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# Discussants

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ABSTRACT

We study the role of informal collaboration in academic knowledge production using published research papers previously presented and discussed at the NBER Summer Institute. We show that papers that have a discussant are published in highly-ranked journals and are more likely to be published in a top journal. Conditional on having a discussant, the quality of a paper's journal outlet increases in the discussant's prolificness and editorial experience. This supports the idea that discussants help reduce information asymmetries that are inherent in the academic publication process. Conversely, using social network analysis we find no evidence that citations accumulate because discussants diffuse information about the paper.

## 1. Introduction

Informal collaboration – receiving feedback and commentary from colleagues on ongoing research papers – is commonplace in academic research. Academics spend enormous amounts of time and money on conference travel,[1] and there is evidence that conferences spur a paper's academic success (de Leon and McQuillin, 2020; Gorodnichenko et al., 2021). More informal collaboration, measured by the number of acknowledged commenters, is associated with a higher number of citations (Laband and Tollison, 2000; Rose and Georg, 2021).[2] Two things are not well understood: The channel through which conferences improve academic success, and the causal impact of acknowledged commenters.

We study the role that discussants in conferences – a special type of informal collaborators – play in academic knowledge production and dissemination. Our laboratory is the National Bureau for Economic Research's Summer Institutes (NBER SIs), a highly selective annual workshop series. We focus on workshops by Finance related NBER groups and programs to minimize the effect of sub-fields' heterogeneity. Our study period is 2000 to 2009. Some workshops always feature discussants while others never do. The reasons for this organizational difference are lost in history, but it is persistent. One organizer speculated in a short survey we conducted, that the difference might be due to "a different norm: everyone reads the papers beforehand, so everyone forms an opinion and is able to ask informed questions", while another called it just "path dependence". As we show in Appendix C, whether there are discussants or not is the only relevant observable difference.

Although manuscripts accepted to NBER SIs are selected on expected high quality, we find that papers with discussants have a higher likelihood of getting published in highly-ranked journals. Having a discussant however does but increase a paper's citation count once controlling for the paper's subfield. The effects of discussants' characteristics are limited. We find that papers discussed by highly prolific discussants and discussants with editorial experience are published in better journals. The experience of a discussant and how connected they are in the academic community have no discernible effect on both a paper's journal outlet and citation count.

The effect of having a discussant on a paper's academic success (i.e., the quality of a paper's journal outlet and the citation count it receives) is identified only if (i) authors do not sort into workshops based on the fact that they have discussants; (ii) papers are of comparable quality; and (iii) the workshops are otherwise identical. Although not perfect, we provide ample evidence that all three assumptions hold. First, qualitative evidence from a survey among workshop organizers suggests that authors do not decide which NBER workshop to

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[1] According to the academic portal econbiz.de/Events/Results, there were at least 900 conferences in economics and business in 2019. There are about 100,000 meetings in medical science each year (Ioannidis, 2012).

[2] Relatedly, the joint editorial Green et al. (2002, p. 1032) advises authors to "circulate their papers and give seminars to colleagues to receive constructive criticism before submitting to a journal".

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submit based on whether it features discussants. We also do not find any indication of differences in the quality of accepted papers between the two categories of workshops.

Second, we examine the characteristics of presentations and discussants. We find that presentations without discussants are on average as long as presentations with discussants. And third, the published papers in our sample are more similar to each other than papers in the typical top-5 Economics journals are to each other. Published manuscripts are also sufficiently topically related irrespective of which category of workshop (with or without discussant) they were presented in. Finally, we control for topics of papers via JEL categories.[3]

The effect of a discussant's characteristics on a paper's academic success on the other hand is identified if (i) organizers match discussants to papers and authors based primarily on topical fit (e.g., whether the discussant knows the relevant literature, methods and data) rather than discussant characteristics (e.g., prolificness, age and gender); and (ii) a discussant discusses the paper irrespective of which session it is in. Although discussants are not assigned randomly, our survey among the NBER SI organizers in our sample shows that they do not match papers and discussants based on experience or prolificness.[4] Survey respondents confirmed that discussants usually accept the invitation. This rules out sorting by discussants that would arise if potential discussants decline to discuss a paper.[5] To control for unobserved group heterogeneity, we introduce fixed effects for the corresponding NBER working group. The group fixed effects also capture the organizers' effects since organizers seldom change during our sample period.

Our findings are consistent with the notion that discussants improve academic success of papers by informing authors of the best fit journal outlet and the chances of publication success. In doing so, they reduce information asymmetries that are inherent in the academic publication process. We also discuss multiple alternative channels through which discussants matter. For example, the quality-improving channel, where discussants' feedback acts to improve the inherent quality of the paper; the motivation channel, where discussants motivate authors to work harder on their papers (in the pre- or post-discussion period); and the inspiration channel, where discussants inspire thoughtful comments from workshop attendees.

While we are unable to provide evidence of (non)existence of all the possible channels, we are able to rule out the *diffusion channel* where discussants may act as seeds of diffusion of information about the paper. We find that a discussed paper is less likely to receive a citation by a discussant than by any other author presenting in the same workshop group. This suggests that discussants' contribution to the diffusion of papers is less than that of other authors. We then show that the academic success of papers is independent of a discussant's *neighborhood centrality* in the network of academic collaboration.[6] Neighborhood centrality is a novel measure we designed to capture a researcher's ability to diffuse information to the wider academic community.[7] These two observations suggest that diffusion is not the main mechanisms through which discussants impact academic success of papers.

Our findings contribute to the empirical work studying the effect of informal collaboration on academic success of papers (Laband and Tollison, 2000; Brown, 2005; Castaldi et al., 2015). However, except for de Leon and McQuillin (2020), these papers only establish correlations between informal collaboration and academic success of papers. de Leon and McQuillin (2020) are the first to use quasi-experimental evidence, namely, the sudden cancellation of the 2012 American Political Science Association Annual Meeting to examine the impact of conferences and find that conferences increase papers' citation counts. Our study provides the first attempt at causal evidence, although not perfect, of the benefits of having discussants at conferences and the channels through which conferences impact knowledge production and dissemination. This literature stream is embedded in a broader literature on peer effects in knowledge production and diffusion. Prominent examples include Waldinger (2012) who finds positive peer effects among members of academic departments; Azoulay et al. (2010), Oettl (2012b) and Borjas and Doran (2015) who report evidence of knowledge spillovers among former co-authors.

Our paper is also related to the literature that seeks to understand information diffusion within scientific communities. de Leon and McQuillin (2020) find that conferences act as avenues for advertising papers through face-to-face interactions. Similar effects were documented by Belenzon and Schankerman (2013) for inventors. Recently, Baruffaldi and Pöge (2020) show that diffusion of scientific insights to industry is greatly facilitated by conferences. We find no evidence of diffusion outside of conferences, which may suggest that the diffusion of papers through online publication is more prominent than through face-to-face interactions. However, we only consider the diffusion effects initiated by discussants.

Overall, our results are in line with recent empirical evidence suggesting that informal collaborators deserve more credit with regards to their contributions to paper authorship than they currently receive (Ponomariov and Boardman, 2016; Oettl, 2012a). Our findings also lend credence to the idea that not only do academic conferences play a role in knowledge production and dissemination, the manner in which they are organized affects how strong their impact is.

## 2. Variable construction

### 2.1. NBER summer institutes

NBER Summer Institutes (SI) are annual meetings with distinct workshops by NBER working groups or programs.[8] Some of the workshops always feature discussions by invited discussants. We consider every program of every NBER SI between 2000 and 2009. This range gives sufficient time for citation trajectories to unfold and is in line with additional data for robustness checks. Given the topical proximity of many Economists to this dataset, we discuss some interesting aspects (e.g., time to publication, age of discussants) in Appendix A.

We focus on the SIs of the following NBER working groups with discussants: "Asset Marketing/Real Estate" (AMRE), "Asset Pricing" (AP), "Corporate Finance" (CF), "Capital Markets in the Economy" (EFEL), "International Finance and Macroeconomic" (IFM), "Finance and Macro" (MEFM), "Economics of Real Estate and Local Public

[3] As an alternative, we repeat the analysis using only the four most similar groups, i.e., those related to monetary Finance.

[4] There are 66 different organizers in our sample. We contacted 60 of them for which we found valid e-mail addresses; 15 responded but 4 respondents said they were not engaged with the selection of discussants. Our knowledge thus relies on the insights of the remaining 11 respondents, who were engaged in the organization of 42 distinct workshops. We asked the organizers the following three questions: "What do you look for when accepting papers? How do you match discussants to papers? How exogenous is the process to authors?"

[5] Being a discussant at a NBER SI is considered a prestigious opportunity and a signal of high standing within the profession.

[6] One network captures co-authorship relationships in Finance and related fields of up to about 50k authors. The other network captures fine-grained informal collaboration links of up to about 7.5k authors within Finance (Rose and Georg, 2021).

[7] We model a diffusion process that is akin to the diffusion of information about products, practices and services (Bandiera and Rasul, 2006; Conley and Udry, 2010; Banerjee et al., 2013). These papers show that information sharing in networks of friendship, peer-to-peer, colleagues and family relations, influence individual decisions, and hence, successful diffusion of products, services and practices.

[8] We do not distinguish between groups and programs, as their workshops follow the same procedure.

Finance" (PERE) and "Risk of Financial Institutions" (RISK).[9] Our comparison group consists of working groups without discussants but with related focus: "Impulse and Propagation Mechanisms" (EFCE), "Forecasting and Empirical Methods in Macro and Finance" (EFFE), and "Monetary Economics" (ME). For every workshop we source the title of each paper and the names of authors and discussants from the online program, and for each author, the affiliation.

In total, 922 presentations took place at 85 distinct workshops between 2000 and 2009. This includes 9 presentations in 3 joint workshops, 36 manuscripts presented multiple times, and 4 presentations whose title is not mentioned in the program.[10] However, not every presentation eventually resulted in a publication: A total of 696 (75%) of the presentations resulted in publication by January 2022.[11] Table A1 lists the empirical publication probability by workshop.

Among the 696 publications are 10 publications as book chapters (including the NBER Macroeconomics Annual), 4 policy publications and 21 Society of Economic Dynamics proceedings. The rest got published in 86 different journals. The most important outlets are *The Journal of Finance* (62 papers) and *The American Economic Review* (60). They are followed by *The Review of Financial Studies* (50), the *Journal of Financial Economics* (44) and the *Journal of Monetary Economics* (43).

### 2.2. Paper characteristics

For each of the presented manuscripts that got published, and for which bibliometric information is available, we compute three measures of academic success. The first measure is the total count of citations a paper garnered by January 2022. We retrieve the yearly citation count from Scopus using code developed by Rose and Kitchin (2019). Second, we use a binary variable equal to 1 indicating publication in one of the top three Finance journals or top five Economics journals, and 0 otherwise.[12] And third, we use the SCImago Journal Rank (SJR) indicator of the journal from the year before publication. This "size-independent indicator of journals' scientific prestige" is an iterative Eigenscore that weights citations to individual documents of the past three years by the SJR indicator of the citing articles (González-Pereira et al., 2010).[13] Table 1 presents the manuscript counts and averages of the three dependent variables by group. As alternative measures of journal quality, we use the journal's *h*-index and the average citation count over the previous five years. Figure A1 compares their distributions graphically.

We obtain the number of pages of the published version of the article, and count the number of years between the presentation at an NBER SI and the final publication. We call the latter variable *age*. Its purpose is to (imperfectly) control for how much the article changed subsequent to the presentation. But it also sheds some light on publication lags: The average manuscript gets published in the third year following presentation (Figure A2). To control for a paper's topics, we collect the Journal of Economic Literature (JEL) codes from EconLit. The codes are determined by staff of the American Economic Association, who maintains EconLit. Although these JEL codes might differ from the ones provided by authors, the advantage of using EconLit is that broad availability and the consistency. We find JEL codes for all but two articles, for which we use the JEL code displayed on the final publication.

### 2.3. Author and discussant characteristics

For each of the 918 authors of the published papers, we compute two variables in the year before publication that we refer to as author characteristics: Euclidean index of citations (see below) and experience. For each of the 260 discussants, we compute the following discussant characteristics: Euclidean index of citations, experience, gender,[14] affiliation rank, affiliation with non-academic institutions ("practitioner"), and editorial membership. The variables are computed in the year of the workshop. We compute the Euclidean index of citations, the experience and affiliation with non-academic institutions using publications data from Scopus as of January 2022 using a code developed by Rose and Kitchin (2019).

We use Euclidean index of citations as a measure of authors' and discussants' prolificness (Perry and Reny, 2016). Unlike conventional measures of academic productivity, the Euclidean index takes into account both publication count and citations to individual papers, making it a more accurate measure.[15] Formally, for each year $t$ we count the total number of citations to each of researcher $i$'s $n$ publications published by $t$, then we take the square root of the sum of the squared citation counts. If $c_{i,k,t}$ is author $i$'s total citation count for paper $k$ by period $t$, then

$$\text{Euclid}_{i,t} = \sqrt{\sum_{k=1}^{n} c_{i,k,t}^2} \tag{2.1}$$

The second characteristic for both authors and discussants is "experience", which for any year $t$ is the number of years since the researcher's first journal publication. If the first publication is in the future, then the experience is 0. The median experience of a discussant at the time of discussion is 10 years (Figure A3). To account for non-linearities of the experience of both authors and discussants, we use experience categories of <2, 2–6, 7–14 and > 15 years of experience. In the analysis we use the experience categories of the youngest and the oldest author separately. Table A2 tabulates the joint experience composition for the youngest and the oldest author.

### 2.4. Co-author and informal collaboration networks

We also examine whether discussants contribute to the academic success of papers through diffusion channels. We focus on two forms of diffusion: *citation-based diffusion*, where a paper is first cited by the discussant, triggering citations by the wider academic community; and *word-of-mouth diffusion* where the discussant informs her colleagues (coauthors and other researchers she collaborates with informally) about the existence and quality of the paper, and the discussant's colleagues inform their colleagues, and so on. Along this chain of information cascade about the paper, some researchers cite it.

We proxy researchers' ability to diffuse information through word-of-mouth to the wider academic community using their position in the network of academic collaboration. Since word-of-mouth diffusion

[9] Some groups change abbreviations over time. For better comparison, we use the abbreviations as of 2020, or the last available year.

[10] For unpublished manuscripts, that are presented multiple times under different titles, we are unable to map them. The number is thus an upper bound.

[11] Many papers change their titles before getting published. We, therefore, conducted an extensive and thorough internet search for each paper based on the authors and abstracts to identify those papers with a different title.

[12] These journals are the *Journal of Financial Economics*, *Review of Financial Studies*, *The Journal of Finance*, *Journal of Political Economy*, *The American Economic Review*, *Quarterly Journal of Economic*, *Review of Economic Studies*, and *Econometrica*.

[13] SJR indicators are based on Scopus and originate from http://www.scimagojr.com/journalrank.php.

[14] We infer the gender from matching the discussant's first name against genderize.io. 10% of all discussions were delivered by females. Already Chari and Goldsmith-Pinkham (2017) show that Finance related NBER workshops are the most male dominated.

[15] Perry and Reny (2016) provide an axiomatic foundation for citation indices and argue that the Euclidean index has a number of advantages over other citation indices such as the *h* index. These desirable properties include depth relevance, scale invariance, and directional consistency.

**Table 1**
NBER groups with and without discussants.

a) Groups with discussants

| | Manuscripts | Share published | Avg. citations (2 yrs.) | Avg. journal SJR | Share top journals |
|---|---|---|---|---|---|
| AMRE | 9 | 77.8 | 6.1 | 4.5 | 28.6 |
| AP | 85 | 87.1 | 19.2 | 10.8 | 88.9 |
| CF | 112 | 84.8 | 16.3 | 10.9 | 81.9 |
| EFEL | 94 | 79.8 | 9.0 | 8.6 | 54.9 |
| IFM | 101 | 79.2 | 12.1 | 7.0 | 41.0 |
| PERE | 77 | 61.0 | 10.7 | 6.3 | 32.6 |
| RISK | 18 | 83.3 | 31.4 | 10.9 | 57.1 |
| Total | 487 | 79.5 | 13.9 | 9.0 | 62.0 |

b) Groups without discussants

| | Manuscripts | Share published | Avg. citations (2 yrs.) | Avg. journal SJR | Share top journals |
|---|---|---|---|---|---|
| EFCE | 143 | 62.2 | 10.9 | 7.1 | 38.9 |
| EFFE | 121 | 71.9 | 11.3 | 5.4 | 21.2 |
| ME | 95 | 74.7 | 13.9 | 7.1 | 42.9 |
| Total | 359 | 68.8 | 11.9 | 6.4 | 33.2 |

*Notes:* Tables summarize presented manuscripts in NBER working groups during NBER Summer Institutes by status of group. Columns "Share published" and "Share top journals" are in percent. Row "Total" accounts for presentation of 9manuscripts in 3joint workshops.

can occur through both formal (co-authorship) and informal interactions (Laband and Tollison, 2000), we consider two distinct networks.

The first network is the co-author network. We construct this network from research articles, reviews and conference proceedings published in 360 Economics journals. We include a journal if it is ranked "C" or higher in selected journal rankings of Combes and Linnemer (2010). We include every ranking by JEL category with at least three publications in our sample. These are: Finance (JEL category G), Micro/Game Theory (D), Public/Political Science (H), Law and Economics (K), Macro/Monetary (E), International (F), Urban/Regional (R) and Econometrics (C).

Formally, let $\mathscr{A}_t$ be the set of papers published in these journals in years $\{t, t+1, t+2\}$ and $\mathscr{N}_t$ be the corresponding set of authors of these papers. The co-author network of year $t$ is a graph, $\mathscr{G}(\mathscr{N}_t, \mathscr{E}_t)$, consisting of all authors in $\mathscr{N}_t$ of papers in $\mathscr{A}_t$, and a set $\mathscr{E}_t$ of undirected links connecting them. An undirected link between any pair of authors $i, j \in \mathscr{N}_t$ exists if they have co-authored at least one paper in $\mathscr{A}_t$. We consider forward looking networks to capture the idea that a discussant who learns about and discusses a paper in $t$, informs coauthors of papers published in the future.

The second network is an informal collaboration network. It is constructed using the CoFE (Collaboration in Financial Economics) dataset of Rose and Georg (2021). The dataset contains manually collected acknowledgments to individual researchers from 5,501 research papers published between 1997 and 2011 in six Finance journals.[16] Rose and Georg (2021) also provide evidence that strategic concerns are not the driving motive behind an acknowledgment. Informal collaborators include all persons that are acknowledged for their intellectual input, excluding named referees. We also remove the managing editor(s) for the year of publication and the previous two years. This prevents overestimating the editors' position in the network.

The network of informal collaboration is constructed similarly, with three small differences. First, $\mathscr{A}_t^i$ is the subset of 5,501 research papers that were published in years $\{t, t+1, t+2\}$, where $t$ ranges from 1997 to 2009. Second, the set of nodes consists of all authors and commenters acknowledged on any of the papers. And third, links are directed author-to-commenter relationships (there are no links based on co-authorship alone).

[16] *The Journal of Finance*, the *Journal of Financial Economics*, *The Review of Financial Studies*, the *Journal of Financial Intermediation*, the *Journal of Money, Credit, and Banking* and the *Journal of Banking and Finance*.

### 2.5. Ability to diffuse information in social networks

We introduce *neighborhood centrality*, a novel centrality measure, to estimate a discussant's ability to diffuse knowledge about a paper. The word-of-mouth diffusion process we model starts from the discussant and propagates outwards to her colleagues, and to colleagues' colleagues, and so on, with potentially diminishing effects. Existing measures of network centrality are not well suited to model this process. Alternative prominent measures of centrality (Eigenvector centrality, its generalization Katz–Bonacich centrality, and its generalization of Katz–Bonacich centrality) capture node influence in strategic interactions (Golub and Jackson, 2010; Ballester et al., 2006; Banerjee et al., 2013). They include repeated interactions, which would be equivalent of a discussant relaying information about a paper to her colleagues, who then relay it back to her.[17] Instead, we expect that learning about an existing paper *once* is sufficient for researchers to cite the paper.

Formally, let $k_{i\tau}$ be the number of $\tau$-th order neighbors of $i$. That is, $k_{i\tau}$ is the number of all nodes at distance (measured as the number of links in the shortest path between a pair of nodes) $\tau$ from $i$. Let $\delta$ be a discount factor of information decay. Then, the neighborhood centrality of $i$ is defined as:

$$n_i(\delta) = \sum_{\tau=1}^{\infty} \delta^{\tau} k_{i\tau} \tag{2.2}$$

Appendix B gives examples and details of the algorithmic steps for computing neighborhood centrality in large networks.

The relevance of $i$'s information to her distant neighbors is discounted by $0 \leq \delta \leq 1$ to account for topical and expertise distances. For small $\delta$, neighborhood centrality is strongly correlated with node degree (i.e., the number of direct neighbors of a node), and for a higher $\delta$, neighborhood centrality becomes more uniform across nodes. We do not take a stance on what the "correct" value for $\delta$ is and instead report results for a range of information decay parameters.

For technical reasons, we only use the largest component of the network, also known as the *giant component*. The neighborhood centrality of nodes (discussants) outside the giant component is zero.

[17] In addition, the interpretation of diffusion centrality adopted by Banerjee et al. (2013) assumes that if an agent receives information from $k$ different sources in period $t-1$, she must transmit that information independently $k$ times to her neighbors in period $t$. Relaxing this assumption – which is not likely to hold in our case – already leads to a different notion of centrality (Genicot and Bramoullé, 2018).

**Table 2**
Samples and their summary statistics.

(a) Journal sample

| | N | Mean | Median | Std.Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Total citations | 596 | 170.50 | 93.00 | 263.80 | 0.00 | 3418.00 |
| Top publication | 596 | 0.51 | 1.00 | 0.50 | 0.00 | 1.00 |
| SJR | 576 | 8.09 | 6.89 | 5.14 | 0.16 | 22.54 |
| # of pages | 596 | 29.62 | 29.50 | 11.56 | 5.00 | 87.00 |
| # of authors | 596 | 2.18 | 2.00 | 0.80 | 1.00 | 5.00 |
| Age | 596 | 3.52 | 3.00 | 2.05 | −1.00 | 14.00 |
| Author total Euclid | 596 | 431.96 | 212.83 | 710.20 | 0.00 | 8311.96 |
| Youngest author experience | 596 | 6.89 | 5.00 | 6.68 | 0.00 | 54.00 |
| Oldest author experience | 596 | 15.14 | 14.00 | 9.76 | 0.00 | 54.00 |
| Discussion | 596 | 0.63 | 1.00 | 0.48 | 0.00 | 1.00 |

(b) Discussants sample

| | N | Mean | Median | Std.Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Total citations | 350 | 187.30 | 108.50 | 293.67 | 0.00 | 3418.00 |
| Top publication | 350 | 0.63 | 1.00 | 0.48 | 0.00 | 1.00 |
| SJR | 344 | 9.10 | 9.02 | 5.38 | 0.16 | 22.54 |
| # of pages | 350 | 30.93 | 31.00 | 11.00 | 5.00 | 65.00 |
| # of authors | 350 | 2.27 | 2.00 | 0.80 | 1.00 | 5.00 |
| Age | 350 | 3.72 | 3.00 | 2.21 | −1.00 | 14.00 |
| Author total Euclid | 350 | 426.74 | 209.23 | 726.64 | 0.00 | 8311.96 |
| Discussant Euclid | 350 | 195.08 | 96.05 | 283.79 | 0.00 | 1721.92 |
| Discussant experience | 350 | 11.47 | 10.00 | 8.22 | 0.00 | 38.00 |
| Female discussant | 350 | 0.13 | 0.00 | 0.33 | 0.00 | 1.00 |
| Discussant is practitioner | 350 | 0.06 | 0.00 | 0.24 | 0.00 | 1.00 |
| Discussant is editor | 350 | 0.43 | 0.00 | 0.50 | 0.00 | 1.00 |
| Discussant co-author neighborhood | 350 | 18.54 | 11.12 | 22.25 | 0.00 | 122.20 |
| Discussant informal neighborhood | 350 | 95.04 | 11.11 | 110.77 | 0.00 | 376.42 |

*Notes:* The "Journal sample" consists of all manuscripts with known titles presented once at SI workshops of Finance-related NBER groups that were (a) published in a journal by January 2020, (b) indexed in the Scopus database and (c) discussed at most once. The "Discussants sample" consists of all papers from the Journal sample discussed once by a known discussant. *Has discussion* = 1 if at least one discussant discussed the paper. *Total citations* is the citation count as of January 2020. *Top publication* = 1 if the paper was published in a Top 5 Economics or Top 3 Finance journal. *SJR indicator* is the SCImago Journal Rank indicator in the year of publication. *# of pages* and *# of authors* are the count of pages and authors, respectively. *Age* is the number of years between the presentation and the publication year. *Author total Euclid* is the authors' combined Euclidean index of citations. *Author total experience* is the sum of authors' experience measured as number of years since their first publication. Both variables are counted in the year before publication. The same logic applies to *Discussant* variables, which were counted in the year of the discussion. *Female discussant* equals 1 if the discussants first name is estimated to be female with probability $\geq 0.5$ as per genderize.io database. *Discussant co-author neighborhood* and *Discussant informal neighborhood* are the discussant's neighborhood centrality measured in the co-author network or the network of informal collaboration corresponding to the year of the discussion.

### 2.6. Samples and summary statistics

We use two main samples, summarized in Table 2. The "Journal sample" consists of all papers from the Presentation sample (i.e., the 845 papers with known titles presented once at the Finance-related NBER SIs between 2000 and 2009) that (a) were published in peer-reviewed journals by January 2020 and (b) has bibliometric information available (this excludes 6 manuscripts).[18] The sample includes 594 observations, 374 (65%) of which with discussant.

We use the Journal sample to examine the difference between having a discussant and not having a discussant (and instead a possibly longer general discussion with the audience). The average paper received 165.3 citations since publication and got published in a journal whose SJR indicator equals 8.07.[19] 51% of the observations got published in a top five Economics or top three Finance journals. Table A3 shows that none of the three measures of academic success of papers correlate highly with the discussant indicator.

The "Discussants sample" includes 346 papers from the Journal sample where we know the identity of the discussant from the SI program (for 4 discussed manuscripts, the program does not mention the discussant's name). This sample serves to understand the effect of a discussant's characteristics. The average discussed paper received 177.5 citations, the impact factor of the publishing journal equals 9.08 on average, and 63% of the papers got published in a top Economics or top Finance journals. Table A4 documents low correlations between author and discussant characteristics.

## 3. Discussions and academic success

### 3.1. Identification considerations

Whether a paper is discussed at a workshop during an NBER SI depends on two consecutive decisions. First, authors apply to a workshop with or without discussants. Then, the workshop organizers accept the paper. The kind of paper-workshop sorting that prevents identification is one where either submission or acceptance is based on whether a workshop has discussants.

Our identifying conditions are thus: (i) authors do not sort into workshops based on whether they have discussants; (ii) papers are of comparable quality (e.g. organizers do not accept papers of different quality); and (iii) the only relevant difference between workshops is whether they feature discussants or not.

We argue that the first condition holds because it is rational for authors to seek a good topical fit with the workshop's theme. No

[18] Scopus does not index every journal entirely; some volumes for some journals are missing, even if the entire journal is covered. This is idiosyncratic and not due to editorial reasons: When the database was initially populated, Scopus simply did not receive meta information in sufficient quality. There is, for instance, one publication from our sample in the *B.E. Journal of Macroeconomics*, which Scopus does not index before 2007.

[19] To put this number into perspective: In 2009 *The American Economic Review*'s SJR equaled 8.1. The highest SJR indicator equals 27.2 and characterizes the *Quarterly Journal of Economics* in 2014.

monetary Economist would write a paper on asset pricing just because the asset pricing group features discussants and the monetary economics group does not. This is corroborated by the fact that some papers were presented in both workshops with and without discussants (when applying for the SI workshops authors may state up to three workshops that they wish to present at). This is also supported by the short survey we conducted. In our survey of the NBER SI organizers, we ask the following question: "What do you look for when accepting papers?". The general consensus from the organizers is to look for a "mix of quality, novelty and fit" with particular emphasis on novelty. Some organizers also mention the importance of an author's ability to present well. The workshop organizers also ensure topical cohesion by accepting papers related to the topic of the workshop only.

In appendix C.1 we show that manuscripts of both categories of workshops are of similar observable pre-workshop quality. We study two observable dimensions: The affiliation ranks of authors and the abstract's readability, which, as Dowling et al. (2018) show, proxies future citation counts. Neither between the papers nor between the categories of groups do we find statistical differences for any of the dimensions.

Another confounding factor, to which the third assumption speaks to, arises if the workshops with discussants differ from workshops without discussants in other dimensions. We probe two dimensions: duration of presentations and topical overlap. We find that presentations last on average 55 min, irrespective of the category of the workshop (Figure C1 upper left panel). In appendix C.2 we show the high topical overlap of the presented papers, and in particular that the overlap does not depend on the category of the workshop. To show this, we apply `tfidf` vectorization on the list of cited journals of the published presentations.

A final concern arises from different behavior of authors before the workshop depending on whether they get or do not get a discussant. For example, authors may polish the paper more when they know a discussant is going to carefully read it. However, the same is true for workshops without discussants: 73% of manuscripts presented in workshops without discussants have a version online and linked in the workshop program. The corresponding figure for manuscripts presented in workshops with discussants is 84%. That the two figures are close indicates that authors generally strive to have a version of their paper online by the time of the workshop, irrespective of whether or not they will have a discussant. Since readability of abstracts is the same for manuscripts in workshops with and without discussants, it is also unlikely that authors put more effort into its preparation just because there is a discussant.

Whether our results can be interpreted causally thus depends crucially on unobservable characteristics that distinguish workshops with discussants from those without discussants. To rule out statistical significance as a result of pure chance (Young, 2019), we additionally perform a Fisher permutation test ("random inference"). This test assesses how likely an effect of our estimated size is when assigning discussants randomly to all workshops of the NBER group. We perform these tests using code developed by Heß (2017) for $2^{10} - 2 = 1022$ possible permutations.

### 3.2. Results

Given paper $i$ published in year $t$, we estimate the following models:

$$\text{Top}_i = \alpha_0 + \alpha_1 \cdot \text{Paper}_i + \alpha_2 \text{Author}_{i,t-1} + \alpha_3 \text{Group}_i + \beta \cdot \text{Discussion}_i + \epsilon_i \quad (3.1)$$

$$\text{SJR}_{i,t} = \alpha_0 + \alpha_1 \cdot \text{Paper}_i + \alpha_2 \text{Author}_{i,t-1} + \alpha_3 \text{Group}_i + \beta \cdot \text{Discussion}_i + \epsilon_i \quad (3.2)$$

$$\log(1 + \text{Citations}_{i,2022}) = \alpha_0 + \alpha_1 \cdot \text{Paper}_i + \alpha_2 \text{Author}_{i,t-1} + \alpha_3 \text{Group}_i + \alpha_4 \text{SJR}_{i,t} + \beta \cdot \text{Discussion}_i + \gamma_t + \epsilon_i \quad (3.3)$$

**Table 3**
The effect of discussions on a paper's journal status.

| | Top (Finance) | | Top (Econ+Finance) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Discussion | 3.399*** | 2.939*** | 1.330*** | 1.039* |
| | (0.000) | (0.000) | (0.002) | (0.075) |
| Constant | −5.012*** | −5.264*** | −2.440** | −1.393 |
| | (0.000) | (0.000) | (0.025) | (0.126) |
| Paper controls | ✓ | ✓ | ✓ | ✓ |
| Author controls | ✓ | ✓ | ✓ | ✓ |
| Group control | ✓ | ✓ | ✓ | ✓ |
| JEL categories | | ✓ | | ✓ |
| $N$ | 593 | 580 | 593 | 593 |
| Pseudo $R^2$ | 0.281 | 0.464 | 0.208 | 0.275 |
| AIC | 515.6 | 386.2 | 674.6 | 619.5 |
| Random inference | 0.0333** | 0.0656* | 0.1174 | 0.1458 |

*Notes:* Table reports estimates of $\beta$ from model (3.1). ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. Standard errors are clustered on NBER group. See Section 2 for variable definition. This analysis uses the Journal sample. In all columns some observations drop because of perfect correlation between binary indicators and the outcome variables.

"Top" equals 1 if the paper was published in a top Finance or top Economics journal. "SJR" is the journal's SCImago Journal Rank indicator. "Citations" is the citation stock of paper $i$. "Paper" consists of a set of paper-specific variables that include the number of pages (of the published version), the number of years since the NBER SI, and the number of authors which enters as fixed effects. "Author" contains the joint author characteristics in $t-1$: the sum of all authors' Euclidean indices of citations, experience category of the youngest author, and the experience category of the oldest author. "Group" contains the average Euclidean index of citations at time of the workshop of all authors presenting in the respective NBER group, as a means to control for the average quality of authors presenting in a group. "Discussion" is a binary variable equal to 1 if the manuscript was discussed at the workshop. In each specification we cluster standard errors on the workshop's NBER group.

Since the variable "discussion" perfectly correlates with the NBER group, we cannot control for NBER group fixed effects. These would also control for field-specific effects. To compensate for this we use JEL categories as per EconLit.

Table 3 presents the results of a logistic regression estimating model (3.1). We find strong evidence that papers that had a discussion have a higher likelihood of getting published in a top Finance journal. The odds ratio equals $e^{2.939} = 18.89$. The effect is unlikely to be driven by random chance as the random inference test suggests. When including top Economics journals in the set of top journals, the effect becomes less significant economically and statistically. Based on the random inference test, we cannot rule out a spurious result for this model however.

Table 4 presents results of the continuous measure of journal quality (model (3.2)). We find that papers with discussants on average get published in journals with a SCImago Journal Rank indicator that is 1.77 (column (2)) to 2.18 (column (1)) higher than papers without discussant. The difference roughly equals that of *Econometrica* (19.932) and *The Journal of Finance* (18.318) in 2017. Using the journal's average citation count as alternative journal quality measure (columns (3) and (4)) we find a similar result. Only when we measure a journal's h-index and control for topics we find a statistically insignificant relationship (column (6)) with the discussion indicator. This result might be driven by the almost bi-modal distribution of this variable Figure A1. The h-index is also the only measure where we cannot reject a spurious result based on the random inference test, which is the case for the other measures.

Table 5 presents the $\beta$ coefficient for citations specifications (model (3.3)). Once controlling for the paper's topic(s) we do not find any

**Table 4**
The effect of discussions on a paper's journal.

| | SJR | | Avg. citations | | h-index | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Discussion | 2.182*** | 1.767* | 0.968*** | 0.678** | 33.00** | 17.36 |
| | (0.005) | (0.077) | (0.002) | (0.037) | (0.010) | (0.217) |
| Constant | 0.166 | 1.523 | 0.723 | 1.159* | 130.5*** | 156.7*** |
| | (0.897) | (0.280) | (0.186) | (0.056) | (0.000) | (0.000) |
| Paper controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Author controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Group control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| JEL categories | | ✓ | | ✓ | | ✓ |
| *N* | 576 | 576 | 576 | 576 | 576 | 576 |
| $R^2$ | 0.277 | 0.321 | 0.261 | 0.307 | 0.162 | 0.242 |
| Random inference | 0.0949* | 0.0656* | 0.0910* | 0.0783* | 0.1321 | 0.2133 |

*Notes:* Table reports estimates of $\beta$ from model (3.2). ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. Standard errors are clustered on NBER group. See Section 2 for variable definition. This analysis uses the Journal sample.

**Table 5**
The effect of discussions on a paper's citation count.

| | log(1+Total citations) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Discussion | 0.260* | 0.108 | −0.0294 | −0.0146 |
| | (0.056) | (0.392) | (0.833) | (0.889) |
| Constant | 3.367*** | 3.417*** | 3.410*** | 4.482*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Paper controls | ✓ | ✓ | ✓ | ✓ |
| Author controls | ✓ | ✓ | ✓ | ✓ |
| Group control | ✓ | ✓ | ✓ | ✓ |
| Publication year FE | ✓ | ✓ | ✓ | ✓ |
| JEL categories | | ✓ | ✓ | ✓ |
| Journal control | | | ✓ | |
| Journal FE | | | | ✓ |
| *N* | 596 | 596 | 576 | 596 |
| $R^2$ | 0.359 | 0.386 | 0.427 | 0.584 |

*Notes:* Table reports estimates of $\beta$ from model (3.3). ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. Standard errors are clustered on NBER group. See Section 2 for variable definition. Table uses the Journal sample.

statistically significant result. The coefficient even turns negative (but imprecisely measured) once we control for the journal quality (column (3)) or the journal itself (column (4)).

We conclude that discussants improve the odds of getting published in highly-ranked journals. Any positive effect a discussant has on a paper's citation count is explained away by topical differences.

### 3.3. Robustness checks

*Monetary groups.* JEL codes might not fully capture all topical dynamics among our sample. Even though we look at a topically closely related set of groups, it is possible to create subsets of even more homogeneous groups. The journal reference cosine analysis in Table C1 indicates that the groups "Impulse and Propagation Mechanisms" (EFCE), "Capital Markets in the Economy" (EFEL), "International Finance and Macroeconomics" (IFM) and "Monetary Economics" (ME) are the topically most similar groups. In Table D1 we estimate all models using publications presented in these four groups only. Results indicate a weaker relationship for the continuous measure of journal quality but a strong relationship on top journal status.

*Readability of manuscripts.* Readability is an acceptable proxy for future citation counts (Dowling et al., 2018). Thus we control for the manuscript's readability in Table D2, which is available for 328 papers. Our variable of interest remains statistically significant in all specifications. Moreover, the inclusion of the readability control affects the economic and statistical significance of the baseline model only slightly (on the same subset). This is another evidence that sorting of discussants to more readable manuscripts is largely absent.

*Logarithmic dependent variables.* The measures for journal quality are not perfectly linear Figure A1. We therefore re-estimate (model (3.2)) using log-transformed dependent variables, although the coefficients are not as straightforward to interpret. Table D3 presents the results. Of the statistically significant relationships identified in Table 4, one looses its statistical significance (column (2)).

*Different statistical models.* The log-transformation is one way of dealing with the skewed citation variable. Two other ways include the inverse hyperbolic sine transformation and the usage of the negative binomial model. Table D4 presents the estimates of a negative binomial regression using the citations count as of January 2022. Table D5 presents the estimates of an OLS regression using inverse hyperbolic sine-transformed citation counts as of January 2022. Neither shows signs of an effect of discussants on citation counts.

*Citation lags.* As another alternative to the citations specification, we compare the citation count after a fixed number of years past publication. This allows us to drop publication year fixed effects and account for dynamic characteristics of citations. We thus alter model (3.3) to the following:

$$\log(1+\text{Citations}_{i,t+u}) = \alpha_0 + \alpha_1 \cdot \text{Paper}_i + \alpha_2 \text{Author}_{i,t-1} + \alpha_3 \text{Group}_i + \alpha_4 \text{SJR}_{i,t} + \beta \cdot \text{Discussion}_i + \epsilon_i \quad (3.4)$$

where $u$ is a varying number of years $\in [0, 1, \ldots, 13]$ after which we compare the papers' citation stocks. Figure D1 plots the resulting $\beta$s. The "base" model represents the coefficient shown in model (3) of Table 5 for reference. Only for $u = 11$ years past publication do we start to see a positive coefficient, which becomes statistically significant for $u = 12$. These results appear to be consistent with the observation in Galiani and Gálvez (2019) that, on average, the citations life-cycle in economics peaks at around 10 years. That is, since economics papers are on average more distinguishable from each other through citations after 10 years, it is logical that this is also the period after which differences in citation counts among papers with and without discussants become more apparent. However, given the decreasing sample size (for $u = 11$ there are 365 observations left), our results should be taken with a grain of salt.

## 4. How discussants can increase a paper's academic success

Discussants can increases a paper's academic success through a variety of channels. The most immediate channel is quality-improvement via comments (feedback channel). Since discussants at NBER SIs put a lot of effort into their discussions and since many participants have

**Table 6**
The effect of discussant status on a paper's academic success.

| | *Logistic* | | *OLS* | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Top (Econ+Finance) | | Journal SJR | | log(1+Total citations) | |
| Discussant Euclid | 0.000176 | 0.000204 | 0.00234*** | 0.00240*** | 0.000377 | 0.000336 |
| | (0.572) | (0.691) | (0.007) | (0.006) | (0.306) | (0.407) |
| Discussant experience <2 | 0.351 | 0.223 | 0.637 | 0.687 | 0.0372 | −0.0434 |
| | (0.131) | (0.394) | (0.361) | (0.386) | (0.901) | (0.871) |
| Discussant experience 7–15 | 0.262 | 0.0253 | −0.850 | −1.113 | 0.00751 | −0.0298 |
| | (0.294) | (0.934) | (0.286) | (0.136) | (0.980) | (0.919) |
| Discussant experience >15 | 0.462 | 0.411 | −0.880 | −0.949 | −0.163 | −0.265 |
| | (0.180) | (0.386) | (0.156) | (0.164) | (0.627) | (0.431) |
| Female Discussant | −0.783 | −0.704 | −1.828* | −1.285 | 0.0602 | −0.0512 |
| | (0.228) | (0.220) | (0.076) | (0.131) | (0.781) | (0.792) |
| Discussant affiliation rank | −0.00183 | | −0.00279** | | −0.000500 | |
| | (0.118) | | (0.027) | | (0.472) | |
| Discussant is practitioner | | −0.394 | | 0.431 | | 0.238 |
| | | (0.496) | | (0.684) | | (0.279) |
| Discussant is editor | | 0.348 | | 1.068*** | | −0.0720 |
| | | (0.144) | | (0.010) | | (0.325) |
| Constant | −1.564 | −1.998 | 3.148** | 2.741 | 4.080*** | 4.164*** |
| | (0.178) | (0.116) | (0.050) | (0.130) | (0.000) | (0.000) |
| Group FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Paper controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Author controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Journal control | | | | | ✓ | ✓ |
| *N* | 315 | 348 | 312 | 344 | 312 | 344 |
| $R^2$ | | | 0.365 | 0.393 | 0.393 | 0.373 |
| Pseudo $R^2$ | 0.345 | 0.374 | | | | |
| AIC | 286.6 | 305.3 | 1801.8 | 1978.7 | 859.5 | 956.5 |

*Notes:* Table shows coefficients of estimations of models (4.2), (4.1), and (4.3). ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. Standard errors are clustered around NBER working group. Reported coefficients in columns (1) and (2) are marginal effects. See Section 2 for variable definitions. Table uses the Discussants sample.

emphasized to us that these discussions are of the highest quality and particularly relevant for their papers, a discussion at the NBER SI is a strong treatment. It is not unheard of that authors felt their paper was "re-written" by the discussant.

But quality improvement via comments and feedback is not the only possible channel. Discussants might also induce authors to work harder, especially in the pre-discussion period (motivation channel). Discussants might also connect the authors to other knowledgeable researchers who then provide helpful feedback (linking channel). And discussants might inspire thoughtful comments from the audience which otherwise would not have arisen (inspiration channel).

Discussants might also improve a paper's academic success without improving its inherent quality. A discussant might tell others about the paper, who then cite it based on the discussant's recommendation and insight (diffusion channel). Discussants might similarly promote the paper to potential referees or editors (promotion channel). And discussants might increase attention to the paper simply by talking about it during the workshop (attention channel).

While we are unable to differentiate between different quality-improving channels, we attempt to differentiate between quality-improving and diffusion channels by examining how discussants' characteristics determine their effect on academic success of papers. We also test for the implications of other possible alternative channels (to quality-improving and diffusion) in Section 4.4 and provide suggestive evidence for their respective (non-)existence.

### 4.1. Quality-improving channel

Highly knowledgeable and experienced discussants, through either direct feedback to authors or through other quality improving channels discussed above (e.g., linking channel and inspiration channel), might help authors to improve the paper's methodology and techniques and to better position the paper in the literature, thereby improving the overall quality of the paper.

The ability of a discussant to improve the quality of the paper will depend on their prolificness, experience, and how they are connected in the academic community, where the latter applies to the linking channel. We measure a discussant's prolificness using the Euclidean index of citation discussed in Section 2.3, experience by the number of years since their first publication, and connectedness in the academic community using neighborhood centrality and affiliation rank since this captures a researcher's connection to other potentially prolific researchers. A positive correlation between these discussant's characteristics and the academic success of a paper would suggest existence of the quality-improvement channel.

We use the Discussants sample, that is, 332 papers that were discussed exactly once by a known discussant at an NBER SI. The econometric specification relates paper success to discussant characteristics in the year of the discussion $z$, controlling for author characteristics in $t-1$ and paper characteristics:

$$\text{Top}_i = \alpha_0 + \alpha_1 \cdot \text{Paper}_i + \alpha_2 \cdot \text{Author}_{i,t-1} + \beta \cdot \text{Discussant}_{i,z} + \delta_{\text{Group}_i} + \epsilon_i \quad (4.1)$$

$$\text{SJR}_{i,t} = \alpha_0 + \alpha_1 \cdot \text{Paper}_i + \alpha_2 \text{Author}_{i,t-1} + \beta \cdot \text{Discussant}_{i,z} + \delta_{\text{Group}_i} + \epsilon_i \quad (4.2)$$

$$\log(1 + \text{Citations}_{i,2022}) = \alpha_0 + \alpha_1 \cdot \text{Paper}_i + \alpha_2 \cdot \text{Author}_{i,t-1} + \alpha_3 \cdot \text{SJR}_{i,t} + \beta \cdot \text{Discussant}_{i,z} + \gamma_t + \delta_{\text{Group}_i} + \epsilon_i \quad (4.3)$$

The variable definition follows that of the previous section. "Discussant" is a vector containing discussant characteristics as measured in the year of the discussion $z$: The Euclidean index of citations of the discussant, the experience categories of the discussant, the estimated gender, the discussant's affiliation rank, whether she is a practitioner

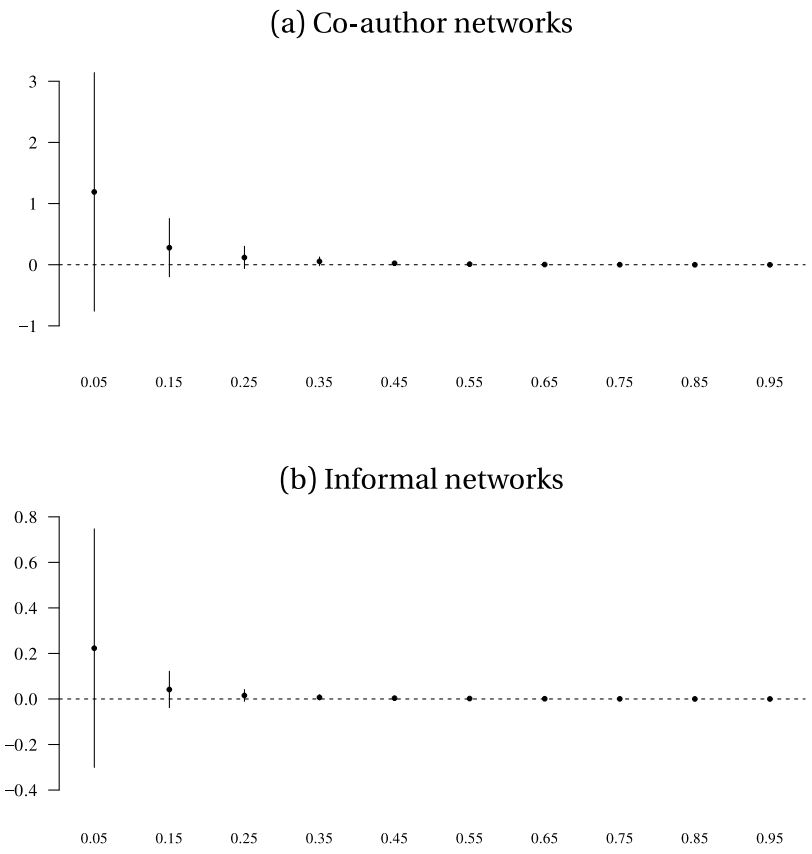


**Fig. 1.** Neighborhood centrality and journal quality. *Notes:* Figures depict coefficients for neighborhood centrality of discussants with different values of $\delta \in [0.05, 0.15, \ldots, 0.85, 0.95]$ for two different networks. Estimation corresponds to model (4.2) with controls for paper, author and discussant characteristics, with NBER group dummies and with standard errors clustered on the NBER group. The top panel shows coefficients for a discussant's neighborhood centrality computed in the co-author networks. The bottom panel shows coefficients for discussant's neighborhood centrality computed in the networks of informal collaboration. Error bars indicate the 90% confidence interval.

(i.e., affiliated with a non-academic institution) and editorial experience. Unlike before, we control for the NBER groups, but we also cluster standard errors on the NBER group.

Table 6 reports the results of the effect of a discussant's characteristics. We find that among characteristics we expect to be relevant for the quality-improvement channel, the journal SJR indicator increases in the discussant's prolificness and affiliation rank. A discussant's experience does not matter at all.

We also examine the correlation between discussants' neighborhood centrality and "Top journal" and "Journal SJR" measures of academic success (we examine the correlation with citation count in the following section and find similar results). We compute the centrality separately in the co-author network and the network of informal intellectual collaboration corresponding to the year of the discussion $z$. The relevant networks thus use papers published in $z, z+1$, and $z+2$. We relate a paper's journal quality to the discussants' neighborhood centrality and control for discussant characteristics in year $z$, for author characteristics in $t-1$ and paper characteristics. We include dummies for the corresponding NBER groups, on which we also cluster standard errors. That is, we include $\text{Neighborhood}_{i,z<t}$, the neighborhood centrality of the discussant of paper $i$, into models (4.1) and (4.2).

Fig. 1 plots the coefficients of neighborhood centrality for the "journal SJR" (the results for "Top journal" are identical) using various values of $\delta \in [0.05, 0.15, \ldots, 0.85, 0.95]$. The top panel uses neighborhood centrality computed in the co-author network, the bottom panel uses neighborhood centrality computed in the network of informal collaboration. None of the coefficients differs significantly from zero.

These observations suggest mixed evidence for the quality-improvement channel. More specifically, our findings indicate that the quality-improvement channel exists only if one can argue that the SJR index of a paper's journal outlet is a stronger indicator of a paper's quality than its citation count and "top journal" publication indicator. Otherwise, the observed effect of a discussant's prolificness on journal SJR indicator may instead indicate that discussant simply help reduce information asymmetries in the publication process as we discuss below.

### 4.2. Information asymmetries

Discussants might inform authors about the best fit journal and provide guidance on how to structure the paper for the recommended journal. In doing so, they inform/signal authors of their own chances of publication success and thereby reducing information asymmetries inherent in the academic publication process. The uncertainty of publication success, coupled with costly submission, lengthy review and low acceptance rates, create benefits to reduction of information asymmetries. This phenomenon is document by Bagues et al. (2019) who show that when submitting an application and getting rejected is costly, being better informed of once own chances of success may affect the willingness to submit.

If discussants indeed inform authors of the best fit journal and reduce information asymmetries, then we would expect higher journal submission rates for papers with discussants than papers without discussants. Our data does not permit observation of submission rates, but we observe the publication propensity for both papers with and without discussants. We use this to proxy the submission rates for the two groups of papers.

We build a sample consisting of all manuscripts with known titles presented once in NBER SIs. The sample includes 846 manuscripts, of which 58% had a discussant. Of the manuscripts with discussants,

**Table 7**
The effect of discussions on publication status (logistic model).

| | (1) | (2) |
|---|---|---|
| | Published | |
| Discussion | 0.486*** | 0.433*** |
| | (0.003) | (0.010) |
| NBER Working Paper | | 1.039*** |
| | | (0.00000) |
| Constant | 0.273* | 0.147 |
| | (0.099) | (0.384) |
| Number of authors FE | ✓ | ✓ |
| *N* | 846 | 846 |
| AIC | 931.706 | 905.009 |

*Notes:* Table reports coefficients of a regression explaining whether a presented manuscript gets published or not. ***, ** and * indicate statistical significance to the 1, 5 and 10 percent level, respectively. *NBER Working Paper* equals 1 if the manuscript is available as a NBER Working Paper. See Section 2 for definitions of other variables. Table uses all manuscripts presented once at SI workshops of Finance related NBER working groups with known title.

79.5% got published, which is 11 percentage points higher than the share of non-discussed manuscripts (68.8%). Table 7 confirms this intuition via a logistic regression. The relationship does not change if we allow for the possibility that authors do not pursue a publication if the paper becomes an NBER working paper.

Further suggestive evidence of this channel follows from the results reported in Table 6 (column (4)), where we find that discussants with editorial background improve chances of publishing in journals with higher SJR indicator ranking. If a discussant indeed informs authors of the best fit journal and how to best prepare the paper for the recommended journal, then we would expect discussants with more editorial experiences to affect the quality of a paper's journal outlet.

These two observations suggest that reducing information asymmetries in the publication process may be one of the main channels through which discussants improve the academic success of papers.

### 4.3. Diffusion channel

It is reasonable to expect diffusion to directly affect the citation count, given evidence on the diffusion of technology, for example, in farming in emerging markets (Conley and Udry, 2010) or in microfinance (Banerjee et al., 2013). By being the first to learn about the existence and quality of the paper, discussants may not only decide to cite the paper themselves, but also let their immediate collaborators know about it.[20] We understand collaboration in a broader sense, including both co-authorship and informal collaboration (Rose and Georg, 2021). Diffusion can happen through regular discussions or through an indirect process where a discussant's collaborators learn about the paper because the discussant cites it. In light of this, we examine two related hypotheses:

(i) The paper is more likely to receive a citation from a discussant than by any other author presenting in the same group (i.e. other discussants and authors of presented papers).
(ii) A discussant's ability to diffuse the paper to the scientific community positively correlates with the paper's citation count.

Hypothesis (*i*) captures citation-based diffusion, where citation of the paper by the discussant induces further citations by other researchers. That is, the paper gets cited by the discussant, followed by researchers who encounter (the citation of the paper) in the discussant's papers, and so on. If, ceteris paribus, the paper is more likely to receive a citation by the discussant than other authors presenting in the same group, then the discussants contribute to citation-based diffusion more than other authors.

Hypothesis (*ii*) captures diffusion through word-of-mouth learning. By being the first to learn about the existence and quality of the paper, a discussant may inform her direct co-authors (formal collaborators) and/or mention it to other researchers (informal collaborators) when providing feedback to their work. A discussant can thus trigger a word-of-mouth diffusion process where their direct collaborators learn about the paper, followed by the collaborators of a discussant's collaborators, and so on. At each stage of this learning process, a proportion of researchers cite the paper. The neighborhood centrality, defined in Section 2.5, captures a discussant's ability to diffuse the paper through word-of-mouth learning. We then expect the neighborhood-centrality of a discussant in the collaboration networks to be positively correlated with a paper's total citation count.

To test the first hypothesis, we study 60,352 citations to the 346 papers from the discussants sample and separate them by identity of citer. We find that as much as 76% of the 346 discussed and published papers were never cited by their discussants.[21] Fig. 2 compares the probability to receive a citation from specific participant groups. A discussed paper is more likely to receive a citation from any of the other authors on the workshop's program than from its own discussant. Annual citations from other workshop discussants are however equally likely. This suggests that others' contribution to citation-based diffusion of the paper is more important than that of the own discussant.

To test the second hypothesis, we examine the correlation between discussants' neighborhood centrality and papers' citation counts. We relate a paper's log citation count to the discussants' neighborhood centrality and control for discussant characteristics in year $z$, for author characteristics in $t-1$ and paper characteristics. We include dummies for the corresponding NBER groups, on which we also cluster standard errors:

$$\begin{aligned}\log(1+\text{Citations}_{i,2022}) = {} & \alpha_0 + \alpha_1 \cdot \text{Paper}_i + \alpha_2 \cdot \text{Author}_{i,t-1} \\ & + \alpha_3 \cdot \text{Discussant}_{i,z<t} + \\ & + \alpha_4 \cdot \text{SJR}_{i,t} + \beta \cdot \text{Neighborhood}_{i,z<t} + \epsilon_{i,t}.\end{aligned} \tag{4.4}$$

In case $\beta$ does not differ from zero, we reject hypothesis (*ii*) stating that increased citation counts are due to discussants' diffusion efforts.

The results, plotted in Fig. 3, indicate that none of the coefficients differs significantly from zero. We therefore reject the hypothesis that discussants with a higher ability to diffuse a paper through word-of-mouth learning (i.e. neighborhood centrality) increase citation count.

A plausible explanation for the lack of evidence of a diffusion channel is that alternative methods through which researchers find papers (e.g. internet search or simply going to the library) are just as important as learning about new papers through social networks.

### 4.4. Alternative channels

While we do not find evidence for the diffusion channel, which is the main alternative to the quality-improving channel, it is worth discussing how other channels could explain our main findings. We briefly discuss these in turn.

[20] Clearly, this does not capture informal chats at the NBER SIs during coffee breaks or over dinner- or at the discussant's home university. Such channels can be important for the diffusion of information about a paper, but they are impossible to quantify. What is more, such channels should not affect a paper with a discussant much differently from a paper without discussant that is also talked about over dinner.

[21] Given our survey of NBER SI workshop organizers this is not entirely surprising: Most editors indicated that they are looking for discussants who provide a new perspective on a paper (i.e. they are not necessarily looking for discussants who work on exactly the same topics as the author).

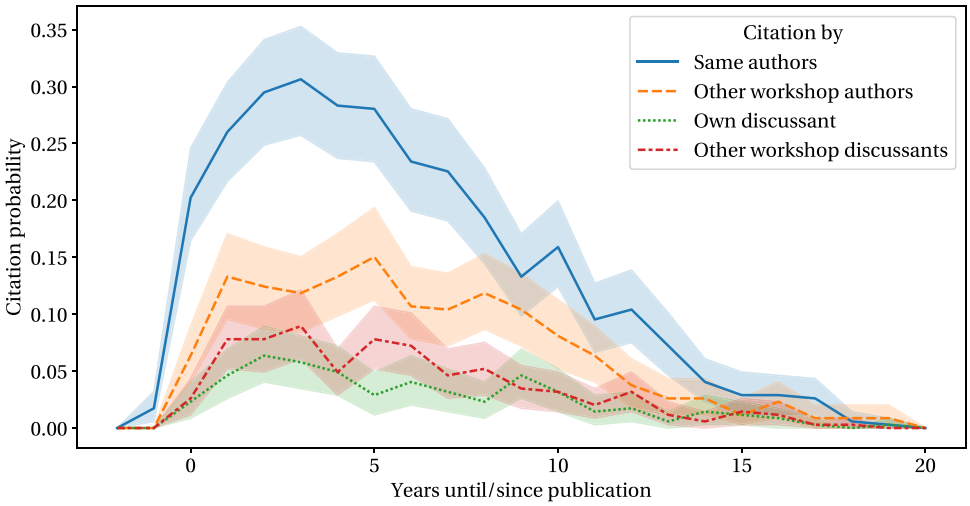


**Fig. 2.** Probability to cite a discussed paper by group of citer. *Notes:* Figure shows the annual probability to receive at least one citation by identity of citing author. Shaded area shows the 95% confidence interval. Figure uses the Discussants sample.

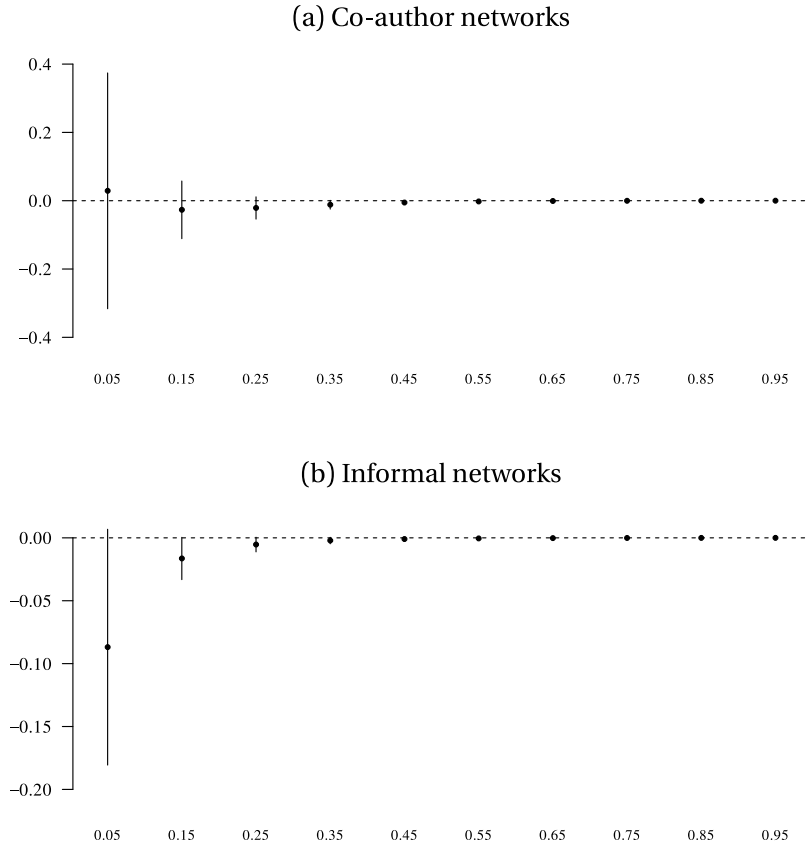


**Fig. 3.** Neighborhood centrality and citation count. *Notes:* Figures depict coefficients for neighborhood centrality of discussants with different values of $\delta \in [0.05, 0.15, \ldots, 0.85, 0.95]$ for two different networks. Estimation corresponds to model (4.4) with controls for paper, author and discussant characteristics, with NBER group dummies and with standard errors clustered on the NBER group. The top panel shows coefficients for a discussant's neighborhood centrality computed in the co-author networks. The bottom panel shows coefficients for discussant's neighborhood centrality computed in the networks of informal collaboration. Error bars indicate the 90% confidence interval.

*Attention channel.* The attention channel posits that the audience memorizes the paper more because they hear about it again from the discussant. If this was true, then the discussant's characteristics should not matter for publication success. There is mixed evidence for this channel in Table 6: A paper's journal quality increases in the discussant's prolificness. It could be the case that a more prolific researcher is a more captivating discussant. But then we could also reasonably expect that more experienced discussants have a similar effect, for which we find no evidence.

*Reviewer bias.* It is possible that a discussant's familiarity with the paper and proximity to the authors, which is established during the workshop, might lead to a form of reviewer and editorial bias as reported in Medoff (2003) and Brogaard et al. (2014). That is, discussed papers are more likely to be accepted in journals where their

discussants serve in the editorial board or act as referees. The results, reported in Table 6 (column (4)), showing that discussants with editorial background improve chances of publishing in journals with higher SJR indicator ranking, indeed suggest that this channel may also be present.

### 4.5. Challenges to identification of how discussants matter

There are multiple challenges to interpreting the above results on how discussants affect academic success of papers (i.e., the effect of discussants characteristics) as causal evidence. If papers were allocated randomly to discussants, then the observed effects of discussants' characteristics would not be biased. This is of course not the case at the NBER Summer Institutes. The results in the above sections can be interpreted as causal if: (i) organizers match discussants to papers and authors based primarily on topical fit (e.g. whether the discussant knows the relevant literature, methods and data) rather than discussant characteristics (e.g. prolificness, experience, gender, etc.); and (ii) discussants discuss a paper irrespective of the session it is in (i.e. no sorting of discussants). That is, the covariance between discussant characteristics on the one side and author- as well as paper characteristics on the other side must be zero.

The survey we conducted among workshop organizers sheds light on the matching of discussants to papers. Organizers have confirmed that discussants rarely reject an invitation. Being a discussant at an NBER SI is considered a prestigious opportunity (Chari and Goldsmith-Pinkham, 2017), thus, invited discussants rarely decline.

One of the biggest threats to identification is assortative matching of say promising papers to prolific discussants. The concern is that a paper that looks really important will attract a discussant who is really important instead of a junior assistant professor who happens to work on the same topic. We asked the organizers the following two questions: "How do you match discussants to papers?" and "How exogenous is the process to authors?" Almost all organizers highlight how important it is for them to have a discussant that can provide "a basis for a lively, productive debate between authors, discussants, and the audience". Furthermore, almost all organizers highlight the importance of a topical fit between discussants and papers, mentioning that discussants are "often authors of good papers that were not chosen for presentation". Some respondents also emphasize that discussants should not be "too close to the author and if possible coming from a different perspective", and one even highlights that discussants should have "No fear of authors" (i.e. probably do not get a very junior person to discuss a big shot, unless you know the junior person is fearless).

With regards to our third question about the exogeneity of the discussant selection process for authors, few organizers explicitly answered the question and those who did emphasized that they "did not consult with authors". Consequently, we do not find assortative matching in the observables in our sample: Seniority or prolificness of authors of discussed manuscripts are not correlated with seniority or prolificness of discussants.

Finally, a confounding factor arises from the differing ability of the organizers to attract discussants. Some organizers might, due to their standing or prominence in the field, reach a wider pool of researchers that could discuss a paper. But organizers tend to be highly regarded and well-connected academics who know their respective field well beyond their personal network. Varying reach within the profession might thus not be a severe issue. Since for half the groups there is no change in the organizer group our sample period, NBER group fixed effects take into account the organizers' time-invariant ability to attract discussants.[22] Additionally, we cluster standard errors on the NBER working group (or joint session) to account for heteroscedasticity.

[22] For the other half there is little change in the organizer groups where often one organizer remains for several years. The only exception are the groups AP and CF which change on a yearly basis. But if organizers change, they do not organize another workshop in another group.

## 5. Conclusion

A handful of papers study informal collaboration and find positive correlation between the extent of informal collaboration (i.e. the number of acknowledged commenters, seminars and conferences) and citation count. Insightful as these seminal findings are, they are not specific for discussants, nor do they tell us much about some underlying mechanisms. Our setting – discussions at Finance-related NBER Summer Institutes – comes much closer to causal inference and allows us to study the underlying mechanisms.

We find that papers benefit from discussants in terms of an increased probability of publication in prestigious journals. The type of discussant does not matter so much, except for prolificness and editorial experience and only when it comes to continuous measures of journal quality.

Our results suggest that conferences should be designed to include dedicated discussants for each paper. Yet for a valid economic analysis of this question, future studies should try to estimate the cost of informal collaboration.

Our findings also offer insights into how discussants and conferences impact knowledge production and dissemination. We find suggestive evidence that discussants act to reduce information asymmetries that are inherent in the academic publication process. We do not find conclusive evidence of a quality-improvement mechanism where discussants improve the inherent quality of papers, nor do we find evidence of discussants acting as seeds of diffusion of information about the paper.

Overall, our study contributes to the broader literature studying processes of knowledge production and dissemination. And understanding these processes is highly relevant as economies shift towards the production of intangible and increasingly knowledge intensive goods.

## CRediT authorship contribution statement

**Michael E. Rose:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Daniel C. Opolot:** Conceptualization, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Co-Pierre Georg:** Validation, Writing – original draft.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.respol.2022.104587. Supplement contains: "Further descriptives" (e.g., on the publication lag, publication propensity and the experience distribution of discussants); "Algorithmic steps to compute neighborhood centrality"; an analysis of "The Similarity of Workshops" (based on presentation duration, readability, authors' affiliation ranks, and topical focus); "Robustness Tests and Sensitivity Analysis"; and an analysis suggesting the absence of "Assortative Matching of Authors and Discussants".

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