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Helpful Behavior and the Durability of Collaborative Ties

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Abstract. Long-term collaborations are crucial in many creative domains. Although there is ample research on why people collaborate, our knowledge about what drives some collaborations to persist and others to decay is still emerging. In this paper, we extend theory on third-party effects and collaborative persistence to study this question. We specifically consider the role that a third party's helpful behavior plays in shaping tie durability. We propose that when third parties facilitate helpfulness among their group, the collaboration is stronger, and it persists even in the third's absence. In contrast, collaborations with third parties that are nonhelpful are unstable and dissolve in their absence. We use a unique data set comprising scientific collaborations among pairs of research immunologists who lost a third coauthor to unexpected death. Using this quasi-random loss as a source of exogenous variation, we separately identify the effect of third parties' traditional role as an active agent of collaborative stability and the enduring effect of their helpful behavior—as measured by acknowledgments—on the persistence of the remaining authors' collaboration. We find support for our hypotheses and find evidence that one mechanism driving our effect is that helpful thirds make their coauthors more helpful.

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Keywords: social networks • innovation • science • knowledge production • collaboration

Introduction

Collaboration is increasingly the norm in many creative domains (e.g., Guimera et al. 2005, Powell et al. 2005, Uzzi and Spiro 2005, Wuchty et al. 2007). Science, in particular, has become more collaborative over the past half century. Today, team-based science accounts for a large share of high-impact output, and research has underlined the growing dominance of collaboration in the physical, biological, and social sciences (Moody 2004, Wuchty et al. 2007, Singh and Fleming 2010). In recent years, much has been learned about why collaborations form and outperform individuals (Singh and Fleming 2010, Sytch and Tatarynowicz 2014, Boudreau et al. 2017, Catalini 2018). Collaborations are superior because they facilitate access to new information and enable knowledge recombination. Repeat collaborations, when they occur, are especially beneficial. Research shows that they entail fewer frictions, promote information transfer, and engender trust among participants. Long-term collaborations therefore enable higher-quality creative production (Jones et al. 1998, Dahlander and McFarland 2013).

Although repeat collaborations are seen as desirable, they are infrequent (Dahlander and McFarland 2013). Moreover, research on why some collaborations persist over a longer term also remains limited. Indeed, most research on this topic has focused on the tie formation stage—for example, why some people work together and others do not (e.g., Boudreau et al. 2017, Catalini 2018, Chai and Freeman 2019, Hasan and Koning 2019). However, several recent studies have begun to examine the mechanisms that produce differential rates of repeat collaboration (Dahlander and McFarland 2013). This work proposes two broad classes of mechanisms that drive persistence (Krackhardt 1998, Burt 2002). One set of mechanisms focuses on the individual and contextual factors that reduce the cost of matching (Boudreau et al. 2017, Catalini 2018, Lane et al. 2021). In these models, shared backgrounds, complementary skills, colocation, and past performance affect when collaborations are likely to form and how productive they are. In this view, persistence derives from high-quality matches and the low costs of coordination.

A second perspective views durability as a function of what people do after a collaboration forms. Research suggests that how individuals interact with each other, consider their long-term prospects, and how they deal with the disagreements that arise increases durability (e.g., Burt and Knez 1996). One mechanism research has suggested that impacts relationship durability is the presence of a third party—an individual who actively mediates the relationship between two individuals (Simmel 1898). Research has shown that dyads embedded in a triad—for example, that have a shared third party—are more likely to persist (Burt 2002, Krackhardt and Kilduff 2002, van Miltenburg et al. 2012). Another mechanism that likely affects behavior within a collaboration is how individuals engage in helpful behavior. Past research defines helpful behavior as activities where the helper neither expects nor receives something in return from the receiver for their help (Takahashi 2000, Shibayama et al. 2012). Experimental research has also suggested that helpful behavior (as well as unhelpful) may also be contagious—for example, it diffuses within a group as other individuals adopt their peers' behavior (Simpson et al. 2017). Consequently, we expect collaborations with helpful thirds will persist longer.

These mechanisms, one structural and the other behavioral, however, are challenging to tease apart in natural contexts. In most settings, structure and behavior are codetermined. As a result, studying the effect of third parties and helpful behavior as distinct mechanisms is empirically challenging. To address this concern, we use a novel research design that exogenously varies the structural properties of collaboration, thus allowing us to identify the independent effect of helpfulness. Our context is scientific collaboration, where we can observe helpful behaviors and collaboration levels in a natural setting. Our data set comprises scientific collaborations—published articles in peer-reviewed journals—among 11,084 pairs of research immunologists, some of whom lost a third collaborator due to an unexpected death and others who had a closely matched collaborator who did not pass. We use the unexpected and essentially random deaths of helpful and nonhelpful thirds to distinguish between the behavioral and structural mechanisms (Azoulay et al. 2010, Oettl 2012a).

We find that triads whose departed third collaborator was helpful—as indicated by acknowledgments in journal articles—continue to collaborate after the death of their third. In contrast, triads that lost a nonhelpful third experienced a 5%–12%-point decline in their probability of repeat collaboration relative to their matched control. The effect of third-party helpfulness was particularly strong when they were of high status and when the treated collaboration did not have a history of helpful behavior. Our results are robust to a range of specifications that control for dyad-specific heterogeneity, both observed and unobserved, as well as differences in productivity, status, and experience.

Our article contributes to at least four agendas in management and organization theory. First, our research contributes to a large and diverse literature on collaboration (e.g., Boudreau et al. 2017, Catalini 2018, Chai and Freeman 2019, Lane et al. 2021) and its consequences (Uribe et al. 2020). Our findings provide evidence of a behavioral mechanism and the structural and spatial ones, which leads to the endurance of collaborations. Second, we also contribute to the social networks literature. One particularly prominent stream of this work focuses on third parties and their effect on performance beyond the tie formation stage (e.g., Krackhardt 1999, Burt 2000, Obstfeld 2005, Zhelyazkov 2017). Third parties, because of the structural role they play, can create stability or instability in a network. Our findings show that third parties also differ in their behaviors (in our case, helpfulness), which affects the dynamics of relationships and collaborations in which they participate. These effects, we show, are persistent even after a third departs, suggesting a possible imprinting effect (Marquis 2003). Finally, we add to the literature on helpful behavior and its consequences. Recent work has shown that helpful behavior has positive effects on the productivity of individuals (e.g., Oettl 2012a, Shibayama et al. 2012). Our research suggests that helpful behavior also affects outcomes at the network level—and not just the individual level, as prior research has demonstrated. In this way, our work also speaks to the literature on generalized exchange (Baker and Bulkley 2014, Simpson et al. 2017). We show that helpful behavior by individuals encourages collaborative endurance as well. Our finding suggests groups lacking helpful individuals may be fragile.

Theory and Hypotheses

Collaboration Endurance and Decay

Many relationships, including collaboration, are prone to decay (Burt 2000, 2002). For instance, a review by Burt (2000) suggests that decay rates can be over 50% over a year, and Dahlander and McFarland (2013) show that rates of collaboration persistence in their context of existing collaborations within a university is only 23%. Prior research has theorized that two sets of mechanisms lead to persistence or decay. In terms of decay, the first set of mechanisms are *frictions*—consisting of disagreements and other disputes—that are natural byproducts of purposeful, though informal, social interaction among individuals who consider themselves equal in standing (Ghosh and Rosenkopf 2014). Debates and misaligned interests are common and, to some extent, expected in most relationships. Among scientists, frictions may arise because of disagreements about research questions, methods, authorship, or credit (Blume and Sinclair 1973). When such disagreement is either too severe or too frequent, a collaboration may be stressed to the point of dissolution. The inability to resolve such issues is heightened when extradyadic means—that is, formal hierarchical relationships or professional norms—are unavailable to resolve the issue (Blau1968). For instance, a dispute may be more easily resolved in a collaboration between an advisor and advisee than between two scientists with equal standing. The second process that may precipitate a collaboration's decay is the process of drift (Shipilov et al. 2006). In any relationship, as other obligations emerge, tastes change, or opportunities for interaction decline, individuals may have less need to collaborate and better outside options. In the absence of mechanisms that facilitate interaction such as seminars, colocation, or committees, interaction and consequently collaboration becomes less likely. In contrast, better matches and aligned incentives will lead to tie persistence. This increased persistence—in the form of repeat collaboration—has also been shown to lead independently to a virtuous cycle of repeat collaboration (e.g., Sytch and Tatarynowicz 2014).

Third Parties and Relationship Endurance

One mechanism that has been highlighted as a force creating stability in informal relationships is the presence of a third party (Simmel 1898, Burt and Knez 1995, Krackhardt 1999). Third parties are other individuals who have a shared connection with the two primary individuals in a collaboration. This third may be another collaborator, colleague, or friend. Third parties hold a privileged position as conduits of information, resources, and trust (Rousseau et al. 1998). They are also enforcers of norms, mediators of disputes, and function as the structural glue that holds networks and communities together (Krackhardt 1999). Scholars who have studied the stabilizing role of the third often conceptualize this individual's social position in two ways. One set of arguments view third parties as active participants in the relationships of those they interact with (Krackhardt 1999). In contrast, another set of mechanisms view third parties as a model of behaviors that are later adopted by members of the groups they belong to (Rousseau et al. 1998). Through these mechanisms, thirds help sustain others' collaborations.

Thirds as Active Joiners

As an active participant, the third often regulates the relationship between two individuals. The third can pursue actions that increase agreement but also arrest a natural tendency for drift. The extant theory posits two primary ways through which a third party acts as a conciliator when disagreements arise. Because the third party is viewed as impartial, the individual can help the disagreeing parties arrive at an agreeable solution (Fisher 1972). A third does this by presenting conflicting positions in a rational way, stripped of their affective qualities. Doing so allows the disputing parties to see the positions with more clarity, thereby increasing the likelihood that the disagreement is resolved. Second, a trusted third can unilaterally impose a decision that resolves issues. The third can do this because the individual's distance from the dyadic concerns allows the third to weigh each position's merits impartially. Further, another party's mere presence can lead to more conformist behavior, potentially reducing the natural tendency to drift apart in the collaboration (Goldfarb et al. 2015).

In addition to serving as a translator and arbitrator, a third can bring people together in more constructive ways. For example, a third can propose collaborative projects involving all three individuals, serving as a "joiner" (Obstfeld 2005). A third can highlight similarities and complementarities that the members may themselves not see. Moreover, a third can bring individuals together at lunches or other social gatherings that increase the likelihood of sustained interaction. Thus, whether thirds actively facilitate agreement or more constructively bring individuals together, they can play an integral, structural role in keeping a collaboration together and thus facilitating their sustained collaboration (Sasovova et al. 2010).

Thirds and Helpful Behavior

The structural perspective, however, de-emphasizes that the third parties vary in their behaviors and attitudes. These dimensions of heterogeneity may lead to differences in whether third parties can only hold a collaboration together through active mediation or create persistent helpful behaviors. Thus, one way to determine whether the mechanism is operative is to examine whether dyadic collaborations persist for thirds that establish more helpful and durable collaborations versus those who cannot.

Recent research suggests that one dimension on which scientists may vary and how they can affect others' research and collaborative outcomes is the extent to which they offer help to others without an expectation of direct reciprocity (Molm et al. 2012, Oettl 2012a, Shibayama et al. 2012). Such helpfulness can take several forms and can vary in how costly the behavior is to the helper. At one extreme of the helpfulness spectrum are third parties that offer no help without direct reciprocation (Cook et al. 1983). For instance, such a third may present ideas or comments and data and materials, but in return, may request coauthorship. Such behavior sends a stark signal: the provision of ideas and material comes with the expectation of formal credit. The latter behavior and the associated expectation of immediate reciprocity can shape the outlook of the various parties involved in the collaboration. Individuals in such environments are likely to learn that collaborations are short-term or one-shot arrangements. Each contribution—ideas, materials, critique, or effort—is accounted for in authorship (Shibayama et al. 2012).

In contrast, helpfulness without expectation of direct exchange lies at the other end of this spectrum. Such helpfulness consists of activities where the helper neither expects nor receives something in return from the receiver for the help (Takahashi 2000, Shibayama et al. 2012). A third party who lies at this end of the spectrum can engage in various, generally observable behaviors that may vary in how costly they are to the third party. Perhaps the lowest cost activity is providing comments and feedback on research ideas, grants, and drafts. Critiques of this sort require little time commitment from the third. A third can also provide costly forms of support. For instance, a third may possess rare specimens, cell lines, data, or facility with a test or procedure that the third shares with others without expecting coauthorship (Oettl 2012a). This material support is costly to the third because the third could have used them or traded the material for formal credit. Whereas self-interest is a broad concept, our understanding builds on the idea that in science, acknowledgments are not "counted" in any meaningful way in standard decisions about promotion, wages, and so on (Merton 1968; Oettl 2012b, a). Thus, helpful behavior without publications is less self-interested than working for authorship in the scientific context.

A third party's helpfulness, in contrast to self-interest, is likely to cause different behaviors to emerge and thus shape collaborative activity and endurance. If the third party behaves in a self-interested manner, the third party's peers are more likely to interpret their collaborations with the third as mere transactions. These people are likely to face more significant frictions when renegotiating the terms of the collaboration at each instance (Uzzi 1997). On the other hand, if the third is helpful, the third' peers are likely to emphasize sharing and the longer-term nature of a collaboration with deficits of effort and material provision balancing out in the long term. For these reasons, each individual who has collaborated with the third should also become more helpful through the individual's experience interacting with the helpful third.

By aiding their collaborators, helpful thirds will affect the character of their collaborators' relationships, independent of their presence in two important ways. First, shared understandings lead to greater community feeling, of belonging together, than mere structural interactions or even homophily (Vaisey 2007). The participants begin to view and interpret the relationships not as just individuals and the connections between them but rather as a distinct collective entity. Furthermore, helpfulness is fundamentally affirming the other party, an investment into the person as they are, strengthening further commitment to the group or collectivity (Saks et al. 2007). When relationships are not seen as the primary entities but rather forming a group of affiliations to which one is committed, these relationships are seen as long-term investments with tolerance for asymmetry (Uzzi 1996, 1997).

Second, such shifts in how collaboration is perceived should also fundamentally change dyadic ties' nature and strength. Helpful behavior is likely to make a connection both stronger and multiplex (Krackhardt 1992). Individuals in such intense and multiplex relationships will interact more intensely and in both professional and social capacities. Second, individuals will have a greater affection for each other, independent of instrumental reasons for interaction (Krackhardt 1992). Finally, the strong ties are likely to be characterized by greater motivation to help, support, and resolve any relationship problems. These behavioral changes to the interaction strengthen each tie and maintain the commitment to the overall group.

On the other hand, if nonhelpful thirds facilitate less long-term cooperation than helpful ones, the collaboration may be viewed as an isolated event requiring repeated renegotiating. The implication of this is that collaborations with nonhelpful thirds have a lower likelihood of persisting than those that lose helpful thirds. An alternative perspective maybe that collaborators of nonhelpful thirds are brought together through the free-riding behavior of that individual. For instance, having a collaborator who does not help may force the remaining individuals to collaborate more to compensate for the nonhelpful third. This substitution effect may notably bring them closer together, leading to greater persistence. If this is the case, we should not expect a significant difference between the long-term durability of collaborations with helpful versus nonhelpful thirds. Thus, one approach to examining whether third parties promote helpful behavior is by looking at whether collaborations that possess a helpful third relative to a nonhelpful one are more likely to persist, even when the third is not present. Because helpful thirds are better able to encourage the adoption of helpful behaviors, we hypothesize the following.

Hypothesis 1. *Among collaborations that lose a third party, those that lose a nonhelpful third have a larger negative marginal effect on the persistence of their collaboration than those that lose a helpful third.*

Third-Party Status and Pre-existing Helpfulness

Two assumptions underlie the theoretical predictions above. First, a third party must be viewed as worthy of emulation (Simpson et al. 2012). Second, the adoption of helpfulness assumes that helpful actions did not predate the third party's arrival (Molm et al. 2012). Therefore, if a third lacks status and his collaborators do not want to emulate him, then the effect of helpful thirds should be weaker. Similarly, if a pair of collaborators are already helpful toward each other, then the third may not add additional positive value to the relationship in this regard.

Status. A substantial literature in management and sociology highlights the importance of social status on individual and organizational outcomes (Podolny 1993, Gould 2002). Social status confers power and influence. Status also confers visibility, credibility, and trust (Podolny 2001, Magee and Galinsky 2008). In some cases, high-status people's behavior is judged to be normative compared with those with lower status (Moore 1968, Simpson et al. 2012). Together, these qualities make high-status individuals more likely to be emulated.

In our context, a third party's social status should affect whether their helpful or nonhelpful behavior is emulated (Flynn et al. 2006, Lount and Pettit 2012, Simpson et al. 2012). In turn, status will strengthen the effect of third-party helpfulness on the durability of collaborative ties. For example, if a third party is helpful and high status, the individual's helpfulness is more likely to diffuse. Similarly, a high-status but nonhelpful third party may serve as a prominent exemplar of nonhelpful behaviors and cause the third's collaborators to act accordingly.

In contrast, low-status thirds are less influential. Whether their behavior is helpful or nonhelpful, it is less salient to their collaborators. This reduced credibility weakens the low-status third's ability to influence others or change their behaviors. As a result, low-status third parties' helpful behavior is less likely to impact the durability of others' collaborations. Thus, we hypothesize the following.

Hypothesis 2 (a). *Among collaborations that lose a third party, the marginal effect of the loss of a helpful third party on collaborative persistence (Hypothesis 1) is larger when that third party is of higher status.*

Pre-existing Helpfulness. Although status may amplify the effect of a third's helpful behavior, pre-existing helpfulness within a group may weaken it. To restate our theory, we predict that helpful thirds increase the helpfulness of their collaborators. As a result of this increased helpful behavior, collaborations become more durable.

Yet, as research shows, groups vary in how helpful each of their members is and whether their collaborations are strong (Molm et al. 2007, 2012). Although many collaborations lack helpful behaviors among members, others have a history of helpfulness (e.g., Lioukas and Reuer 2015). We argue that collaborations that have a history of helpfulness will be less affected by the presence of a helpful third (Molm et al. 2012). In these collaborations with pre-existing helpfulness, trust, generosity, and reciprocal exchange—ingredients of strong networks—are already present. We theorize that a helpful third may be less consequential to the social dynamic in these settings precisely because helpful behavior within the collaboration already exists. When helpful behavior is already present, it should not change by adding the marginal helpful person to the group. Thus, we hypothesize the following.

Hypothesis 2 (b). *Among collaborations that lose a third party, the marginal effect of the loss of a helpful third party on collaborative persistence (Hypothesis 1) is larger when the focal dyad did not have a prior history of helpful behavior independent of the third.*

Empirical Tests

Data and Sample

Empirically distinguishing between the mechanisms in our theory is challenging. The effect of helpful behavior and social structure is endogenous and thus challenging to tease apart. A desirable empirical context in which to study collaboration patterns should be one in which (1) collaboration is a common characteristic, (2) a proxy for helpful behavior is readily available in a systematic fashion, and (3) the field is large enough to identify unexpected deaths of third parties, which allow us to exogenously vary collaboration over time. One such setting is the field of academic immunology. In terms of research, immunology is a significant and vital discipline. Its organization is very similar to other medical and biological sciences. Most of the funding also comes from the National Institutes of Health, specifically the National Institute of Allergy and Infectious Diseases (NIAID).

We construct our sample data set from multiple data sources. We measure collaboration activity, tie formation, scientist productivity, and scientist location using data from the ISI Web of Science. For this, we collect bibliometric data on the 639,439 articles published in the 136 ISI Journal Citation Reports-defined immunology journals between the years 1910 and 2010.

We construct helpfulness data using acknowledgment counts from the *Journal of Immunology* (JI) (the preeminent journal within the field of immunology), as in Oettl (2012a). We examine the 50,541 articles published in JI between 1950 and 2007 and apply name-matching algorithms to identify the authors acknowledged in each article. There are, on average, 3.04 acknowledgments per article.

We collect data on immunologist deaths from two sources: (1) the titles of articles within the set of 639,439 immunology articles (such as: "Berenice Kindred 1928–1985") and (2) the "In Memoriam" column of the bimonthly American Association of Immunology newsletter. Whereas we identify 360 immunologists who died between 1978 and 2008, we restrict the sample to scientists with uncommon names (to avoid type II errors) and who had a career age[1] of less than 50 at the time of death (were still research active). Although we do make efforts to exclude authors who likely died of natural causes, there is still a chance that some coauthors may have anticipated some of the deaths. However, any remaining anticipated deaths are likely to bias our results toward zero. After these considerations, we are left with 138 immunologists who passed away during our sample period. We call these the treatment group or the treated k's, and the year of death we call the treatment year.

We construct a set of control immunologists to match these treated immunologists using coarsened exact matching without replacement, following Oettl (2012a). An ideal control immunologist would match a treated immunologist based on the relevant criteria, such as productivity, helpfulness, and age, but differ on their death year. For each of the treated immunologists, we look for similar immunologists based on the following: year of first publication, number of coauthors by the treatment year, number of publications by the treatment year, number of citations received by 2010 for papers written before the treatment year, and the number of acknowledgments received by the treatment year. We then randomly select one control immunologist who is similar along these characteristics for each treated immunologist.

Our empirical methodology is similar to recent studies that make use of the death of individuals to infer spillovers but with important distinctions (Azoulay et al. 2010, Oettl 2012a, Jaravel et al. 2018). Our paper differs from Oettl (2012a), in particular, which studies the question of whether coauthors affect the productivity of an individual focal scientist by looking at the effects of the unexpected death of a coauthor and finds a differential effect between helpful and nonhelpful coauthors. In contrast, our manuscript studies the question of how third parties affect the collaboration of a pair of focal scientists by examining the effect of the unexpected death of a third party. Furthermore, whereas Oettl (2012a) uses an individual scientist as the unit of analysis and the productivity of said scientist as the dependent variable, our manuscript uses a pair of focal scientists as the unit of analysis and the act of publishing a joint paper (collaboration) as the dependent variable, while explicitly controlling for the overall productivity of the individuals in the focal pair. As a result, our empirical design controls for the effects found in Oettl (2012a) while identifying new dimensions by which third parties affect the durability of collaborative ties.

Identifying Authors

Because the study relies on collaboration patterns, we must identify which immunologists are collaborating directly. One limitation of the ISI Web of Science data is that during our study period, the information on authors lists only the first initial, a middle initial (if present), and the last name for each author of a paper. Furthermore, since our empirical objective is to identify collaboration rates, it is first necessary to disambiguate authors (that is, to distinguish B Jones from BL Jones). We rely on heuristics developed by Tang and Walsh (2010) to disambiguate between authors who share the same name. The heuristic considers backward citations of two focal papers. If two papers reference similar papers (inversely weighted by how many times the paper has been cited, i.e., how obscure or famous it is), then the likelihood of the papers belonging to the same author increases, and we link the two papers to the same author. We repeat this process for all papers with authors who have the same first initial and last name, and we exclude scientists who do not have more than two publications linked to their names.

Identifying Triads and Dyads

Our final sample for analysis is constructed as follows. We first look at the intersection of two data sets: our scientist death data set (138 scientists) and our ISI immunology paper data set (639,439 articles). We identify all articles on which the 138 scientists were authors: there are 4,510 of these articles. Next, we identify all authors on these 4,510 articles and identify the set of unique pairs i and j of authors appearing on these 4,510 articles (excluding k). That is, for each article in which one of the treated or control k's participated, we take all of the dyads among the entire coauthor pool and follow them to see how their collaborations evolve. Although the common belief is that large coauthoring teams characterize publishing in immunology, this is not inherently the case in our data. The mean coauthor count (including k) of these 4,510 articles is 4.9, and the median 4. That is, for the median paper, we identify three dyads that do not contain k.[2] From these 4,510 articles, we identify 12,239 dyads l. These 12,239 dyads consist of 1,803 unique scientists (excluding k).

We replicate this process to identify dyads for our control k's. We identify 10,759 dyads for the control k's resulting in a total of 22,998 total dyads across treated and control k's.

Table 1. Summary Statistics for Dying k's

Variable	Mean	Std. dev.	Min.	Max.
Year of Death	2,000.43	5.38	1,983	2,008
Career Age	29.30	11.15	5	50
Coauthors	22.91	26.44	1	169
Publications	46.97	44.43	4	256
Impact-Factor-Weighted Publications	220.55	286.67	10.59	1,913.09
Citations	2,050.91	2,986.34	35	20,923
Acknowledgments	4.04	6.12	0	33
Helpful (0/1)	0.41	N/A	0	1
Productive (0/1)	0.33	N/A	0	1
Helpful and Productive (0/1)	0.23	N/A	0	1
N		138		

We keep all dyads l in the sample until either dyad member i or j has gone three years without publishing a paper, even if that scientist later publishes a paper. We consider these dyads to be at risk for collaborating. Keeping dyads that are not at risk for collaborating in the sample adds a preponderance of zeros and thus downwardly biases our results through attenuation bias. However, we do confirm that our results are robust to relaxing this assumption. We further limit the sample to those dyads that were at risk for collaboration, based on these criteria, at the treatment time, that is, the time of the death of k for the treated k's. Relaxing this assumption and keeping in the sample dyads that had stopped being at risk for collaboration before the treatment time had a minimal effect on the results. Next, we convert this cross-section of l dyads into a panel for every year that the dyad is at risk for collaborating, resulting in a final sample of 192,859. This implies that the mean dyad is at risk for collaborating for 8.4 years.

Variables

The summary statistics for the variables are in Tables 1 and 2, and the cross-correlations in Table A.1 are in the appendix.

ij Collaboration. We created a dummy variable $Collab_{lt}$ to indicate whether a paper was published in the year t that included both members i and j of the dyad l as coauthors. This is our primary dependent variable, and we use it to assess the persistence of collaboration in the dyad.

Death of k. To estimate the effect on the dyad caused by the death of k, we code the variable D_{lt} to indicate the years after the passing of k on the dyad l where k was the third party. Thus, for the dyads involved with the treated k's, this variable is zero up to and including the year of k's passing and then one for the subsequent years. For the dyads involved with the control k's, this variable is always zero.

Acknowledgments of k. Following Oettl (2012a), we consider acknowledgments in papers as a sign that the scientist acknowledged for contributing to the paper without receiving formal coauthorship was helpful. Hence, we measure the treated and control authors' helpfulness by the number of acknowledgments they received by the treatment time. This is a fixed variable for each k.

Helpful k. To simplify the interpretation of three-way interactions, we classify authors as helpful if they were above the median on this count and as nonhelpful if they were below the median. This is a fixed variable for each k.

Dyad Fixed Effects. We control for the stable (time-invariant) characteristics of each dyad using dyad fixed effects. These fixed effects capture the stable

Table 2. Summary Statistics for Full Sample Analysis

Variable	Mean	Std. dev.	Min.	Max.
ij Collaboration	0.14	0.34	0	1
Death of k	0.24	0.42	0	1
Helpful k	0.42	0.49	0	1
Acknowledgments of k	3.38	5.91	0	55
ij Collaboration (3yr)	0.43	0.72	0	3
ij Publications (total) (3yr)	7.84	10.42	0	151
ij Colocation (3yr)	0.41	0.9	0	3
ijk Colocation (3yr)	0.24	0.69	0	3
ijk Publications (joint)	0.73	1.69	0	25
k First Authorships	9.64	8.85	0	66
k Last Authorships	17.44	23.7	0	208
k IF-weighted Publications	223.45	193.58	5.32	1,913.09
k Editor	0.02	0.15	0	1
k Univ Status	390.88	350.36	1	1,000
k Career Age	31.86	11.13	2	54
k Eigenvector Centrality	0.04	0.08	0	0.25
ij Prior Acknowledgments	0.1	0.61	0	15
ij Prior IF-wt Pubs (total)	2.1	12.14	0	546.9
ij Prior IF-wt Pubs (joint share)	0.02	0.1	0	1
k Prior Collab with i or j	0.37	0.48	0	1
ij Knowledge Proximity	0.15	0.21	0	1
Observations		192,859		

characteristics of all three parties, *i*, *j*, and *k*, including (but not limited to) their cohorts, age differentials, and *k*'s productivity and helpfulness.[3]

Calendar Year Dummies. Studies have shown general trends in the likelihood of collaboration over time (e.g., Guimera et al. 2005, Wuchty et al. 2007). One may be concerned that these trends might be confounded with the effect of the passing of *k*. Hence, we include as controls a full set of dummy variables for the calendar years. This is the most flexible and conservative way to control for overall trends in collaboration. Including both *dyad*- and *calendar year*-fixed effects requires that any additional control variables be both dyad-specific and time-varying.

Collaboration Age Dummies. Collaborations have a natural decay over time, and this might be confounded with the passing of *k*. We thus control for the collaboration age with a full set of dummy variables for each year since the first paper on which all of *i*, *j*, and *k* appeared. This is the most flexible and conservative way to control for the age of collaboration. These indicators are time-varying for each dyad *ij*.

Publication Count Dummies. Since the passing of a coauthor might affect the productivity of a scientist (Azoulay et al. 2010, Oettl 2012a), there is a worry that we may confound a drop in overall productivity as reduced collaboration. We control for this possibility using a full set of dummies to capture the time-varying count of the total number of papers that *i* and *j*, the members of the dyad *l*, published in the year *t*. These indicators are time-varying for each dyad *ij*.

Indirect Tie Count Dummies. Since embeddedness in networks can have a substantial effect on collaboration, we control for it with the number of third-party coauthors that *i* and *j* have in year *t*. To account for nonlinearities in this measure, we estimate these tie counts as individual dummy variables. These indicators are time-varying for each dyad *ij*.

Colocation Dummy. Since being located at the same institution is likely to increase the propensity to collaborate, we use a dummy variable indicating whether *i* and *j*, the members of the dyad *l*, were at the same institution at the time *t*. We were unable to establish a location for a number of scientists, and hence all dyads where one of these scientists was a member were assumed to be colocated. We tested the robustness of this assumption by replicating the analysis assuming that all those dyads were not colocated and obtained very similar results. This is a time-varying indicator for each dyad *ij*.

ij Collaboration (3yr). This is similar to the *ij* Collaboration, but we now sum up the three years before the death of *k* to create a time-invariant measure for each dyad. If the collaboration age of the dyad were less than three years, we would sum the available years. This is a fixed variable for each dyad *ij*.

ij Publications (Total) (3yr). We count the total number of publications *i* and *j* published in the three years before the death of *k* to control for the productivity of the dyad. We include all papers in which either *i* or *j* appeared as an author. If the collaboration age of the dyad was less than three years, we sum the available years. This is a fixed variable for each dyad *ij*.

ij Colocation (3yr). This is similar to the colocation dummy, but we now sum up the three years before the death of *k* to create a time-invariant measure for each dyad. If the collaboration age of the dyad was less than three years, we sum the available years. This is a fixed variable for each dyad *ij*.

ijk Colocation (3yr). This is similar to the *ij* Colocation (3yr), but we now include *k* and sum up the three years before the death of *k* to create a time-invariant measure for each dyad of all three *i*, *j*, and *k* being colocated. If the collaboration age of the dyad was less than three years, we sum the available years. This is a fixed variable for each dyad *ij*.

ijk Publications (Joint). Since the intensity of collaboration between an *ij* dyad on the one hand and *k* on the other hand, could be confounded with both helpfulness and dyadic collaboration, we count the total number of papers the triad *ijk* published together before the death of *k*. This is a fixed variable for each dyad *ij*.

i or j Prior Collab with k. A relationship between *i* or *j* and *k* may have existed prior to the triad's formation and thus be influenced by *k*'s type and the durability of the relationship between *i* and *j*. To control for this, we include a dummy set to 1 if either *i* or *j* collaborated with *k* prior to the triad's formation. This is a fixed variable for each dyad *ij*.

ij Knowledge Proximity. Over time, the interests of the members of the dyad *i* and *j* could drift apart. To account for this, we collected data on the research interests of each of the scientists, specifically the MeSH keywords—Medical Subject Headings as defined by the NIH—associated with their publications. Using these, we construct an annual measure of research interest similarity between each of our dyad members *i* and *j*. We define research interest similarity as a correlation coefficient defined as:

$$Knowledge\ Proximity(ijt) = \frac{1}{M} * \sum_{m} (MeSH_{mit} * MeSH_{mjt}),$$

where m ranges over all MeSH keywords and M is the total number of MeSH keywords in the union of i and j's keywords. Thus, the *Knowledge Proximity* measure ranges from 0 to 1. We include this as a time-varying measure through the use of 20 dummies to reflect different levels of it, to account fully for any nonlinearity. However, using a simple linear term did not significantly change the results. We further include a time-invariant measure to capture the proximity between i and j at the time of the death of k and interact it with the death of k.

k First Authorships. Being the first author on a paper often signifies project leadership. Thus the number of papers published as a first author is a clear measure of academic standing and productivity. We count the total number of papers k published as a first author before treatment time. This is a fixed variable for each k.

k Last Authorships. Being the last author on a paper often signifies leadership of the laboratory in which the project took place and which funded the project. Thus, the number of papers published as the last author is a clear measure of academic standing, productivity, and resources. We count the total number of papers k published as the last author before treatment time. This is a fixed variable for each k.

k IF-weighted Publications. Another key measure of academic standing is the total number of papers a scientist has published. We additionally consider the quality of the journals in which these papers were published by weighting each publication with the impact factor of the journal in which it appeared and count all publications in which k appeared as an author before treatment time. This is a fixed variable for each k.

k Editor. Being an editor in the top journal of the field is one of the critical markers of status in the academic community. We create a dummy variable for each k, indicating if the author ever was the editor at the *Journal of Immunology* before treatment time. This is a fixed variable for each k.

k Univ Status. Another key indicator of academic standing and access to resources is the status of the university or research institute with which one is affiliated. We proxy for the university's status within the field of immunology by counting the number of papers in immunology published by scientists affiliated with it.[4] We then sort the universities and number them from 1 onward, capping it at 1,000, with 1 being the highest ranked. In regressions, we take the logarithm of this rank and multiply it by −1 so that higher values correspond to a higher status. We attach each k to the university they were affiliated at the treatment time. This is a fixed variable for each k.

k Career Age. Scholars more advanced in years are often more respected and have access to more resources. We thus count the years from the first paper k published to the treatment year. This is a fixed variable for each k.

k Eigenvector Centrality. A scientist's status is derived from the number of papers published and the other scientists with whom one publishes. We thus calculate the eigenvector centrality for each k in the treatment year based on a 10-year window of publications prior to that time. Given that the networks change over time, we scale the centrality measure so that at each point in time, the most central scientist has centrality measure of 1. This is a fixed variable for each k.

ij Prior Acknowledgments. If helpful k's select to work with helpful i's and j's and those collaborations then are likely to last longer, we may confound the causal effect of the helpfulness of k on the dyad with the care with which the helpful k's select their partners. In our data, we find no evidence that dyads with a helpful third-party differed in terms of their helpfulness before the collaboration with the third party from dyads that had a nonhelpful third party, in line with recent evidence suggesting that individuals do not select partners on this basis (e.g., Simpson et al. 2014). However, we formally take this potential selection process into account in our estimations to further reduce concerns. First, this possibility is, in principle, controlled for by the dyad fixed effects. Additionally, we add as a control variable the interaction of the number of acknowledgments i and j received before the beginning of the triadic collaboration with the passing of k. We use the minimum of the acknowledgments that i and j as individuals had received, but the results are similar if we use the maximum or the average. This is a fixed variable for each dyad ij.

ij Prior IF-weighted Publications (Total). Alternatively, i and j could already be productive scientists and have established a working relationships. Hence, we control the number of papers in which either i or j (or both) appeared as a coauthor prior to the dyad working together with k. We further add weights to the publications based on the journal's impact factor in which they appeared. This is a fixed variable for each dyad *ij*.

***ij* Prior IF-weighted Publications (Joint Share).** An additional possibility is that *i* and *j* were already in a close working relationship. We thus calculate the percentage of all the papers that *i* and *j* published (before the dyad began working with *k*) that were jointly authored. This is a fixed variable for each dyad *ij*.

Methods

We test our theory in two steps. First, we will match carefully between the treatment and control *k*'s to have a balanced sample and do simple split-sample tests to see if we find a differential effect when a helpful *k* passes away versus a nonhelpful *k*. Second, we will use the full sample to examine the effects of various control variables and test the contingent Hypotheses 2(a) and 2(b).

Our broad empirical strategy requires us to estimate both the effect of a collaborator's death and the marginal effect of this death when the collaborator is helpful (or not). This is because if we were only to estimate the effect of death for those helpful versus not helpful, we would be unable to discern the impact of a helpful collaborator in mitigating the negative impact of a coauthor's death. As previously discussed, we include control/counterfactual *k*'s and dyads (units that are never treated) in our specifications to reduce estimate bias in line with recent work (Goodman-Bacon 2021).

Thus, our empirical strategy depends on leveraging unexpected deaths, as they are unlikely to be correlated with factors in the error term. For instance, deaths that were anticipated by collaboration partners may have affected their collaboration patterns in anticipation of *k*'s passing many years before the event, thus potentially biasing our results. We build on the strategy used by Azoulay et al. (2010), Oettl (2012a), and Jaravel et al. (2018).

Table 3. Balance Test for Matched Dyads at the Time of *k*'s Death

Variable	Sample means: Treated *k*'s	Sample means: Control *k*'s	Variance Ratio
ij Collaboration (3-yr sum)	0.201	0.201	1.00
ij Publications (total) (3-yr sum)	4.024	3.980	1.03
ij Colocation (3-yr sum)	0.052	0.052	1.00
ijk Colocation (3-yr sum)	0.031	0.032	1.04
Collaboration Age	3.260	3.279	1.04
Death Year of k	2,000.134	2,000.134	1.00
Helpful k	0.516	0.516	
Productive k	0.575	0.580	
Observations	4,601	8,134	

Notes. No difference is statistically significant. If collaboration had lasted less than three years, the three-year sums include only the available years.

Testing Hypothesis 1

Even though we carefully match the treatment and control *k*'s, there is no reason a priori to expect the triads where the *k*'s were members to be fully balanced across the treatment and control groups. We address this concern using the coarsened exact matching (CEM) algorithm (Blackwell et al. 2009, Iacus et al. 2012). This allows us to find treated dyads for which a similar control dyad can be found and assign weights to each dyad to obtain a balanced sample. We match dyads at the treatment time, that is, the time of *k*'s passing for the treatment group and the matched time for the control group, and then apply these weights for the dyad's entire life. From our initial sample of 12,239 treated dyads, we can find matches for 4,601 of them.

Table 3 presents the test of balance at the treatment time. As can be seen, the dyads are balanced both in terms of the sample means as well as variances on all of the variables considered: (1) the rate of their collaboration in the past three years, (2) the number of papers they individually published in the previous three years, (3) whether the members of the *ij* dyad were at the same institution over the three years before the death of *k*, (4) whether the members of the *ijk* triad were at the same institution over the past three years, (5) the years since the triadic collaboration began, (6) the treatment year, (7) the dummy indicating whether *k* was helpful, and (8) a dummy indicating whether *k* was above the median in terms of the number of papers published, labeled a productive *k*. The treatment and control groups appear well balanced, with no difference statistically significant.

In the split-sample regressions, we estimate the following model:

$$Collab_{lt} = \beta D_{lt} + \sum_{m} \gamma_m X_{ltm} + \phi_l + \eta_t + \theta_{lt} + \epsilon_{lt}, \qquad (1)$$

where $Collab_{lt}$ is a dummy variable indicating whether the dyad l published a paper together in year t, D_{lt} is a dummy indicating whether the third party k in the dyad l had passed away by time t, X_{ltm} is a series of control variables, ϕ_l is a vector of dyad l fixed effects, η_t is a vector of fixed effects for the calendar year t, θ is a vector of collaboration age dummies, and ϵ_{lt} is the error term. We further add dummy variables for the publication count of the dyad, the indirect tie count of the dyad, and the colocation dummy for the dyad. A statistically significant value for the parameter β indicates that the death of k affected the rate of collaboration in the dyad l. Our preferred estimation method is the linear probability model, that is, ordinary least squares (OLS), since it allows for a straightforward interpretation of interactions, on which we rely heavily.[5] We confirm that the results are robust to using the logit estimator.

A key issue in regressions dealing with network data is the handling of network dependency (Snijders 2011). We use a variant of the Lindgren (2010) model to deal with this concern. Similar models have been used, for instance, by Kleinbaum et al. (2013) as well as van Miltenburg et al. (2012). Lindgren (2010) clusters separately by each member i and j of each dyad and thus assumes that dyads with a shared member can show correlation, but dyads without a shared member are independent. Whereas Lindgren (2010) demonstrates through simulation that this method works very well in large data sets, such as ours, Snijders (2011) expresses concern that the assumption in the Lindgren (2010) model that two dyads are independent if they do not share a member may not always be satisfied in practice.

Our data have two potential sources of network dependency through overlap: (1) through the individuals who might be involved in multiple dyads and (2) through the multiple dyads that are linked to the same k. In our data, approximately 10% of individual i's and j's work with more than a single k, but there are no ij-dyads linked to more than one k. Hence, we assume two dyads to be independent only if they do not share a common member and are associated with different k's. We correct our standard errors by three-way clustering to deal with these dependencies at the i, j, and k levels.[6] Thus, our assumption is much weaker than the assumption Lindgren (2010) makes and hence less susceptible to the criticism by Snijders (2011).

We begin by testing Hypothesis 1: whether collaborations bridged by helpful thirds will survive longer than those bridged by nonhelpful thirds. The split-sample results are presented in Table 4. Model (1) uses the full matched sample arising from the 12,735 matched treated and control dyads described in Table 3. We find a negative but not significant effect from the death of k on the level of collaboration in the dyad. In Model (2), we only include those dyads that were connected to a nonhelpful k. The result is stronger and negative, with the death of k driving a 9.4 percentage point decrease in the probability of collaborating in a given year. Given that the mean likelihood of any of our ij coauthors collaborating in a given year is 0.14, this 0.094 reduction corresponds to a 67% reduction in the likelihood of collaborating in a given year.

In Model (3), we consider only those dyads that were connected to a helpful k and find a positive and significant coefficient. In Models (4) through (6), we add more fixed effects. First, we control for the productivity of the members of the dyad. Second, we control for the network embeddedness of the dyad. Third, we control for the colocation of the dyad members. These have a marginal effect in Model (4), comparing it with Model (1). Model (5) shows a slightly larger negative impact than Model (2). The positive and significant effect in Model (3) has entirely disappeared in Model (6). As such, whereas collaboration rates decline after the death of nonhelpful k's, they do not when the k is helpful. In concert, these results paint a clear picture of the differential effects from the passing of helpful versus nonhelpful third parties and provide supportive evidence for Hypothesis 1.

Robustness Tests for Hypothesis 1

To consider the effects of a range of additional control variables and to study the contingent Hypotheses 2(a) and 2(b), we return to the full sample. We use the same regression model as in Equation (1), but add interactions of the death of k with time-invariant characteristics of the dyad or k. Since all these stable characteristics are entirely collinear with the dyad fixed effects by design, we cannot include their main effects in the regressions. Hence, only

Table 4. Propensity of i and j to Collaborate—Matched Sample Analysis

	(1) All k's	(2) Nonhelpful k's	(3) Helpful k's	(4) All k's	(5) Nonhelpful k's	(6) Helpful k's
Death of k	−0.036	−0.094***	0.030**	−0.045	−0.116***	0.010
	(0.053)	(0.035)	(0.014)	(0.034)	(0.038)	(0.008)
Dyad fixed effects	Y	Y	Y	Y	Y	Y
Calendar year dummies	Y	Y	Y	Y	Y	Y
Collaboration age dummies	Y	Y	Y	Y	Y	Y
Levels of proximity dummies	N	N	N	Y	Y	Y
Publication count dummies	N	N	N	Y	Y	Y
Indirect tie count dummies	N	N	N	Y	Y	Y
Colocation dummy	N	N	N	Y	Y	Y
R^2	0.357	0.422	0.290	0.548	0.653	0.403
Observations	99,837	52,339	47,498	99,804	52,309	47,457

Note. Robust standard errors in parentheses, clustered by i, j, and k.
$^{**}p < 0.05$; $^{***}p < 0.01$.

Table 5. Propensity of *i* and *j* to Collaborate—Full Sample Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Death of k	−0.024	−0.108**	−0.094**	−0.062***	−0.062***	−0.123***	−0.063***	−0.124***
	(0.045)	(0.047)	(0.037)	(0.021)	(0.021)	(0.029)	(0.021)	(0.029)
Death of k × Helpful k		0.149***	0.084***	0.045**	0.047**	0.125***	0.048**	0.126***
		(0.044)	(0.027)	(0.021)	(0.021)	(0.043)	(0.021)	(0.044)
Death of k × ij Collaboration (3yr)			−0.149***	−0.138***	−0.137***	−0.136***	−0.136***	−0.135***
			(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
Death of k × ij Publications (total) (3yr) (log)			0.038**	0.041***	0.042***	0.042***	0.042***	0.042***
			(0.015)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Death of k × ij Colocation (3yr)			0.011	0.011	0.013*	0.012	0.013	0.012
			(0.009)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)
Death of k × ijk Colocation (3yr)			0.035	0.029	0.027	0.024	0.027	0.024
			(0.023)	(0.020)	(0.018)	(0.018)	(0.018)	(0.018)
Death of k × ijk Publications (joint) (log)			−0.149**	−0.143**	−0.145**	−0.139*	−0.145**	−0.138*
			(0.070)	(0.068)	(0.071)	(0.072)	(0.071)	(0.072)
Death of k × i or j Prior Collab with k			0.010	0.016	0.013	0.014	0.014	0.015
			(0.018)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
Death of k × ij Knowledge Proximity			0.156**	0.068	0.070	0.067	0.068	0.065
			(0.067)	(0.059)	(0.071)	(0.075)	(0.071)	(0.075)
Death of k × k First Authorships (log)				0.047***	0.047***	0.031***	0.048***	0.032***
				(0.012)	(0.012)	(0.011)	(0.012)	(0.011)
Death of k × k Last Authorships (log)				−0.023	−0.024	−0.051***	−0.023	−0.050***
				(0.016)	(0.015)	(0.014)	(0.016)	(0.015)
Death of k × k IF-weighted Publications (log)				0.016	0.016	0.046**	0.015	0.045**
				(0.022)	(0.022)	(0.019)	(0.022)	(0.019)
Death of k × k Editor				−0.089***	−0.091***	−0.091***	−0.088***	−0.088***
				(0.027)	(0.027)	(0.028)	(0.027)	(0.028)
Death of k × k Univ Status (log)				−0.015***	−0.016***	−0.004	−0.016***	−0.004
				(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
Death of k × k Career Age (log)				−0.067***	−0.064***	−0.027	−0.064***	−0.027
				(0.021)	(0.021)	(0.016)	(0.021)	(0.017)
Death of k × k Eigenvector Centrality				0.025	−0.004	−2.822***	−0.014	−2.830***
				(0.211)	(0.221)	(0.921)	(0.223)	(0.936)
Death of k × ij Prior Ack's (log)					0.015	0.018**	0.034***	0.038***
					(0.010)	(0.008)	(0.008)	(0.010)
Death of k × ij Prior IF-wt Pubs (total) (log)					−0.023*	−0.023*	−0.023*	−0.023*
					(0.012)	(0.012)	(0.012)	(0.012)
Death of k × ij Prior IF-wt Pubs (joint share) (log)					0.172***	0.185***	0.176***	0.188***
					(0.051)	(0.053)	(0.051)	(0.053)
Death of k × Helpful k × k Eigenvector						2.839***		2.838***
						(1.020)		(1.037)
Death of k × Helpful k × ij Prior Ack's (log)							−0.064***	−0.064***
							(0.014)	(0.016)
Death of helpful k		0.0404	−0.0104	−0.0177	−0.0152	0.0023	−0.0153	0.0022
		(0.0332)	(0.0408)	(0.0281)	(0.0275)	(0.0301)	(0.0274)	(0.0301)
Dyad fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Calendar year dummies	Y	Y	Y	Y	Y	Y	Y	Y
Collaboration age dummies	Y	Y	Y	Y	Y	Y	Y	Y
Levels of proximity dummies	Y	Y	Y	Y	Y	Y	Y	Y
Publication count dummies	Y	Y	Y	Y	Y	Y	Y	Y
Indirect tie count dummies	Y	Y	Y	Y	Y	Y	Y	Y
Colocation dummy	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.548	0.551	0.564	0.565	0.565	0.566	0.565	0.566
Observations	192,859	192,859	192,859	192,859	192,859	192,859	192,859	192,859

Notes. Interacted variables are measured at the time of the death of *k* and mean-centered except dummy variables. If collaboration had lasted less than three years, the three-year sums include only the available years. Robust standard errors are in parentheses, clustered by *i*, *j*, and *k*.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

interactions with time-varying variables, specifically Death of *k*, are included.

The results are presented in Table 5. In Model (1), we estimate only the main effect of the Death of *k* and find a nonsignificant negative result. In Model (2), we add the interaction with the Helpful *k* dummy variable and now find that the Death of *k*, effectively corresponding to nonhelpful *k*'s, is negative and significant as in the split-sample regression. The interaction term, corresponding to the difference of helpful and nonhelpful k's is positive and significant. At the bottom of the table, we calculate the total effect as the sum of these two and its statistical significance. We find a slightly positive, but nonsignificant result.

In Models (3) through (5), we add a range of control variables to remove any effects of potential confounds. We do this by adding control variables as interactions with the Death of k. Notice that we cannot add their main effect, since, by construction, they are time-invariant properties of the dyad in question or k (and hence of all dyads connected to k). They are thus entirely collinear with the dyad fixed effects and cannot be estimated.

First, we may be concerned that the dyads connected to helpful and nonhelpful might differ in their collaboration intensity. That is, there may be additional confounders that bias our main effect. We therefore control for a range of measures capturing the intensity of collaboration: an actual measure of collaboration, the number of papers they published, whether they have been colocated recently as a dyad or as a triad with k, and the number of articles published together with k. The coefficients are as expected. Regression to the mean would suggest that more intense periods of collaboration are followed by less intense, as evidenced by the first control variable. More productive scholars, as well as colocated scholars, tend to work together. Lastly, dyads that were more dependent on k for writing papers tend to work less together. The main variables of interest, however, shrink in magnitude but retain their signs and significance.

Another potential concern could be that acknowledgments do not represent a good measure of helpfulness. First, acknowledgments in a top journal could be a noisy measure of helpfulness, thereby inflating our standard errors, and reducing the likelihood we find an effect at all. Second, these measures could correlate with the resources a scientist has available rather than the willingness to help per se. Third, one could acknowledge someone because of their high status and wish to earn favor rather than because they were helpful. Fourth, acknowledgments could also signify asymmetric power relations and deference to authority. All three mechanisms are in effect related to the academic status of the third party. Hence, we control for the status of k in as many ways as possible by adding controls for first authorship, last authorships, impact-factor-weighted publications, editorship, university status, career age, and eigenvector centrality. As a result of adding these controls as interactions in Model (4), we notice that both the main effect of the death of k and the interaction with helpful k decrease somewhat in magnitude but remain statistically significant. The total impact of the death of a helpful k becomes slightly more negative but is still clearly not significant.

One could also be concerned that the helpfulness of k is the result of intense collaboration in the dyad or the triad rather than its cause. Although we cannot entirely disentangle the microsequence of events, we can consider the characteristics of the collaboration between i and j before the dyad collaborated with k. We do this by controlling for the acknowledgments i and j had received before they collaborated with k, for the number of papers i and j had published in total, and for the share of their total publications that were joint publications. These cover the range of aspects of their overall helpfulness, the intensity of their collaboration, and their standing in the academic community. In Model (5), we add these as interactions and find that the effects of the death of k, both helpful and nonhelpful, are little changed.

Testing Hypotheses 2(a) and 2(b)

We then turn to examine the contingent Hypotheses 2(a) and 2(b). We use the eigenvector centrality of k as the key measure of status and the prior acknowledgments of i and j as the measure of prior helpful behavior. If the coefficient for the three-way interaction of Death of $k \times$ Helpful $k \times k$ Eigenvector is positive and significant, we consider it evidence in support of Hypothesis 2(a). If the coefficient for the three-way interaction of Death of $k \times$ Helpful $k \times ij$ Prior Acknowledgments is negative and significant, we consider it evidence in support of Hypothesis 2(b). We examine each hypothesis separately in Models (6) and (7) as well as jointly in Model (8). As can be seen, the results are clearly in support of the hypotheses. In both Models (6) and (8), the coefficient of Death of $k \times$ Helpful $k \times k$ Eigenvector is positive and significant, which supports Hypothesis 2(a). Also, in both Models (7) and (8), the coefficient of Death of $k \times$ Helpful $k \times ij$ Prior Acknowledgments is negative and significant, which supports Hypothesis 2(b).

In Table 6, we consider additional robustness tests to increase our confidence in these results. First, we have simplified the analysis and enabled the interpretation of three-way interactions by dichotomizing helpfulness. In Model (1), we replicate the results of the previous table but with the count of acknowledgments of k as the measure of helpfulness rather than a dummy. The pattern of results is not changed, including the signs and significance of the key variables. Second, one may be concerned that the three-way interactions we presented are not robust to the presence of the other control variables in similar three-way interactions. In Model (2), we include an interaction of all the control variables with the two-way interaction of the Death of $k \times$ Helpful k. Although the coefficients

Table 6. Propensity of i and j to Collaborate—Robustness Tests

	(1) Count	(2) Saturated	(3) 5 years	(4) All years	(5) Logit
Death of k	−0.076***	−0.130***	−0.067***	−0.034**	−3.099***
	(0.022)	(0.034)	(0.021)	(0.016)	(0.479)
Death of k × k Ack's (log)	0.108**				
	(0.044)				
Death of k × Helpful k		0.155***	0.080**	0.035***	4.542***
		(0.046)	(0.031)	(0.013)	(0.720)
Death of k × ij Collaboration (3yr)	−0.136***	−0.053	−0.128***	−0.131***	−1.084***
	(0.021)	(0.063)	(0.023)	(0.012)	(0.165)
Death of k × ij Publications (total) (3yr) (log)	0.043***	0.048***	0.027***	0.010***	0.439***
	(0.011)	(0.010)	(0.004)	(0.003)	(0.141)
Death of k × ij Colocation (3yr)	0.013	0.014*	0.002	−0.007***	0.185
	(0.008)	(0.007)	(0.006)	(0.002)	(0.114)
Death of k ×ijk Colocation (3yr)	0.023	0.033*	0.018	0.010***	0.150
	(0.019)	(0.017)	(0.013)	(0.003)	(0.138)
Death of k × ijk Publications (joint) (log)	−0.139*	−0.368***	−0.122*	−0.090***	−0.207
	(0.073)	(0.109)	(0.062)	(0.026)	(0.137)
Death of k × i or *j Prior Collab with k*	0.015	0.017	0.018**	0.008*	0.285
	(0.012)	(0.016)	(0.008)	(0.005)	(0.221)
Death of k × ij Knowledge Proximity	0.067	0.065	0.007	−0.023	−0.891*
	(0.075)	(0.048)	(0.062)	(0.033)	(0.524)
Death of k ×k First Authorships (log)	0.036***	−0.000	0.020**	0.009*	0.463*
	(0.012)	(0.013)	(0.009)	(0.005)	(0.259)
Death of k × k Last Authorships (log)	−0.042***	−0.021	−0.043***	−0.020***	−0.883**
	(0.015)	(0.014)	(0.012)	(0.006)	(0.352)
Death of k × k IF-weighted Publications (log)	0.035	0.042*	0.038**	0.019***	0.960**
	(0.021)	(0.021)	(0.017)	(0.007)	(0.405)
Death of k × k Editor	−0.089***	−0.820***	−0.077***	−0.045***	−0.874
	(0.031)	(0.098)	(0.021)	(0.011)	(0.563)
Death of k × k Univ Status (log)	−0.007	0.004	−0.001	−0.002	−0.133
	(0.006)	(0.008)	(0.005)	(0.002)	(0.098)
Death of k × k Career Age (log)	−0.034**	−0.007	−0.028*	−0.025***	−1.123**
	(0.017)	(0.027)	(0.014)	(0.007)	(0.492)
Death of k × k Eigenvector Centrality	−1.541**	−2.729***	−1.563**	−1.226**	−91.818***
	(0.620)	(0.995)	(0.691)	(0.539)	(17.471)
Death of k × ij Prior Ack's (log)	0.021***	0.024***	0.001	−0.006	0.840*
	(0.005)	(0.008)	(0.005)	(0.004)	(0.462)
Death of k × ij Prior IF-wt Pubs (total) (log)	−0.023*	−0.039***	−0.014*	−0.008**	0.083
	(0.012)	(0.015)	(0.008)	(0.004)	(0.105)
Death of k × ij Prior IF-wt Pubs (joint share) (log)	0.187***	0.149*	0.142***	0.049***	1.301
	(0.053)	(0.087)	(0.041)	(0.014)	(0.856)
Death of k × k Ack's (log) × k Eigenvector	2.474**				
	(1.088)				
Death of k × k Ack's (log) × ij Prior Ack's (log)	−0.028***				
	(0.009)				
Death of k × Helpful k × k Eigenvector		2.838***	1.553**	1.170**	92.862***
		(1.037)	(0.752)	(0.466)	(17.896)
Death of k × Helpful k × ij Prior Ack's (log)		−0.050***	−0.016	0.002	−1.090**
		(0.013)	(0.012)	(0.008)	(0.516)
Death of k × Helpful k ×ij Collaboration (3yr)		−0.088			
		(0.068)			
Death of k × Helpful k × ij Publications (total) (3yr) (log)		−0.030**			
		(0.012)			
Death of k × Helpful k × ij Colocation (3yr)		−0.004			
		(0.011)			
Death of k × Helpful k × ijk Colocation (3yr)		−0.031*			
		(0.018)			
Death of k × Helpful k × ijk Publications (joint) (log)		0.334***			
		(0.106)			
Death of k × Helpful k × i or j Prior Collab with k		0.003			
		(0.022)			
Death of k × Helpful k × ij Knowledge Proximity		−0.045			

Table 6. (Continued)

	(1) Count	(2) Saturated	(3) 5 years	(4) All years	(5) Logit
		(0.100)			
Death of k × Helpful k × k First Authorships (log)		0.034**			
		(0.016)			
Death of k × Helpful k × k Last Authorships (log)		−0.029			
		(0.024)			
Death of k × Helpful k × k IF-weighted Publications (log)		−0.011			
		(0.031)			
Death of k × Helpful k × k Editor		0.770***			
		(0.101)			
Death of k × Helpful k × k Univ Status (log)		−0.001			
		(0.009)			
Death of k × Helpful k × k Career Age (log)		−0.020			
		(0.039)			
Death of k × Helpful k × ij Prior IF-wt Pubs (total) (log)		0.035**			
		(0.016)			
Death of k × Helpful k × ij Prior IF-wt Pubs (joint share) (log)		0.003			
		(0.103)			
Dyad fixed effects	Y	Y	Y	Y	Y
Calendar year dummies	Y	Y	Y	Y	Y
Collaboration age dummies	Y	Y	Y	Y	Y
Levels of proximity dummies	Y	Y	Y	Y	Y
Publication count dummies	Y	Y	Y	Y	Y
Indirect tie count dummies	Y	Y	Y	Y	Y
Colocation dummy	Y	Y	Y	Y	Y
R^2	0.566	0.569	0.522	0.464	
Observations	192,859	192,859	306,202	660,509	192,859

Notes. Interacted variables are measured at the time of the death of k and mean-centered except dummy variables. If collaboration had lasted less than three years, the three-year sums include only the available years. Robust standard errors are in parentheses, clustered by i, j, and k.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

related to the hypothesized three-way interaction effects decrease in magnitude, they retain the same sign and significance.

As explained in the data construction section, we follow each dyad for three years after the last paper by one of the dyad members and consider in this time the dyad to be at risk for collaborating. In Models (3) and (4), we relax this assumption first by following the dyad for five years and then until the end of the data sample. The expected result of adding more almost entirely zero observations is that all coefficients move toward zero. This clearly happens. Interestingly, the three-way interaction, including Prior Acknowledgments of i and j, goes to zero. Given that following the dyad longer means that we are moving further away from the time before the collaboration with k when this variable was the measure, this is also an expected result. Finally, in Model (5), we use the fixed-effects logit estimator instead of the OLS. The results are very similar to the OLS results.

Summary of Results

In summary, the results indicate strong support for the hypotheses and suggest that dyads with third-party collaborators who are helpful are more durable. However, the third party's effect seems to depend on the third's status and the nature of the dyad prior to the collaboration. In particular, high-status, helpful collaborators have a more substantial impact, and dyads that were helpful and strongly collaborative prior to working with the third party have a weaker effect. There were two key empirical challenges that we tackled in establishing these results.

First, the dyads ij are not randomly assigned to the third party k; in particular, the helpful k's may have chosen, on average, more collaborative dyads ij. As stated earlier, the dyad fixed effects used in the regression models, as well as the extensive controls, take explicitly into account many potential deviations from random assignment. Furthermore, we found no evidence that dyads with a helpful third party differed in terms of their helpfulness before collaborating with the third party from dyads that had a nonhelpful third party. And finally, we argue and provide evidence that dyads with a history of strong pre-existing collaboration are less affected by the third party k. Hence, the remaining effect is not driven by dyad-level differences before collaborating with k.

Second, acknowledgments might not measure helpfulness but could instead be acknowledgments of status or reflect the resources available to k. Since high status and resources are highly correlated, these two

Table 7. Change in *i*'s Helpfulness

	(1)	(2)	(3)
Prior Papers by i (log)	−0.068	−0.076*	−0.074*
	(0.045)	(0.044)	(0.045)
Prior IF-weighted papers by i (log)	0.133***	0.138***	0.134***
	(0.028)	(0.028)	(0.028)
Prior Forward Cites to i (log)	0.025*	0.024*	0.026*
	(0.015)	(0.014)	(0.014)
Acknowledgments of k (log)	0.095***	0.082***	0.018
	(0.022)	(0.025)	(0.028)
Exposure of i to k		0.017***	0.010**
		(0.005)	(0.005)
Exposure of i to k × Ack's of k (log)			0.004***
			(0.001)
Prior Acknowledgments of *i* dummies	Y	Y	Y
i Career Age dummies	Y	Y	Y
Initial coauthoring calendar year dummies	Y	Y	Y
R^2	0.647	0.652	0.654
Observations	4,073	4,073	4,073

Note. Robust standard errors are in parentheses, clustered by *i* and *k*.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

are effectively the same concern. If acknowledgments were simply reflections of the third party's status, that is, scientists either strategically or reflexively acknowledged high-status others in their field, we would expect those acknowledgments to have less effect. We argue in Hypothesis 2(a) and find in the regressions the opposite: a high-status *k* who has received lots of acknowledgments seems to have a greater impact on the dyad, not a lesser impact. Furthermore, we have measured status in as many ways as possible (e.g., university status, past productivity, and network centrality) and find a consistent pattern in the results.

Mechanism Tests

As a further piece of supportive evidence, in Table 7, we consider how the measure of a scientist's helpfulness changes when the individual collaborates with a helpful coauthor. The observations here are *ik* interactions, where we limit ourselves to the *k*'s who passed away. The dependent variable here is the logarithm of the number of acknowledgments *i* had received by the time of *k*'s death, and we control for a range of factors that may have led *k* to start collaborating with *i*. First, we include full sets of dummies for the number of acknowledgments *i* received before the beginning of the collaboration, for *i*'s career age (i.e., years since first paper) when the collaboration began, and for the calendar year in which the collaboration started. Second, we control for the number of papers *i* published before the collaboration, the impact-factor weighted number of papers, and the citations *i* had. We use OLS to estimate and use robust standard errors clustered by *i* and *k*, both members of the dyads in question. Because we control for prior acknowledgments of *i*, we can interpret the point estimates as changes in helpfulness.

Model (1) shows that working with a helpful coauthor is associated with an increase in the focal scientist's helpfulness measure. Models (2) and (3) then add a consideration for the duration of the interaction, the exposure of *i* to *k*, that is, the time from the first paper published by *i* and *k* together to *k*'s passing. This time period is exogenous to the interaction and thus gives us more confidence that the results are causal; in other words, working with a helpful coauthor leads to an increase in the focal scientist's helpfulness. In particular, the results in Model (3) show that the longer *i* worked with a helpful *k*, the more helpful *i* was likely to become. The main effect of exposure of *i* to *k* captures the fact that any more extended interaction is more likely to be associated with increased acknowledgments than a shorter interaction. However, there is a real effect coming from being exposed to a helpful coauthor.[7] One concern here is that helpful *k*'s select more helpful *i*'s for collaboration. Although this could be the case, we control for it as much as possible by including a very flexible specification of the helpfulness of *i* before collaborating with *k* and by considering how the increase in *i*'s measured helpfulness correlates with the exogenously determined period of time of collaboration with *k*.

In summary, the results support our three hypotheses and allow us to rule out the null hypotheses. We have considered an extensive range of alternative explanations and potential statistical issues, showing that the results are robust. The findings indicate a clear difference in the durability of collaborations when the third party was helpful versus when not. Furthermore, this effect is positively moderated by the third party's status and negatively moderated by the prior helpfulness of the dyad in question.

Discussion and Conclusion

Why do some collaborations persist and others decay? We propose that collaborators who have previously worked with a helpful third party relative to a nonhelpful one will have more enduring collaborations. We test this hypothesis in the context of scientific collaboration by examining collaborative persistence among several thousand pairs of research immunologists who lost a third collaborator due to unexpected death.

We find that dyads whose departed third collaborator was helpful—as indicated by acknowledgments in journal articles—continue to collaborate after the death of their third. In contrast, dyads, who lost a nonhelpful third, experienced a 12% decline in their probability of repeat collaboration. Furthermore, we find that the effect of third-party helpfulness was particularly strong when the third was of high status and when a pair of collaborators did not have a history of helpful behavior. Our results are robust to many alternative specifications. They persist even when we account for both unobserved and observed dimensions of heterogeneity across dyads and other third parties' characteristics, including their status, age, productivity, and prominence.

Perhaps the primary stream of research to which our findings contribute is the research on collaboration. Researchers have made considerable progress on understanding the factors driving the formation of new collaborations (e.g., Boudreau et al. 2017, Catalini 2018, Chai and Freeman 2019, Lane et al. 2021) and their consequences on interaction and performance (Sytch and Tatarynowicz 2014, Uribe et al. 2020). Unlike much prior work, our research takes existing collaborations as our starting point and ask: why do some ties endure, and others do not (e.g., Burt 2000, Dahlander and McFarland 2013)? Answering this question is both important and challenging. Persistent, repeated interaction has been recognized as a sign of a healthy relationship and has also been linked to trust, altruism, joint problem solving, and exchange of goods and information (Uzzi 1996, 1997; DiMaggio and Louch 1998; Gulati and Gargiulo 1999; Uzzi and Lancaster 2004; Rivera et al. 2010). Past studies have argued that dyads embedded in triads are more likely to endure (e.g., Krackhardt 1998, 1999). Building on the work of Dahlander and McFarland (2013) and Krackhardt (1998), we identify an important contingency in a well-established finding: that third parties lead to more stable connections. Our theory and results extend this work, questioning the implicit assumption in this work that thirds are homogeneous and thus impact their networks uniformly. We show that thirds vary in important ways—in our case, their helpfulness—and this has implications for how thirds affect network ties. In this way, the departure of a helpful third party, which instilled helpful behavior in the triad, increases the likelihood of the remaining ties enduring compared with when a departed third was not helpful. The durability of collaboration, thus, also stems from a combination of behaviors and structural ties. This finding also suggests a possible mechanism through which network structure varies over time due to early imprinting of behaviors or norms that may shape interaction (e.g., Marquis 2003). This interaction, in turn, is likely to drive the structure of social networks and potentially their long-term durability. Future research should consider the different ways in which early behavioral changes can affect network structure more broadly. These mechanisms may be useful in thinking about how to change network dynamics, particularly in conflict-prone situations (e.g., Paluck et al. 2016).

Theoretically, our article also identifies a unique property of our mechanism. Our findings suggest that individuals' helpful behavior—in our case, third parties in scientific collaborations—can help ignite and encourage helpful behavior in others and lead to the endurance of their collaborations. Thus the increase in tie durability we observe is simply the first-order effect; it does not capture the transfer of future helpfulness from these dyad members to subsequent individuals through their newly formed network ties. As such, helpfulness may constitute a positive externality as it is a property that will propagate through the network.

We also see several important directions for future research. Our present study has not theorized about third parties who play a negative role in a relationship. Third parties in our data are either helpful or nonhelpful; thus, we do not speculate about nor test the negative impact that third parties can have on social groups (Labianca and Brass 2006). Negative interactions, though relatively less common in organizational settings, can create distrust among collaborators. Beyond closed triads, in environments where the two structurally equivalent alters monitor each other, a third party engaging in deleterious behavior could potentially establish ongoing rivalry or even animosity between the alters that might endure beyond the presence of the third party. Thus, third parties can play a multifaceted role within triads and larger network structures. Many avenues for exciting research remain to be investigated to understand more clearly the positions they represent.

We also see possibilities for understanding how the behaviors we observe taking root in small triads spread through larger structures (Centola et al. 2005).

Table A.1. Cross-correlation Table

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1 *ij Collaboration*	1.00																				
2 *Death of k*	−0.15	1.00																			
3 *Helpful k*	−0.10	0.12	1.00																		
4 *Acknowledgments of k*	−0.06	−0.00	0.58	1.00																	
5 *ij Collaboration (3yr)*	0.38	−0.06	−0.17	−0.10	1.00																
6 *ij Publications (total) (3yr)*	−0.00	−0.03	0.19	0.15	0.07	1.00															
7 *ij Colocation (3yr)*	0.24	−0.10	−0.04	−0.02	0.49	0.04	1.00														
8 *ijk Colocation (3yr)*	0.17	−0.10	−0.13	−0.08	0.38	−0.04	0.70	1.00													
9 *ijk Publications (joint)*	0.26	−0.03	−0.08	−0.05	0.46	0.06	0.27	0.32	1.00												
10 *k First Authorships*	−0.09	0.13	0.55	0.23	−0.17	0.10	−0.07	−0.10	−0.05	1.00											
11 *k Last Authorships*	−0.04	0.00	0.41	0.36	−0.09	0.19	0.05	−0.00	0.03	0.41	1.00										
12 *k IF-weighted Publications*	−0.07	0.04	0.61	0.66	−0.13	0.19	−0.02	−0.10	−0.03	0.49	0.78	1.00									
13 *k Editor*	−0.02	−0.04	0.18	0.45	−0.05	0.06	−0.01	−0.04	−0.04	0.08	0.08	0.24	1.00								
14 *k Univ Status*	−0.01	−0.12	0.09	−0.06	−0.08	0.10	0.02	−0.03	−0.09	0.13	0.09	0.04	0.01	1.00							
15 *k Career Age*	−0.08	0.25	0.35	0.13	−0.10	−0.11	−0.21	−0.21	−0.07	0.38	0.08	0.28	−0.00	−0.08	1.00						
16 *k Eigenvector Centrality*	−0.12	0.31	0.33	−0.01	−0.17	−0.21	−0.21	−0.17	−0.14	0.49	−0.08	0.12	−0.08	0.02	0.70	1.00					
17 *ij Prior Acknowledgments*	−0.03	0.03	−0.00	0.02	−0.04	0.11	−0.05	−0.04	−0.02	−0.03	−0.03	0.00	0.02	−0.01	−0.00	−0.02	1.00				
18 *ij Prior IF-wt Pubs (total)*	0.09	−0.04	0.06	0.05	0.13	0.19	0.14	−0.01	−0.03	0.03	0.05	0.04	0.04	0.05	−0.05	−0.08	0.06	1.00			
19 *ij Prior IF-wt Pubs (joint share)*	0.11	−0.05	0.01	0.01	0.16	0.04	0.21	0.07	−0.01	0.00	0.00	−0.01	0.00	0.05	−0.08	−0.08	−0.01	0.43	1.00		
20 *k Prior Collab with i or j*	0.04	−0.09	−0.02	0.08	−0.04	0.05	0.04	0.12	0.08	−0.12	0.18	0.09	0.03	−0.03	−0.25	−0.33	−0.02	−0.09	−0.13	1.00	
21 *ij Knowledge Proximity at k death*	0.18	−0.04	0.24	0.16	0.27	0.20	0.28	0.08	0.15	0.17	0.23	0.20	0.04	0.15	−0.15	−0.14	−0.03	0.26	0.33	0.01	1.00

Note. Since the regressions use a large number of fixed effects, these unconditional raw correlations should be interpreted with caution.

Obstfeld (2005) argues that a larger group may need a sufficient distribution of tertius iungens skill—the ability to bring people together—to foster adequate connectivity and mobilize for collective action. Our article complements this argument and suggests that adequate distribution of collaboratively oriented actors may be necessary for the emergence of large-scale collaboration, particularly collaboration that is collective in the sense of being resilient to the possible removal of individual actors, including those same collaboratively oriented actors.

In addition to these contributions, our results indicate a possible answer to the first question we pose: will the collaborative relationships that underpin science and innovation become less resilient as helpful behavior wanes? Our findings indicate that, on average, a decline in helpful behavior will indeed make collaboration networks less resilient (Shibayama et al. 2012, Haeussler et al. 2014). Further, if helpfulness declines among the highest status scientists, the weakening of collaborative networks may be exacerbated.

Finally, to be sure, our paper is not without limitations. Perhaps the primary limitation of our paper is our approach in measuring helpful behavior. Our empirical strategy uses a behavior measure based on acknowledgments in one prestigious journal. Being acknowledged in a top journal may already be an indicator of status and prestige and limits the scope of our results. Whereas we control for status in our models, future work must construct broader and more representative measures of helpful behavior. Another limitation of our research is that it is limited to the context of scientific collaboration and one academic domain in particular. Our research's critical scope condition is that our results are most likely to apply in contexts with similar modes of collaboration, incentives, and conventions about the assignment of credit. In future work, it would be fruitful to theorize and empirically study the extent to which our mechanism applies in other settings. Finally, because we rely on archival data, we cannot gain qualitative insight into how actual behaviors within each collaboration shifted due to a helpful third. We think that future work will benefit from observing these changes to understand better the nuanced mechanisms driving our effects.

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Endnotes

[1] We define career age as the time since the first published paper for each scientist.

[2] We identify all symmetric ties of coauthors excluding k. So in this example, there are three coauthors remaining after k is excluded. These three coauthors form three symmetric ties ($N*(N-1)/2$, i.e., Metcalfe's law).

[3] Since we classify k at a single point in time (k's death), k's characteristics do not vary within the dyad and thus are captured by the dyad fixed effects.

[4] For robustness, we also considered impact-factor-weighted publications and total citations. The results were very similar.

[5] If the model is $z = ax + by + cxy +$ (other variables), the effect of a unit change in x is simply $a + cy$. In particular, this does not depend on the value of the other variables. This allows us to calculate the net effect of the passing of a helpful k easily when that k was productive or nonproductive and to test its significance. The main alternative model, the logistic model, is nonlinear and hence the derivative with respect to x includes all the variables in the model; thus, the effect of a unit change in x depends not only on the value of y but also on the value of x and all of the control variables (Ai and Norton 2003, Hoetker 2007, Greene 2010). Since our results are consistent with both OLS and logistic regression, we are confident that we are capturing the real underlying effect seen in the data.

[6] We implement three-way clustering in Stata through the use of the programs "reghdfe" (Correia 2016) and "clus_nway" (Kleinbaum et al. 2013).

[7] The results are robust to controlling for the exposure time also with a full set of dummy variables.

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