



# How novelty in knowledge earns recognition: The role of consistent identities<sup>☆</sup>



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## ABSTRACT

The novelty of scientific or technological knowledge has a paradoxical dual implication. Highly novel ideas are subject to a higher risk of rejection by their evaluating audiences than incremental, “normal science” contributions. Yet the same audiences may deem a contribution to knowledge valuable *because* it is highly novel. This study develops and tests an explanation of this dual effect. It is argued that the recognition premium that highly acclaimed authors’ work enjoys disproportionately accrues to work that is consistent with the authors’ previously developed identity. Because high novelty is a salient identity marker, authors’ past recognition for highly novel work helps same authors’ new highly novel work earn positive audience valuation. It is further argued that, because recognition for novelty is partly inherited from mentors, disciples of highly acclaimed producers of novel work are more likely to have their work prized for its novelty. In contrast, the authors’ or their mentors’ recognition earned for relatively less novel work does not trigger similar spillover effects and leaves the authors vulnerable to the novelty discount. Unique data on the productivity, career histories, and mentoring relations of academic electrical engineers support these arguments.

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## 1. Introduction

Technologists, scientists, and organizations involved in production of new knowledge face a continual predicament. On the one hand, the evaluating audiences expect each new contribution to diverge from pre-existing accepted knowledge and view novelty as a major criterion of merit (Dirk, 1999; Guetzkow et al., 2004). On the other hand, high novelty may reduce the contribution’s value in its audience’s eyes. Divergence from existing paradigms subjects knowledge to skepticism and a higher risk of rejection (Boudreau et al., 2012; Mueller et al., 2012; Staw, 1995), even in organizations dedicated to the production of novelty such as product design com-

panies (Kelley and Littman, 2005) and academic journals (Starbuck, 2003).<sup>1</sup>

Why is novelty sometimes an advantage and sometimes a liability? What is required for highly novel knowledge to earn evaluating audiences’ recognition rather than neglect or skepticism? The answers that these questions receive in specific organizational settings are consequential. These answers shape the rewards of knowledge producers’ careers, and thereby the social inequalities among scientists and technology developers. They are also vital to the success of entrepreneurs who attempt to commercialize innovative ideas.

Existing scholarship offers some explanations of the dual effect of novelty on recognition. First, the hypothesis known as Planck’s principle suggests that younger audiences are relatively open to divergence from prior knowledge, while older audiences tend to resist it. Proposed by and named after the originator of quantum theory, Planck’s principle has been invoked in influential statements of the noncumulative nature of science (e.g., Feyerabend, 1970; p. 203; Kuhn, 1962; p. 151). Second, differences in the audiences’ valuation of novelty may be attributable to cultural variation.

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<sup>1</sup> “Originality” is an alternative term referring to divergence from prior knowledge, used in the literature interchangeably with “novelty” (cf. Boudreau et al., 2012; Dirk, 1999; Guetzkow et al., 2004; Staw, 1995).

For example, the Oriental tradition has historically valued the novelty of creative products less than the Western tradition has (Lubart, 1990; Niu and Sternberg, 2006). Third, novelty encounters resistance among audiences if its harmful uses become apparent (Cropley et al., 2010; McLaren, 1993). Fourth, there is experimental evidence that individuals primed to feel uncertainty tend to reject highly novel outcomes in favor of non-novel outcomes that have proven practical use (Mueller et al., 2012). Fifth, studies have attested that audiences are more receptive to highly novel contributions when the standards of dominant paradigms, in contrast to which novelty is defined in the field, become ambiguous. Such crises may occur because of social fragmentation in the field (Sgourev, 2013) or because prominent producers deliberately blur the standards (Rao et al., 2005).

These arguments have expanded our understanding of the varying valuation of novelty and ignited further interest in the subject. Yet they have done little to explain why the same audience, while simultaneously appraising multiple contributions, values their novelty differently. Planck's principle and the cultural explanation are only suited for explaining variation between audiences; uncertainty and paradigm crises may only explain variation between different points in time. The harm explanation addresses audience- and time-specific variation but its application is limited to the rare situations in which the harmfulness of knowledge visibly varies. As a result, these arguments offer little explanatory edge in typical settings where expert audiences evaluate modern science or technology, such as when funding agencies consider competing grant proposals, when investors evaluate competing business plans, when papers are selected for conference presentation, or when journal editors decide which contributions should be published.

To develop an explanation that avoids these limitations and applies in typical, everyday practice of innovation appraisal, I build on two theoretical ideas. First, I draw on the notion that audience recognition is self-perpetuating – other things being equal, audiences grant more recognition to authors' outputs to the extent that the authors are already recognized for their work (Merton, 1968). Second, I revisit the idea that audiences reward producers' consistency, particularly consistency with the producer's previously developed identity (Zuckerman et al., 2003; Hsu and Hannan, 2005; Leahey, 2007; White, 2008; Hannan, 2010). I argue that past recognition does not equally benefit all types of authors' work; instead, its rewards disproportionately accrue to contributions that align with the professional identities that their authors have developed. Because high novelty is a salient identity marker, recognition earned for novel work will disproportionately channel the rewards toward novel work. I further argue that recognition for novelty is not necessarily earned personally by the authors; authors partly inherit it from their mentors. Taken together, these ideas predict that, to the extent that the authors or their mentors have earned recognition for highly novel work, novelty makes audiences more likely to grant recognition to the authors' subsequent work. Conversely, if authors or their mentors have a relatively modest record of acclaimed novel work, the share of the past recognition premium channeled toward highly novel work will not be sufficient to compensate for the audiences' tendency to discount highly novel contributions.

I examined this argument with specially collected data on the productivity, career histories, and professional networks of academic electrical engineers. The analysis supported the predictions. It showed that the audience recognition earned by engineers or their mentors for highly novel work transforms the novelty of the engineers' subsequent contributions from a liability into an advantage in the pursuit of further recognition; recognition earned for less novel work does not accomplish a similar transformation.

## 2. Background theory

### 2.1. Novelty as unusual recombination of antecedent knowledge

Before considering how past recognition moderates the effect of novelty on the recognition of new knowledge by its audiences, it is necessary to clarify the concept of novelty. This study follows the long tradition that conceptualizes novelty as unusual recombination of elements of prior knowledge. Early statement of the recombinant nature of innovation is typically credited to Schumpeter, particularly to his work on the business cycles (Schumpeter, 1939). In the recent decades, the conceptualization of novelty as unusual recombination of antecedents has become standard in the study of innovation (Fleming, 2001; Fleming and Sorenson, 2001; Henderson and Clark, 1990; Kogut and Zander, 1992; Nelson and Winter, 1982; Weitzman, 1996). Measures that capture the unusualness of recombination of elements have been used to quantify novelty and originality in technology (Hall et al., 2001; Dahlin and Behrens, 2005; Valentini, 2012), science (Boudreau et al., 2012; Uzzi et al., 2013), and artistic creation (Simonton, 1980a,b).

The history of technology is replete with instances of impactful recombination of disparate knowledge. For example, Millard (1990) showed how Edison's innovations routinely recombined older elements. Notably, the phonograph blended ideas from products developed for the telegraph, telephone, and electric motors. Hargadon and Sutton (1997) reported 30 remarkable innovations developed by the product design company IDEO, ranging from water bottles to computers, each of which is a combination of older technologies from more than one industry. Thus, the original Apple computer mouse, a revolutionary early IDEO product, combined insights from electronics with the trackball design from gaming machines. More recently, developers of the internet telephony pioneer Skype used the peer-to-peer networking software previously developed for the music sharing application Kazaa, but applied it to voice transmission instead (Aamoht, 2011).

The recombination view of novelty is particularly apt in mathematics-intensive fields, such as information theory examined in this study. Unless a mathematical contribution introduces new axioms, it is entirely derived from elements of previous knowledge. It may only diverge from previous knowledge by bringing these familiar elements together in unfamiliar, unusual combinations. As mathematician Henri Poincaré wrote,

the mathematical facts worthy of being studied . . . are those which reveal to us unsuspected kinship between other facts, long known, but wrongly believed to be strangers to one another. . . . [Most combinations] formed of elements drawn from domains which are far apart . . . would be entirely sterile. But certain among them, very rare, are the most fruitful of all (Poincaré, 1913; p. 386).

In practice, the judgments of unusualness of recombinations tend to be domain-specific rather than absolute. Unless ideas are impactful enough to attract attention in multiple domains of knowledge, their novelty is appraised within a single domain; the audience in the domain defines the ideas' unusualness relative to the knowledge shared in that domain rather than to the entire body of existing knowledge (Davis, 1971).

### 2.2. The rewards of past recognition

The outputs of highly recognized producers receive better audience evaluations. In the context of knowledge production, this tendency was notably articulated by Merton (1968), who labeled it the Matthew effect. Researchers have detected a similar tendency of audiences to overrate the output of prominent producers in experimental settings (Berger et al., 1972) and in markets of goods and services (Podolny, 1993, 2005).

Prominent producers may reap a recognition premium through two mutually nonexclusive mechanisms. First, the spillover of past recognition into fresh recognition by audiences may be mediated by perceptions of producers' competence. People expect high-status individuals to be better performers, and the performance expectations translate into better-than-merited evaluations of actual outputs (Correll and Ridgeway, 2006). Second, the same relationship between past recognition and audience evaluations may be mediated by resources. As Merton (1968) pointed out, recognition helps producers attract funding, capable collaborators, and other resources that enable better work and ease the dissemination of its results. Whereas the first mechanism is purely perceptual and may be decoupled from actual quality, the second mechanism improves the quality of the output by acclaimed producers.

### 2.3. *The rewards of consistency*

It is telling that “recognition” means appreciation as well as perceiving to be familiar.<sup>2</sup> The link between appreciation and familiarity is not just semantic but also empirical—research in various fields has suggested that audiences value contributions more highly if these contributions are consistent with what the audiences are already familiar with.

In an argument largely anticipated by Fleck (1935), Kuhn (1962) insisted that, except in rare periods of paradigm shift, the recognition of a contribution by a scientific community critically depends on whether or not the community views it as consistent with the currently dominant paradigm. Anecdotal examples (Starbuck, 2003) and quantitative evidence (Boudreau et al., 2012; Shadish et al., 1995) attest that scientific audiences indeed reward alignment with the dominant knowledge canon. Even when the audiences are open to divergence from the canon, they tend to grant high recognition to those diverging elements that are grounded in extremely familiar combinations of prior work (Uzzi et al., 2013). The notion that audiences reward consistency with familiar cognitive constructs is also prominent in organization studies and economic sociology. Researchers have found that stock markets pay a premium for stocks covered by securities analysts who specialize in stock issuer's industrial sector category (Zuckerman, 1999); product markets offer better survival chances to new companies that effectively communicate their belonging to a category of similar aspiring market entrants (Kennedy, 2008); and audiences reward films for being consistent with an existing genre (Hsu, 2006).

While the audiences reward consistency with familiar prior knowledge, they also reward consistent producer identities. Academic job markets reward scholars who have developed simple, easily recognizable identities by specializing in narrow subfields (Leahey, 2007); specialization in non-academic job markets brings similar benefits (Zuckerman et al., 2003; Ferguson and Hasan, 2013). Researchers who consistently collaborate within academic disciplines outperform those colleagues who dilute their identity by collaborating across specializations (Birnbbaum, 1981). Knowledge-intensive organizations face similar consistency pressures—actions that are misaligned with established organizational identities cause the stakeholders to devalue organizations (Hsu and Hannan, 2005; Hannan, 2010). The notion that consistent producer identities improve the appraisals of the producers' output has given rise to common business practices such as corporate branding (Aaker, 1996; Keller, 2000) and to competitive strategies aimed at defending the firm's identity domain (Livengood and Reger, 2010).

The rewards of consistent identities are not unconditional. Evidence from markets of services and cultural goods shows that the rewards taper off in later stages of producers' careers (Faulkner, 1983; Zuckerman et al., 2003) and when identity-defining classification schemes erode (Hsu et al., 2012; Ruef and Patterson, 2009). Research has yet to determine whether these contingencies are paralleled in knowledge production, and how often their impact is sufficient to cancel out the benefits of maintaining a consistent professional identity.

### 3. Hypotheses: The rewards of consistent novelty

The audiences' dual tendency to prize the outputs of recognized producers and of producers with consistent identities has a straightforward implication for the question that motivated this study. Insofar as producing knowledge of consistently high novelty is a salient identity marker, this tendency implies that recognition earned for highly novel work helps new highly novel work earn the recognition of knowledge audiences.

#### 3.1. *Recognition for novelty*

The ample evidence just reviewed attests that, rather than appraise contributions solely on merit, the audiences of knowledge take appraisal cues from the author's previous work. On the one hand, the audiences offer a recognition premium to contributions by authors who are already recognized for previous work. On the other hand, audiences' recognition disproportionately accrues to contributions that are consistent with the authors' professional identity. When the same audience enacts both of these appraisal logics, the extra recognition that the Matthew effect brings to authors is not distributed evenly across their subsequent contributions but is rather disproportionately channeled to work that is consistent with what the authors earned the recognition for.

Knowledge producers' professional identities are usually defined in terms of the area or topic to which they have contributed. Yet consistently high novelty is also a feature that defines knowledge producers' identities. Research disciplines develop tacit but widely shared criteria of novelty, and academic audiences view commitment to novelty as a defining feature of the author's personal character (Guetzkow et al., 2004). A consistent record of producing novel, seminal work makes authors highly visible in scientific and technological fields (Simonton, 1994). Academic training and everyday research practice routinely expose scientists and technologists to exemplars of work by such visible innovators (Latour and Woolgar, 1979).

To the extent that knowledge producer's identity is defined by the consistent novelty of their work, their highly novel work benefits from the Matthew effect more than their less novel work. That is, recognition earned for highly novel work disproportionately boosts the recognition of the author's highly novel later contributions, as compared to less novel ones. Therefore, I hypothesize that

**H1.** The effect of novelty of new contributions to knowledge on their recognition by the audience is more positive to the extent that their authors have previously received recognition for highly novel work.

Importantly, the logic of the argument implies that recognition earned for relatively less novel work is not disproportionately channeled toward highly novel subsequent work. I therefore do not expect recognition of this sort, or high recognition in general, to bring authors a premium for novelty. It is only the specific kind of recognition that is earned for highly novel work that is predicted to do so.

<sup>2</sup> Cf. *reconnaître* in French, *erkennen/ankennen* in German, *reconocer* in Spanish.

### 3.2. Recognition for novelty inherited from mentors

Producers' activities earn them only part of their esteem. The other, significant part is an extension of the esteem enjoyed by their associates (Podolny, 1993, 2005). For academic scientists, a highly visible association that shapes audience appraisals and career outcomes is that with mentors (Collins, 1998; Malmgren et al., 2010; Zuckerman, 1977). Academics are keenly aware of mentoring relations, and the names of academic mentors become students' salient, career-long identity markers. In mathematics and related disciplines, including the sub-discipline of information theory examined in this study, the Mathematics Genealogy Project (genealogy.math.ndsu.nodak.edu) embodies this salience. The ambition of the project, run in association with the American Mathematical Society, is to record and publish all mentor-student lineages.

Insofar as the appraising audiences perceive the authors in conjunction with their mentors, the authors inherit the recognition premium that their mentors receive for highly novel work. I therefore predict that

**H2.** The effect of novelty of new contributions to knowledge on their recognition by the audience is more positive to the extent that their authors' mentors have previously received recognition for highly novel work.

Co-authorship is another visible association in knowledge production. However, I do not expect recognition for novelty to spill over to co-authors in the same way as they spill over from mentors to protégés. While being trained by someone acclaimed for novel work may signal that the author has acquired the penchant and the skills needed to produce novel work, co-authoring with such person may also create the opposite signal that it is that person who deserves the credit for novelty.

### 4. The empirical setting

To examine the hypotheses, I compiled a comprehensive database of the creative output of U.S. academic electrical engineers specializing in information theory.

Information theory is a sub-field of electrical engineering concerned with the mathematical representation of stored or transmitted information. The field was launched almost single-handedly by Claude Shannon in 1948. Among other seminal contributions, Shannon (1948) introduced the term *bit* to quantify information and developed the notions of information entropy, information redundancy, and channel capacity. Since then, information theory has developed a distinct identity and expanded institutionally. The field's main professional organization, established in 1951, sponsors multiple conferences and workshops and distributes prestigious professional awards. Its monthly flagship journal, now named *IEEE Transactions on Information Theory*, has been published since 1953. Today, information theory has extensive commercial applications, notably in Internet technologies, wireless communication, and sound and image processing.

The empirical setting of information theory allows the collection of relevant, high-quality data. The well-developed identity and organization of the field help clearly demarcate the community of information theorists. The size of the field enables the collection of systematic bibliographic data, a task that requires complex, often manual disambiguation of author identities; it also makes manual coding of the author's demographic information a manageable task. The technological relevance of information theory allows the tracing of the practical applicability of contributions with patent data. The mathematical nature of the discipline creates a further methodological advantage. Because accuracy, verified in the review process, is a necessary condition for publication of mathematical

results, it is nearly invariable among published results in information theory. When accuracy varies, it is an important criterion of quality that determines the recognition of novel work; the omission of the accuracy variable (almost inevitable because accuracy is hard to quantify) may then bias statistical models of recognition, particularly if highly novel work tends to be less accurate. By using data from information theory, the accuracy variable is effectively controlled and this concern minimized.

### 5. Sample

The initial sample of 343 information theory faculty includes all individuals who (1) were employed, as of June 2010, as tenured or tenure-track professors in electrical engineering units (either independent departments or combined with other areas, typically computer science) in one of the 96 U.S. institutions classified as "very high research activity" in the Carnegie Classification of Institutions of Higher Education; and (2) had published in *IEEE Transactions on Information Theory* or listed information theory as a field of interest on personal Web sites. The ProQuest Dissertations and Theses database was then used to expand the sample of information theorists. The names of initial sample members' Ph.D. advisers, advisees, and advisers' advisees were added, bringing the total number of individuals defined as information theorists to 4029.

Records of publications authored or co-authored by individuals in the sample were obtained from the Thomson Reuters Web of Knowledge (TRWK). Publications were matched to authors by the last name and all initials. If TRWK contained no publications under the individual's name in any of the six Web of Science subject categories in which information theory publications most commonly appear, no publications were matched to this name.<sup>3</sup>

A disambiguation algorithm was then applied to detect ambiguous author names. The algorithm, detailed in Appendix A, is conservative. It is designed to retain in the sample only those publications whose authors' identity is unambiguous. The algorithm flags a name as ambiguous if there is a risk that publications by someone other than the person in question were matched to this name. The risks fall into three types: common names, unrealistic timing of publications, and unrealistic clustering of publications. Publications with at least one ambiguous author name were removed from the sample. Editorials, reviews, letters, and response papers were also removed. The resulting sample contained 19,918 publications authored by 1946 individuals. A manual check with a 1% random subsample of the disambiguated publications showed that 98.5% of the publications were correctly attributed to authors.

### 6. Measures

Because the dependent variable and the criteria of novelty are time-varying, the data are organized as a set of publication-years: the variables have values for each year between the year of publication and the end of the observation period. A publication-year (not to be confused with the year of publication) enters the data set once for each author, with respective author-level variable values. Table 1 reports the correlation matrix and shows the mean, standard deviation, and sources of data for each variable.

<sup>3</sup> The six most common Web of Science subject categories in which information theory publications appear are "Engineering, electrical & electronic"; "Telecommunications"; "Computer science"; "Information systems"; "Physics, multidisciplinary"; "Optics"; and "Artificial intelligence automation and control systems".

**Table 1**  
Descriptive statistics, correlation coefficients, and sources of variables.

Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Source	
Yearly citation count	1.83	5.69	0	288																	1	
Female	.04	.20	0	1	-.01																	1, 2, 7
Top-5 Ph.D. department	.17	.38	0	1	.09	-.05																2, 3, 4
Information theory faculty	.48	.50	0	1	.08	-.01	.14															2, 6, 7
Degree centrality	43.97	77.01	1	778	.03	-.06	.23	-.01														1, 2
Publication age	6.94	5.24	1	27	-.07	<.01	-.02	-.04	.18													1
(Publication age) <sup>2</sup>	75.65	106.3	1	729	-.07	<.01	-.03	-.03	-.21	.94												1
Publication's citations in patents	26.00	58.33	0	556	.09	-.04	.14	.58	.07	.04	.04											1, 5
Number of authors	2.83	2.16	1	24	<.01	-.04	-.01	-.09	.50	.03	.06	-.06										1
10. IEEE TITF publication	.11	.32	0	1	.10	-.03	.03	.17	-.03	-.03	-.03	.12	-.11									1
Publication novelty	.01	.02	0	.25	-.08	-.01	-.04	-.01	.13	.11	.18	-.02	.15	-.05								1
Author's total citation count	4.56	2.15	0	8.63	.09	-.04	.17	.24	.43	.27	.23	.31	.11	.05	.01							1
Citation count of author's higher-novelty work	3.96	2.37	0	8.44	<.01	-.04	.16	.16	.43	.30	.27	.22	.14	-.01	.05	.82						1
Citation count of author's lower-novelty work	2.95	2.17	0	7.79	.12	-.02	.18	.29	.36	.15	.12	.36	.01	.10	-.06	.83	.49					1
Adviser's total citation count	5.79	1.67	0	8.63	.04	-.06	.36	.16	.18	.10	.09	.11	-.02	.03	-.07	.34	.26	.39				1, 2
Citation count of adviser's higher-novelty work	5.34	1.83	0	8.44	.03	-.05	.40	.16	.20	.12	.10	.11	-.02	.01	-.06	.33	.32	.93				1, 2
Citation count of adviser's lower-novelty work	3.99	2.03	0	7.77	.07	-.05	.18	.15	.14	.09	.08	.10	<.01	.03	-.07	.29	.08	.47	.77	.57		1, 2

Note: N = 140,940 publication-years; N = 44,595 publication-years in adviser variables. All individual citation count variables are logged to reduce the positive skew. The sources are coded as follows: (1) Thomson Reuters Web of Knowledge; (2) ProQuest Dissertations and Theses Database; (3) Gourman Report (1980–1997); (4) U.S. News and World Report; (5) United States Patent and Trademark Office; (6) Carnegie Classification of Institutions of Higher Education (7) Google web search.

6.1. Dependent variable

Academic work gets cited overwhelmingly because citers recognize its usefulness rather than deficiencies (Shadish et al., 1995; Case and Higgins, 2000). The count of citations that a publication received within a year thus reflects the yearly increment in audience recognition. This count is the dependent variable in the analysis. In all analyses reported below, the variable lags three years behind the predictor variables. The three-year lag is a realistic estimate of the time between the perception of these factors by the citers and the appearance of the citation in print.<sup>4</sup>

The latest dependent variable values date from 2009. Because of the time lag, the latest year of publication in the analysis is 2006. The exclusion of post-2006 publications reduced the number of publications in the analysis from 19,918 to 15,373.

6.2. Publication novelty

Scholars have suggested a number of recombination-based measures of novelty and originality, tailored to capture the unusualness of element combinations in particular settings at hand (Simonton, 1980a,b; Hall et al., 2001; Boudreau et al., 2012; Valentini, 2012; Uzzi et al., 2013). I adopt the measure of novelty by Dahlin and Behrens (2005), tailored to capture the unusualness of knowledge recombination in publications that reference antecedent knowledge, such as patents and research papers. It quantifies how unusual the combinations of the referenced elements of knowledge in the focal publication are among the pre-existing combinations in its knowledge domain. For each publication *i*, I consider its pairings with every prior publication *j* written by authors who fit the definition of the information theorist on p. 11 above. The overlap score *os<sub>ij</sub>* is then defined as the count of documents cited by both *i* and *j*, divided by the sum of unique citations in *i* or *j*. To capture how usual the combination of knowledge in *i* was relative to prior combinations in the domain, *os<sub>ij</sub>* is summed over all publications *j* and divided by the count of *j*. Finally, to convert the variable of usualness into that of unusualness, the scale is reversed by subtracting every variable value from the maximum in the given publication year.

The resulting combination-based measure of novelty may range between 0 and 1. In my data, it ranges between 0 and 0.25. The low extreme represents publications that only cite documents that have been most frequently cited in prior work. Such publications recombine only the antecedent elements of knowledge that have been most usually, routinely recombined in the field. The high extreme of the measure represents publications that only cite antecedents that have never before been cited by their authors' professional peers. This indicates that the publication recombines knowledge elements in a way that is unique in the field.

To examine the validity of the novelty measure, I hired three advanced doctoral students in information theory at a leading research university, all with multiple publications in top journals in the field. The doctoral students independently rated the novelty of the articles that they had cited in their published work. For comparison with the scores on the 4-point ordinal scale that the raters used, the novelty variable was recoded into quartile categories.<sup>5</sup>

<sup>4</sup> IEEE Publishing Operations, the publisher of the journals that information theorists typically target, informed me that the median time between manuscript submission and publication in *IEEE Transactions on Information Theory* is stably close to 17 months. This is typical for IEEE research journals. The 3-year lag allows for the additional 19 months that it takes the citers to absorb the information from the cited publication, craft the manuscript, and make unsuccessful publication attempts.

<sup>5</sup> The raters received the following instructions: Think about two types of papers. Papers of Type 1 are closely related to the preceding work in the field and continue this work. Papers of Type 2 diverge from the preceding work in the field; ideas in

Weighted Cohen's kappa, a measure of agreement of the raters' combined scores with the recoded novelty variable, was 0.50 (the raters' individual kappas were 0.53, 0.50, and 0.43). This value falls short of the 0.75 threshold of "excellent agreement" but is above the 0.40 acceptability threshold (Fleiss et al., 2003; p. 609), showing that the variable is consistent with the raters' concept of novelty.

This or other possible validity checks certainly do not remove the inevitable limitations of the measure. For example, the measure assigns equal weight to all combinations of cited antecedents, without accounting for the fact that some antecedents have impacted the citing publication more than others. (Thus, Dahlin and Behrens, 2005 have had a disproportionate impact on this study by developing its novelty measure.) Such limitations of measures of novelty computed with systematic, longitudinal quantitative data must be weighed against the advantages of using such data.

### 6.3. Recognition for novelty

An author's recognition for previous high-novelty work is measured as the citation count of his or her publications (other than the focal publication) that had a novelty score above the yearly sample median. The count is computed similarly for the Ph.D. advisers of the author of the focal publication and averaged if the author had multiple advisers. Both citation counts are cumulative, reflecting the notion that recognition at a given time is the total of past instances of recognition. I also computed the total cumulative citation count and the cumulative citation count of publications of below-median novelty, for the authors and for their advisers. All citation count variables had a strong positive skew. They were logged in the regression models to reduce the skew.

### 6.4. Control variables

To ensure the robustness of the models in estimating the effect of past recognition on the recognition of novel contributions, a set of publication-level and author-level control variables was included. First, I control for three social status markers. Gender and the top rank of the author's degree-granting institution are salient social status markers that affect the audiences' valuation of authors' work (Cohen and Zhou, 1991; Sauer et al., 2010). The gender of 233 authors (collectively authoring 523 publications) was impossible to determine. When department rankings were published at longer intervals than one year, the rank closest to the Ph.D. conferral year was used. Employment at a top institution is also a sign of academic status. Because institutional affiliation cannot be reliably matched to authors in TRWK, I included a dummy that marks publications authored by members of the original sample of 343 information theory faculty, all of whom had by 2010 attained employment at top research institutions. Second, the count of co-authorship and adviser-advisee ties (degree centrality) captures the involvement in the network of academic peers; it is a factor that may potentially affect the authors' recognition. The measure considers all ties ever created prior to the focal year. Third, I control for two types of time dependence. The full set of year dummies controls for any variation resulting from specifics of the calendar year. The age of the publication accounts for the effect of the time that elapsed since its appearance in print. Because citations tend to peak and then drop, I also include the quadratic term of the publication age. Fourth, I control for the number of times each publication was cited in patents. This variable captures the technological feasibility of the publication's ideas, an important reason why audiences prize or discount

novelty (Boudreau et al., 2012). Fifth, I included a count of publication co-authors, to account for the citation premium of co-authored work (Wuchty et al., 2007). Sixth, a publication-level dummy indicator controls for being published in the field's main journal, *IEEE Transactions on Information Theory*. Omission of this variable may bias the models because it is a major predictor of the citation count; it is also negatively correlated with novelty, consistent with the tendency of leading journals to avoid highly novel work (Siler et al., 2015). Seventh, to correct the models for possible heterogeneity across subfields, I include the full set of Web of Science subject area dummies.

## 7. Model

The Poisson regression, a standard model for dependent count variables, assumes that the variance of the dependent variable is equal to its mean. The dispersion of the citation count variable greatly exceeds this threshold, and the Poisson regression fits the data poorly. Therefore, I used the negative binomial regression model, which is not sensitive to over-dispersion. The Vuong test did not significantly favor the negative binomial model corrected for zero inflation over the noncorrected model.

The  $p$  values of the model coefficients may potentially be inflated because of two types of interdependence. First, publications authored by the same person may violate the assumption of independence. Second, interdependence may exist among repeated observations for the same publication. The standard errors in all models reported below were therefore corrected for author-level and publication-level clustering. Clustering on multiple dimensions yields reliably unbiased standard errors (Petersen, 2009). Because major statistical packages do not implement correction for clustering on more than one dimension, I wrote a Stata ado-file that corrects negative binomial model estimates for clustering on two dimensions.<sup>6</sup>

## 8. Results

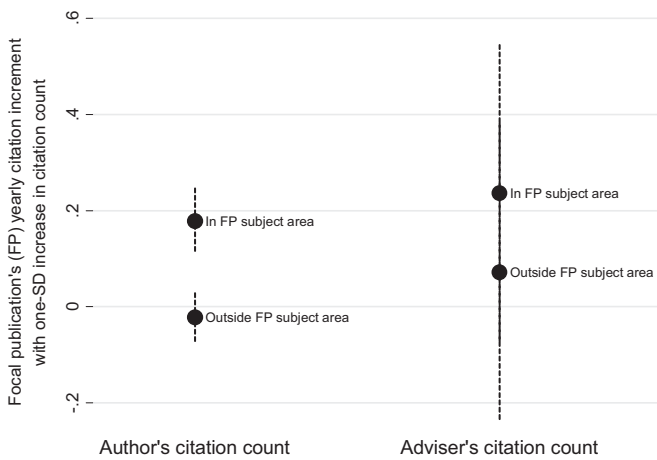
### 8.1. The effect of authors' and their mentors' recognition within and across subject areas

Hypotheses 1 and 2 hinge on the idea that the spillover of recognition from the author's or her mentors' past work to her new contribution is more extensive if that past work and the new contribution are of the same identity-defining type. Before proceeding to test the hypotheses, I will examine this underlying idea with a typology of knowledge that is familiar to the practitioners in the field and is commonly used in bibliometric research.

Fig. 1 plots the yearly citation increments of the publications in the dataset as a linear function of their authors' and authors' doctoral advisers' cumulative past citations. The plot distinguishes the increments received for work in the same Web of Science subject area as the focal publication and those received for work in a different subject area. For every standard-deviation increase in the author's cumulative citation count within the subject area, a given publication received an increment of 0.18 citations per year ( $p < 0.001$ ). Citations outside the focal publication's subject area had no such effect; in fact, they non-significantly lowered the yearly

they are novel and distantly related to the preceding work. Please give each paper that you cited a score as follows: 1 – This is clearly a Type 1 paper; 2 – This is probably a Type 1 paper; 3 – This is probably a Type 2 paper; 4 – This is clearly a Type 2 paper.

<sup>6</sup> The Stata code that implements correction for clustering on two dimensions in linear and logit models is available at [www.kellogg.northwestern.edu/faculty/petersen/htm/papers/se/se\\_programming.htm](http://www.kellogg.northwestern.edu/faculty/petersen/htm/papers/se/se_programming.htm). Using multiple fixed effects is an alternative to such correction; it also yields unbiased estimates, but only if the effect of one dimension is constant across the levels of the other (Petersen, 2009). In this analysis, negative binomial models with fixed author and publication effects fail to converge.



**Fig. 1.** The yearly citation increment of a publication as a linear function of authors' and their advisers' total citation count. The 95% confidence intervals, adjusted for publication-level clustering, are denoted by dashed lines (solid when overlapping). One author is randomly selected for multiple-authored publications.

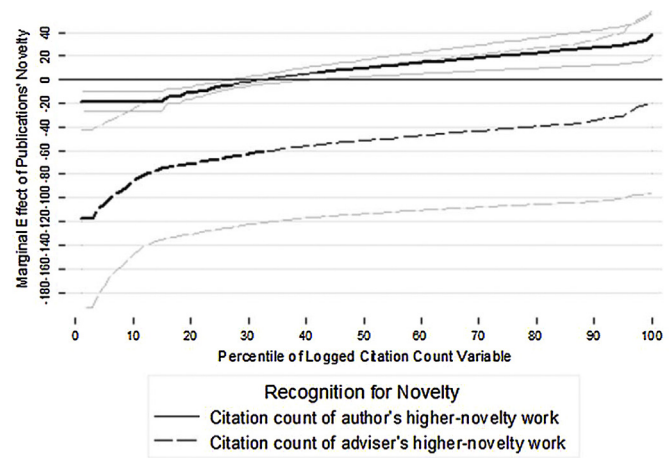
citation increment. The effects of within-area and outside-area citations are statistically different, as suggested by the non-overlap of the confidence intervals and confirmed by the Wald test ( $F = 19.57$ ,  $p < 0.001$ ). Authors' within-area citations thus earn significantly more new citations to their later publications than across-area citations. The ordering of the effect sizes is the same for adviser's citations—the effect of within-area citations is larger—albeit the two effects are statistically non-distinguishable from each other or from zero.

Without testing the study's hypotheses, this simple comparison demonstrates their underlying logic. It shows that past recognition, at least the portion earned by the author rather than inherited from the mentors, better helps a publication get cited if it was earned for work that is similar to that publication. I will now examine, in greater detail, if the same holds true when the similarity of publications is defined by their degree of novelty rather than by the area of knowledge to which they jointly belong.

## 8.2. The effect of author's and their mentors' recognition for novelty

Table 2 reports the results of negative binomial models of the citation count. The models test the hypotheses by examining the interaction effects of publication novelty with indicators of the authors' and their academic mentors' recognition for novelty. Model 1 is the baseline model that includes only the control variables and the novelty variable. The control variables show no unexpected effects. In the absence of the recognition variables, there is no significant relationship between novelty and the publication's yearly citation count. Models 2 and 3 examine the effects of the author's total citation count. The positive and significant coefficient of the citation count in Model 2 is consistent with the Matthew effect—it shows that better cited scholars are more likely to have their fresh work cited by peers. In Model 3, I added the interaction term between publication novelty and the total citation count. Unlike the main effect, the interaction effect is not significant, attesting that citers do not prize novelty in the work of better cited authors above novelty in the work of less cited ones.

Hypothesis 1 is tested in Model 4. In this model, I split the individual citations into those earned for work of higher (above sample median) and lower novelty. The contrast between the effects of these two components of the citation count is telling. The effect of the interaction between the novelty of the publication and the citation count of its author's previous novel work is positive and



**Fig. 2.** The marginal effect of publications' novelty on citation count as recognition for novelty varies. The gray lines show 95% confidence intervals. The marginal effect lines are thicker where zero is outside the interval.

significant. Thus, as predicted in Hypothesis 1, novelty helps publications get cited to the extent that their authors are already recognized for novel work. In contrast, the negative and significant interaction effect of citations received for lower-novelty work indicates that such citations make novelty a hindrance to attracting citations to subsequent work. They do, however, attract citations to publications of lower novelty, as evidenced by the main effect.

Models 5–7 replicate the analysis in Models 2–4, substituting Ph.D. advisers' recognition variables for those of the authors. The total citation count of the author's adviser, unlike the author's own citation count, is not significantly related to the publication's yearly citation increment. The other results in this set of models parallel the findings for the authors' recognition. The interaction effect in Model 6 shows that having a highly cited mentor does not make novelty a significant citation-boosting factor. The effect of the interaction between the novelty of the new contribution and the citation count of the mentor's previous higher-novelty work in Model 7 is positive and significant. This result supports Hypothesis 2. Again, we find that past recognition—in this case, the part of it inherited from the mentor—helps authors attain more audience recognition for novelty if earned for higher-novelty work.

Hypothesis 2 was tested with fewer cases than Hypothesis 1 due to the omission of records with missing or ambiguous adviser information. Because the adviser records in the ProQuest Dissertations and Theses database become less complete as they go back in time, adviser information was typically less available for older, better-published authors. Omitting the authors whose adviser identity was missing or ambiguous therefore led to a disproportionate decrease in the sample of publication-years. One consequence of such listwise deletion is that almost 68% of the valid values of the author's recognition variables are excluded from Model 8, the full model with the authors' as well as the advisers' recognition effects. Despite being estimated with a different sample, much smaller and non-randomly selected, the full model reproduces the results supporting Hypothesis 1.

While publication novelty was unrelated to publication's yearly citation increment in the base model (Model 1), the main effect of novelty was significantly negative in the models with interaction terms which tested the hypotheses (Models 4, 7, and 8). This indicates that novelty inhibits the citation of publications by authors who lack recognition for previous work or by these authors' advisees; such publications have a better prospect of getting cited if they are relatively less novel.

Fig. 2 offers a more nuanced representation of the hypothesized effects. The figure plots the marginal effect of publications' novelty

**Table 2**  
Effects of novelty and recognition on yearly citation counts of information theory publications.

	Negative binomial models of citation count in year $t + 3$																																																																																																																																				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8 (full)																																																																																																																													
<i>Author-level control variables</i>																																																																																																																																					
Female	0.023 (0.111)	0.090 (0.103)	0.089 (0.103)	0.037 (0.101)	0.077 (0.133)	0.077 (0.133)	0.118 (0.142)	0.086 (0.119)																																																																																																																													
Top-5 Ph.D. department	0.471** (0.076)	0.512** (0.072)	0.512** (0.072)	0.455* (0.074)	0.391* (0.107)	0.393* (0.106)	0.463* (0.100)	0.467* (0.097)																																																																																																																													
Information theory faculty	0.095 (0.060)	0.003 (0.062)	0.004 (0.063)	0.014 (0.062)	0.140 (0.136)	0.140 (0.136)	0.112 (0.139)	0.032 (0.135)																																																																																																																													
Degree centrality	>−0.001 (<0.001)	−0.001** (<0.001)	−0.001** (<0.001)	−0.001** (<0.001)	<0.001 (0.001)	<0.001 (0.001)	0.001 (0.001)	−0.001 (0.001)																																																																																																																													
<i>Publication-level control variables</i>																																																																																																																																					
Publication age	−0.053** (0.009)	−0.076** (0.010)	−0.073** (0.010)	−0.072** (0.009)	−0.050** (0.015)	−0.051** (0.016)	−0.055** (0.016)	−0.082** (0.015)																																																																																																																													
(Publication age) <sup>2</sup>	>−0.001 (0.001)	<0.001 (0.001)	<0.001 (0.001)	0.001 (<0.001)	−0.001 (0.001)	−0.001 (0.001)	>−0.001 (0.001)	0.002 (0.001)																																																																																																																													
Citations in patents	0.003** (0.001)	0.002** (0.001)	0.002** (0.001)	0.002** (0.001)	0.006 (0.004)	0.006 (0.004)	0.007 (0.004)	0.003 (0.003)																																																																																																																													
Number of authors	0.016 (0.014)	0.022 (0.015)	0.022 (0.015)	0.021 (0.014)	0.003 (0.018)	0.003 (0.019)	0.001 (0.019)	0.012 (0.021)																																																																																																																													
IEEE TIT publication	1.204** (0.130)	1.186** (0.131)	1.186** (0.130)	1.122* (0.126)	1.331** (0.175)	1.331** (0.175)	1.324** (0.175)	1.218** (0.172)																																																																																																																													
Year dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes																																																																																																																													
Subject category dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes																																																																																																																													
Publication novelty	−0.13 (2.36)	−0.22 (2.33)	−2.93 (1.97)	−18.89** (4.24)	−131.31** (12.42)	−116.68* (56.38)	−117.99** (38.36)	−131.07** (30.52)																																																																																																																													
<table border="0" style="width:100%; border-collapse: collapse;"> <tr> <td style="width:10%;"></td> <td style="width:10%; text-align: center;">Model 1</td> <td style="width:10%; text-align: center;">Model 2</td> <td style="width:10%; text-align: center;">Model 3</td> <td style="width:10%; text-align: center;">Model 4</td> <td style="width:10%; text-align: center;">Model 5</td> <td style="width:10%; text-align: center;">Model 6</td> <td style="width:10%; text-align: center;">Model 7</td> <td style="width:10%; text-align: center;">Model 8 (full)</td> </tr> <tr> <td><i>Recognition variables (logged)</i></td> <td colspan="4" style="text-align: center;"><i>Author variables (Models 2–4)</i></td> <td colspan="3" style="text-align: center;"><i>Adviser variables (Models 5–7)</i></td> <td style="text-align: center;"><i>Author</i></td> <td style="text-align: center;"><i>Adviser</i></td> </tr> <tr> <td>Total citation count</td> <td></td> <td>0.10** (0.02)</td> <td>0.10** (0.02)</td> <td></td> <td>0.02 (0.02)</td> <td>0.02 (0.04)</td> <td></td> <td></td> <td></td> </tr> <tr> <td>Citation count of higher-novelty work</td> <td></td> <td></td> <td></td> <td>−0.06** (0.02)</td> <td></td> <td></td> <td>−0.11** (0.03)</td> <td>−0.06* (0.03)</td> <td>−0.10** (0.03)</td> </tr> <tr> <td>Citation count of lower-novelty work</td> <td></td> <td></td> <td></td> <td>0.17** (0.02)</td> <td></td> <td></td> <td>0.16** (0.04)</td> <td>0.22** (0.03)</td> <td>0.10** (0.03)</td> </tr> <tr> <td><i>Interaction with recognition variables: novelty × ...</i></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td>Total citation count</td> <td></td> <td></td> <td>0.59 (0.66)</td> <td></td> <td></td> <td>−2.48 (8.26)</td> <td></td> <td></td> <td></td> </tr> <tr> <td>Citation count of higher-novelty work</td> <td></td> <td></td> <td></td> <td>6.68** (1.62)</td> <td></td> <td></td> <td>11.21* (5.49)</td> <td>10.58** (3.94)</td> <td>11.88* (5.56)</td> </tr> <tr> <td>Citation count of lower-novelty work</td> <td></td> <td></td> <td></td> <td>−6.37** (1.33)</td> <td></td> <td></td> <td>−16.36* (6.36)</td> <td>−20.29** (4.21)</td> <td>−6.86 (5.87)</td> </tr> <tr> <td>Yearly observations</td> <td>140,940</td> <td>140,940</td> <td>140,940</td> <td>140,940</td> <td>44,595</td> <td>44,595</td> <td>44,595</td> <td>44,595</td> </tr> <tr> <td>Publications</td> <td>13,578</td> <td>13,578</td> <td>13,578</td> <td>13,578</td> <td>6360</td> <td>6360</td> <td>6360</td> <td>6360</td> </tr> <tr> <td>Authors</td> <td>1553</td> <td>1553</td> <td>1553</td> <td>1553</td> <td>1042</td> <td>1042</td> <td>1042</td> <td>1042</td> </tr> <tr> <td>Log likelihood</td> <td>−250,553</td> <td>−230,100</td> <td>−230,094</td> <td>−229,468</td> <td>−75,855</td> <td>−75,854</td> <td>−75,694</td> <td>−75,329</td> </tr> </table>										Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8 (full)	<i>Recognition variables (logged)</i>	<i>Author variables (Models 2–4)</i>				<i>Adviser variables (Models 5–7)</i>			<i>Author</i>	<i>Adviser</i>	Total citation count		0.10** (0.02)	0.10** (0.02)		0.02 (0.02)	0.02 (0.04)				Citation count of higher-novelty work				−0.06** (0.02)			−0.11** (0.03)	−0.06* (0.03)	−0.10** (0.03)	Citation count of lower-novelty work				0.17** (0.02)			0.16** (0.04)	0.22** (0.03)	0.10** (0.03)	<i>Interaction with recognition variables: novelty × ...</i>										Total citation count			0.59 (0.66)			−2.48 (8.26)				Citation count of higher-novelty work				6.68** (1.62)			11.21* (5.49)	10.58** (3.94)	11.88* (5.56)	Citation count of lower-novelty work				−6.37** (1.33)			−16.36* (6.36)	−20.29** (4.21)	−6.86 (5.87)	Yearly observations	140,940	140,940	140,940	140,940	44,595	44,595	44,595	44,595	Publications	13,578	13,578	13,578	13,578	6360	6360	6360	6360	Authors	1553	1553	1553	1553	1042	1042	1042	1042	Log likelihood	−250,553	−230,100	−230,094	−229,468	−75,855	−75,854	−75,694	−75,329
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Note: The constants are omitted. Standard errors, adjusted for author-level and publication-level clustering, are in parentheses. The data set includes publications authored or co-authored by individuals employed, as of June 2010, as information theory faculty at U.S. institutions classified as “very high research activity” in the Carnegie Classification of Institutions of Higher Education, their Ph.D. students, Ph.D. advisers, and advisers’ Ph.D. students. The count of observations reflects listwise deletion.

\*  $p < 0.05$ .

\*\*  $p < 0.01$ .

on their lagged yearly citation count across the full range of the two higher-novelty citation count variables, calculated for models with the respective interaction terms (Models 4 and 7). This simultaneously visualizes the sign and the magnitude of the variables’ moderating effects. To show the two variables on one horizontal axis, their scales were standardized by converting the original values into percentile categories.

Both moderating variables cause marked variation in the marginal effect of a publication’s novelty. Novelty significantly lowered the number of citations that publications received if the citation count of their authors’ higher-novelty work was below the 27th percentile; but novelty earned a significant citation increment if it was above the 42nd percentile. The plot makes it clear that the effect of novelty on the citation count switches from negative to positive as the author’s recognition for novel work increases. The author’s recognition for novelty thus not only counteracts the novelty aversion but is also capable of transforming the novelty of a contribution from a liability

into an advantage that helps in attaining the audience’s recognition.

Ph.D. adviser’s recognition for novelty similarly improves the chances that an authors’ work will be valued for its novelty. However, the effect of adviser’s recognition is not pronounced enough to transform novelty from a liability into an advantage. Advisers’ citation count for higher-novelty work only prevents novelty from being a significant impediment to citations when it is above the 33rd percentile; yet novelty brings a negative citation increment even at the highest values of adviser’s recognition for novelty.

## 9. Robustness checks

### 9.1. Alternative model specifications

It stands to reason that the degree to which the audience associates authors with their Ph.D. advisers’ work decays with time. If so, the effect of the context of the mentor is more



precisely captured if the recognition variables are adjusted for time decay. I adjusted the mentor recognition variables for a 5% yearly decay, multiplying each post-Ph.D. variable value by  $0.95^{(\text{focalyear} - \text{author's Ph.D. attainment year})}$ . Neither the 5% nor the 10% yearly decay adjustment changed the sign or significance of the variables' effects. Nor did those change when the models were re-estimated with non-logged citation counts. Further, I tried using above-median thresholds of novelty in the calculation of the recognition variables, raising the threshold to the top quintile, and again to the top decile. I re-estimated all reported models with different time lags between the dependent variable and the predictors, trying 2-, 4-, and 5-year lags. I also re-estimated Models 4 and 7 without the interaction term for the citation count of lower-novelty work. The hypothesized effects persisted in all these specifications.

Next, I considered the results' sensitivity to multiple authorship. When a publication has more than one author, its citation count may be influenced by the identity of the focal author and of other authors. Co-author's recognition may have muffled the recognition effects of the focal authors that were hypothesized and observed or, alternatively, biased them in a way that led to false acceptance of the hypotheses. The former alternative would improve the rigor of the tests: if the focal authors' effect is detectable even despite the noise from the co-authors, this testifies to the robustness of this effect. To rule out the second alternative, I re-estimated all models in the subsample of single-authored publications and again in the subsample of co-authored ones. The hypothesized effects were reproduced in both subsamples. Furthermore, I re-estimated all models with the subsample of co-authored publications adding, to each recognition variable, the same variable averaged across the focal author's co-authors. The hypothesized effect of the author's recognition persisted, although 81.7% of the observations were lost because the information on co-authors' citation count or novelty was missing. The loss of observations was too large for the negative binomial models testing the effects of the adviser's recognition to converge.

This study shares the sample selection problem inherent in most quantitative analyses of the success of creative work. Such analyses can only examine creative products that are successful enough to enter the dataset but cannot account for the processes that prevent other products from achieving that minimal success. Thus, the analysis in this article could only consider published work rather than the process by which novel work does or does not get published in the first place. I checked the robustness of the results to sample selection in two ways. First, the inverse Mills ratio (Heckman, 1979) was entered in all regression models. The inverse Mills ratio is the hazard of non-selection predicted by variables that correlate with the selection variable—in this case, with the dummy indicator of having no publications. All hypothesis-testing effects persisted in the models with the Mills ratio. Second, I reran the models on a subsample of authors who have survived at least 10 years in the data. These authors are relatively less affected by selection in the publication process because it is easier for them to get their output into print due to Matthew-like effects and to better knowledge of the publication opportunities. All the hypothesized effects retained their size and direction in the subsample. The standard errors increased because of the loss of observations and, as a result, the statistical significance of the interaction effect that tested H2 became borderline: it was significant at  $p = 0.078$  in Model 7 and at  $p = 0.107$  in the full Model 8. When all other interaction effects were removed from the model, it was significant at  $p = 0.081$ .

All results of alternative regression specifications are available on request.

## 9.2. An alternative test design: Constant quality and recognition shocks

The effects of producers' recognition may be confounded by the objective quality of their work. This problem is endemic to empirical analyses of reputational effects (Simcoe and Waguespack, 2011; Azoulay et al., 2014), and this analysis is no exception. To the extent that the controls for quality in the models are imperfect, the authors' recognition for novelty, either earned or inherited from the mentors, may correlate with citations because the high-novelty output of these authors or their mentors is objectively better, rather than because of audience recognition. Individual fixed effects do not resolve this problem because individuals' recognition and quality vary with time.

To net out the effect of product quality and detect the effect of the recognition for higher-novelty work, the study design must capture variation in the recognition of the products by the audience that is guaranteed to not be confounded by the variation in those products' actual quality. One way to accomplish this is to examine an exogenous recognition shock, such as receiving a prominent professional award, and its effect on the appraisal of a product that was created *before* the shock. Because the objective quality of each product is constant in this design, a change in its appraisal by the audience in the wake of the shock can be triggered by a change in producers' recognition but not by a concomitant change in the product's actual quality (Azoulay et al., 2014).

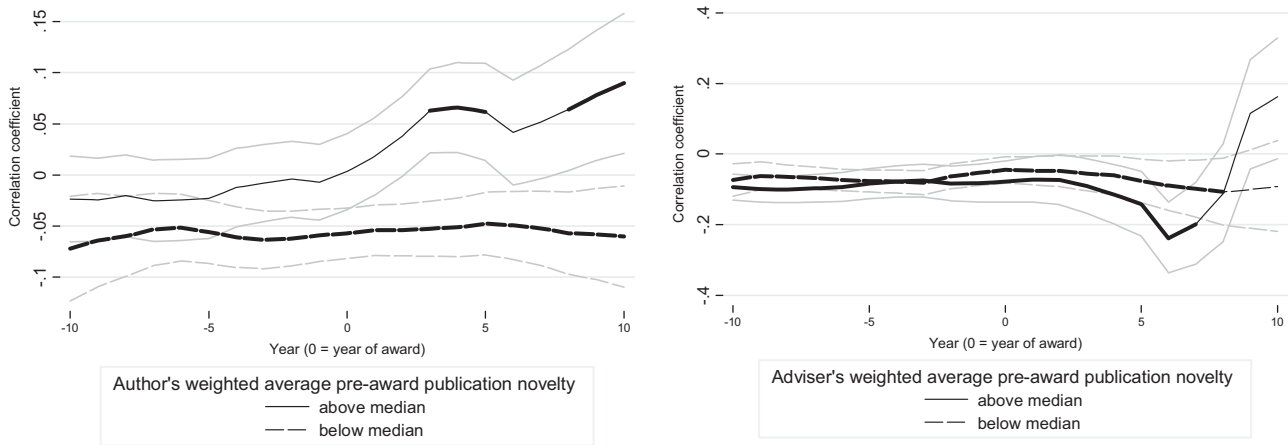
I examined the effect of the Shannon Award and the IEEE fellowship, two major professional accolades awarded for long-term work in information theory. The Shannon Award is given to one person annually by the IEEE Information Theory Society "to honor consistent and profound contributions to the field of information theory." The status of IEEE Fellow is conferred annually upon individuals with "an extraordinary record of accomplishments in any of the IEEE fields of interest."<sup>7</sup> The sample contains publications by seven Shannon Award recipients and 125 IEEE Fellows.

Because professional awards simultaneously boost the recipients' peer recognition and highlight the nature of their prior work, the hypotheses predict that, among the awardees whose prior work is highly novel, the relationship between the novelty and the citation rate of contributions that they published *before* the award will become more positive *after* the award (and after a delay required for the effect of the award to diffuse). They predict no similar upturn in this relationship if the awardee's prior work is not highly novel. To operationalize these predictions, novelty  $N$  of author  $a$ 's work prior to award year  $y$  was defined as the weighted average novelty of the author's past publications,  $N_{ay} = \sum_p N_p \times C_{p(y-1)} / (P_{(y-1)} \times \sum_p C_{p(y-1)})$ , where  $p$  indexes the publications by author  $a$ ,  $P$  is  $a$ 's publication count, and  $C$  is the citation count of  $p$ . The weighting ensures that a publication's contribution to this aggregate measure is proportional to its citation count.

I traced the pre- and post-award temporal trend in the correlation between publications' novelty and their yearly citation count, separately for publications authored by awardees whose  $N_{ay}$  was above and below the median.<sup>8</sup> As shown in Fig. 3, the correlation between the novelty and the yearly citation increment of pre-award publications is stably negative for those awardees whose pre-award work was relatively less novel; the award event has no visible impact on this correlation. In contrast, the correlation

<sup>7</sup> The award criteria are posted at [www.itsoc.org/honors/claude-e-shannon-award](http://www.itsoc.org/honors/claude-e-shannon-award) and [www.ieee.org/membership\\_services/membership/fellows](http://www.ieee.org/membership_services/membership/fellows).

<sup>8</sup> Note that, in this analysis,  $N_{ay}$  varies not only between individuals but also between publications because the focal publication's novelty is omitted from the calculation.



**Fig. 3.** Correlation between the novelty and yearly citation count of pre-award publications among award recipients and their advisees, by novelty of their pre-award published work. The awards are the Shannon Award and IEEE fellowship. The averages are weighted by publications' total citation count. The correlation coefficients are computed in a three-year moving time frame. The gray lines show 95% confidence intervals; the lines are thicker where zero is outside the interval.

among those whose pre-award work was above median novelty spikes after the award, reaching positive and significant values in the third post-award year and, after a slight dip, again after the eighth year. I reproduced the same plot for publications by award recipients' advisees. The advisees' two lines run roughly parallel, until the higher-novelty line dips and then surges upward in years seven to ten after the adviser's award. Even though this upsurge does not make the correlation coefficient significant, it is sufficient to make the positive coefficient for higher novelty and the negative coefficient for lower novelty statistically different from each other at  $p=0.05$  in years nine and ten. A comparison of the slopes instead of the correlation coefficients yielded substantively the same results, showing the expected post-award upturns among the awardees whose prior work was of above-median novelty and none among the other awardees.

This demonstration of recognition effects in a constant-quality test design does not guarantee that the quality mechanisms had no role in producing the results reported earlier. Yet the finding that the relationship between the novelty and the recognition of publications that predate recognition shocks becomes more positive after these shocks attests that the recognition mechanism operates in the empirical setting at hand. The two hypotheses of this study were premised on the presence of the recognition spillover mechanism, not on the irrelevance of the quality mechanism.

## 10. Discussion

### 10.1. Contributions

This project was motivated by the puzzling dual implication of novelty for the recognition of knowledge. Novel, unusual recombinations of knowledge may be subject to a higher risk of rejection by evaluating audiences. Yet audiences may also deem a contribution valuable precisely *because* it is highly novel. I argued that the latter outcome becomes more likely when the authors of knowledge or their mentors have established a record of recognized novel work. The empirical results supported the argument: indeed, highly novel publications received more citations to the extent that their authors or authors' mentors were already recognized for novel work.

This study contributes to creativity and innovation research by expanding the scope of the existing explanations of the audiences' alternately favorable and dismissive appraisals of novelty. Previously suggested explanations accounted for the variation in the appraisal of novelty between audiences or between time periods.

In contrast, the explanation offered here aspired to explain why the same audience, while simultaneously appraising multiple contributions, may value their novelty differently.

This study tellingly supplements the existing arguments about the role of social status in the recognition of creative work. The research that documented Matthew-like effects in various creative activities (e.g., [Burton et al., 2002](#); [Higgins et al., 2011](#); [Zuckerman, 1977](#)) has been silent on whether high-status actors' recognition premium helps transform novelty from a liability into an advantage. An affirmative answer to this question is now emerging in studies on artistic creativity. [Sgourev and Althuizen \(2014\)](#) suggested that artists' high status activates the audiences' perception of their creative competence—that is, a capability to do work that is both highly novel and of high quality. This perception, in turn, predisposes the audiences to appreciate high-status artists' stylistic novelty. [Koppman \(2014\)](#) presents a similar mediation mechanism, in which the positive relationship between a person's high-status background and successful entrance into a creative career is mediated by cultural capital, which signals the person's creative competence to gatekeepers.

My results confirm the basic intuition that audiences prize novelty when they simultaneously see the producer as high-status and creatively competent. However, they suggest that high status does not necessarily trigger perceptions of creative competence. It may do so in artistic work, where audiences normally assume that highly innovative output is a precondition of professional prominence. But in knowledge production, where prominence may also be attained while doing routine, normal-science work, the perceptions of status and creative competence are causally unbundled. The connotation of the author's creative competence must be *added* to perceptions of status for the audiences of knowledge to reward novelty in the author's work. Without this added connotation, status may fail to affect the rewards of novelty or even reduce them.

The results of the study enrich our understanding of the function of mentoring relations in professional communities. While the mentoring literature has focused on the functions of mentoring relations for the mentors and their protégés, this study highlights the informational function of mentoring for observers who have no apparent stake in the mentoring relation at hand. The findings show that, in granting professional recognition to producers of knowledge, the audience may consider not only their mentors' easily visible status markers such as prestigious awards but also more nuanced information, such as the extent of novelty of the mentors' work.

## 10.2. Practical implications, limitations, and future directions

The study's simple practical message to scientists who seek audience recognition is that they have a better chance to succeed if they visibly commit to novel rather than incremental, normal-science work. By seeking out mentors known for divergent ideas or building up a record of novel contributions, authors communicate to the audience that they are committed to specializing in high-novelty work. The practicability of this recommendation certainly depends on how much awareness scientists have of the novelty of their own output. This question remains open. It may be hard for the scientists to know how novel their own work is in the audience's perception, and harder still to control it. Hence, it may also be difficult to strategically pursue recognition for novelty. Future research examining how accurately authors' own assessments of the novelty of their work correspond to audiences' assessments may clarify the feasibility of strategic reputation building.

The other question that this project leaves unanswered is how recognition of highly novel ideas may be attained early in authors' careers. We saw that recognition for earlier novelty helps with recognition of subsequent novelty. But how was the earlier recognition attained? It stands to reason that the author's previous professional record also determines early recognition, but the elements of that record that matter are different from those at advanced career stages and are more difficult to capture empirically. For example, reputations of educational establishments may matter. The role of the author's personality traits, such as motivation, may also be considerable at early career stages.

The argument and findings of this study are generalized to pre-commercial science and technology; the implications for marketed products remain largely open. The one evidently straightforward implication is that novel pre-commercial ideas that benefit from their authors recognition for novelty have a better chance of eventual market success, because pre-commercial recognition by experts helps with subsequent commercialization, particularly by attracting investors. But does commercial producers' past recognition affect the appeal of highly novel *marketed* products to consumer audiences? Although this question is outside the purview of this project, the goal is to generate interest in them. An effort to answer it would engage disciplines that this study did not draw upon, particularly marketing, and a different type of empirical evidence.

A simple working hypothesis to guide this effort is that, in evaluating original, innovative products, consumer audiences are as much influenced by the producers' past record as the knowledge audiences studied here. The hypothesis would predict that, other things being equal, producers who have a visible record of novel products will earn a larger consumer following when they introduce highly innovative, ground-breaking products; conversely, similar products by producers who have no such record will have a relatively low consumer appeal. The history of innovation offers anecdotal evidence consistent with these predictions. For example, IBM successfully entered the emerging personal computer (PC) market in the 1980s, whereas the market was not receptive to similar PCs produced by the Digital Equipment Corporation (DEC). IBM was famously good at innovating in diverse areas, whereas DEC had no novelty credentials beyond its increasingly obsolete minicomputer technology (Christensen, 1997; p. 125–128). The independent and innovative Facebook quickly dethroned MySpace in the emerging online social networking sector after the latter was acquired by News Corporation, a behemoth of pre-Internet mass media. Because consumers ever more actively co-create the value of innovative products (Prahald and Ramaswamy, 2004), the role of producers' public image in determining such contrasts of success and failure may be increasing relative to the traditionally emphasized role of capabilities and management. If so, established firms

aspiring to introduce disruptive technologies would be well advised to focus, alongside other management and marketing efforts aimed at supporting innovation, on establishing an image as highly creative innovators.

Explaining the dual effect of novelty on recognition is an ambitious undertaking, and the recognition spillover explanation is not intended to be exhaustive. The features of the piece of knowledge itself (rather than those of its authors) are an obvious type of potential explanations not considered here. This study aspires to stimulate a systematic inquiry into this and other moderators of the relationship between novelty and audience recognition. By suggesting one kind of moderators, it highlighted more gaps in our understanding than it was able to fill.

## Appendix A.

### *Disambiguation of author identities*

The Thomson Reuters Web of Knowledge (TRWK) database identifies authors of publications by their last name and all initials (LNAI) only. It also records the authors' institutional affiliations; yet, because of inconsistent formats of institutions' names and the inconsistent author-institution matching in cross-institutional co-authorships, institutional affiliations cannot be reliably matched to individuals in TRWK without manual, case-by-case identity checks. Matching publications to authors by LNAI generates pervasive and often irresolvable ambiguity. Authors with ambiguous LNAIs were therefore removed from the sample.

This appendix describes the criteria that define ambiguous LNAI in the study. Each successive criterion of ambiguity was applied only to cases not deemed ambiguous under preceding criteria.

#### A.1. *Common names*

The person's last name may be too common for reliable identification with LNAI. The following categories of cases were flagged as ambiguous because of common names:

- a) Two or more people in the sample of information theorists have identical LNAI (74 individuals removed).
- b) Five or more people in the sample of information theorists have the same last name. The chance that another author has an identical LNAI is unreasonably high for individuals with such common last names (549 additional individuals removed).
- c) The person's last name and first initial (LNFI) do not identify them uniquely among all authors who have published under the "engineering (electrical & electronic)" category in TRWK (353 additional individuals removed).

#### A.2. *Unrealistic timing of publications*

LNAI was flagged as ambiguous if no publication under this LNAI falls within the 11-year period centered at the years in which the corresponding individuals in the sample obtained their Ph.D. (202 additional individuals removed).

#### A.3. *Unrealistic clustering of publications*

A recently developed set of methods in information science uses clustering of publications to disambiguate author identities (Gurney et al., 2012; Smalheiser and Torvik, 2009). The following multi-stage clustering algorithm was applied to identify authors with unrealistic clustering of publications.

- a) Select all publications in TRWK with an LNFI matching the researcher not flagged in stages 1 or 2 above.
- b) Identify relations between the selected publications. Two publications are related if (1) they have a shared author LNFI, (2) there are no conflicting second or higher initials in the author's name in the two publications, and (3) the two publications satisfy at least one of the following five criteria:
- 1) One publication cites the other.
  - 2) The publications have at least three references in common (bibliographic coupling).
  - 3) The publications have at least three citing publications in common (co-citation).
  - 4) The publications have at least two author LNFI in common.
  - 5) The publications both have only one author address and this address is the same.
- c) Identify clusters of selected publications in such a way that all publications within a cluster are directly or indirectly related, while there are no relations between publications in different clusters. (In graph theory, such clusters are called connected components.)
- d) Flag clusters as suspect if any of the following are true:
- 1) All publications in the cluster are outside the six most-common TRWK subject areas in which information theory publications appear: engineering (electrical and electronic); telecommunications; computer science; information systems; physics (multidisciplinary); optics; computer science (artificial intelligence automation and control systems).
  - 2) The cluster contains no publications in the electrical engineering category.
  - 3) The cluster has no publications with a perfect LNAI match.
  - 4) The cluster contains at least one publication with incorrect second or higher initials in the author's name.
  - 5) The year of the earliest publication in the cluster is more than eight years before the author's Ph.D. year.
- e) Remove the "suspect" label from a cluster if it contains publications with a student-advisor match.
- f) Flag LNAI as ambiguous if either of the following is true:
- 1) 80% or more of publications under the author's LNFI are in "suspect" clusters of any size (760 additional individuals removed).
  - 2) The author has more than 10 disconnected clusters of two or more publications (86 additional individuals removed).

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