Messeri (1988) suggests two opposite forces in driving the relationship between age and receptivity to new scientific theories. On the one hand, older scientists tend to have stronger commitments to existing paradigms. On the other hand, older scholars also have more accrued resources that help buffer the increased intellectual risk taken in advocating speculative theories. He finds that the first adopters of the theory of plate tectonics tended to be older. Levin et al. (1995) re-estimate the effects of age on the probability of accepting Darwin's theory of evolution using a semi-parametric hazard model that controls for censored data, and finds that age effects are statistically insignificant. Wray (2003) suggests that middle-aged scientists initiated more scientific revolutions than young scientists given the proportion of each group in the total

[12] Galenson and Weinberg (2000) provides a case study of the profession of modern American painting, in which a shift of demand in the criteria for quality (increased premium placed on innovation/increased demand for innovation in painting) produced a dramatic change in the age at which artists produced their best work.

population of scientists. In the field of bacteriology, Wray (2004) confirms again that middle-aged scientists are responsible for a higher number of significant discoveries than young scientists.

In contrast, Rappa and Debackere (1993) finds that young scientists played a major role in populating the field of neural networks during its emergence. Gingras et al. (2009) find that young researchers accumulate a basic set of references until they are about 40, and after that, they tend to stick to their set of references and stop following the growing number of recent publications as actively.

A different but related question is whether the death of scientists facilitates the spread of new scientific ideas. Azoulay et al. (2019) investigate how the premature death of eminent scientists alters the research activities in the affected fields. They find that after the death of a star scientist, there is a surge in contributions from outsiders that draws upon different scientific corpus, which provides an opportunity for the fields to evolve in new directions.

As scientific research is increasingly collaborative, it may be inappropriate to look at young and senior scientists separately. Certain configurations of team structure may bring about better synergies than others. Packalen and Bhattacharya (2019) finds that though young researchers are more likely to build on new ideas, collaborating with experienced researchers also matters. Papers with a young first author and a more experienced last author are more likely to try out new ideas than other combinations. Callaway (2015) suggests that young researchers are innovative but they also need some mentorship from senior researchers.[13]

[13] Sekara et al. (2018) highlight the role of experienced scientists as chaperones who help young researchers publish in high-impact venues.

3 Data and sample construction

3.1 Data

The primary data source for this paper is MEDLINE, a bibliographic database of biomedical research. It is exceptional in its comprehensiveness, containing more than 30 million works dating back to the 1870s. MEDLINE provides information on not only a publication's authors, publication year and journal, but also the full text of an article's title and abstract, which makes it possible to extract the main ideas/concepts in an article.[14] Another advantage of MEDLINE is that it also includes Medical Subject Headings (MeSH) that indicate the main area of study for an article.[15] MeSH terms are valuable for identifying potential adopters of a concept by limiting the sample to people working on similar topics.

A second important data component is the Unified Medical Language System (UMLS), which is a repository of biomedical terms developed by the US National Library of Medicine (Bodenreider, 2004). Many previous studies use words or word combinations in the text to represent its main ideas. Nevertheless, a shortcoming of this approach is that different expressions of the same concept may be considered different concepts. UMLS, which covers the entire biomedical domain, helps us overcome this problem by disambiguating over 2 million names for approximately 900,000 concepts. Each concept has a unique ID that links to

[14] Article titles are available as early as 1964. Generally, there are no abstracts for publications before 1975. But some abstracts are added by a PubMed Central scanning project that digitizes the back issues of participating journals. For more details, see https://www.nlm.nih.gov/bsd/mms/medlineelements.html .

[15] MeSH descriptors are organized in categories and subcategories up to thirteen hierarchical levels, forming a quasi-tree structure. An article is usually tagged with multiple MeSH terms of different levels of specificity by independent professionals at the National Library of Medicine. We use the set of level-4 major-topic MeSH terms to define the main topics of an article. For example, the article (PMID=7983732) is tagged with "Retroviridae" (B04.820.650), "Mutation" (G05.365.590), and "Transferases" (D08.811.913).

various expressions and synonyms.

A third crucial data source is the "Author-ity" MEDLINE author disambiguation database (Torvik and Smalheiser, 2009) that assigns each author a unique ID so that we can track the full history of each researcher's publications as well as their collaboration networks. Additionally, we utilize MapAffil (Torvik, 2015) to limit our sample to US-based scientists,[16] and Genni 2.0 to obtain ethnicity-specific gender predictions based on author names.

3.2 Sample construction

Our analytical data sample is constructed in two steps: first, we obtain a list of new important ideas introduced or "born" in each year. Then, for each idea in our list, we identify all relevant publications in the same research area as the new idea's potential adopters.

The first step is relatively computationally intensive as it involves analyzing the text of the title and abstract of each publication and identifying all the UMLS concepts incorporated in it. Yet it is conceptually straightforward since UMLS provides a list of terms linked to unique concept IDs. After harvesting all concepts in the publication corpus, we can identify the first year in which a concept appears in MEDLINE, which is defined as the concept's birth year or cohort. Within each cohort of concepts, we rank ideas by the cumulative number of mentions received by each concept up until 2018 and take the top 2% of ideas from each cohort. The resulting list of ideas represents the most important new ideas born in each year. These include revolutionary concepts such as Polymerase Chain Reaction (C0032520), HIV infections (C0019693), Functional Magnetic Resonance Imaging (C0376335).[17] Each year we identify approximately 110 to 150 new concepts.

[16] We exclude all scientists who are ever associated with a non-US institution and include US based scientists whether they are at a university or other type of research organization.

[17] C0032520, C0019693, and C0376335 are unique concept ID's in UMLS.

In the second step, for each new idea i born in year t, we track who adopts it over a period of ten years (i.e., up to the year $t + 10$). Let IA_i be the innovating article or articles that first introduce idea i and I_i be the set of innovators on these paper(s).[18] Based on the MeSH terms that appear on any paper in IA_i, we find all potential adopting papers, defined as the papers with at least one common major-topic MeSH term as any of the papers in IA_i. These potentially adopting paper-idea pairs - ideas crossed with the papers written after the birth of the idea that overlap topically with the paper that introduced the idea - are our unit of analysis. Thus, to identify papers that have a reasonable likelihood of adopting an idea i that was introduced in year t', we identify all papers j published in year $t' \in [t + 1, t + 10]$ that share one or more major MeSH codes with idea i. We then identify the first and last authors on paper j, and the innovators in I_i that are closest to the first and the last author in the coauthorship network from year $t'-3$ to $t'-1$ and record the number of steps in the shortest network path to reach the innovators. This network distance represents how far the potential adopters are from the idea.

Finally, we restrict the birth year of our new ideas to the time window 1980 to 2008 so that we can fully observe each idea cohort for ten years - our publication data end in 2018[19] . Then we take a 10% random sample and obtain our analytical sample with 12,125,501 paper-idea level observations. Table 1 shows the summary statistics. Career age, defined as the number of years since a researcher's first publication, of innovators and potential adopters are the key variables of interest.[20]

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[18] Some ideas are introduced by multiple articles in the same year. We do not attempt to identify the first article because of publication lags and difficulty identifying the precise timing of publication.

[19] More recent MEDLINE data is available, however, Author-ity is updated till 2018.

[20] Due to data limitations, we do not have researchers' biological ages. Kwiek and Roszka (2022) indicates that career age is a good proxy for science, technology, engineering, mathematics and medicine disciplines, while it has worse performance for humanities and social sciences.

Table 1. Summary Statistics

	Mean	SD	Median	Min	Max
Adoption	0.096	3.09	0	0	100
Career age of first author of potentially adopting paper	11.23	9.76	8	0	43
Career age of last author of potentially adopting paper	15.31	10.70	14	0	45
Career age of nearest innovator for first author	18.02	8.40	17	1	42
Career age of nearest innovator for last author	18.02	8.40	17	1	42
Years since introduction	5.61	2.84	6	1	10

Notes: Sample contains 12,125,501 paper-idea pairs - ideas crossed with the papers written after the birth of the idea that overlap topically with the paper that introduced the idea. *Adoption* is a binary indicator that equals 1 if the paper adopts the relevant new idea, and 0 otherwise. It is multiplied by 100 so that it can be interpreted as the adoption rate in percentage points.

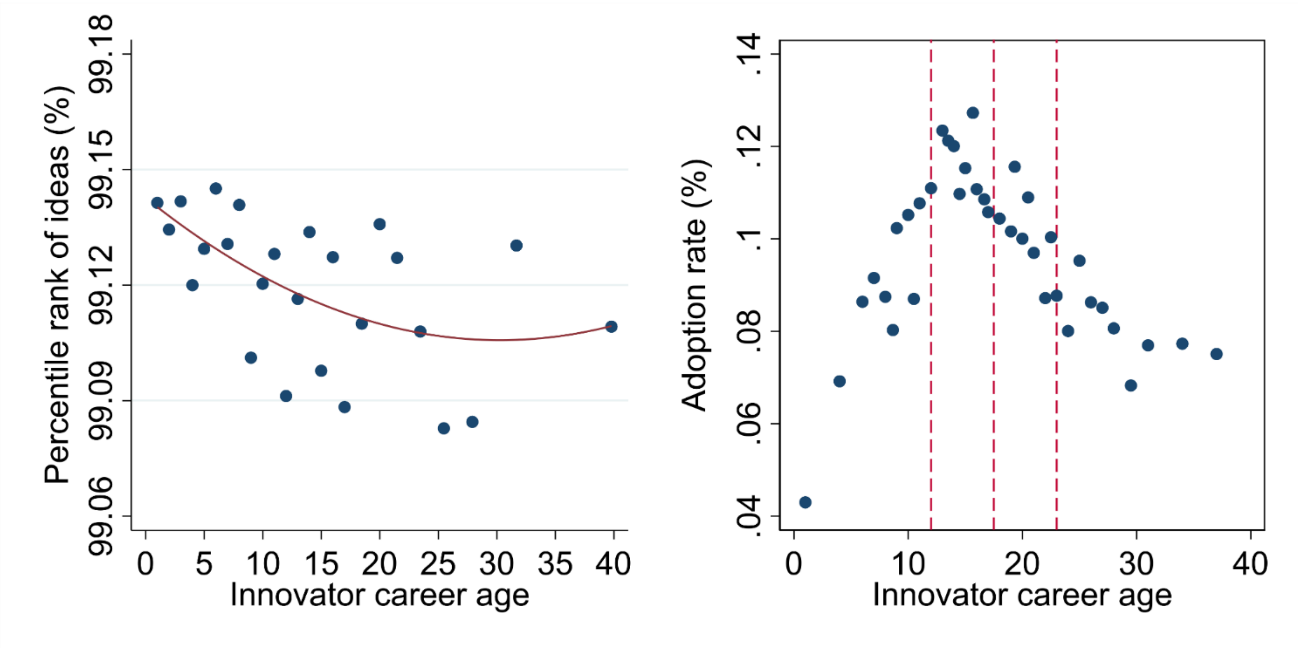
4 Empirical analysis

4.1 Descriptive analysis

We first empirically examine whether the conventional belief that young researchers are more creative and produce better new ideas holds. Although the new ideas we study are the most important innovations in their respective cohorts, there are still differences among them, with some ideas being more applicable or applicable more broadly. We plot the mean within-cohort ranking, based on the cumulative number of mentions up to 2018 conditional on the birth year of new ideas introduced by innovators at different career ages in the left panel of Figure 1. There is a negative relationship where younger innovators' ideas are at higher (i.e., better) percentiles than the ideas of older innovators. Although this analysis is purely descriptive, it at least suggests that young innovators' ideas are not clearly worse than their counterparts. In the regression analysis below, we will extract idea-fixed effects to better represent the quality of a new idea. There we see a similar negative association between innovator career age and idea quality (Appendix Figure A1).

If young innovators produce better (and certainly not worse) ideas, their ideas are not adopted as much in the first ten years after they are introduced, as shown in the right panel of Figure 1. Thus, new ideas introduced by the youngest innovators are adopted less not because their ideas are inherently of lower quality; rather there appear to be other factors driving differences in adoption over the career. There is a clear inverted V shape in the adoption rate as innovator age increases. The three red dashed lines separate the four quartiles of innovator age. Adoption rates peak in the second quartile, among young to middle-aged innovators, while new ideas by the youngest and oldest group of innovators are adopted less.

Figure 1. Idea ranking, adoption rate and innovator age



Notes: The left panel shows the percentile rank of new ideas introduced by innovators at different career ages. The right panel shows the 10-year adoption rate of new ideas introduced by innovators at different career ages. The *x*-axis in both panels indicates innovator career age. The *y*-axis in the left panel shows the average ranking of new ideas in our sample with 0 (not shown) indicating the worst new idea and 100 indicating the best. We restrict our sample to the top 2% of ideas (i.e., the 98th to 100th percentiles). An idea at the 99.1 percentile (for instance) is better than 99.1% of ideas in its cohort. The ranking is generated from within-cohort comparisons of total mentions up to 2018. The adoption rate in the right panel is a binary variable for whether each idea is used in each potentially adopting article (defined based on overlap in Medical Subject Headings) published in the first 10 years after the idea is first introduced. The vertical dashed lines in the right panel represent the quartiles of innovator career age.

Thus, it appears that the inverse-V in adoption of innovators ideas is likely driven by factors other than idea quality, including characteristics of both innovators and potential adopters. For instance, innovator's prominence and network connections may increase the visibility of the new ideas they introduce. For another, potential adopter's access to new ideas and inclination to adopt them may also matter. We explore these possibilities below.

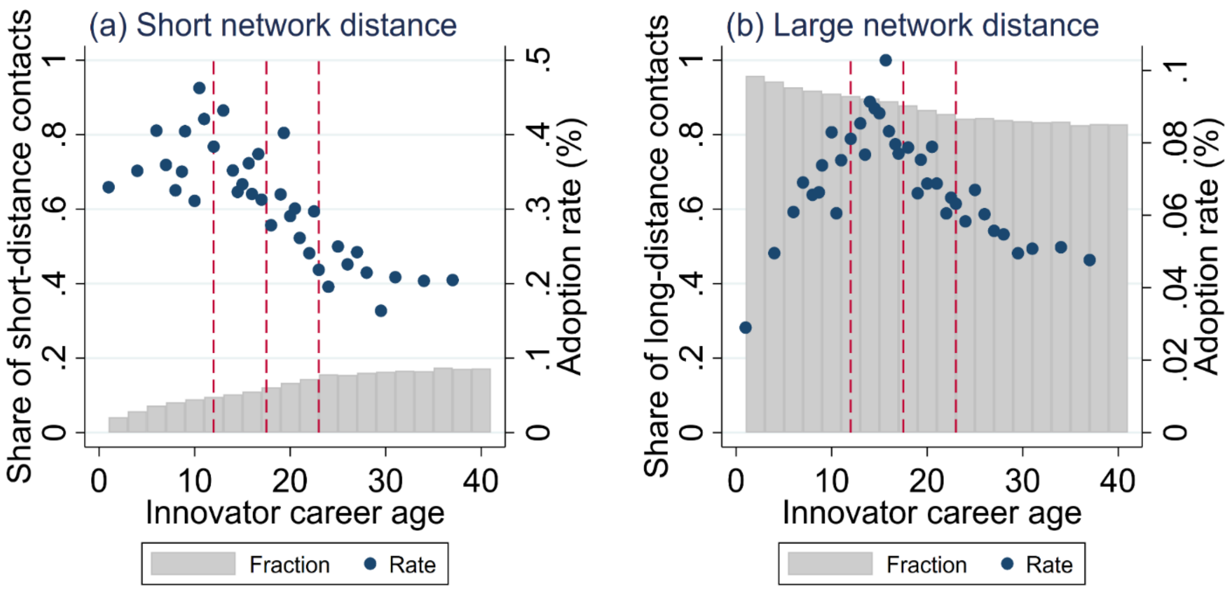
Given that network distance is a major factor in the adoption of ideas, we separately look at adoptions at short and large network distances. Figure 2 shows how adoption varies with innovator career age by network distance (a short distance is less than or equal to 3). As reflected by the difference in scales between the two panels, adoption rates at short network distances are many times higher than at large network distances. Adoption rates decline as network distance increases for a range of reasons, some causal, such as the longer path that ideas need to travel, and some non-causal, such as a growing gap in research foci as distance grows.[21] Beyond that, there is a clear contrast between the left and right panels.[22] The inverted-V shape pattern holds at large network distances (right panel) but, at short network distances, adoption rates decline with innovators' age. This finding suggests that young innovators may rely more heavily on their networks to spread their new ideas. This possibility, in turn, suggests that network proximity may, to some extent, compensate for the lack of well-established publication history to attract potential adopters. As shown by the gray bars in each panel, far

[21] Appendix Figure A2 shows that adoption rate declines exponentially with network distance.

[22] Appendix Figure A3 shows, in more detail, the adoption rates for different combinations of adopter career age and innovator career age respectively for short and large network distances. It shows a clear shift of the peak adoption from innovators with 5 or fewer years of experience at short network distances to adopters with more than 10 and fewer than 20 years of experience at larger network distances.

more researchers are at large distances than short distances and that is particularly true for young innovators (i.e., young innovators networks are, not surprisingly, particularly circumscribed).[23] Thus, the overall pattern of adoption (shown in the right panel of Figure 1) reflects the pattern at large network distances, which favors mid-career researchers.

Figure 2. Network distance and adoption rate



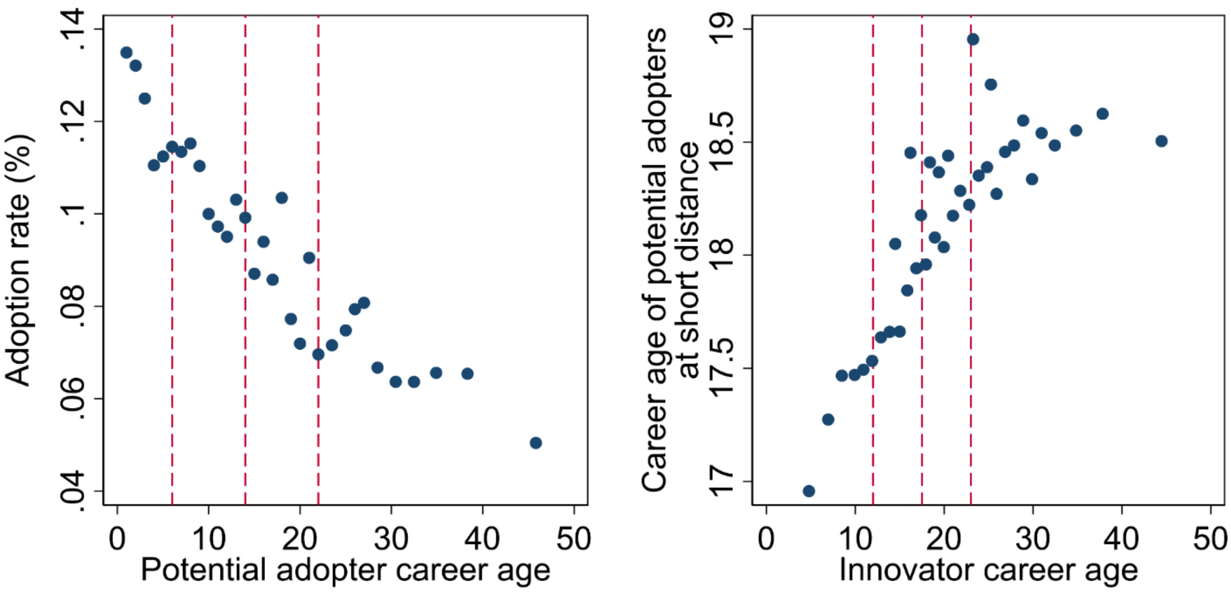
Notes: The gray bars show the fraction of short-distance contacts (left panel), defined as a distance of 3 or lower, and large-distance contacts (right panel), defined as 4 or higher, for innovators at each career age. These correspond to the left *y*-axes. The scatter points plot the 10-year adoption rate as a function of innovator age at short (left panel) and large (right panel) network distances respectively. The right *y*-axes correspond to the adoption rates. The adoption rate is a binary variable for whether each idea is used in each potentially adopting article (defined based on overlap in Medical Subject Headings) published in the first 10 years after the idea is first introduced. The vertical dashed lines indicate the quartiles of innovator career age.

While older researchers are better connected than younger researchers, networks tend to

[23] Older innovators are better connected in terms of both the counts of people at short distances and network centralities. Appendix Figure A4 shows that both betweenness centrality and eigenvector centrality increases with innovator career age.

exhibit homophily, and the literature suggests that young researchers may be particularly likely to adopt new ideas, which would tend to increase adoption of the ideas introduced by young innovators. The left panel of Figure 3 shows that adoption probability declines monotonically with the career age of potential adopters, indicating that young researchers are indeed more open to try out new ideas than older researchers. Moreover, the right panel of Figure 3 describes the relationship between innovator career age and the average career age of the potential adopters at short network distances. There is a strong positive association between innovator age and potential adopter age. That is, younger innovators are close to younger researchers, which is advantageous since having a larger number of young potential adopters at short network distances facilitates the utilization of a new idea. Unfortunately, this advantage of young innovators at short network distances is limited by the relatively smaller share of contacts at short distances, especially among young innovators.

Figure 3. Age of potential adopters and adoption rate



Notes: The left panel plots the 10-year adoption rate against potential adopter's career age. The adoption rate is a binary variable for whether each idea is used in each potentially adopting article (defined based on overlap in Medical Subject Headings) published in the first 10 years after the idea is first introduced. For innovators at every career age, the right panel plots the mean career age of potential adopters at short network distances from those innovators. The vertical dashed lines in the two panels indicate the quartiles of career age for potential adopters (left panel) and innovators (right panel) respectively.

Taken together, the diffusion of young innovators' ideas face three forces, two that benefit young innovators and one that benefits older innovators. Adoption of the ideas introduced by young innovators is high because they are close to young potential adopters who tend to adopt new ideas (positive effect), they tend to have better ideas (positive effect), but they have fewer network connections at short distances (negative effect). This explains why young innovators' ideas are more adopted at short distances even though their overall adoption rate is lower. Put differently, moving from the youngest researchers to those in the second quartile of age (i.e., early mid-career) the benefits of better network position dominate the disadvantages of worse idea quality, but past the early mid-career, the disadvantage of worse idea quality is greater than the benefits of better connections. This leads to the peak in the inverted-V-shaped adoption rate. Thus, early mid-career innovators possess some of the strengths of both young and old innovators - they are relatively better connected (than young innovators) and have relatively good ideas (compared to old innovators).

4.2 Regressions

The above descriptive figures illustrate the relationship between the important variables, but do not permit causal inference or hold other variables constant. This section turns to a regression framework to investigate how the age of innovators, the age of potential adopters, and network distance influence the diffusion of important new ideas. Formally, we estimate models of the form:

$$\begin{aligned} A_{i,j} = {} & \alpha + \beta Dist_{i,j} + \rho Age_j + \gamma InnoAge_{i,j} \\ & + \delta_1 Near_{i,j} \times Age_j + \delta_2 Near_{i,j} \times InnoAge_{i,j} \\ & + \delta_3 Near_{i,j} \times Age_j \times InnoAge_{i,j} + \zeta_{i,t} + \iota_p + u_{i,j}, \end{aligned} \tag{1}$$

where $A_{i,j}$ represents whether paper j adopts new idea i; $Dist_{i,j}$ represents the shortest network distance of paper j's last author to any of the innovators of idea i (i.e. I_i). A full set of network distance dummies are included in the regression, but for the sake of space, in the distance-interacted terms we create an indicator variable "*Near*" which represents a network distance less than or equal to 3. Age_j is the career age of the last author on paper *j*. $InnoAge_{i,j}$ represents the career age of the innovator of idea *i*, who is closest to article *j*'s last author. We choose the last authors on potential adopting papers to construct the potential adopter age variables because they are more likely to be principal investigators of research projects and decide research directions, including the ideas that labs explore. On the other hand, our expectation is that first authors play a more active role in writing. In the robustness analyses, we will explore the impact of different combinations of first and last authors on potential adopting papers.

There are two sources of endogeneity that need to be addressed. First, researchers surely vary in terms of their openness to new ideas due to their personalities, cultural, family, or institutional backgrounds and other factors. To address these differences in the adoption propensities of potential adopters, we include last author fixed effects ι_p. These control for time-invariant differences in the adoption rates of individual researchers.

The second source of endogeneity is unobserved differences in the quality / usefulness of ideas, which may change over time. To address these differences, we include idea-by-year fixed effects, represented by $\zeta_{i,t}$. Specifically, we track the diffusion of new ideas for a window of ten years after ideas are first introduced. Researchers age over time and there can be time patterns in the use of ideas as attention to some new ideas wanes and others build over time. Our idea-by-year fixed effects control for any such patterns non-parametrically.

Our identification strategy leverages variations across potentially adopting papers in terms of which author on the innovating paper(s) is closest to the last author on each potentially adopting paper in terms of network distance. For a new idea, the length of the shortest network path connecting the last author on a potentially adopting paper and one of the innovators indicates the distance between a potential adopter and the new idea. We use the age of that nearest innovator to characterize the age of the innovator for each potentially adopting paper. Given that network distance is also held constant, our identification comes from within-idea variations in terms of the age of the innovator who is closest to the last author of the potentially adopting paper controlling for the adoption propensity of the last author on each potentially adopting article.

Our inclusion of idea-by-year fixed effects has the potential to absorb the effects of innovating author age. That is, for any given idea, the team of innovators is fixed and thus the characteristics of innovators do not vary across potentially adopting articles and are inseparable from the idea-by-year fixed effects. Because the closest innovator varies across potentially adopting papers, there will be variation in innovator age across potentially adopting papers. This variation makes it possible to control for flexible idea-specific time-varying patterns and delineate the impact of innovator career age on the adoption of a new idea.

We divide potential adopters and innovators into four quartiles, denoted by Q1, Q2, Q3 and Q4 from the youngest to oldest in terms of career age. The three quartiles cutoffs for innovator career age are 12, 17, and 23; and those for potential adopter career age are 7, 12, and 18. The oldest group Q4 is the reference group. Baseline regression estimates are reported in Table 2. The prefix "*Inno*" in the labels represents the nearest innovator's age group and the prefix "*Ad*" represents potential adopter's career age.

Columns (1)-(2) of Table 2 are OLS estimates, Columns (3)-(4) control for idea-by-year fixed effects, and Columns (5)-(6) additionally control for author fixed effects. The OLS estimates in Column (1) show that, when interactions with the "*Near*" distance dummy are excluded, adoption peaks in the second youngest age quartile - the estimated coefficient on *InnoQ2* is the highest, followed by *InnoQ1*, *InnoQ3* and last by *InnoQ4*. When we include interactions between *Near* and age in Column (2), adoption at short network distances is flat between the youngest and second youngest quartiles - the sum of the coefficients on *InnoQ1* and *Near*InnoQ1* are not statistically different from the sum of the coefficients on *InnoQ2* and *Near*InnoQ*2.[24] This result aligns with the descriptive Figure 2, which indicates that, as a whole, new ideas introduced by the youngest innovators are adopted less than those by middle-aged innovators, although at short network distances the two groups have similar adoption rates.

Estimates that include idea-by-year fixed effects in Column (3) and (4) are smaller than the OLS estimates. At long distances, after accounting for idea fixed effects and idea-specific trends, ideas introduced by the second youngest quartile of innovators have slightly higher adoption than those introduced by the youngest innovators, although the differences are smaller than suggested by the OLS estimates and statistically insignificant. At short distances, ideas introduced by the youngest and middle-aged groups of innovators also have similar adoption rates. Across all columns, adoption is lowest in the oldest and second oldest quartiles. This result is robust to how we define age groups. For instance, if we dichotomize age at median, the younger group has a higher adoption rate than the older group. The estimated relationship between adoption, innovator age and the interaction between innovator age and distance are robust to including fixed effects for potential adopters (in Columns (5) and (6)).

Lastly, we turn to potential adopter age. Across all specifications, the younger potential adopters are more likely to try out new ideas and adoption declines monotonically in career age at both short and large network distances. Regardless of network distance, young researchers are more receptive to new ideas. This is a consistent pattern in both descriptive figures and various regression specifications, including those that include potential adopting author fixed effects and is particularly strong at short network distances.

[24] The F test statistic is 1.14 and the corresponding p value is 0.28.

Table 2. Baseline regressions

	(1)	(2)	(3)	(4)	(5)	(6)
InnoQ1	0.0335**	0.0178**	0.0335**	0.0140**	0.0291**	0.0130**
	(0.0025)	(0.0022)	(0.0043)	(0.0047)	(0.0044)	(0.0048)
InnoQ2	0.0485**	0.0319**	0.0340**	0.0167**	0.0323**	0.0176**
	(0.0027)	(0.0024)	(0.0039)	(0.0042)	(0.0039)	(0.0043)
InnoQ3	0.0281**	0.0162**	0.0226**	0.0105**	0.0227**	0.0112**
	(0.0025)	(0.0023)	(0.0034)	(0.0038)	(0.0035)	(0.0038)
Near		-0.0351**		0.0039		0.0350**
		(0.0092)		(0.0073)		(0.0079)
Near X InnoQ1		0.1096**		0.0769**		0.0629**
		(0.0136)		(0.0084)		(0.0086)
Near X InnoQ2		0.1126**		0.0742**		0.0622**
		(0.0132)		(0.0082)		(0.0083)
Near X InnoQ3		0.0725**		0.0498**		0.0482**
		(0.0111)		(0.0075)		(0.0077)
AdQ1	0.0833**	0.0521**	0.0729**	0.0444**	0.0502**	0.0129
	(0.0027)	(0.0024)	(0.0026)	(0.0028)	(0.0100)	(0.0100)
AdQ2	0.0475**	0.0281**	0.0370**	0.0202**	0.0196**	-0.0020
	(0.0024)	(0.0022)	(0.0026)	(0.0028)	(0.0074)	(0.0075)
AdQ3	0.0192**	0.0133**	0.0094**	0.0051*	-0.0020	-0.0088*
	(0.0024)	(0.0022)	(0.0027)	(0.0029)	(0.0050)	(0.0052)
Near X AdQ1		0.3242**		0.3008**		0.3154**
		(0.0178)		(0.0088)		(0.0095)
Near X AdQ2		0.1281**		0.1112**		0.1171**
		(0.0116)		(0.0074)		(0.0078)
Near X AdQ3		0.0343**		0.0244**		0.0275**
		(0.0104)		(0.0074)		(0.0077)
Distance=1	2.1446**	2.0222**	2.1024**	1.9763**	2.1026**	1.9451**
	(0.0702)	(0.0703)	(0.0153)	(0.0153)	(0.0158)	(0.0155)
Distance=2	0.4328**	0.3118**	0.4247**	0.2977**	0.4557**	0.2975**
	(0.0129)	(0.0134)	(0.0067)	(0.0066)	(0.0074)	(0.0068)
Distance=3	0.1298**		0.1369**		0.1665**	
	(0.0042)		(0.0040)		(0.0048)	
Distance=4	0.0470**	0.0401**	0.0649**	0.0577**	0.0829**	0.0752**
	(0.0023)	(0.0023)	(0.0029)	(0.0029)	(0.0035)	(0.0035)
Distance=5	0.0167**	0.0124**	0.0308**	0.0264**	0.0384**	0.0345**
	(0.0019)	(0.0019)	(0.0025)	(0.0025)	(0.0028)	(0.0028)
Idea-by-year F.E.	No	No	Yes	Yes	Yes	Yes
Author F.E.	No	No	No	No	Yes	Yes
R-squared	0.0023	0.0025	0.0110	0.0111	0.0464	0.0465
N	11,505,729	11,505,729	11,505,689	11,505,689	11,462,124	11,462,124

Note: This table reports estimates of a simplified version of Equation (1) for whether each of 2,699 ideas (born from 1982 to 2008) is adopted by each potentially adopting article on (i) dummy variables for the quartile of the age distribution of innovators (InnoQ1 (youngest) to InnoQ3 (next to oldest) with InnoQ4 (the oldest) being excluded), (ii) dummies for the quartile of the age distribution among potential adopters (AdQ1 (youngest) to AdQ3 (next to oldest) with AdQ4 (the oldest) being excluded), and (iii) distance fixed effects. (Unlike Equation (1), it excludes interactions between each of these and the potential adopter being near the innovator in the collaboration network.) Additional controls are indicated. The unit of observation is an idea-potential adopter pair. That is each idea appears once for each article published in the first 10 years after the idea was introduced that might potentially adopt it (based on overlap in Medical Subject Heading codes). On average there are 4,263 potential adopting articles per idea. Potential adopter age is measured using the age of the last author on each potentially adopting paper and innovator age is measured using the age of the author on the innovating article(s) that is closest to the potential adopter. Robust standard errors are reported in the parentheses.

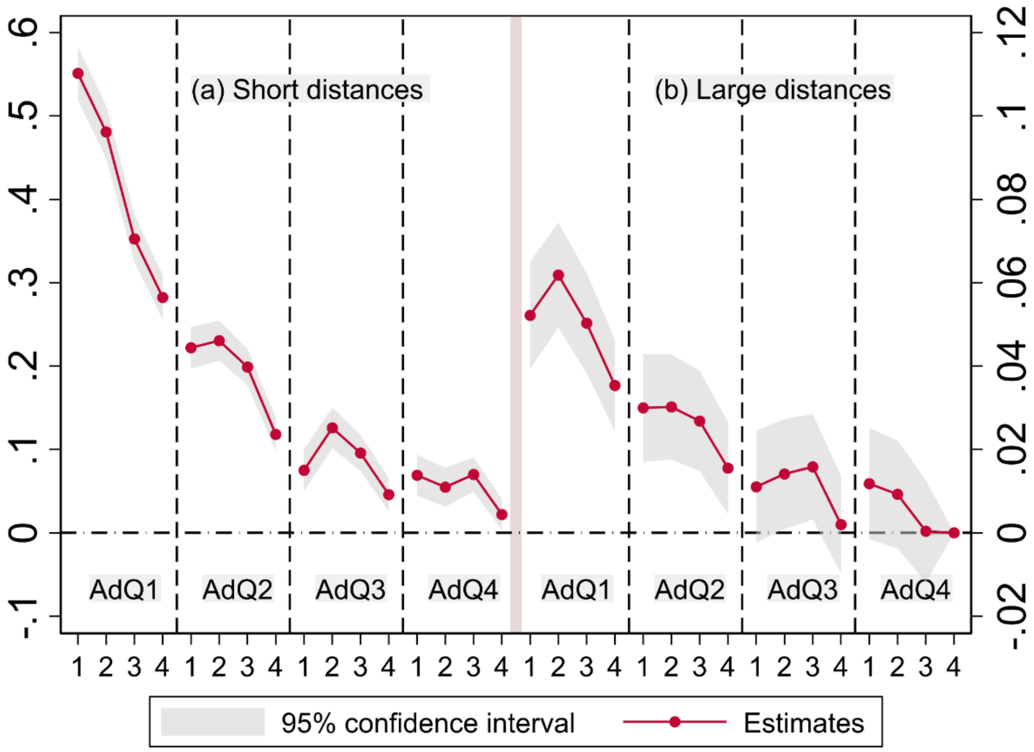
Table 3. Regressions with three-way interactions

	(1)	(2)
Near X InnoQ1 X AdQ1	0.2167**	0.2170**
	(0.0250)	(0.0258)
Near X InnoQ2 X AdQ1	0.1484**	0.1311**
	(0.0248)	(0.0256)
Near X InnoQ3 X AdQ1	0.0077	0.0017
	(0.0231)	(0.0238)
Near X InnoQ1 X AdQ2	0.0542**	0.0464**
	(0.0212)	(0.0215)
Near X InnoQ2 X AdQ2	0.0742**	0.0680**
	(0.0208)	(0.0211)
Near X InnoQ3 X AdQ2	0.0219	0.0230
	(0.0192)	(0.0195)
Near X InnoQ1 X AdQ3	-0.0152	-0.0208
	(0.0215)	(0.0217)
Near X InnoQ2 X AdQ3	0.0443**	0.0429**
	(0.0210)	(0.0212)
Near X InnoQ3 X AdQ3	-0.0116	-0.0134
	(0.0194)	(0.0196)
InnoQ1 X AdQ1	0.0050	-0.0124
	(0.0076)	(0.0078)
InnoQ2 X AdQ1	0.0173**	0.0041
	(0.0079)	(0.0081)
InnoQ3 X AdQ1	0.0146*	0.0068
	(0.0078)	(0.0080)
InnoQ1 X AdQ2	0.0027	-0.0074
	(0.0076)	(0.0078)
InnoQ2 X AdQ2	0.0054	-0.0015
	(0.0080)	(0.0081)
InnoQ3 X AdQ2	0.0109	0.0057
	(0.0079)	(0.0080)
InnoQ1 X AdQ3	-0.0027	-0.0059
	(0.0081)	(0.0082)
InnoQ2 X AdQ3	0.0029	0.0003
	(0.0085)	(0.0086)
InnoQ3 X AdQ3	0.0135	0.0123
	(0.0084)	(0.0084)
Idea-by-year F.E.	Yes	Yes
Author F.E.	No	Yes
R-squared	0.0112	0.0466
N	11,505,689	11,462,124

Note: This table reports estimates of Equation (1) for whether each of 2,699 ideas (born from 1982 to 2008) is adopted by each potentially adopting article on (i) dummy variables for the quartile of the age distribution among innovators (InnoQ1 (youngest) to InnoQ3 (next to oldest) with InnoQ4 (the oldest) being excluded), (ii) dummies for the quartile of the age distribution among potential adopters (AdQ1 (youngest) to AdQ3 (next to oldest) with AdQ4 (the oldest) being excluded), (iii) interactions between each of these and the potential adopter being near (distance <=3) the innovator in the collaboration network, and (iv) distance fixed effects. Additional controls are indicated. The unit of observation is an idea-potential adopter pair. That is each idea appears once for each article published in the first 10 years after the idea was introduced that might potentially adopt it (based on overlap in Medical Subject Heading Codes). On average there are 4,263 potential adopting articles per idea. Potential adopter age is measured using the age of the last author on each potentially adopting paper and innovator age is measured using the age of the author on the innovating article(s) that is closest to the potential adopter. Robust standard errors are reported in the parentheses. For brevity, estimates on some of the regressors are omitted in this table. For the full table, please see Appendix Table A1.

To explore the possibility that potential adopters have a differential tendency to adopt ideas by different innovators, we include three-way interaction terms ($Near_{i,j} \times Age_j \times InnoAge_{i,j}$) in the regression. For brevity, Table 3 reports only the estimates on the interaction terms of the two age variables (the other coefficients, including lower-order interactions are reported in Appendix Table A1). The bottom part of the table shows that the youngest potential adopters tend to choose middle-aged innovators' ideas at large network distances. In contrast, at short network distances[25], the youngest researchers are disproportionately more likely to adopt new ideas introduced by the youngest innovators.

Figure 4. Predicted rates of adoption for different age combinations of innovators and potential adopters



Notes: This figure plots estimates of 10-year adoption for combinations of innovator career age and potential adopter career age based on the estimates in Table 2. The 1, 2, 3, 4 on the *x*-axis indicate innovator

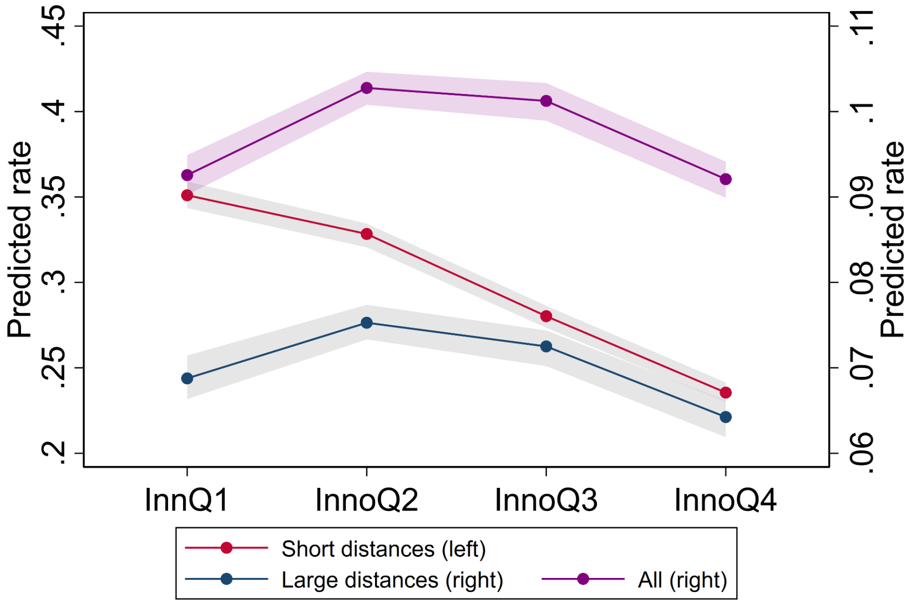
[25] The estimates at short network distances for each age combination is the sum of the coefficients on *InnoQ X AdQ* and that on *Near X InnoQ X AdQ*.

age quartiles. AdQ1-AdQ4 indicate the age of potential adopters. The left half (left y-axis) shows estimates at short network distances, and the right half (right y-axis) shows those at large distances.

To facilitate comparison, Figure 4 plots the predicted adoption rates based on the regressions in Table 3 for different combinations of innovator and potential adopter career age, after partialling out idea-by-year fixed effects. The vertical red-shaded line separates the figure into two halves where the left part represents adoption rates at short network distances (left y-axis) and the right part those at the large network distances (right y-axis). The four categories of innovator age and potential adopter age interact to yield a total of 16 groups on the x-axis. The labels on the x-axis represent innovator age group, and the different sections (separated by dashed vertical lines) represent potential adopter age group from the youngest to oldest. For example, the first dot in the figure represents the youngest researchers' predicted adoption rate of new ideas introduced by innovators in the lowest quartile of career age at short network distances.

The figure shows a number of patterns. First, the contrast in the scales indicates how much higher adoption is at close distances than at large distances. Second, the different sections in Figure 4 show that the decline in adoption with career age for potential adopters is present for both short and large network distances. But the differences are more pronounced at short network distances. Third, holding the age of potential adopters fixed (i.e., within each section), adoption exhibits an upside down V-shape with the peak at innovator age group Q2 or is flat. That is, adoption rates are highest among innovators in the second age quartile. The sole statistically significant exception is for the youngest group at short network distances (the first section in Figure 4), where the adoption rate of youngest innovators' ideas by potential adopters in the youngest group is highest. This exception illustrates that not everyone in proximate networks heavily adopts young innovators' ideas, but rather that it is other young innovators who play the most critical role in adopting the ideas of the youngest innovators. Moreover, comparing the first section in the left half and that in the right half shows that the strong tendency for the youngest potential adopters to adopt young innovators' new ideas is only present in proximate networks, not large network distances. This implies that the advantage of having young potential adopters in proximate networks is attenuated as network distance enlarges.

Figure 5. Predicted adoption rates by innovator age quartile



Notes: This figure plots estimates of 10-year adoption by innovator age quartile based on the estimates in Column (2) of Table 3. The *x*-axis indicates the age quartile of innovators. Red represents estimates at short network distance (left *y*-scale), and blue for large distances (right *y*-scale). Purple represents all network distances (right *y*-scale). The confidence intervals are imputed using bootstrap with 100 random draws.

Figure 4 shows the probability that an idea introduced by an innovator of each age will be adopted by any potential adopter of a given age and proximity. To move from these individual probabilities, we need to account for the differences in network position of innovators (i.e., to use weights needed to sum these probabilities across the population of potential adopters to calculate an overall adoption rate of the new ideas by innovators at different career ages). Figure 5 plots the predicted adoption rates for ideas by innovators at different career ages at short, large, and all distances respectively. The red curve in Figure 5 shows that, at short distances, adoption declines with innovator age. Intuitively, the youngest innovators have younger potential adopters nearby in their networks who are more receptive to new ideas and especially to the new ideas of young innovators. At larger distances (blue), adoption is hump-shaped in innovator age. Intuitively, middle-aged innovators' ideas are used more because they have more potential adopters at short network distances to them and because, as we show below, they are more prominent. While for the older groups of innovators, even conditional on idea quality, their new ideas are adopted less, which more than offset their better network connections. When nearby and distant adoption are combined, the pattern mirrors that for large distances because so many more potential adopters are at large network distances.

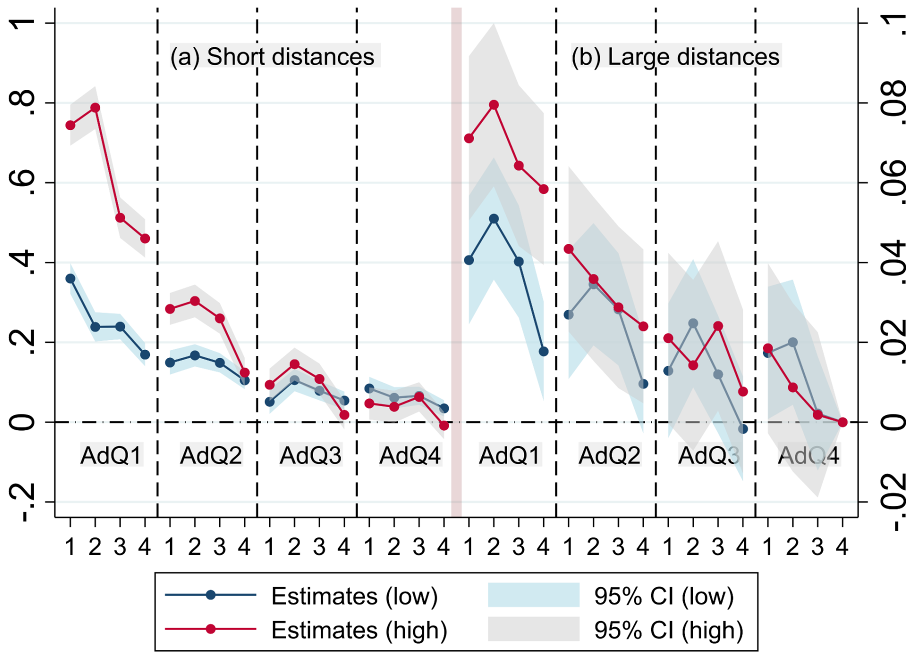
4.3 Potential mechanisms

Why are ideas introduced by young innovators disproportionately adopted by young potential adopters at short distances while those by middle-aged innovators are adopted more among older and more distant contacts? This subsection explores whether journal visibility, researcher prominence, or network centrality can help explain these patterns.

4.3.1 Journal impact/visibility

It is possible that young innovators choose higher visibility outlets to publish their new ideas (e.g., because it improves career prospects). If so, this may drive the pattern we observe that young researchers are more likely to use ideas introduced by other young innovators. To explore this possibility, we take the impact factor of the journal that publishes each new idea and split the sample in half at the median impact factor among the journals that publish new ideas. We repeat the regressions in Table 3 for the two subsamples and plot the estimates in Figure 6. The red points are for the subsample of new ideas initially published in higher-impact journals and the blue points are for the other subsample. Because the intercepts for the high and low curves are effectively collinear with our fixed effects, we normalize both curves to be zero for the age combination of *InnoQ4* X *AdQ4* at large distances.[26]

Figure 6. Journal visibility



Notes: This figure plots estimates of 10-year adoption for combinations of innovator career age and potential adopter career age based on a version of the estimates reported in Table 3 estimated for two subsamples divided by median journal impact factor. The 1, 2, 3, 4 on the *x*-axis indicate innovator career age quartiles. AdQ1-AdQ4 indicate the age of potential adopters. The left half (left *y*-axis) shows estimates at short network distances, and the right half (right *y*-axis) shows those at large distances. The red points represent ideas that are first published in journals with above median impact factors; the blue points represent ideas that are first published in journals with below median impact factors.

The figure reveals three patterns. First, for most pairs of innovator and potential adopter age, ideas published in higher impact journals (red curves) are as or more likely to be adopted than those published in lower impact journals (blue curves). Second, the gap between the red curves and the blue curves is greatest in the first and fifth sections, which correspond to the youngest potential adopters *AdQ1*. That is to say, young researchers' adoption behavior is more

[26] The estimated constant term in the lower impact subsample is 0.012, while that for the higher impact subsample is 0.030.

affected by journal ranking. Third, while the youngest potential adopters are particularly likely to adopt ideas published in high impact journals, at short network distances, the (blue) curve for low impact journals peaks among the youngest innovators.[27] Intuitively, young researchers also appear to be particularly able to recognize the value of new ideas introduced by nearby young innovators that are published in *less* prestigious journals.

4.3.2 Researcher prominence

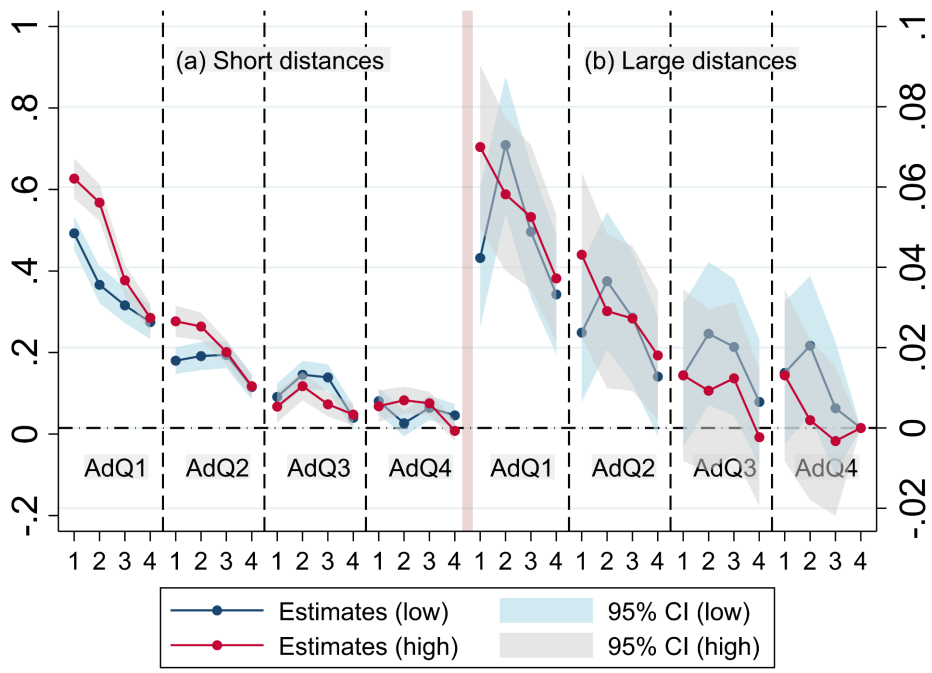
We also explore the role of innovator prominence in the diffusion of their new ideas. Relatively speaking, middle-aged innovators have accumulated coauthors and visibility. They are often more prominent in terms of publication records. We expect that innovators with more publications will be known more widely, especially at large distances. Therefore, we conduct a similar subsample analysis and split the sample in two at the median number of publications in the previous three years.

Two things are worth noting in Figure 7. First, for the youngest adopters at short distances (in the first section), the blue curve is exceptionally steep between *InnoQ1* and *InnoQ2* and considerably stepper than the red curve. This finding implies that the higher adoption rate of the youngest potential adopters' of youngest innovators' ideas at short network distances is driven by the subsample of innovators with less prominent publication records. Second, at large distances the inverted-V shape pattern is less prominent (sometimes, to the point of being absent) for the red curves more than the blue curves (this is also substantially true for Figure 6). This pattern suggests that higher visibility, in terms of both journal visibility and innovator visibility, seem to help the youngest innovators publicize their new ideas at distant networks. Thus, while prominence consistently increases adoption, less prominent young researchers

[27] The only other curve for short distances to peak among the youngest innovators is that for the oldest potential adopters, but the peak is not statistically different from that for the third quartile of innovators.

benefit from relatively high adoption by young potential adopters at short distances, while at long distances, prominence seems to particularly benefit young innovators. Moreover, at long network distances, the blue curves (for less prominent innovators) show a strong inverted-V. This pattern indicates that less prominent mid-career innovators' ideas are more likely to be used by distant potential adopters than ideas introduced by less prominent innovators of other age groups.

Figure 7. Results by innovator prominence

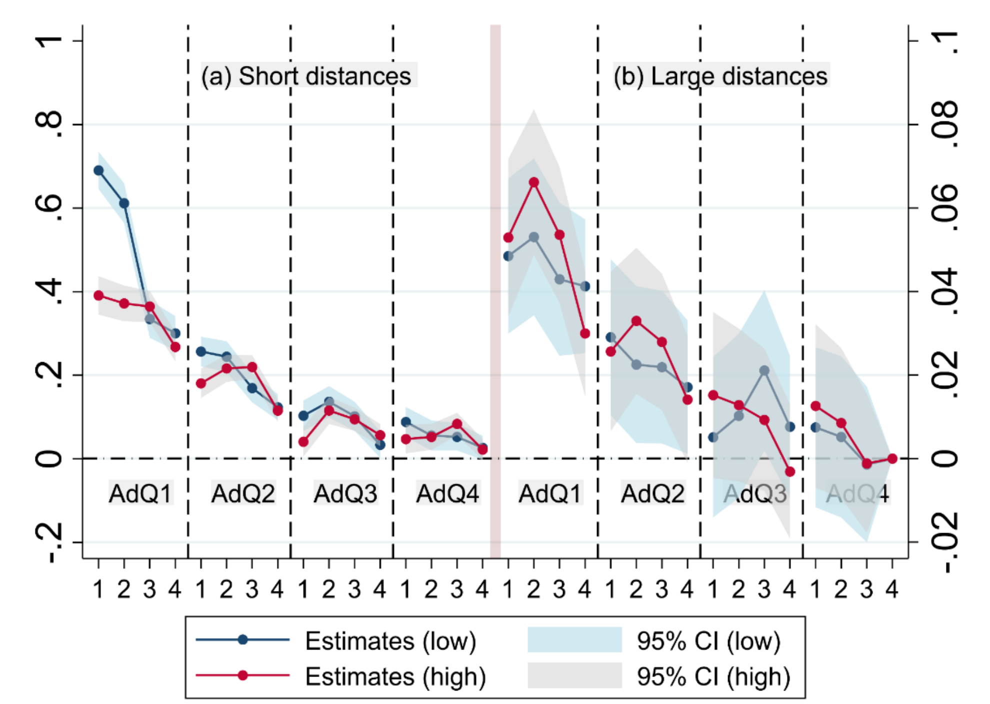


Notes: This figure plots estimates of 10-year adoption for combinations of innovator and potential adopter age based on a version of the estimates reported in Table 3 estimated for the two subsamples divided by median prominence of the nearest author on the paper that introduced the idea. The 1, 2, 3, 4 on the *x*-axis indicate innovator career age quartiles. AdQ1-AdQ4 indicate the age of potential adopters. The left half (left *y*-axis) shows estimates at short network distances, and the right half (right *y*-axis) shows those at large distances. The red points represent the sample of new ideas introduced by innovators with above the median prominence; the blue points represent introduced by innovators with below the median prominence. Innovator prominence is measured by the number of publications in the previous three years.

4.3.3 Network centrality

Network centrality may also play a role in these age patterns because senior researchers are more likely to occupy more central positions in networks. Therefore, we repeat the subsample analysis and split the sample in two at the median of innovator network centrality. We measure network centrality using eigenvector centrality which applies higher weights for contacts who themselves are better connected. (Alternative centrality measures, such as betweenness centrality, produce similar results.)

Figure 8. Results by innovator network centrality



Notes: This figure plots estimates of 10-year adoption for combinations of innovator and potential adopter age based on a version of the estimates reported in Table 3 estimated for the two subsamples divided by median network centrality of the nearest author on the paper that introduced the idea. The 1, 2, 3, 4 on the *x*-axis indicate innovator career age quartiles. AdQ1-AdQ4 indicate the age of potential adopters. The left half (left *y*-axis) shows estimates at short network distances, and the right half (right *y*-axis) shows those at large distances. The red points represent the sample of new ideas introduced by innovators with above the median centrality; the blue points represent introduced by innovators with below the median centrality.

In Figure 8, as in Figures 6 and 7, in the first section (i.e., among the youngest potential adopters at short network distances), the blue points (for low centrality innovators) show uniquely high adoption of ideas introduced by the youngest innovators. That is to say, young researchers are relatively more open to try out new ideas introduced by young innovators situated in less favorable network positions. Put differently, having young researchers nearby in networks is very important for young innovators who fall behind in terms of publication records or network connections compared to other innovators.

Taken together, the first sections in Figures 6, 7, and 8 indicate that network proximity and youth of potential adopters can help to make up for the potential disadvantages (i.e. less favorable network positions, publication history and journal visibility) faced by young innovators. Young researchers in close networks are more able to recognize the potential of new ideas from less-prominent young innovators.

Turning to the right panels of Figures 6, 7 and 8, which depict the adoption at distant networks. Figure 8 represents something of a departure from Figures 6 and 7. Specifically, In figure 8, the red curves (the high category subsample) show a stronger inverted-V than the blue curves whereas in Figures 6 and 7, the blue curves (for the low category subsample) showed a stronger inverted-V pattern. This difference suggests stronger publication records and higher journal visibility weaken, while network centrality strengthens, potential adopters' tendency to adopt mid-career innovators' new ideas.

5 Simulation analysis

5.1 Decomposition

In this subsection, we provide some statistics to show the relative strength of the three main factors in determining the adoption rates of new ideas by innovators at different career stages: 1) network distance, 2) age of potential adopters, and 3) adoption rate conditional on network distance and potential adopter age. We choose the adoption rate of ideas by *InnoQ*2 as our anchoring point and delineate the relative strength of these three forces in determining the disparity between *InnoQ*1 and *InnoQ*2.[28]

Table 4 reports results for short, large and all network distances separately. The first row shows the actual adoption rate of new ideas introduced by innovators in *Q1* and *Q2*, and the second row their predicted rate based on our regression model. The *Dif.* Columns show the difference in adoption rates (i.e., *InnoQ1* - *InnoQ2*). Our regression estimates are consistent with actual data in terms of the signs of the gaps. At short network distances, *InnoQ1*'s adoption rate is higher than that of *InnoQ2*, while it is opposite at large distances. Because most potential adopters are at a larger distance, the larger distance estimates dominate the overall adoption rate.[29]

However, the magnitudes of the gaps are somewhat different in data versus model predictions. On the one hand, at short distances, the actual gap in adoptions of *InnoQ1* and *InnoQ2* is smaller than that estimated by our regressions. On the other hand, at large distances, the data exhibit a bigger gap than our model. The main reason is that the ideas of younger innovators are of higher quality and the descriptive statistics do not hold idea quality constant as in our fixed-effects regressions. This also illustrates the importance of controlling for idea-fixed effects to accurately measure the gap in adoptions of *InnoQ1*'s and *InnoQ2*'s ideas. In relative terms, at short network distances, *InnoQ1*'s adoption rate is 7.1% higher than that of *InnoQ2*, while at large distances, it is about 9.1% lower than that of *InnoQ2*.

[28] Similar decomposition analysis can be conducted for other age groups (*InnoQ3* and *InnoQ4*). However, the contrast between *InnoQ1* and *InnoQ2* is most interesting given the sharp differences at short and large distances and its potential implication on effective measures to facilitate the diffusion of ideas by the youngest innovators.

[29] The overall difference is more negative than the long distance differences because the weights used to sum up short and large distances are different for *InnoQ1* and *InnoQ2*. Specifically, *InnoQ2* has more short distance contacts than *InnoQ1*.

Table 4. Decomposition exercise

		Short network distances			Large network distances			All distances		
		InnoQ1	InnoQ2	Dif.	InnoQ1	InnoQ2	Dif.	InnoQ1	InnoQ2	Dif.
Actual rate		0.367	0.360	**0.007** (1.98%)	0.068	0.085	**-0.017** (-19.55%)	0.093	0.114	**-0.020** (-18.60%)
Predicted rate		0.351	0.328	**0.023** (7.10%)	0.069	0.075	**-0.007** (-9.11%)	0.092	0.103	**-0.011** (-10.24%)
Hypothetical Scenarios	C1. Distance distribution	0.351			0.069			0.099		0.007 [65.82%]
Hypothetical Scenarios	C2. Age distribution	0.345		-0.006 [-25.50%]	0.068		-0.000 [-3.98%]	0.092		-0.000 [-7.12%]
Hypothetical Scenarios	C3. Preferential adoption	0.340		-0.011 [-47.20%]	0.069			0.091		-0.001 [-8.78%]
Hypothetical Scenarios	C4. Adoption rates	0.352		0.001 [4.73%]	0.071		0.003 [42.32%]	0.095		0.003 [26.19%]

Notes: The numbers in the *Dif.* columns represent the difference in adoption rate between *InnoQ1* and *InnoQ2* (i.e. *InnoQ1-InnoQ2*). Adoption rates are in percentage point units. The percentages in parentheses give the difference relative to the adoption rate of *InnoQ2* and are calculated by dividing the difference by the adoption rate of *InnoQ2* (i.e. *(InnoQ1-InnoQ2)/InnoQ2)*. The percentages in square brackets give the share of the difference that is explained by each factor and are obtained by dividing the difference in counterfactual adoption rates of *InnoQ1* and *InnoQ2* by the regression-predicted difference (i.e. $(InnoQ1' - InnoQ2')/(\widehat{InnoQ}1 - \widehat{InnoQ}2)$). Blank cells indicate that the corresponding adoption rates are unchanged in the counterfactual scenario.

Next, we consider two counterfactual scenarios where we change the network position of *InnoQ1* and composition of potential adopters. C1 assumes that *InnoQ1* has *InnoQ2*'s network distance distribution (i.e. a larger share of potential adopters at short distances). C2 assumes that *InnoQ1* has *InnoQ2*'s age distribution of potential adopters (i.e. older potential adopters). Recognizing the very high adoption rate of *InnoQ1*'s ideas by *AdQ1* at short distances and lower adoption of *InnoQ1*'s ideas in essentially all other cases, our third and fourth counterfactuals equalize the adoption rates of *InnoQ1* and *InnoQ2* in two different ways. C3 conditions on age and network distance, and assumes that young potential adopters treat *InnoQ1* and *InnoQ2* in the same way at short distances (i.e. turns off young potential adopters' preferential adoption of *InnoQ1* at short distances); C4 conditions on age and network distance, and assumes that potential adopters at all ages treat *InnoQ1* and *InnoQ2* in the same way at all distances. The numbers in the *InnoQ1* column in the hypothetical scenarios section represent the predicted counterfactual adoption rates for *InnoQ1*. The numbers in square brackets represent the ratio of the difference caused by each counterfactual scenario to the estimated difference between *InnoQ1* and *InnoQ2*. (No numbers are provided for *InnoQ2* because the simulations only involve changing *InnoQ1*'s network features.)

In the first counterfactual scenario, only the weights that sum up adoption at short and large network distances are varied. If young innovators have a larger share of proximate network connections (i.e., to match *InnoQ2*), it would increase their adoption rate from 0.092 to 0.099%, which would reduce the difference in the adoption rate of *InnoQ1* and *InnoQ2* by 65.8%.[30] This indicates that differences in share of proximate network connections is the main reason

[30] It is worth noting that our decomposition is conducted after partialling out idea-time fixed effects. That is, our estimates are conditional on idea quality. The ratios represent how much of the difference in adoption rates between the two groups of ideas can be explained by each of those factors, excluding idea-year fixed effects.

for the gap in adoption rate of new ideas introduced by *InnoQ1* and *InnoQ2* innovators.

In the second hypothetical scenario, applying the age distribution of *InnoQ2*'s potential adopters to *InnoQ1* will reduce *InnoQ1*'s adoption rate because *InnoQ1* had the advantage of being close to young potential adopters who are more open to trying out new ideas. The reduction is greater at short distances than at large distances because *InnoQ1* relies more heavily on nearby young potential adopters to utilize their ideas.

The third counterfactual turns off young potential adopters' disproportionately higher adoption rate of *InnoQ1*'s ideas at short distances. Doing so would lower *InnoQ1*'s adoption rate and that accounts for 47% of the higher adoption rate of *InnoQ1* relative to that of *InnoQ2* at short distances. Nevertheless, this change at short distances does not change the overall adoption rate very much since the overall rate is dominated by the large numbers of potential adopters at large distances.

Finally, we apply the age-specific adoption rates of potential adopters for *InnoQ2* to *InnoQ1* at both short and large network distances. The adoption rate of *InnoQ1* is raised at large distances. This result is expected because *InnoQ2*'s ideas are adopted more than *InnoQ1*'s when network distance is large. At short distances giving *InnoQ1* the lower adoption rate of *InnoQ2* reduces adoption by *AdQ1* but it increases adoption slightly more by *AdQ2* and *AdQ3* (there is little change by *AdQ4*). When these effects at short distances are combined, there is a slight increase in adoption of *InnoQ1* from giving them *InnoQ2*'s adoption rates. Overall, giving *InnoQ1* the adoption rates of *InnoQ2* reduces the gap in adoption between *InnoQ1* and *InnoQ2* by 26%.

5.2 The impact of aging

The aging of the scientific workforce is not only due to the aging of the population, but also caused by a multitude of factors: delay in age of entry due to a prolonged training process (Jones, 2009), a large baby boom cohort of scientists and declining retirement rate of older scientists after the elimination of mandatory retirement in 1994 (Ashenfelter and Card, 2002; Blau and Weinberg, 2017), and a slowdown in faculty hiring in universities (Fons-Rosen et al., 2023).

This subsection simulates different aging scenarios and examines how they affect the diffusion of new ideas. The consequences of an aging scientific workforce are threefold. First, since younger researchers are more open to new ideas, the aging of potential adopters slows down the diffusion of new ideas. Second, innovators at different career stages have different advantages in promoting the usage of their new ideas. Hence, the aging of innovators alters the adoption rate of new ideas. Finally, the aging of innovators will also lead to changes in the quality of new ideas.

This section quantifies each of these effects. To do this, we first estimate the rate of aging in our data from the pre-2000 period to the post-2010 period (Appendix Figure A5). The average career age of innovators and potential adopters increased by 1.7 and 1.5 years between these periods. To align with our estimates, we calculate changes in the shares of innovators/potential adopters in each age quartile. We then apply this rate of aging over the next 20 years only for potential adopters, then only for innovators, and lastly for both potential adopters and innovators. That is, we conduct two one-sided analyses and then a two-sided analysis. In all three cases, we generate separate results for the change in adoption among people at short distances, those at long distances, and overall. The results are reported in Table 5.

We first hold the age distribution of innovators constant. Looking at S1-1 to S1-3, aging potential adopters is harmful for the adoption of new ideas introduced by innovators in all age groups. The numbers in S1-1 for aging nearby potential adopters are comparable to those in

S1-2 for distant potential adopters.[31] One might extrapolate from this result on aging of potential adopters at short distances to think about the effects of changes in network structure. Specifically, even in the absence of aging, if young researchers are increasingly excluded from proximate networks of innovators, this could also be detrimental for idea diffusion. Thus, it is important that researchers at all career stages have the opportunity to be close to the new important ideas.

Table 5. Simulation results

	InnoQ1	InnoQ2	InnoQ3	InnoQ4	Overall
Actual rate	0.093	0.114	0.100	0.081	0.097
Predicted rate	0.092	0.103	0.101	0.092	0.097
S1-1. Aging potential adopters at short distances	0.090 (-2.70%)	0.010 (-3.28%)	0.098 (-2.81%)	0.089 (-3.12%)	0.11 (-2.97%)
S1-2. Aging potential adopters at large distances	0.090 (-2.73%)	0.010 (-3.16%)	0.097 (-3.63%)	0.0902 (-2.27%)	0.111 (-2.96%)
S1-3. Aging all potential adopters	0.087 (-5.44%)	0.096 (-6.45%)	0.095 (-6.44%)	0.087 (-5.39%)	0.091 (-5.93%)
S2-1. Aging innovators					0.096 (-1.07%)
S2-2. Lower idea quality	0.086 (-7.33%)	0.096 (-6.58%)	0.094 (-6.69%)	0.085 (-7.36%)	0.090 (-6.99%)
S2-3. Aging innovators + lower idea quality					0.089 (-8.06%)
S3. Aging potential adopters and innovators					0.090 (-6.84%)
S4. Aging potential adopters and innovators + lower idea quality	0.081 (-12.76%)	0.089 (-13.02%)	0.088 (-13.13%)	0.080 (-12.75%)	0.083 (-13.83%)

Notes: This table shows the simulated adoption rates for researchers nearest to innovators at different

[31] Intuitively, while (as we show in Figure 2) there are considerably more long-distance potential adopters than short-distance potential adopters, the effects of adopter age in Figure 4 at long distances are considerably smaller than those at short distances. When combined, the effects of aging short-distance potential adopters are comparable to that of aging long distance potential adopters.

career ages. The numbers in the parentheses give the predicted change in each simulation relative to the regression-predicted adoption rates and are calculated by dividing the difference between simulated and predicted adoption rates by the predicted rate.

Next turn to S2-1, if we keep the age distribution of potential adopters unchanged and only age innovators, the adoption rates for *InnoQ1*-*InnoQ4* stay the same but the weights used to sum them change. Specifically, the share of innovators in the older age groups, *InnoQ3* and *InnoQ4,* increase while the share in younger age groups, *InnoQ1* and *InnoQ2*, decline. This shift leads to a slight decrease in the overall adoption rate of new ideas since the adoption rate first increases and then decreases with innovator career age (Figure 5). In this simulation (the results of which are shown in the last column), the increase at younger ages is slightly more than offset by the decrease at older ages. Two opposing forces are at play in S2-1, on the one hand, the aging of innovators improves network connectedness. On the other hand, holding all else constant, *InnoQ4*'s ideas have the lowest adoption among all four innovator age groups (*InnoQ4* is the lowest in all eight sections in Figure 4). If we assume that *InnoQ4*'s ideas are adopted at a rate that is equal to the average of the other three groups, adoption would increase by 10%.[32] That is to say that, focusing on the network connectedness of innovators alone, aging increases adoption by 10% because of the better connectedness of older innovators, but this increase is completely offset by the lower adoption of *InnoQ4*'s ideas conditional on network position.

Simulation S2-1 conditions on idea quality (i.e., holds constant the idea fixed effects) even as innovators age. Simulation S2-2 takes into consideration that the aging of innovators produces lower quality new ideas. Specifically, we retrieve the idea fixed effects from our main regressions and estimate the relationship between the idea fixed effects and average age of all innovators who introduced the idea. We find that a one-year increase in innovator age is

[32] The counterfactual adoption rate is 0.106492, which is equivalent to (0.106492-0.096824)/0.096824=9.99%.

associated with 0.004 percentage points lower adoption. Applying these lower idea fixed effects while holding all else constant in S2-2, indicates that the lower quality of new ideas associated with the aging of innovators reduces adoption by 6.99%. Combining the aging of innovators with decreasing idea quality implies a decline in adoption of 8.06% (in S2-3). Thus, idea quality is the primary way in which the aging of innovators affects the adoption of new ideas, accounting for 87% of the reduction in adoption.

Finally, in S3 and S4, we age both potential adopters and innovators (i.e., conduct a two-sided analysis). Simulation S3 holds idea quality constant while S4 accounts for changes in idea quality. We find that the simulated overall adoption rate is reduced by 6.84% with the older scientific workforce but unchanged idea quality. If, as in S4, we allow idea quality to vary as innovators age the overall negative impact of aging is 13.83%. That is to say, half of the total negative impact of the aging scientific workforce can be ascribed to declining idea quality, 40% is due to the aging of potential adopters, and the rest less than 10% is explained by aging of innovators holding idea quality constant.

6 Robustness analysis

6.1 Nearest author on papers

The above analyses focus on the last authors on relevant papers in calculating potential adopters' career ages and their network distances to innovators. Although last authors on papers may play the leading role in deciding whether to work on a new idea or not, first authors may also influence this decision and often generate the first drafts of manuscripts. Therefore, for a potential adopting paper of a certain new idea, we find the author (regardless of position) who is nearest to the innovators of this idea, and consider him or her as the focal potential adopter. Then we use the focal researcher's career age and network distance to the idea as regressors. Focusing only on specifications with idea-by-year fixed effects (i.e. those in columns (3)-(6) of Table 2, the regression estimates, which are reported in Table 6, are quite similar to those in

Tables 2 and 3.

Table 6. Nearest author

	(1)	(2)	(3)	(4)
Near		0.0083	0.0230**	0.0509**
		(0.0074)	(0.0095)	(0.0101)
InnoQ1	0.0320**	0.0117**	0.0114	0.0190**
	(0.0046)	(0.0050)	(0.0072)	(0.0073)
InnoQ2	0.0307**	0.0135**	0.0047	0.0115*
	(0.0040)	(0.0043)	(0.0066)	(0.0067)
InnoQ3	0.0210**	0.0087**	-0.0007	0.0036
	(0.0036)	(0.0040)	(0.0064)	(0.0065)
Near X InnoQ1		0.0775**	0.0299*	0.0207
		(0.0089)	(0.0157)	(0.0158)
Near X InnoQ2		0.0673**	0.0290**	0.0200
		(0.0080)	(0.0140)	(0.0141)
Near X InnoQ3		0.0472**	0.0520**	0.0514**
		(0.0076)	(0.0133)	(0.0134)
AdQ1	0.0724**	0.0445**	0.0352**	0.0189
	(0.0027)	(0.0029)	(0.0058)	(0.0117)
AdQ2	0.0364**	0.0193**	0.0149**	0.0010
	(0.0026)	(0.0028)	(0.0058)	(0.0094)
AdQ3	0.0089**	0.0044	0.0011	-0.0099
	(0.0027)	(0.0030)	(0.0061)	(0.0076)
Near X AdQ1		0.2764**	0.2161**	0.2344**
		(0.0090)	(0.0160)	(0.0169)
Near X AdQ2		0.1086**	0.0792**	0.0874**
		(0.0074)	(0.0132)	(0.0136)
Near X AdQ3		0.0256**	0.0257*	0.0320**
		(0.0075)	(0.0133)	(0.0136)
Near X InnoQ1 X AdQ1			0.2171**	0.2193**
			(0.0266)	(0.0276)
Near X InnoQ1 X AdQ2			0.0649**	0.0552**
			(0.0223)	(0.0226)
Near X InnoQ1 X AdQ3			-0.0038	-0.0130
			(0.0225)	(0.0227)
Near X InnoQ2 X AdQ1			0.1255**	0.1232**
			(0.0244)	(0.0253)
Near X InnoQ2 X AdQ2			0.0655**	0.0575**
			(0.0202)	(0.0205)
Near X InnoQ2 X AdQ3			0.0236	0.0211
			(0.0203)	(0.0205)
Near X InnoQ3 X AdQ1			-0.0254	-0.0275
			(0.0236)	(0.0245)
Near X InnoQ3 X AdQ2			0.0155	0.0148
			(0.0194)	(0.0197)
Near X InnoQ3 X AdQ3			-0.0154	-0.0189
			(0.0195)	(0.0197)
R-squared	0.0112	0.0113	0.0113	0.0463
N	10,346,201	10,346,201	10,346,201	10,298,124

Notes: The table reports estimates of Equation (1) for whether each of 2,699 ideas (born from 1982 to 2008) is adopted by each potentially adopting article on (i) dummy variables for the quartile of the age distribution among innovators (*InnoQ1* (youngest) to *InnoQ3* (next to oldest) with *InnoQ4* (the oldest) being excluded), (ii) dummies for the quartile of the age distribution among potential adopters (AdQ1 (youngest) to AdQ3 (next to oldest) with

AdQ4 (the oldest) being excluded), (iii) interactions between each of these and the potential adopter being near (distance <=3) the innovator in the collaboration network, (iv) distance fixed effects. Potential adopter age is measured using the age of the author who has the shortest path to any of the innovators of a new idea. Innovator age is measured using the age of the author on the innovating article(s) that is closest to the potential adopter. Idea-by-year fixed effects are controlled in all regressions. The unit of observation is an idea-potential adopter pair. That is each idea appears once for each article published in the first 10 years after the idea was introduced that might potentially adopt it (based on overlap in Medical Subject Heading Codes). Robust standard errors are reported in the parentheses. Estimates on some regressors are omitted for brevity and are reported in Appendix Table A2.

6.2 Team configuration on papers

Team configurations on the paper may also affect the likelihood of working on a new idea. Packalen and Bhattacharya (2019) found that young first author combined with senior last author are most likely to try out new ideas. Table 7 includes the age of the first author interacted with that of the last author. Adding this set of fully interacted age terms has little effect on the parameters in Table 3, so we only report the estimates on the newly included terms. After controlling for the regressors in Eq. (1), the newly added variables are not significant other than for the combinations with the youngest first authors. The combination of a young first author and a young-to-middle-aged last author (relative to an old last author) has the highest probability of trying out new ideas, which aligns with the finding in Packalen and Bhattacharya (2019).

Table 7. Team configuration

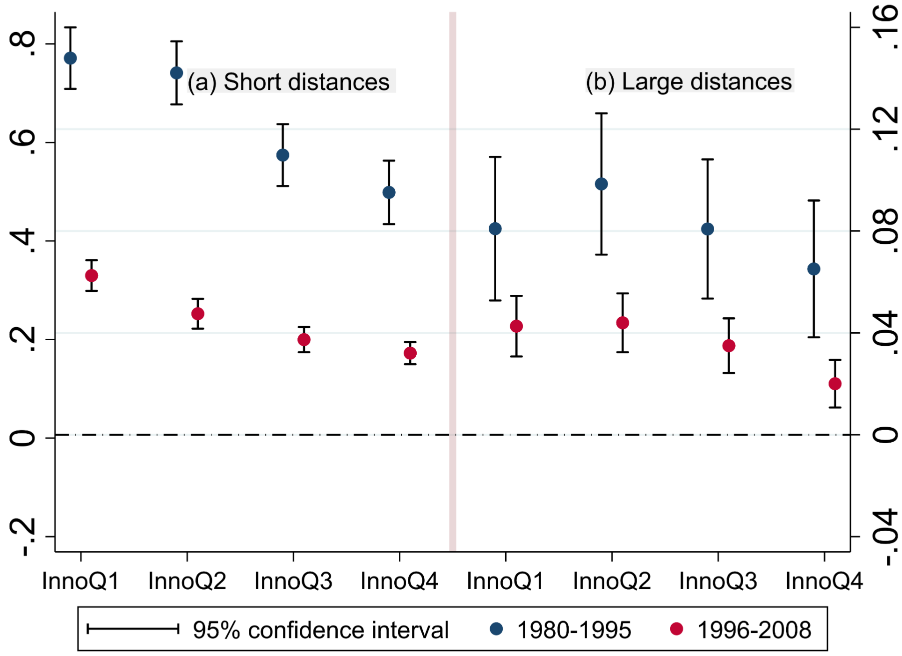
	(1)	(2)
FirstQ1 X LastQ1	0.0268**	0.0264**
	(0.0092)	(0.0093)
FirstQ1 X LastQ2	0.0360**	0.0355**
	(0.0100)	(0.0100)
FirstQ1 X LastQ3	0.0182*	0.0178*
	(0.0098)	(0.0098)
FirstQ2 X LastQ1	0.0090	0.0090
	(0.0089)	(0.0089)
FirstQ2 X LastQ2	0.0088	0.0088
	(0.0098)	(0.0098)
FirstQ2 X LastQ3	-0.0095	-0.0096
	(0.0098)	(0.0098)
FirstQ3 X LastQ1	-0.0000	-0.0000
	(0.0091)	(0.0091)
FirstQ3 X LastQ2	-0.0007	-0.0007
	(0.0099)	(0.0099)
FirstQ3 X LastQ3	-0.0047	-0.0047
	(0.0100)	(0.0100)
R-squared	0.0124	0.0124
N	7,266,141	7,266,141

Notes: The table re-estimates the regressions in Column (6) of Table 2 and Column (2) of Table 3 with additional regressors on the interactions of the age quartiles of first author and last author on a potential adopting paper. This table highlights the estimates on the newly added regressors and omits other estimates for brevity. The full table is reported in Appendix Table A3.

6.3 Time window

Given that our important new ideas span the 1980 to 2008 idea cohorts, we can split them by birth year into earlier idea cohorts (1980-1995) and later idea cohorts (1996-2008). This allows us to investigate whether there is a fundamental change as information technologies become more widespread for more recent cohorts of new ideas. We estimate Eq. (1) for the two groups of new ideas respectively. Figure 9 focuses on adoption among the youngest group of potential adopters - estimates are largely unchanged for the other age groups.

Figure 9. Adoption by young potential adopters in different time windows



Notes: This figure plots the estimated adoption rates for early and later cohorts of new ideas by young potential adopters. InnoQ1-InnoQ4 on the *x*-axis indicate innovator age quartile. Red points represent the sample of new ideas introduced between 1980 and 1995; the blue points represent ideas introduced between 1996 and 2008. We include the same controls as in Column (2) of Table 3.

Figure 9 shows that adoption of new ideas in the earlier cohort (blue points) are higher than those in the later cohort (red points), yet the gap is more pronounced at short distances than large distances. This implies that young researchers' preference to adopt young innovators' ideas at proximate networks, though still significant, have weakened over time. Earlier cohorts of new ideas benefited more from young researchers at nearby networks for their diffusion. This might be due to the lack of effective means for publicizing their new ideas in earlier years.

7 Conclusion

Researchers have tended to study the relatively glamorous production of ideas more than their adoption. We view this emphasis as unfortunate because the diffusion and utilization of the important new ideas that exist is likely to be important for science. Fortunately, advances in natural language processing and network analysis make it possible to identify important, new ideas and track their utilization in research networks.

We use a two-way fixed effects strategy to conduct a two-sided analysis of how career ages of innovators and potential adopters affect the diffusion of new ideas through collaboration networks and use the estimates to simulate the effect of an aging biomedical research workforce on the adoption of new ideas. Our strategy controls for differences in both the “applicability” of each idea (and how it changes over time) and the propensity of potential adopters to adopt new ideas. We find that at large network distances and overall, adoption follows an inverted-V in innovator age, peaking among early middle-aged innovators. In contrast, at short distances, adoption declines monotonically with innovator age primarily because young innovators are closer to young potential adopters who are disproportionately more likely to use their ideas. Moreover, younger innovators tend to produce better ideas. Our study highlights the importance of creating inclusive networks that integrate young researchers who are usually at a disadvantage in terms of network connections.

We use these estimates to simulate how the continued aging of the biomedical research workforce would affect the adoption of important new ideas. We simulate a 14% reduction in 20 years with the aging of innovators accounting for 8% of that reduction, the vast majority (7%) due to lower quality ideas being introduced. Yet, the aging of potential adopters accounts for a 6% decline in adoption (43% of the total). Thus, accounting for the aging of innovators and potential adopters is important.

Just as research has tended to focus on the production of innovation so has much of the policy discussion. We believe that focusing on promoting the utilization of important new ideas is a promising avenue for policy given that we have found disparities in the utilization of ideas that might be addressed and because promoting the diffusion and utilization of important, new ideas, while far from free (as it entails time and often travel), might be less expensive than producing more ideas.

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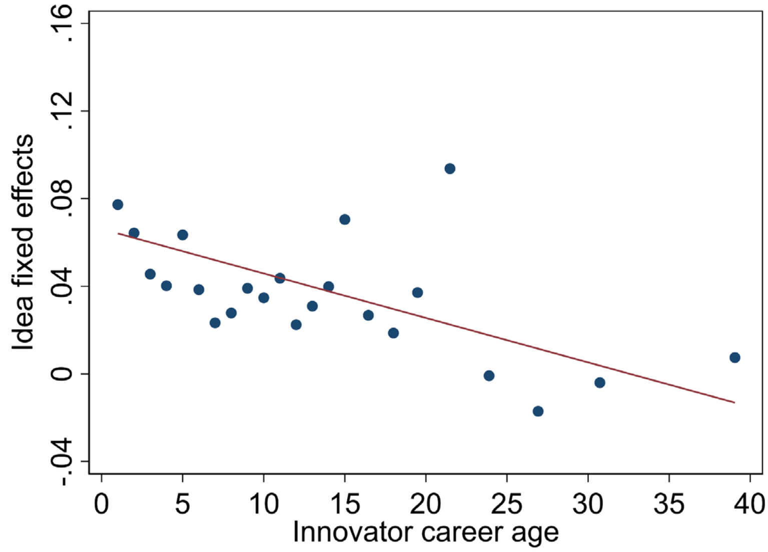
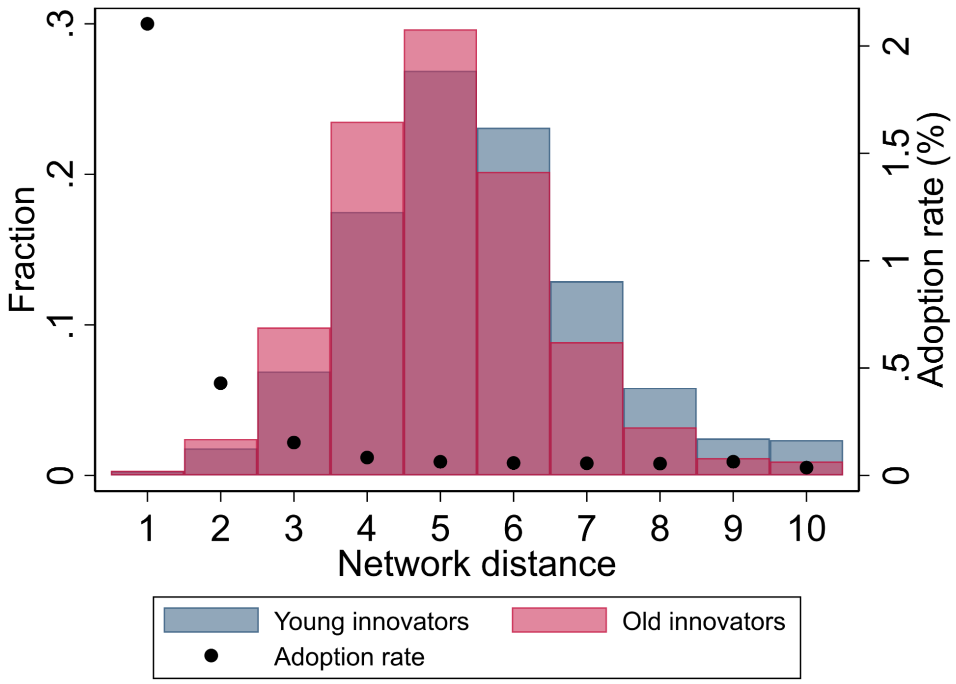
Appendix

Figure A1. Idea quality measured by idea fixed effects



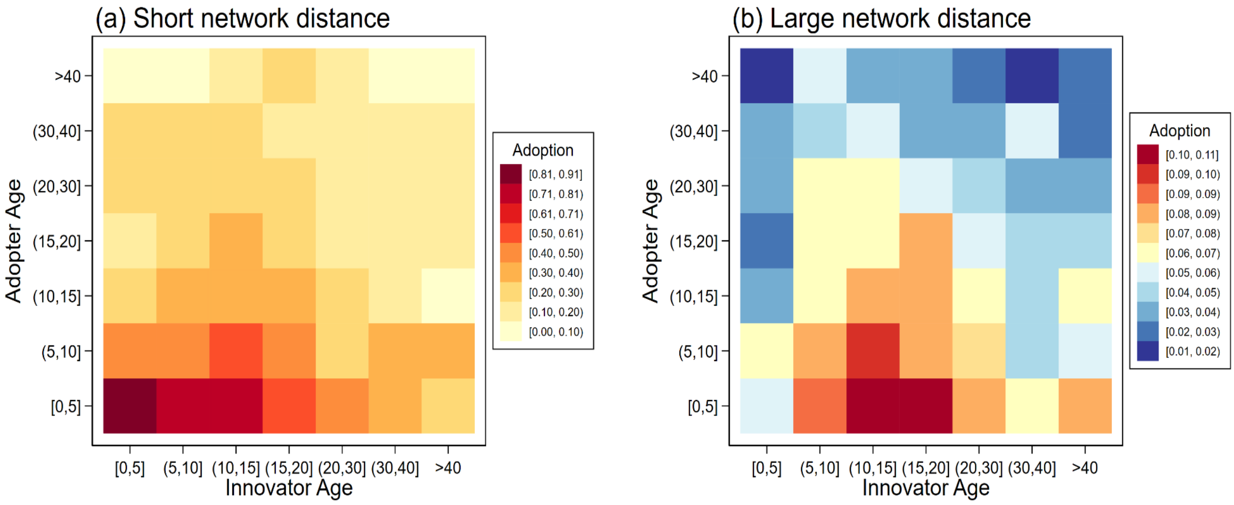
Notes: This figure shows the relationship between idea quality (measured by idea fixed effects) and innovator career age. The idea fixed effects are retrieved from the regression in Column (1) of Table 3.

Figure A2. Innovator age and the distribution of network distance



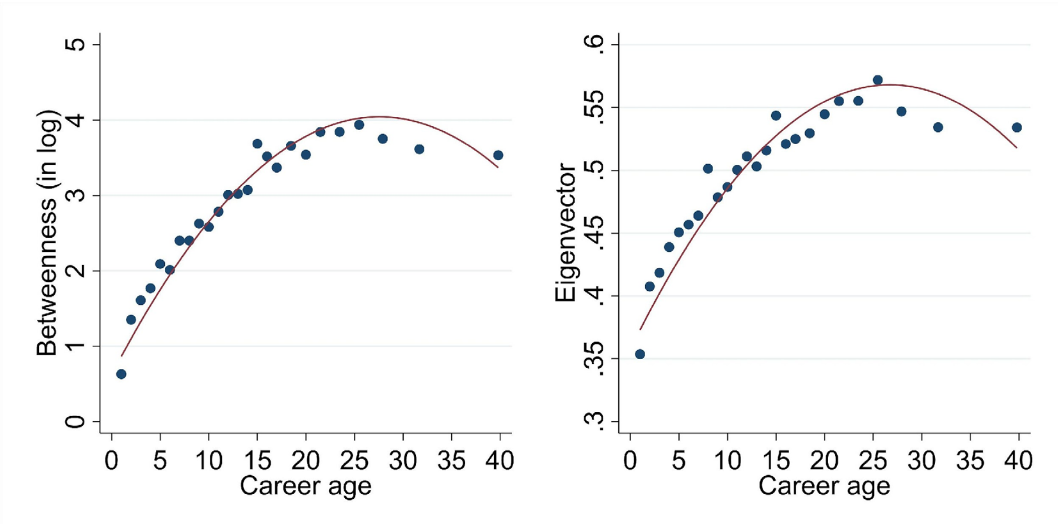
Notes: This figure shows the distribution of network distance from young (blue bars) and old (red bars) innovators to potential adopters. Innovators were identified as young if their age was less than or equal to the median career age of innovators (17 years). The black points give the adoption rate at each network distance. The scale for the histograms are on the left axis; the scale for the scatter plot are on the right axis. The bar at distance 10 includes distances 10 to 15. Distances over 15 are excluded.

Figure A3. Age combinations and adoption rate



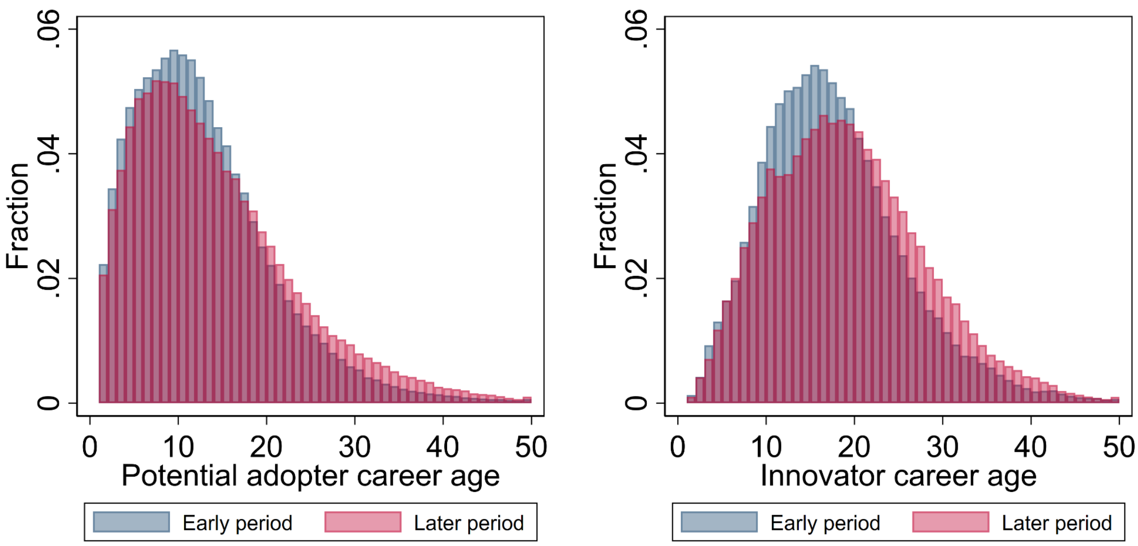
Notes: The figure shows the adoption rate of ideas introduced by innovators of varying ages according to the age of potential adopters at short network distances (left panel), defined as a distance of 3 or lower, and long distances (right panel). The *x*-axis represents innovator age and *y*-axis represents potential adopter age. The color indicates the adoption rate. High adoption rates are coded with warmer colors. Note that the scale of adoption rate varies between the left and right panels.

Figure A4. Centrality of innovators



Notes: This figure shows the relationship between innovator centrality and career age. Betweenness centrality measures the extent to which a researcher is positioned as a bridge along the shortest path between two other researchers. Eigenvector centrality is a weighted count of nearby people where the weights (1) decline exponentially with distance and (2) are higher for people who are themselves more central. Hence, eigenvector centrality (also known as Katz-Bonacich centrality) is defined recursively, weighting connections to people who are themselves better connected more to measure researcher's influence in networks. The betweenness centrality of a node (left panel) is measured by the number of shortest paths between two nodes which pass through the focal node. To reduce computation, we set a cutoff of 4 on the length of path considered. Eigenvector centrality (right pane) is calculated for nodes in the largest connected component. Since the distribution of eigenvector centrality has a long right tail, here we plot the percentile rank of an innovator's eigenvector centrality (namely, 0.1 means a researcher at the bottom 10% in the distribution, and 0.9 means a researcher's eigenvector centrality is higher than 90% researchers in the distribution). Both innovator centrality measures are calculated at the year of innovation.

Figure A5. Aging



Notes: This figure shows the change of age distribution for potential adopters (left panel) and innovators (right panel) from the pre-2000 period (blue bars) to the post-2010 period (red bars).

Table A1. Full Table 3

	(1)	(2)
AdQ1	0.0354**	0.0135
	(0.0056)	(0.0114)
Near X AdQ1	0.2250**	0.2418**
	(0.0157)	(0.0164)
AdQ2	0.0155**	-0.0009
	(0.0056)	(0.0091)
Near X AdQ2	0.0806**	0.0878**
	(0.0131)	(0.0135)
AdQ3	0.0020	-0.0102
	(0.0059)	(0.0074)
Near X AdQ3	0.0219*	0.0265**
	(0.0132)	(0.0135)
InnoQ1	0.0118*	0.0194**
	(0.0068)	(0.0069)
Near X InnoQ1	0.0353**	0.0242
	(0.0150)	(0.0151)
InnoQ2	0.0092	0.0165**
	(0.0066)	(0.0067)
Near X InnoQ2	0.0235	0.0153
	(0.0145)	(0.0146)
InnoQ3	0.0004	0.0050
	(0.0063)	(0.0063)
Near X InnoQ3	0.0476**	0.0459**
	(0.0133)	(0.0133)
Near	0.0220**	0.0528**
	(0.0095)	(0.0100)
InnoQ1 X AdQ1	0.0050	-0.0124
	(0.0076)	(0.0078)
InnoQ2 X AdQ1	0.0173**	0.0041
	(0.0079)	(0.0081)
InnoQ3 X AdQ1	0.0146*	0.0068
	(0.0078)	(0.0080)
InnoQ1 X AdQ2	0.0027	-0.0074
	(0.0076)	(0.0078)
InnoQ2 X AdQ2	0.0054	-0.0015
	(0.0080)	(0.0081)
InnoQ3 X AdQ2	0.0109	0.0057
	(0.0079)	(0.0080)
InnoQ1 X AdQ3	-0.0027	-0.0059
	(0.0081)	(0.0082)
InnoQ2 X AdQ3	0.0029	0.0003
	(0.0085)	(0.0086)
InnoQ3 X AdQ3	0.0135	0.0123
	(0.0084)	(0.0084)
Near X InnoQ1 X AdQ1	0.2167**	0.2170**

	(0.0250)	(0.0258)
Near X InnoQ2 X AdQ1	0.1484**	0.1311**
	(0.0248)	(0.0256)
Near X InnoQ3 X AdQ1	0.0077	0.0017
	(0.0231)	(0.0238)
Near X InnoQ1 X AdQ2	0.0542**	0.0464**
	(0.0212)	(0.0215)
Near X InnoQ2 X AdQ2	0.0742**	0.0680**
	(0.0208)	(0.0211)
Near X InnoQ3 X AdQ2	0.0219	0.0230
	(0.0192)	(0.0195)
Near X InnoQ1 X AdQ3	-0.0152	-0.0208
	(0.0215)	(0.0217)
Near X InnoQ2 X AdQ3	0.0443**	0.0429**
	(0.0210)	(0.0212)
Near X InnoQ3 X AdQ3	-0.0116	-0.0134
	(0.0194)	(0.0196)
Distance=1	1.9733**	1.9428**
	(0.0153)	(0.0155)
Distance=2	0.2965**	0.2965**
	(0.0066)	(0.0068)
Distance=4	0.0577**	0.0753**
	(0.0029)	(0.0035)
Distance=5	0.0264**	0.0345**
	(0.0025)	(0.0028)
Network distance	Yes	Yes
Idea-by-year F.E.	Yes	Yes
Author F.E.	No	Yes
N	11,505,689	11,462,124
R-squared	0.0112	0.0466

Table A2. Full Table 6

	(1)	(2)	(3)	(4)
Near		0.0083	0.0230**	0.0509**
		(0.0074)	(0.0095)	(0.0101)
InnoQ1	0.0320**	0.0117**	0.0114	0.0190**
	(0.0046)	(0.0050)	(0.0072)	(0.0073)
InnoQ2	0.0307**	0.0135**	0.0047	0.0115*
	(0.0040)	(0.0043)	(0.0066)	(0.0067)
InnoQ3	0.0210**	0.0087**	-0.0007	0.0036
	(0.0036)	(0.0040)	(0.0064)	(0.0065)
Near X InnoQ1		0.0775**	0.0299*	0.0207
		(0.0089)	(0.0157)	(0.0158)
Near X InnoQ2		0.0673**	0.0290**	0.0200
		(0.0080)	(0.0140)	(0.0141)
Near X InnoQ3		0.0472**	0.0520**	0.0514**
		(0.0076)	(0.0133)	(0.0134)
AdQ1	0.0724**	0.0445**	0.0352**	0.0189
	(0.0027)	(0.0029)	(0.0058)	(0.0117)
AdQ2	0.0364**	0.0193**	0.0149**	0.0010
	(0.0026)	(0.0028)	(0.0058)	(0.0094)
AdQ3	0.0089**	0.0044	0.0011	-0.0099
	(0.0027)	(0.0030)	(0.0061)	(0.0076)
Near X AdQ1		0.2764**	0.2161**	0.2344**
		(0.0090)	(0.0160)	(0.0169)
Near X AdQ2		0.1086**	0.0792**	0.0874**
		(0.0074)	(0.0132)	(0.0136)
Near X AdQ3		0.0256**	0.0257*	0.0320**
		(0.0075)	(0.0133)	(0.0136)
Near X InnoQ1 X AdQ1			0.2171**	0.2193**
			(0.0266)	(0.0276)
Near X InnoQ1 X AdQ2			0.0649**	0.0552**
			(0.0223)	(0.0226)
Near X InnoQ1 X AdQ3			-0.0038	-0.0130
			(0.0225)	(0.0227)
Near X InnoQ2 X AdQ1			0.1255**	0.1232**
			(0.0244)	(0.0253)
Near X InnoQ2 X AdQ2			0.0655**	0.0575**
			(0.0202)	(0.0205)
Near X InnoQ2 X AdQ3			0.0236	0.0211
			(0.0203)	(0.0205)
Near X InnoQ3 X AdQ1			-0.0254	-0.0275
			(0.0236)	(0.0245)
Near X InnoQ3 X AdQ2			0.0155	0.0148
			(0.0194)	(0.0197)
Near X InnoQ3 X AdQ3			-0.0154	-0.0189
			(0.0195)	(0.0197)
InnoQ1 X AdQ1			0.0001	-0.0178**
			(0.0081)	(0.0084)
InnoQ1 X AdQ2			-0.0005	-0.0095
			(0.0080)	(0.0082)
InnoQ1 X AdQ3			-0.0004	-0.0037
			(0.0085)	(0.0086)
InnoQ2 X AdQ1			0.0219**	0.0087
			(0.0080)	(0.0083)
InnoQ2 X AdQ2			0.0078	0.0009
			(0.0080)	(0.0081)
InnoQ2 X AdQ3			0.0021	-0.0010
			(0.0084)	(0.0085)
InnoQ3 X AdQ1			0.0147*	0.0068
			(0.0082)	(0.0084)

InnoQ3 X AdQ2			0.0099	0.0052
			(0.0082)	(0.0083)
InnoQ3 X AdQ3			0.0121	0.0116
			(0.0086)	(0.0087)
Distance=1	2.1169**	1.9919**	1.9890**	1.9578**
	(0.0151)	(0.0150)	(0.0150)	(0.0153)
Distance=2	0.3956**	0.2711**	0.2699**	0.2723**
	(0.0067)	(0.0066)	(0.0066)	(0.0068)
Distance=3	0.1330**			
	(0.0041)			
Distance=4	0.0659**	0.0589**	0.0589**	0.0758**
	(0.0030)	(0.0031)	(0.0031)	(0.0037)
Distance=5	0.0329**	0.0284**	0.0285**	0.0359**
	(0.0026)	(0.0026)	(0.0026)	(0.0030)
R-squared	0.0112	0.0113	0.0113	0.0463
N	10,346,201	10,346,201	10,346,201	10,298,124

Table A3. Full Table 7

	(1)	(2)
Near	0.0234**	0.0291**
	(0.0090)	(0.0117)
InnoQ1	0.0104*	0.0052
	(0.0060)	(0.0083)
InnoQ2	0.0163**	0.0100
	(0.0053)	(0.0080)
InnoQ3	0.0117**	0.0022
	(0.0048)	(0.0076)
Near X InnoQ1	0.0624**	0.0453**
	(0.0105)	(0.0183)
Near X InnoQ2	0.0765**	0.0485**
	(0.0102)	(0.0177)
Near X InnoQ3	0.0484**	0.0580**
	(0.0094)	(0.0162)
LastQ1	0.0141*	0.0070
	(0.0073)	(0.0096)
LastQ2	0.0120*	0.0050
	(0.0073)	(0.0094)
LastQ3	0.0040	-0.0017
	(0.0075)	(0.0097)
Near X LastQ1	0.2629**	0.1997**
	(0.0115)	(0.0205)
Near X LastQ2	0.0922**	0.0892**
	(0.0091)	(0.0162)
Near X LastQ3	0.0227**	0.0295*
	(0.0090)	(0.0160)
Near X InnoQ1 X LastQ1		0.0056
		(0.0098)
Near X InnoQ1 X LastQ2		0.0082
		(0.0094)
Near X InnoQ1 X LastQ3		0.0050
		(0.0096)
Near X InnoQ2 X LastQ1		0.0130
		(0.0102)
Near X InnoQ2 X LastQ2		0.0080
		(0.0099)
Near X InnoQ2 X LastQ3		0.0036
		(0.0101)
Near X InnoQ3 X LastQ1		0.0116
		(0.0101)
Near X InnoQ3 X LastQ2		0.0119
		(0.0098)
Near X InnoQ3 X LastQ3		0.0144
		(0.0100)
InnoQ1 X LastQ1		0.1965**
		(0.0328)
InnoQ1 X LastQ2		-0.0048
		(0.0263)
InnoQ1 X LastQ3		-0.0189
		(0.0259)
InnoQ2 X LastQ1		0.1085**
		(0.0324)
InnoQ2 X LastQ2		0.0251
		(0.0258)
InnoQ2 X LastQ3		0.0328
		(0.0254)
InnoQ3 X LastQ1		0.0087
		(0.0301)

InnoQ3 X LastQ2		-0.0004
		(0.0238)
InnoQ3 X LastQ3		-0.0338
		(0.0235)
FirstQ1	0.0156**	0.0157**
	(0.0061)	(0.0061)
FirstQ2	0.0105	0.0106
	(0.0067)	(0.0067)
FirstQ3	0.0104	0.0105
	(0.0067)	(0.0067)
FirstQ1 X LastQ1	0.0268**	0.0264**
	(0.0092)	(0.0093)
FirstQ1 X LastQ2	0.0360**	0.0355**
	(0.0100)	(0.0100)
FirstQ1 X LastQ3	0.0182*	0.0178*
	(0.0098)	(0.0098)
FirstQ2 X LastQ1	0.0090	0.0090
	(0.0089)	(0.0089)
FirstQ2 X LastQ2	0.0088	0.0088
	(0.0098)	(0.0098)
FirstQ2 X LastQ3	-0.0095	-0.0096
	(0.0098)	(0.0098)
FirstQ3 X LastQ1	-0.0000	-0.0000
	(0.0091)	(0.0091)
FirstQ3 X LastQ2	-0.0007	-0.0007
	(0.0099)	(0.0099)
FirstQ3 X LastQ3	-0.0047	-0.0047
	(0.0100)	(0.0100)
Distance=1	1.8869**	1.8858**
	(0.0193)	(0.0193)
Distance=2	0.2985**	0.2978**
	(0.0082)	(0.0082)
Distance=4	0.0551**	0.0551**
	(0.0037)	(0.0037)
Distance=5	0.0206**	0.0206**
	(0.0032)	(0.0032)
R-squared	0.0124	0.0124
N	7,266,141	7,266,141