The effect of in-person conferences on the diffusion of ideas

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Abstract

As the academic community debates the future of in-person conferences, it is important to understand how effective they are at diffusing ideas. Most previous attempts to analyze this question have struggled to separate causation from correlation and used potentially biased measures like self-reported learning. Here, we propose a novel approach using scheduling conflicts. When multiple presentations of interest to an attendee are scheduled at the same time, the attendee is less able to see them, on average. If seeing presentations influences future research, then conflicting presentations should influence research less than unconflicting ones. Analyzing conflicts in the personalized schedules of 1960 attendees of 20 computer science conferences reveals that when an attendee is able to see a paper presentation, she is almost twice as likely to cite the paper in her future work. The effect is robust to underlying differences between attendees, papers, and paper authors, and is even larger for a stronger measure of influence – citing the presented paper multiple times. Given the substantial learning effects of in-person presentations, it will be important to ensure that attempts to turn conferences hybrid or virtual do not imperil knowledge diffusion.

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Introduction

Conferences are ubiquitous in academic research and industries where workers need to keep abreast of developments in their fields (Hansen and Budtz Pedersen 2018). The costs of these conferences are significant, both in financial terms (Jones and Li 2015; Hanly 2012), and environmental ones (Storz 2019; Klöwer et al. 2020) - where a single academic conference can represent as much as 7% of an individual’s annual CO₂ emissions (Spinellis and Louridas 2013). Whether these resources are well spent has been long-debated (Ioannidis 2012). Do conference attendees learn new ideas? Or perhaps the benefits of conferencing are primarily for networking (Chai and Freeman 2019; Zajdela et al. 2021; Campos, Leon, and McQuillin 2018)? For researchers considering submitting their papers to conferences, as well as those considering whether to invest time into organizing a conference, the size of the learning effects matters.

These questions have only become more important in recent years as alternative channels for diffusing research have become available. In particular, if conference presentations have little effect, then fast-growing alternative channels – such as preprint releases or virtual conferences (Klöwer et al. 2020; Thorp 2020; Skiles et al. 2021; Reshef et al. 2020; Jarvis, Weiman, and Johnson, n.d.) – might be more efficient.

Measuring the effect of conferences is challenging for several reasons. First, accumulating evidence of idea diffusion takes time. A scientist may be influenced by a conference presentation, but then it may take time for those insights to be incorporated into their work and even longer before they are published. Second, it is challenging to understand how a conference influences attendees. Perhaps the formal presentations influence them, or perhaps influence happens via informal activities like hallway discussions, receptions and dinners. Third, distinguishing between correlation and causation is difficult because researchers attend conferences where they believe the work will be relevant and conference organizers try to choose work of high quality. This means that the natural comparison group – papers not presented – will be on average less relevant and of lower quality. It is important that these differences in quality and relevance are not misconstrued as arising because of the conference. Thus, while it is clear that work presented at conferences achieves higher impact (Hansen and Budtz Pedersen 2018) and that attendees self-report learning important information at conferences (Lalonde et al. 2007), it is unclear if those papers and individuals would have achieved similar outcomes without the conferences.

Existing research that accounts for these challenges is very limited. In our estimation, the study that comes closest is by Leon and McQuillin (2018), where the authors estimate the causal effect of conferences on citations using the unexpected cancellation of a major political science conference. By comparing that year’s conference to prior instances, as well as to a smaller conference used as a control, Leon and McQuillin estimate that being presented at a conference increased a paper’s chances of being cited at least once within four years after the conference by 5%. However, the study left several questions unresolved. First, it could not identify which
conference activities caused the effects (since all were canceled). Second, the loss of the conference changed the development of the underlying papers because presentations were of works-in-progress, so what was lost was both attendees viewing the presentation and the improvements to the underlying papers. Lastly, because their study considered perhaps the largest change to conferencing that a field could make – entirely missing its most important one – the effects may not generalize to the more typical decisions that conference attendees and organizers face, whether or not to attend specific talks and how to best structure conferences.

Here, we develop an approach that helps address the challenges of the previous literature. Specifically, by analyzing conferences from 2013-2019, we are able to observe long-term effects. By focusing on conference presentations, we can separate the effect of formal and informal activities. And by exploiting scheduling conflicts, particularly those that are idiosyncratic to the presentation’s relevance for any particular researcher, we can separate out much (if not all) of the correlational impact to get at the causal effect of conference presentations.

Results

In our analysis, we examine the individualized schedules of 1960 users of the conference scheduling software Confer for 20 prominent computer science conferences held between 2013-2019. Because users “Like” the papers they are interested in, and these may be scheduled at the same time, we observe when attending one paper precludes attending another that is also of interest. For linguistic parsimony in the discussion that follows, we refer to someone who Liked a presentation and who has no scheduling conflicts as “attending” that presentation. In practice, of course, some proportion of them will not, but will instead talk outside, collaborate with coauthors, etc. While important, these phenomena do not influence our estimates because of our empirical strategy (described below) and, thus, our estimates will be reflective of actual attendance.

Does seeing a paper presented matter?

An initial estimate

Within two years of the conference, 4.4% of people who attended a talk (with no scheduling conflict) cite that paper. This represents two effects: a baseline chance that they would have cited the paper even if they had not seen it and the additional effect due to seeing the presentation. We call these the “baseline interest effect” and “presentation effect,” respectively. Adding information from those who experienced conflicts enables us to disaggregate these effects.

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1 https://confer.csail.mit.edu
Consider for example those attendees that were forced to choose between two presentations they wanted to attend that happened to be scheduled at the same time. On average, they only cited 3.4% of these papers within two years. Again, this number reflects both the baseline interest and the presentation effects. But now, the presentation effect is only 50% on average, reflecting the one session attended (100% effect) and the other not attended (0% effect). Notice that imperfect attendance, i.e. Liking presentations but not attending them, is accounted for by the baseline effect, since it is unaffected by scheduling conflicts.

Subtracting these two estimates thus yields:

\[
\text{Baseline} + 100\% \text{presentation} - \left( \text{Baseline} + 50\% \text{presentation} \right) = 50\% \text{presentation}
\]

\[
4.4\% - 3.4\% = 1.0\%
\]

\[
\Rightarrow 100\% \text{presentation} = 2.0\%
\]

That is, accounting for just the sessions with no conflicts and those where two papers conflict, yields an estimate of 2.0% increase in likelihood of citation by an attendee, an 83.3% increase over the baseline effect of 2.4% (=4.4% - 2.0%). In practice, the presentation effect can be disentangled from confounding factors even more precisely.

Adjusted estimate

Our initial estimate may be confounded by a number of factors related to differences among papers or users. For example, paper presentations with fewer scheduling conflicts might be of higher quality, because conference organizers intentionally featured these presentations in the overall schedule. Additionally, users who are more likely to have schedules with many conflicts may be less likely to cite papers overall. We control for potential underlying differences in papers and users using a mixed linear regression model with fixed effects for each paper and user-conference. Conceptually, this adjustment means that our model now estimates how the number of conflicts changes citation rates after taking out any characteristics of the particular user or the particular paper, thus greatly reducing the chances for endogeneity. We use the following specification:

\[
I(\text{citation}_{ijk} = 1) = \left( \frac{1}{\#\text{co-scheduled}} \right) \cdot \tau + P_k + C_{ij} + \epsilon_{ijk}
\]

Where, \(I(\text{citation}_{ijk} = 1)\) is an indicator for whether user \(j\) cited paper \(k\) from conference \(i\) within some time-frame, \(\tau\) measures the “presentation effect”, \(P_k\) is the paper fixed effect, and \(C_{ij}\) is the fixed effect for attendee \(j\) at conference \(i\), and \(\epsilon_{ijk}\) is the error. We refer to estimates of \(P_k + C_{ij}\) averaged across the dataset as the “baseline interest effect.” As (# co-scheduled) presentations goes to infinity, the user has a diminishing chance to see any of them and the expression reduces to only the baseline interest effect and error.
To measure the citation rate associated with a particular level of scheduling conflict (rather than the overall presentation effect $\tau$), we also use the same specification but replace the $\tau$ term in (1) with three indicators denoting 0 conflicts, 1 conflict, and 2+ conflicts. The corresponding regression tables are shown in Table S3 in the Supplementary Information.

**Figure 1.** Coefficients of scheduling conflicts from regressions predicting a user citing the presented paper 1 or more times within 2 years (Panel **A**) and 5 years (Panel **B**), controlling for fixed effects for the paper and user-conference. Error bars represent 95% confidence intervals.

Figure 1 displays the estimated percent of *Liked* papers used cited within 2 years and 5 years of the conference. Probability of citation declines precipitously the more scheduling conflicts a user had. While papers with no conflicts (only 1 co-scheduled presentation) are cited an average of 4.7% within two years, the rate declines to 3.9% and 3.0% for papers with 1 and 2+ conflicts, respectively. In relative terms, these declines are 17.1% and 35.4%, respectively. Declines in long-term citations are qualitatively similar, but from higher baseline levels.

Do these changes in citation patterns reflect real influences on the attendee’s research?

Thus far, we have assumed that citations reflect the influence a paper has had on a conference attendee’s research, following an extensive literature that has made this assumption (Nicolaisen 2007; Bornmann and Daniel 2008; Tahamtan and Bornmann 2019). However, recent research shows that only about 46% of citations reflect meaningful influence on the citing authors (Teplitskiy et al. 2022). However, when authors cite a particular paper multiple times, the paper is
more likely to have had substantive influence (Jurgens et al. 2018). Consequently, to better measure substantive influence, we replace the outcome variable in (1) with an indicator for citations in two or more of the attendee’s papers. The estimates are shown in Figure 2.

![Figure 2](image)

**Figure 2. Coefficients of scheduling conflicts from regressions predicting a user citing the presented paper 2 or more times within 2 years (Panel A) and 5 years (Panel B), controlling for fixed effects for the paper and user-conference. Error bars represent 95% confidence intervals.**

The lower rates of citation compared to Figure 1 show that citing a Liked paper in two or more of an attendee’s own papers is relatively rare. However, the rates for unconflicted papers are much higher than for ones with scheduling conflicts. Two years after the conference, attendees cite Liked papers twice or more about 1.7% of the time when there are no scheduling conflicts, and 0.84% when there are 2 or more. For this better proxy of influence, this decline in relative terms is 46.3%. The declines for 2+ citations within 5 years (Figure 2B) are qualitatively similar, but from higher baselines.

**Quantifying effect sizes**

To quantify the effect size across various levels of scheduling conflicts, we estimate regression specification (1) on all conferences together, using citation in 1+ publications within 2 years as the dependent variable. The estimated baseline interest effect is $\tau = 0.027$ and the presentation effect $\tau = 0.020$ (see Tables S4 and S5 for the regression results).
These effects suggest that having the opportunity to see a paper presentation in person nearly doubles the probability of citation (2.7% → 2.7% + 2.0% = 4.7%). When impact is measured as citation in 2+ publications within 2 years, the corresponding values are baseline interest effect = 0.0061 and presentation effect $\tau = 0.0096$, suggesting a near tripling of citation probability (0.61% → 1.57%). We underscore that these presentation effects appear despite attendees having asynchronous access to these papers online.

Figure 3B shows that as the longer the time after the conference, the larger the estimated presentation effect. Within five years after a conference, presentations increase the chances that an attendee cites a paper by 2.7%.

We interpret the presentation effect $\tau$ as causal because we assume scheduling conflicts are effectively random after accounting for the other regression controls. However, scheduling conflicts could also be endogenous. For example, users might consciously avoid scheduling conflicts when an author from their institution is presenting and might cite authors from their institution more than others. This would induce a correlation between citations and conflicts that was not due to the conference itself. To estimate how much this potential confounding factor we re-estimate specification (1) on data from only those timeslots where users did not Like any papers by same-institution authors. The remaining data consists of Liked papers in timeslots none of
which have the same-institution “pull.” This restriction makes the presentation effect estimate change by 5% (0.20 → 0.19, see Table S6). If being at the same institution, which has been extensively documented as being central to knowledge diffusion (Kabo et al. 2014; Duede et al. 2021; Catalini 2017), produces no meaningful change in our results, we posit that other confounders are unlikely to.

Conclusion

By addressing many of the challenges that faced the previous literature, this study provides unusually strong evidence that in-person conference presentations substantially affect the diffusion of knowledge. By leveraging plausibly exogenous scheduling conflicts, we observe that seeing a presentation nearly doubles the probability of citing of that work. A more rigorous definition of learning than citation (Jurgens et al. 2018, Teplitskiy et al. 2022), shows even stronger effects - with presentations nearly tripling learning rates. Importantly, these strong presentation effects were observed even though all papers were easily available online. So the presentations really matter. This evidence for the importance of conference presentations affirms the common choice to center conferences around these activities versus, for example, informal networking or award receptions. It also suggests that knowledge diffusion at conferences is more inclusive than if informal activities (which are less inclusive (Forrester 2021)) had been central.

Our findings raise the stakes for the ongoing debate about virtual/hybrid conferencing. While virtual conferences have many advantages, including low environmental impact, decreased financial cost, and increased accessibility (Skiles et al. 2022), they also pose challenges, including easy distractions, physical strain, and technological failures. One could easily imagine these challenges hindering the diffusion of knowledge sufficiently to make virtual conferences less attractive than in-person.

Emerging evidence highlights the limits of virtual learning. During the pandemic, virtual K-12 education was associated with large and persistent learning losses (Fitzpatrick et al. 2020; Christakis, Van Cleve, and Zimmerman 2020; Stringer and Keys 2021). In the U.S., such losses were largest in districts with less in-person instruction (Halloran et al. 2021).

Thus, as we collectively reconsider the future of academic conferences, it is important to understand that conferences, and in-person presentations in particular, are central to how academic knowledge diffuses.
Data and Methods

Scheduling conflicts
The research design uses scheduling conflicts in a user’s personal conference schedule for (conditionally) exogenous variation in the user’s opportunities to attend paper presentations. We then connect variation in opportunities to subsequent citing. Consider an individual who is interested in only 1 paper presentation in a particular timeslot A and 2 papers co-scheduled in a different timeslot B. Interest in a presentation does not guarantee attendance (which we do not measure). Accordingly, denote by \( \tau \) the probability that the individual attends the presentation in A (Figure 3). If papers of interest are assigned to timeslots at random, conditional on a number of key covariates, the probability of the individual attending either of the talks in B is also \( \tau \). On average, talks in B will be attended with probability \( \tau/2 \). Similarly, for a timeslot with \( n \) papers, the average probability of attendance is \( \tau/n \). Scheduling conflicts thus approximate a randomized experiment in which an individual is assigned different levels of opportunity to attend presentations.

![Dose Illustration](https://confer.csail.mit.edu/)

**Figure 4.** Illustration of how the number of co-scheduled presentations of interest affect dosage of the presentation effect. In general, \( n \) co-scheduled presentations correspond to a \( \tau/n \) dose.

We apply this strategy to data from conference scheduling software Confer (https://confer.csail.mit.edu/, see SI: Illustration of the software). Many conferences use scheduling software deployed via apps and websites to help attendees create their personal schedules. Confer lets users browse the presentations scheduled at a conference, “Like” some as being of interest, and displays a convenient, individualized schedule.

Several features of the research design deserve emphasis. First, scheduling conflicts are defined at the user level, among the presentations the user Likes. Using this fact, and fixed effects for the papers in our statistical models below, we can account for scheduling conflicts that exist in the overall conference schedule, as well as the role of stable paper characteristics like quality or author prestige. Second, the baseline or “control” relative to which the treatment of opportunities is measured is not complete lack of access to the information, but asynchronous access to the paper online. This feature of the design mimics the realistic choice facing conference attendees: to attend a conference and see information in person or read it online at one’s convenience?
To measure information absorption and utilization we focus on whether the user cited the presented papers in their own work in the subsequent years. To standardize our analysis across older and newer conferences, we focus on citations in 2 years past conference (“short-term citations”) and 5 years past conference (“long-term citations”). Additionally, we measure whether the user cites the presented paper 2 or more times, taking this as a signal of deeper impact.

Citations data
We used Microsoft Academic Graph (MAG) to retrieve Confer users’ citation records. For each Confer user, we first queried MAG with the name as registered in Confer. If it returned a unique entry, then we concluded the match. In cases of multiple results, we employed the following disambiguation heuristics. For each MAG result, we checked if (1) the author published any paper in our sample of conferences in the past decade, and (2) the author’s MAG research fields included those related to Confer conferences (e.g., CS, HCI). To test matching accuracy, one of the authors (S.P.) randomly sampled 20 user-MAG matches. 90% of them were correct, as compared to manual Googling of the individuals. Both of the wrong matches were users with common names and no publications (junior scholars), who were matched to more senior scholars with the same names.
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Supplementary Information for

The effect of in-person conferences on the diffusion of ideas

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1. Illustration of the software

*Confer*, the conference scheduling software used in the study, is available as a webpage (https://confer.csail.mit.edu/) and a phone app. Figures S1-S3 below show screenshots of the webpage version of the software.

**Fig. S1.** *Confer* main page.
In this paper we propose Fractal, a high performance and high productivity system for supporting distributed graph pattern mining (CPM) applications. Fractal employs a dynamic (auto-tuned) load-balancing based on a hierarchical and locality-aware work stealing mechanism, allowing the system to adapt to different workload characteristics. Additional...

Although deep learning models perform remarkably well across a range of tasks such as language translation and object recognition, it remains unclear what high-level logic, if any, they follow. Understanding this logic may lead to more transparency, better model design, and faster experimentation. Recent machine learning research has leveraged stat...

Fig. S2. Confer’s “My Papers” interface and the “Like” functionality.
2. Descriptive statistics

The amount of Likes (papers marked by users as being of interest) varied substantially across conferences. Figure S4 shows that two annual conferences comprise most of the data: the ACM Conference on Human Factors in Computing Systems (“CHI”) and the ACM Conference On Computer-Supported Cooperative Work And Social Computing (CSCW).
Figure S5 shows that for the modal Liked paper, there were no scheduling conflicts. When scheduling conflicts occurred among a Liked paper and another presentation or event, e.g. banquet, in the same timeslot, the number of such conflicts was typically 1 and occasionally 2. In less than 1% of cases users had 4 or more other papers or events of interest in the same timeslot as a paper of interest. Note, these counts are computed at the timeslot and not the paper level to avoid double- or triple-counting conflicting papers in the same timeslot.
Fig. S5. Distribution of timeslot conflicts, where research and non-research presentations, e.g. banquet, are both considered as a conflict to a research presentation. The counts are at the time-slot, not Liked paper, level to avoid counting a timeslot with multiple conflicts multiple times.

Full vs. analytic sample

The full dataset contained many observations with missing values on critical covariates, particularly presentation type and the timeslots of presentations. Additionally, the conferences contained a number of sessions that are of a social or celebratory nature, or are keynote or poster sessions. Consequently, a number of exclusion criteria were applied to the full sample to reduce it to the sample used in the analyses, the “analytic sample.”

Of the 3061 sessions across all the conferences, 2177 had a valid “type”. Of the ones with a valid type, 1150 are classified as “paper”, “workshop” or “journal”. The other categories are shown in Table S1 and include types such as “lunch”, “coffee”, and “tutorial.”

168 sessions matching these keywords were excluded from the analytic sample, in the sense that we do not measure how often papers presented in these sessions are cited but do include them when counting how many scheduling conflicts to a research paper a user had in a particular timeslot. As a robustness check, we also count timeslot conflicts excluding these sessions, and find that the two measures, \( n_{\text{timeslot\_conflicts\_all}} \) and \( n_{\text{timeslot\_conflicts\_research}} \) are correlated at 0.994 (see Figure S1). Consequently, we rely on the former measure in the rest of the analyses.
| Keyword                         | Number of sessions |
|--------------------------------|--------------------|
| tutorial                       | 65                 |
| course                         | 60                 |
| coffee                         | 56                 |
| student                        | 42                 |
| lunch                          | 41                 |
| keynote                        | 38                 |
| poster                         | 38                 |
| panel                          | 33                 |
| award                          | 31                 |
| demo                           | 31                 |
| reception                      | 28                 |
| registration                   | 12                 |
| lasting impact                 | 7                  |
| banquet                        | 5                  |
| steering committee             | 3                  |
| townhall                       | 3                  |
| uist closing                   | 2                  |
| <=1 or >=9 or more presentations in the session (and not one of the keywords above) | 12 |
| Total                          | 470                |

**Table S1.** The first column contains keywords from titles of sessions that were taken to indicate that the session was not composed of typical research talks. The second column shows how many titles included that keyword.

Second, we excluded from the analytic sample conferences that took place in 2019 or later. This restriction was to ensure that citations could be tracked for a full two years, plus the year of the
conference. For robustness, we repeat our analysis including 2019 conferences, *i.e.* only excluding those in 2020, and find qualitatively similar results, which are available upon request.

Third, we excluded from the analytic sample *Likes* where the user had cited the paper before the conference. Such cases occurred in “Lasting Impact” sessions, where the paper(s) presented had been published many years prior to the conference, or the paper was matched to an Arxiv preprint. There were 68 such cases.

Table S2 and Figure S6 provide the basic descriptive statistics and correlation table, respectively, among the main variables in the analytic sample. Nominal variables like *conference_name* and *user_id*, are not shown.

| Variable                     | Count    | Mean     | Std      | Min      | 25%      | 50%      | 75%      | Max      |
|------------------------------|----------|----------|----------|----------|----------|----------|----------|----------|
| n_timeslot_conflicts_all     | 78351.0  | 0.72     | 1.01     | 0.0      | 0.0      | 0.0      | 1.0      | 11.0     |
| n_timeslot_conflicts_research| 67884.0  | 0.63     | 0.90     | 0.0      | 0.0      | 0.0      | 1.0      | 8.0      |
| is_cited_1                   | 78351.0  | 0.02     | 0.15     | 0.0      | 0.0      | 0.0      | 0.0      | 1.0      |
| is_cited_2                   | 78351.0  | 0.04     | 0.19     | 0.0      | 0.0      | 0.0      | 0.0      | 1.0      |
| is_cited_2_twice_or_more     | 78351.0  | 0.01     | 0.10     | 0.0      | 0.0      | 0.0      | 0.0      | 1.0      |
| is_cited_5                   | 37838.0  | 0.06     | 0.23     | 0.0      | 0.0      | 0.0      | 0.0      | 1.0      |
| is_cited_5_twice_or_more     | 37838.0  | 0.02     | 0.14     | 0.0      | 0.0      | 0.0      | 0.0      | 1.0      |
| is_same_institution          | 78351.0  | 0.04     | 0.20     | 0.0      | 0.0      | 0.0      | 0.0      | 1.0      |
| conference_size_n_papers     | 78351.0  | 694.82   | 522.22   | 126.0    | 290.0    | 631.0    | 755.0    | 2319.0   |
| conference_year              | 78351.0  | 2016.41  | 1.48     | 2013.0   | 2015.0   | 2017.0   | 2018.0   | 2019.0   |

*Table S2.* Descriptive statistics for the main variables in the analytic sample.
Fig. S6. Correlation table among the main variables in the analytic sample.
Supplementary tables

Table S3. Estimates from OLS and mixed linear models predicting probability of citation within 2 years (dependent variables with “is cited 2”) and 5 years (“is cited 5”). Odd-numbered models are OLS with no controls and even-numbered models are mixed linear models with paper and user-conference fixed effects.

| Dependent variable: | is_cited_2 in 1+ pub | is_cited_2 in 2+ pubs | is_cited_5 in 1+ pub | is_cited_5 in 2+ pubs |
|---------------------|---------------------|---------------------|---------------------|---------------------|
|                     | OLS                 | linear mixed-effects| OLS                 | linear mixed-effects|
| (1)                 | (2)                 | (3)                 | (4)                 | (5)                 |
| 1 co-scheduled talk | 0.044***            | 0.047***            | 0.014***            | 0.016***            |
|                     | (0.001)             | (0.001)             | (0.001)             | (0.001)             |
| 2 co-scheduled talks| 0.033***            | 0.039***            | 0.009***            | 0.011***            |
|                     | (0.001)             | (0.002)             | (0.001)             | (0.001)             |
| 3+ co-scheduled talks| 0.020***           | 0.030***            | 0.005***            | 0.008***            |
|                     | (0.002)             | (0.002)             | (0.001)             | (0.001)             |
| Paper F.E.          | No                  | Yes                 | No                  | Yes                 |
| User-conference F.E.| No                  | Yes                 | No                  | Yes                 |
| Observations        | 78,351              | 78,351              | 78,351              | 78,351              |
| R²                  | 0.039               | 0.012               | 0.060               | 0.023               |
| Adjusted R²         | 0.039               | 0.012               | 0.060               | 0.023               |
| Log Likelihood      | 21,004.950          | 66,455.740          | 2,614.029           | 19,849.970          |
| Akaike Inf. Crit. | - | 41,997.910 | 132,899.500 | -5,216.059 | - | 39,687.940 |
|------------------|---|------------|-------------|-------------|---|----------|
| Bayesian Inf. Crit. | - | 41,942.290 | 132,843.900 | -5,164.812 | - | 39,636.700 |
| Residual Std. Error | 0.188 (df = 78348) | 0.104 (df = 78348) | 0.231 (df = 37835) | 0.145 (df = 37835) | - | - |
| F Statistic | 1,060.949*** (df = 3; 78348) | 324.156*** (df = 3; 78348) | 810.201*** (df = 3; 37835) | 299.407*** (df = 3; 37835) | - | - |

*Note:* *p<0.1; **p<0.05; ***p<0.01
Table S4. Estimates from OLS and mixed linear models predicting probability being cited within 2 years in 1+ publications (models (1) and (2)) and 2+ publications (models (3) and (4)). Odd-numbered models are OLS with no controls and even-numbered models are mixed linear models with paper and user-conference fixed effects.

| Dependent variable: | is_cited_2 | is_cited_2_twice_or_more |
|---------------------|------------|--------------------------|
|                     | OLS        | linear                   |
|                     | mixed-effects | mixed-effects |
| (1)                 |            |                          |
| 1 / (num. co-scheduled talks) | 0.030*** | 0.020*** |
|                     | (0.002)     | (0.003)                  |
| Constant            | 0.015***    | 0.027***     |
|                     | (0.002)     | (0.002)                  |
| Paper F.E.          | No         | Yes                      |
| User-conference F.E.| No         | Yes                      |
| Observations        | 78,351     | 78,351                   |
| R²                  | 0.002       | 0.001                   |
| Adjusted R²         | 0.002       | 0.001                   |
| Log Likelihood      | 21,008.320  | 66,461.870              |
| Akaike Inf. Crit.   | -42,006.630 | -132,913.700           |
| Bayesian Inf. Crit. | -41,960.290 | -132,867.400             |
| Residual Std. Error (df = 78349) | 0.188 | 0.104 |
| F Statistic (df = 1; 78349) | 175.189*** | 94.447*** |

Note: * p<0.1; ** p<0.05; *** p<0.01
Table S5. Estimates from mixed linear models predicting probability of citation in 1+ and 2+ publications within 1 to 5 years after the conference. The specifications include paper and user-conference fixed effects.

| Dependent variable: | Cited in 1+ pub |  |  |  |  | Cited in 2+ pubs |  |  |  |  |
|---------------------|----------------|---|---|---|---|-----------------|---|---|---|---|
|                     | 1 year (1)     | 2 years (2) | 3 years (3) | 4 years (4) | 5 years (5) | 1 year (6) | 2 years (7) | 3 years (8) | 4 years (9) | 5 years (10) |
| 1 / (num. co-scheduled talks) | 0.017*** | 0.020*** | 0.021*** | 0.022*** | 0.027*** | 0.005*** | 0.010*** | 0.011*** | 0.012*** | 0.014*** |
| [0.002] | [0.003] | [0.003] | [0.004] | [0.005] | [0.001] | [0.001] | [0.002] | [0.002] | [0.002] | [0.003] |
| Constant | 0.015*** | 0.027*** | 0.035*** | 0.042*** | 0.044*** | 0.002*** | 0.006*** | 0.009*** | 0.012*** | 0.015*** |
| [0.002] | [0.002] | [0.003] | [0.003] | [0.005] | [0.001] | [0.001] | [0.002] | [0.002] | [0.002] | [0.003] |
| Paper F.E. | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| User-conference F.E. | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 78,351 | 78,351 | 72,581 | 58,194 | 37,838 | 78,351 | 78,351 | 72,581 | 58,194 | 37,838 |
| Log Likelihood | 36,322.220 | 21,008.320 | 12,649.130 | 6,586.281 | 2,617.718 | 96,764.400 | 66,461.870 | 50,819.800 | 35,161.780 | 19,854.900 |
| Akaike Inf. Crit. | 72,634.430 | 42,006.630 | 25,288.260 | 13,162.560 | 5,225.435 | 193,518.800 | 132,913.700 | 101,629.600 | 70,313.570 | 39,699.800 |
| Bayesian Inf. Crit. | 72,588.090 | 41,960.290 | 25,242.290 | 13,117.700 | 5,182.730 | 193,472.500 | 132,867.400 | 101,583.600 | 70,268.710 | 39,657.100 |

Note: *p<0.1; **p<0.05; ***p<0.01
**Table S6.** Robustness check: estimates from mixed linear models predicting probability of citation in 1+ pub 2 years after the conference. Model 1 estimates the model on the full analytic sample and Model 2 only on those timeslots that had no *Liked* papers with same-institution authors.

| Dependent variable: | is_cited_2 |
|---------------------|------------|
|                     | (1)        | (2)        |
| one_over_n_all      | 0.020***   | 0.019***   |
|                     | (0.003)    | (0.003)    |
| Constant             | 0.027***   | 0.025***   |
|                     | (0.002)    | (0.002)    |

|                  | (1)         | (2)         |
|------------------|-------------|-------------|
| Paper F.E.       | Yes         | Yes         |
| User-conference F.E. | Yes     | Yes         |
| Observations     | 78,351      | 73,358      |
| Log Likelihood   | 21,008.320  | 22,335.470  |
| Akaike Inf. Crit.| -42,006.630 | -44,660.940 |
| Bayesian Inf. Crit.| -41,960.290 | -44,614.920 |

*Note:* *p<0.1; **p<0.05; ***p<0.01