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DISCUSSION PAPER SERIES

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Michael Gibbs
University of Chicago and IZA

Friederike Mengel
University of Essex and Erasmus University Rotterdam

Christoph Siemroth
University of Essex

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Innovator Networks Within the Firm and the Quality of Innovation*

Using data from over 28,000 innovators within a firm, we study how network position affects innovation, measured by the quality of ideas proposed in a formal suggestion system. Network degree is associated with higher quality ideas. Bridging across structural holes is negatively related to idea quality in the short run, conditional on degree, but has positive effects in the medium run. Bridging also has positive and persisting effects on the quality of colleagues' ideas, suggesting a positive externality from 'brokers.' Network size is not related to idea quality, after controlling for degree and bridging. Compared to working from the office, remote work leads to lower average network degree and bridging. This weakening of networks may explain the reduced quality of innovation during remote work found in prior literature.

JEL Classification: D7, D8, O3

Keywords: networks, innovation, structural holes, network centrality, working from home, hybrid work

Corresponding author:
Michael Gibbs
University of Chicago
Booth School of Business
5807 S. Woodlawn
Chicago, IL 60637
USA

E-mail: michael.gibbs@chicagobooth.edu

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1 Introduction

Innovation is a central driver of economic growth, productivity, and competitiveness in both advanced and emerging economies. For policymakers and firm decision-makers, it is important to understand which conditions are more likely to generate high quality innovation, and where such innovation is most likely to occur. Such knowledge helps to allocate valuable resources to generate innovation or to design an organizational structure that facilitates high quality innovation.

A long-standing idea in the social sciences is that networks matter for innovation. They facilitate knowledge transfer and diffusion. They stimulate creativity by allowing agents access to different types of knowledge and perspectives. An aspect of network position that is deemed particularly important for innovation is brokering across structural holes (densely related clusters of agents with only weak ties across clusters). Such brokerage provides access to alternative ways of thinking and behaving and a "vision of options otherwise unseen" (Burt, 2004). By combining knowledge and ideas across structural holes between groups, such brokers might make networks more innovative compared to a state where groups remain isolated.

Despite the importance of innovation, the empirical literature testing these ideas using within-firm data is surprisingly sparse. This reflects the significant difficulty of getting high quality data on employee innovations. In this paper, we contribute to the literature by analyzing the effect of network characteristics on employee innovation. We obtained records of *all* ideas submitted on a firm's formal employee suggestion system, which it deems strategically important and which serves to manage the firm's internal innovations. Thus, we study actual innovations of significant economic value to the firm, as well as their actual evaluation by the firm and its clients, rather than artificial tasks or proxies such as simulated ideas, patents, etc. that have typically been used in prior research.[1]

The paper proceeds as follows. We first present a simple model to guide the empirical analysis. Heterogeneous employees generate new ideas of varying quality. Access to a network of colleagues provides additional knowledge, ideas, and perspectives, which improves expected idea quality. These added insights may diminish with network distance from those colleagues. The employee may collaborate on the idea with colleagues, in which case all contribute effort to improving the quality of the idea, but collaboration requires some communication or coordination cost.

[1] Patents are often used in research because they are publicly available. However, a patent typically consists of a series of many innovations by many innovators combined. Our data is more fine-grained and contains every incremental innovation, thus giving us a more complete picture of innovation activity within the firm and allowing us to link network position of the innovator to the original generation of an idea. Moreover, we see innovations that are suggested but not implemented internally, whereas patents only represent ideas that have survived many internal rounds of review and testing.

The model predicts that network degree – the number of direct collaborators – improves expected idea quality under weak conditions. The effect of bridging is ambiguous. While accessing new knowledge from different clusters of employees improves idea quality, it also comes with increased coordination and communication costs. That said, bridging has positive externalities, because the new knowledge and perspectives diffuse through the bridging employee's network and improve expected quality for their colleagues.

The bulk of the paper analyzes rare and high quality data on the quality of ideas generated by innovating employees. These ideas might be about improving internal processes, about new products, or about cutting costs, among others. The company has a long-standing employee suggestion system, to which it devotes significant resources. Employees are asked to suggest ideas that may be valuable to the company and its clients. The ideas are evaluated rigorously by company executives, and in some cases by clients. Those of sufficient quality are then implemented, and some are rated by clients ex post. We therefore study actual innovations by employees that are of economic significance for the firm. We deploy two measures of idea quality: whether the idea was accepted for implementation, and whether the customer rated the idea highly.

Since we observe all submitted ideas, we can reconstruct the underlying innovator networks. We observe who employees collaborated with (if anyone) on their ideas, in each period of time. This allows us to measure the employee's degree (number of collaborators), network size, and bridge centrality (a measure of the extent to which they bridge across structural holes). In our main empirical analyses, we use employee fixed effects. Hence, we follow the same employee over time and use the variation in network position over time to estimate the effects.

We find that degree is significantly positively associated with the quality of employee innovation. Employees tend to generate higher quality ideas when they have a higher degree. The effect size is substantial, with every additional neighbor increasing an innovator's average idea acceptance probability by about 2.5 percentage points. Lagged degree is not related to current innovation. After controlling for degree, bridging tends to *reduce* individual idea quality in the short run, but past bridging is beneficial to current idea quality. At the same time, if a colleague in the network has high bridge centrality, an employee's ideas tend to be of higher quality. Thus, bridging has positive externalities for the network, with benefits that persist over time. These findings are consistent with the model predictions that bridging can be costly to the employee in the short run, but has net benefits in the medium run, as well as to his or her colleagues. In the aggregate the effect of bridging is positive. Finally, network size is not related to employee innovation quality, after controlling for degree and bridge centrality.

Additional analyses show that bridging nodes produce a wider range of idea types than non-bridging nodes and they produce ideas for a wider range of clients. This suggests that nodes with high bridge centrality do indeed have access to a more diverse set of insights and perspectives, allowing them to produce more diverse innovation.

Recently, CEOs have expressed concerns about a decline in productivity and innovation due to increased working from home or hybrid home-office work (Stewart, 2023; Smith, 2024). Many firms are mandating that employees return to the office, and are seeking ways to coordinate days allowed for remote work. Indeed, researchers find that remote work tends to inhibit the quality of social networks (Carmody et al., 2022; Yang et al., 2022).

In the latter part of the paper, we investigate the effect of remote work on innovator networks. In the early periods of the sample, all employees worked at the office [WFO]. In the middle period, they all worked from home [WFH] during the Covid-19 pandemic. In the latter periods, employees worked in a hybrid mode, in which they spent some time at the office and some working remotely. Compared to working at the office, degree (number of direct collaborators) declined during working from home. In the subsequent hybrid period, even more negative effects on network structure are observed with reduced degrees, network size, and bridge centrality. These findings highlight the difficulty of maintaining effective networks with remote work. They may therefore explain recent evidence that innovation suffers from remote work compared to WFO.

2 Literature

Our work builds on a body of social science research studying relationships between network position, individual creativity and innovation. See Coleman (1990) for a summary of earlier work, and Burt (2005) for more recent sociological research in this area. This literature emphasizes that innovation often stems from combining ideas or pieces of knowledge (Jacobs, 1969; Weitzman, 1998; Obstfeld, 2005). Hence, social connections between employees play a key role for innovation.

Muthukrishna and Henrich (2016) argue that innovation is an emergent, cultural phenomenon. It benefits from sociality, transmission fidelity, and cultural variance. Thus extensive interaction, good communication, and exposure to different "cultures" are desirable. In the firm, it helps employees make analogies and find new solutions by adopting different perspectives (Hargadon and Sutton, 1997).

Weak ties may generate creativity by providing access to novel information and perspectives outside of the employee's regular group (Granovetter, 1973; Perry-Smith, 2006; Rajkumar et al., 2022). Strong ties tend to be associated with greater homophily (redundancy of knowledge and perspective) and norms for conformity, both of which may inhibit creativity. However, if the knowledge transfer is sufficiently complex, strong ties may be helpful, especially for implementation of an idea (Hansen, 1999; Reagans and McEvily, 2003). Strong ties can also benefit cooperation (Coleman, 1990) and strong and weak ties can also be complements (Rost, 2011).

Burt (2004) highlights the potential of brokerage across structural holes (weak ties between denser sub-networks): "People whose networks bridge the structural holes between groups have an advantage in detecting and developing rewarding opportunities. Information arbitrage is their advantage. They are able to see early, see more broadly, and translate information across groups." He finds that brokers have better performance, higher promotion rates, and ideas deemed more valuable by colleagues. See also Burt (1992) or Burt (2005).

Most of this body of work has relied on ethnographic methods involving field research and interviews, or employee surveys. Ideas are often collected as part of the research; e.g., in a survey. Though these ideas will be related to the employee's work, they were not generated on the job and are in that sense artificial. Moreover, their evaluation is hypothetical, as these ideas are not actually used. The ideas that we observe, on the other hand, are those actually emerging in the work-environment, and their evaluation is real and of consequence to the company. Good ideas are implemented by the company or their clients. Another advantage of our data collection is the substantial sample size of about 29,000 unique innovators. In addition, we observe innovation during times with different degrees of remote work.

Our research is also related to the literature on scientific creation, which either studies peer effects in innovation without paying attention to network structure (Geroski and Mazzucato, 2002; Weinberg, 2007; Waldinger, 2012), or studies the impact of co-author networks on the productivity of scientists (Mohnen, 2022). Anderson and Richards-Shubik (2022) study a strategic model of network formation and show that larger research teams tend to produce papers with higher impact. Aggregate network properties have also been shown to affect the performance of creative artists (Uzzi and Spiro, 2005), entrepreneurs (Vega Redondo et al., 2023) or innovation in manufacturing (Kim and Lui, 2015). While they are not explicitly studying networks, Wu et al. (2019) show that team size is an important parameter when studying scientific breakthroughs.

Other work focuses not on the generation of ideas, but their diffusion. Cheng and Weinberg (2024b,a), for example, study how the diffusion of new scientific ideas relates to the age and gender of innovators. Earlier work on the diffusion of innovation is summarized in Rogers (2003). There is a substantial theoretical literature on diffusion of innovations along interfirm and R&D networks (Goyal and Moraga-Gonzalez, 2001; Cowan and Jonard, 2007; Ghiglino, 2012; Dasaratha, 2023). In empirical work, Ahuja (2000) finds that increasing structural holes in such interfirm networks has a negative effect on innovation.

Given recent growth in remote work, research is emerging on its effects. Some studies find that productivity is lower with WFH (Gibbs et al., 2023; Emanuel and Harrington, 2024; Künn et al., 2022). Others do not, in occupations that do not require collaboration or communication (Bloom et al., 2014; Choudhury et al., 2019). Coordination and communication costs are higher in WFH and hybrid compared to WFO (Teevan et al., 2020; DeFilippis et al., 2022; Yang et al., 2022; Gibbs et al., 2023). These reduce the ability of employees to develop and maintain social networks. Emanuel and Harrington (2024) find that engineers who work in closer proximity to teammates received more feedback, fostering human capital development. This worsened when the firm switched to WFH during the pandemic. A study of Microsoft employees (Yang et al., 2022) found that firm-wide remote work caused networks to become more static, and narrower (lower network size and degree), with less bridging across structural holes. Our findings on network structure and remote work are in line with these results. Communication also became more asynchronous. Similarly, Carmody et al. (2022) found significant reductions in weak ties, which only partially recovered in subsequent hybrid work mode.

How does remote work affect innovation? In a lab experiment, Grözinger et al. (2020) find that creativity declines significantly when communicating via chat instead of face-to-face. Brucks and Levav (2022) analyze data from lab and field experiments across five countries. They find that videoconferencing reduces the creativity of ideas. Gibbs et al. (2024) find that innovation suffered in both WFH and hybrid modes compared to WFO. Atkin et al. (2022) use smartphone geolocation data to measure face-to-face interactions (or meetings) between workers at different establishments in Silicon Valley and find substantial returns to face-to-face meetings. Not surprisingly, working in-person appears to be important for the intangible interactions that foster innovation.

3 Conceptual Framework

In this section we present a conceptual framework modeling how networks are formed and how innovation takes place within the firm. The model we present is simple and highly stylized, but rich enough to illustrate the diverse impacts that network position can have on innovation quality.

Expertise and Similarity. There are N innovators. Each innovator is characterized by a K-dimensional vector of *individual expertise* $(f_{ik})_{k=1,\dots,K}$, which we interpret broadly to denote their knowledge, training and education in different dimensions, the insights they have, the perspectives they take, etc. For simplicity, we assume that expertise is binary; i.e., $f_{ik} \in \{0, 1\}$.

The similarity s between two innovators i and j is defined as the number of dimensions k in which $f_{ik} = f_{jk}$.

Networks. A link between any two innovators is formed with probability $p \in [0, 1]$ as in the classical Erdoes-Renyi network model (Erdoes and Renyi, 1959). We add homophily to the model by assuming that p is increasing in s, the similarity between two innovators.[2] If two similar innovators meet, it is easier for them to find common ground and start working on an idea together as they "speak the same language." It can also reflect the fact that two employees who are similar are more likely to work in the same team or same unit, and hence are more likely to meet in the first place.

This process defines a network; i.e., a collection of nodes (innovators) $\mathcal{N} = \{1, \ldots, N\}$ and a set of edges (links between the nodes) defined as $\Xi = \{(i, i')|i \neq i' \in \mathcal{N}\}$, where an element (i, i') indicates that i and i' have developed an idea together (possibly with others). The set of i's first-order neighbors (FONs) is denoted by $\mathcal{N}_i^1 = \{i' \in \mathcal{N}|(i, i') \in \Xi\}$. i's degree is then given by $d_i = |\mathcal{N}_i^1|$; i.e., the number of different people that i generates ideas with. We denote by $d(i, i')$ the geodesic distance between nodes i and i'; i.e., the length of the shortest path in the network connecting i and i'. By definition, $d(i, i) = 0$ and $d(i, i') = 1$ if i and i' are first-order neighbors.

Figure 1 illustrates which types of networks are likely to emerge in a simple example with $N = 3$ and $K = 2$. Our setting is of course characterized by larger N. Typical networks emerging in our setting will be such that groups of similar expertise will be linked in relatively dense clusters with the occasional link "bridging" across such clusters. See Figure 2 for networks resulting from simulations with larger N and for an example of a network from our data.

Innovation. A node's innovative potential κ derives from both their individual expertise in the different dimensions, as well as from what they can learn from others in their network $\mathcal{N}_i$. We assume that

$$\kappa_i = \sum_{k=1,\ldots,K} \max_{i' \in \mathcal{N}_i} \left(\delta^{d(i,i')} f_{i'k} \right). \tag{1}$$

In dimensions where nodes do not have expertise themselves, they can learn from others in the network. However, this learning is discounted at a rate $\delta \in [0, 1]$ with network distance. δ is a decay rate measuring how much knowledge is lost along each link it travels in the network from

[2]Our model can hence be seen as a version of a stochastic block model (Holland et al., 1983; Lee and Wilkinson, 2019). Bramoulle et al. (2012) also include homophily in a network formation model which includes network-based search.

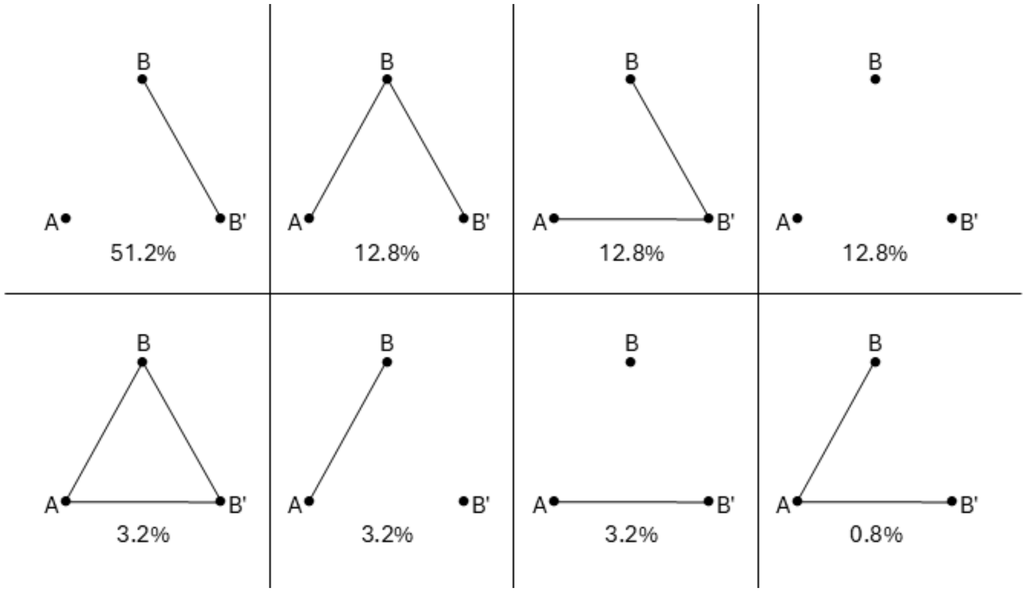

Figure 1: The figure shows an example of network formation with $K = 2$ and three innovators. A has individual expertise (0,1) and B and B′ both have expertise (1,0). We further assume that $p(s = 0) = 0.2$ and $p(s = 2) = 0.8$. In this case our network formation process will lead to a network like in the top leftmost panel in over half the cases. The similar nodes are linked and node A is isolated. In just over a quarter of cases (top center-left and center-right), the network will be such that either B or B' will be "bridging": i.e., providing a link to dissimilar node A. The other cases are less likely. Rarest is where A bridges between B and B'.

i' to i.[3] Thus, individual expertise of nodes closer in the network add more to the innovative potential of a node, as the expertise does not decay as much. δ may reflect the likelihood and intensity of communication along these links. The maximum operator captures that duplicate or redundant expertise is not expected to improve the innovative potential.

Quality of Innovation. The quality of an innovation z is given by

$$Q_z = \sum_{i \in \mathcal{N}(z)} \left(\frac{\kappa_i}{|\mathcal{N}(z)|} + \rho e_{iz} \right), \tag{2}$$

where $\mathcal{N}(z)$ is the set of nodes collaborating on idea z, and e_{iz} is the amount of effort i invests in the generation and development of the idea. The first term is the average innovative potential among the co-authors. We use the average rather than the sum to capture that simply adding co-innovators with little expertise will not increase the innovative potential of the group.[4] The second term reflects the fact that the quality of an innovation is higher the more effort

[3] This is a common way to model information diffusion in the networks literature. See e.g. Jackson (2008) or Goyal (2023) for good summaries of the literature.

[4] We will see below that degree has a positive impact on innovation quality under weak conditions. If we used the sum instead, this effect will be even more pronounced.

the co-innovators put into developing the idea. ρ is a scaling factor representing the relative contribution of potential versus effort to innovation quality.

Innovators choose effort optimally, trading off the expected benefit from producing a high quality innovation against the effort costs (e.g., opportunity costs of time). Specifically, we assume that

$$e_{iz} = \arg\max_{e} \left(B \cdot q(Q_z) - \tfrac{1}{2}[c(e)]^2 \right),$$

where $q(Q_z) \in [0,1]$ is the probability that idea z gets accepted, which is increasing in idea quality ($q'(Q_z) > 0$). $B > 0$ are the benefits obtained in case of innovation acceptance.[5] $c(e)$ is the cost of effort, which is decreasing in the average pairwise similarity of i's co-authors $\overline{s}_{iz} = \sum_{i,i' \in \mathcal{N}_z} \frac{2 s_{ii'}}{|\mathcal{N}(z)|(|\mathcal{N}(z)|-1)}$. If coauthors are very dissimilar, then higher costs are incurred as language, expertise, practices, and perspectives may differ and require more "translation." The higher costs may also reflect further physical distance between co-authors as very dissimilar innovators are less likely to be working in the same team. Innovators will choose effort optimally to balance the marginal cost of effort with the marginal increase in idea quality.

Network Position and Idea Quality. We can now ask how the network position of co-innovators affects innovation quality. There are many network characteristics one could consider. We focus on three that have been discussed prominently in the prior literature and are highly relevant in the theory outlined: (i) Degree d_i, (ii) Network Size; and (iii) Bridge Centrality BC_i. By using these three measures, we cover each of the categories of nodal statistics derived in the taxonomy of centrality measures in Bloch et al. (2023). Degree and network size are similar to "neighborhood" and "walk" nodal statistics, which relate to the reach of a node. Bridge centrality is related to the "intermediary" node statistics, which measures how important an individual is as a connector between other nodes. See Table 1 in Bloch et al. (2023). We summarize the theoretical predictions at an intuitive level here. More formal statements can be found in Appendix A.

Degree. A high degree d_i is generally beneficial for the quality of ideas involving node i via a positive effect on both components of Q_z in equation (2). First, it weakly increases the knowledge component by increasing i's innovative potential (as long as $\delta > 0$, see equation (1)).

[5] These benefits include formal bonuses plus implicit rewards such as increased likelihood of promotion. Both formal and informal rewards are present in our empirical setting, see the following section.

Second, having more co-innovators directly contributes to idea quality via the co-innovators' effort contribution.[6]

Network Size. Network size matters as well. As knowledge travels through the network, nodes benefit from the perspectives and insights of those they are directly and indirectly linked to in the network. The importance of network size compared to degree depends on δ. The higher is δ, the relatively more important is network size. For δ close to zero, degree will be much more important than network size. Note that network size only affects the quality of i's ideas via the first component as long as the growth in the network happens at a geodesic distance larger than two, as in that case neither i's nor i's neighbors' effort provision will be affected. See Appendix A for more details.

Bridge Centrality. The third characteristic of interest is bridge centrality, defined as

$$BC_i = \frac{b_i}{\sum_{j \in \mathcal{N}_i^1} d_j^{-1}},$$

where b_i is i's betweenness centrality (Freeman, 1977). Betweenness measures the share of shortest paths between any two agents in a network that pass through node i. More formally, i's betweenness centrality is $b_i = \sum_{j \neq i \neq k} \frac{p_{jk}(i)}{p_{jk}}$, where p_{jk} is the number of shortest paths between nodes j and k and $p_{jk}(i)$ is the number of those paths that pass through i. The denominator in the definition of BC_i captures that bridging is not just about being on many shortest paths, but also about being located between many high degree nodes; i.e., bridging densely connected parts of the network (Hwang et al., 2006). Our empirical results below, however, show that this is not crucial. Qualitatively the same patterns emerge if betweenness centrality is used instead of bridge centrality. Figure 2 (bottom right) shows a network from our data and highlights the three nodes with the highest values of bridge centrality.

Nodes that have high bridge centrality are linked over-proportionately to dissimilar nodes and hence will benefit from knowledge in more dimensions, increasing their innovative potential and the first component of Q_z. However, there is also a potential cost to such bridging, reflected in lower optimal effort levels due to higher translation costs. Hence, the overall impact of bridging on innovation quality is ambiguous and depends on parameters such as ρ.

The differential impact of bridging on the knowledge and effort components has other interesting implications. First, as knowledge travels through the network, not only does one's own network position matter, but so do the positions of neighbors, their neighbors, etc. If one of

[6] It is possible that there is an opposite equilibrium effect if a co-author team incurs higher coordination and translation costs because of an additional neighbor. In Appendix A, we show that the class of situations where this equilibrium effect is not present or can be neglected is fairly large.

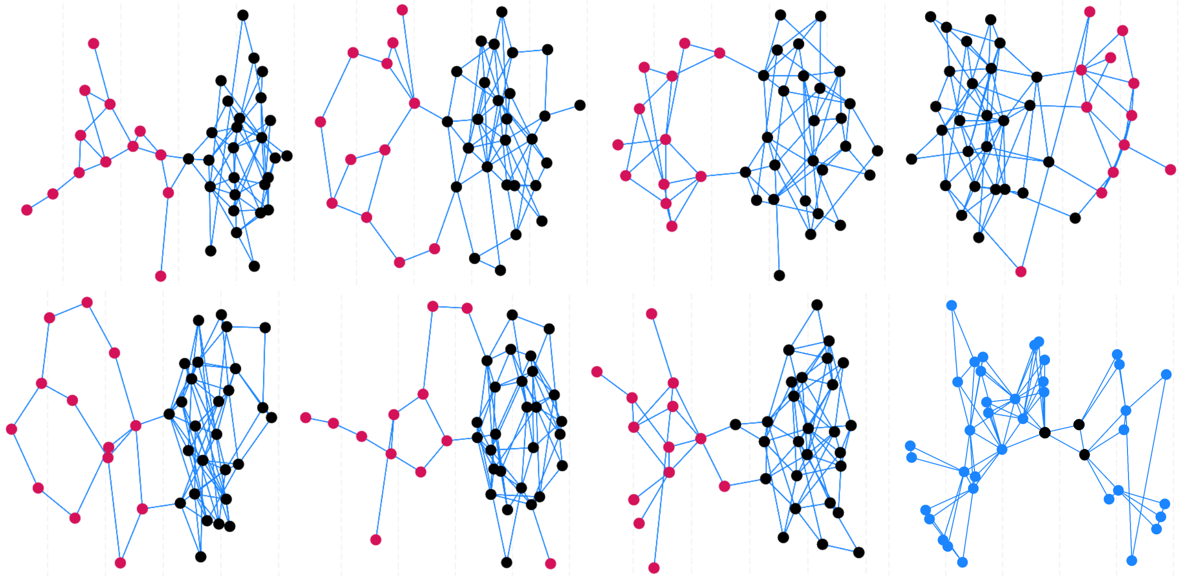

Figure 2: Networks resulting from seven simulations of our network formation process with $N = 40$ and two types $(0, 1)$ and $(1, 0)$ identified by black and red nodes. $p(2) = 0.2$ and $p(0) = 0.01$. Bottom right: A network of 40 innovators from our data. The three "bridging nodes" with highest bridge centrality in this network are coloured black

my neighbors has excellent access to information (e.g., because they bridge), then (depending on δ) I stand to benefit as well. In fact, in contrast to the bridging node, who may have to incur costs to coordinate with the new node's different culture, I will not suffer from higher effort costs. In this sense bridging has a positive externality. There are costs to the person who bridges, as they have to engage in translation and coordination. The benefits of bridging, by contrast, apply to everyone in the network, though (depending on δ) they diminish for the neighbors of the bridging node.

In addition (going beyond the static model), while the higher effort cost of bridging is likely to be short-lived—it ceases when the interaction ceases—the knowledge effect can last even when the network position of the node changes and bridging stops. This means that while the short term effect of bridging is ambiguous, bridging can have medium or long term benefits to the bridging node.

4 Setting and Data

We use anonymized employee data from HCL Technologies, a large IT services company based in India. Additional details about the company and the innovation process may be found in our prior research with HCL data; see Gibbs et al. (2017, 2024).

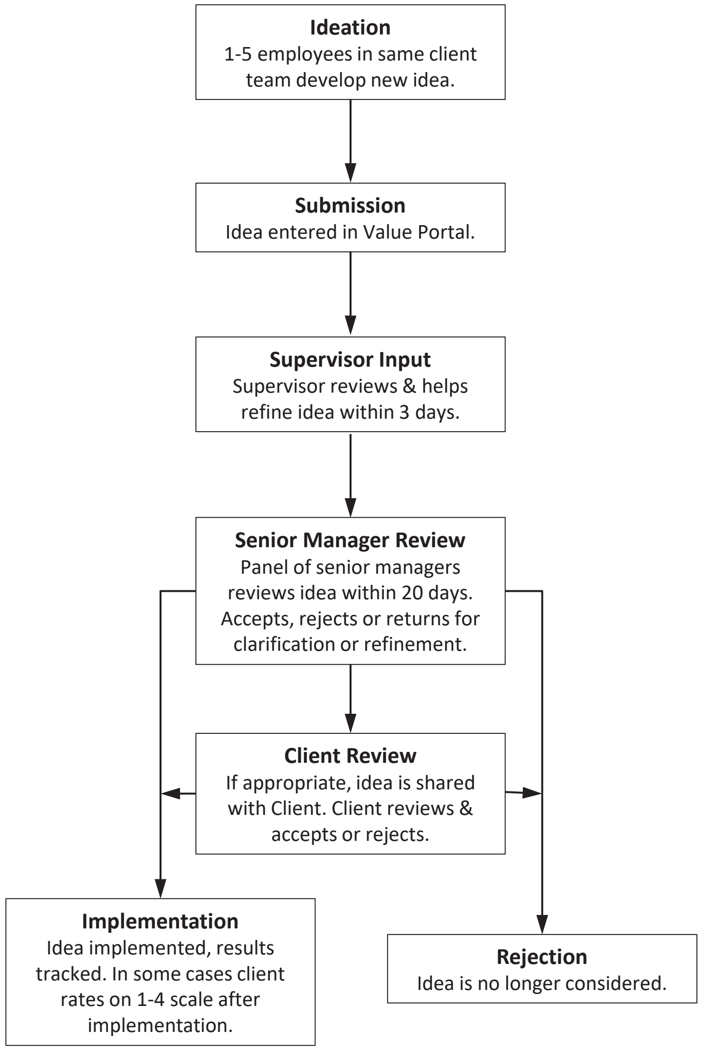

Figure 3: Process for Evaluating New Ideas.

IT services is a highly competitive industry. For many years, HCL has emphasized innovation, with the goals of being more differentiated from competitors, and being more like long-term partners for clients (Hill et al., 2008). The company has taken significant steps to instill a culture in which all employees see innovation as a key part of their job. A cornerstone is the Idea Portal, an intranet system which employees use to submit new ideas about how to improve processes or products. All employees are encouraged to participate in the Idea Portal. This system is viewed by company leaders as highly valuable for HCL.

4.1 Data

Two aspects of our data are notable: how we measure innovation and employee networks. Most related studies do not have direct measures of innovation. Instead, they use proxies such as asking employees to submit a hypothetical new idea to the researcher, and then having colleagues rate the idea. Others use proxies such as patents. Our measure is of actual innovations by each employee, developed as part of their jobs. And we observe the universe of ideas submitted in our sample period (whereas elsewhere many internal ideas that never lead to patents are not observed). Moreover, the measure of quality is the firm and/or client's evaluation of the business value of the idea.

Studies of organizational networks use various means to measure network position. Some use surveys in which employees are asked to name the colleagues with whom they tend to interact. Others make inferences from patterns of email communication or social network connectivity. We measure network position based on co-authorship in ideas submitted to the Idea Portal (whether accepted or rejected). This is an imperfect measure, since it does not include information on colleagues with whom the employee is connected, but did not collaborate on an idea in that period. However, it has the virtue that it is directly tied to our outcome of interest, employee innovation. In essence, we focus on innovators and their relationships that are most relevant for their innovation work.

Figure 3 illustrates the process by which ideas are evaluated. The system was developed many years ago, and did not change during our sample period. Since it uses the HCL intranet, the system worked the same even across times with different levels of remote work. Employees receive small financial bonuses if one of their ideas is accepted for implementation. Employees may come up with new ideas spontaneously, or try to ideate proactively. Both may be done individually or with colleagues. If the employee has a new idea that they believe may be valuable, they can (with up to four colleagues) submit a description of the idea, including estimates of resources needed, and potential benefits. The supervisor is expected to review the idea within three days, and reject it, help the employee refine it, or approve it for consideration. If an idea is approved, it is reviewed within three weeks by a panel of senior executives, who reject or approve the idea. If approved and likely to have direct effect on a client, the idea may then be submitted to the client for final approval.[7] Accepted ideas are then implemented.

Note that participation by executives involves significant company resources. That, and submission of many issues to clients for consideration, reflect the importance that the company places on this system. Thus, we study the quality of innovations that are economically meaningful to the company.

Our primary focus is on how the structure of an employee's network affects his or her innovation. We measure innovation as the quality of ideas suggested by each employee. Quality is measured by whether or not the idea was accepted for implementation (IdeaAccepted), or by

[7]Other ideas, for example on internal processes, do not need client approval.

Table 1: Summary statistics on node-period level (one period is 6 months)

	Mean	SD	Min	Max	N
WFO					
IdeaAccepted	0.685	0.448	0.000	1.000	32970
ClientApproval	0.458	0.478	0.000	1.000	32970
Degree	1.528	1.858	0.000	25.000	32970
Bridge Centrality	0.078	0.313	0.000	4.895	32970
Network Size	4.293	8.003	1.000	93.000	32970
HighDegree-NW	0.154	0.361	0.000	1.000	32970
HighCentrality-NW	0.239	0.427	0.000	1.000	32970
HighDegree-NW≥ 2	0.071	0.257	0.000	1.000	32970
HighCentrality-NW≥ 2	0.096	0.295	0.000	1.000	32970
WFH					
IdeaAccepted	0.615	0.464	0.000	1.000	5574
ClientApproval	0.421	0.471	0.000	1.000	5574
Degree	1.430	1.814	0.000	33.000	5574
Bridge Centrality	0.075	0.309	0.000	4.219	5574
Network Size	3.801	5.288	1.000	38.000	5574
HighDegree-NW	0.138	0.345	0.000	1.000	5574
HighCentrality-NW	0.233	0.423	0.000	1.000	5574
HighDegree-NW≥ 2	0.068	0.252	0.000	1.000	5574
HighCentrality-NW≥ 2	0.095	0.294	0.000	1.000	5574
Hybrid					
IdeaAccepted	0.523	0.481	0.000	1.000	9966
ClientApproval	0.344	0.457	0.000	1.000	9966
Degree	1.123	1.618	0.000	23.000	9966
Bridge Centrality	0.061	0.279	0.000	6.000	9966
Network Size	2.970	3.630	1.000	27.000	9966
HighDegree-NW	0.171	0.376	0.000	1.000	9966
HighCentrality-NW	0.191	0.393	0.000	1.000	9966
HighDegree-NW≥ 2	0.063	0.244	0.000	1.000	9966
HighCentrality-NW≥ 2	0.063	0.243	0.000	1.000	9966

whether or not the customer rated the idea with 3 or 4 on a scale of 1-4, with a higher rating being better (ClientApproval).[8]

Table 1 displays summary statistics. These include the outcome variables, but also our main explanatory network variables. HighDegree-NW is a dummy variable equal to 1 if and only if that employee has another employee in the network who is in the top 10% of the degree distribution that period. HighDegree-NW≥ 2 is a dummy variable equal to 1 if and only if that employee has another employee in the network who is not a coauthor (so distance $d_{ij} \geq 2$) and is in the top 10% of the degree distribution. The definitions for HighCentrality-NW and HighCentrality-NW≥ 2 are analogous. Our sample includes all ideas and innovators on the Idea Portal between April 2016 and September 2021.

[8]The client rating itself is often missing and when it is not missing, it is almost always good. Thus, clients rate good ideas highly, but they do not rate bad ideas. Our ClientApproval measure avoids these 'selective missing rating' issues by classifying bad ideas as those without a good client rating.

In previous work (Gibbs et al., 2024), we studied the effects of remote work modes on employee innovation. HCL had three work modes during the sample period, which also apply to the data used in this paper. In the first phase, employees worked from the office. During the Covid-19 pandemic, employees worked from home. Since then, the company has moved to a hybrid mode in which employees are allowed to sometimes work from home, but are also expected to work regularly from the office. All three work modes were company-wide policy, so employees were not able to switch from one work mode to the other. This paper differs from that prior work by its focus on networks, and by using a different set of employees (innovators from all divisions, rather than employees from select divisions). As a secondary research question, below we analyze how networks differed by work mode (working from office (WFO), working from home (WFH) or hybrid work).

4.2 Empirical Strategy

In our model, networks are formed exogenously via a random similarity-based process. While anecdotally network formation in the company has some features of similarity-based random "water-cooler encounters," it is clear that network position is to some degree endogenous: employees can choose who to work with. This means that certain employees, say those who typically have good ideas, might end up having a higher degree as many others are happy to work with them. Or it might mean that employees with certain job roles, perhaps that are meant to facilitate interaction between teams, end up with a higher bridge centrality. To address these issues, our main regression specifications include employee fixed effects. Thus, the estimates are based on variation in network position of the same employee, rather than on variation of network position across employees.

The unit of observation in our dataset is the employee-period, where a period is 6-months from April to September ("Summer") or from October to March ("Winter").[9] We index the employee by i and the period by $t = 1, 2, \ldots$. For outcome variable y_{it}, we the estimate by OLS:

$$y_{it} = \alpha_i + \beta \text{Degree}_{it} + \gamma \text{Bridge Centrality}_{it} + \delta \text{Network Size}_{it} + \zeta \text{Summer}_t + \eta t + \varepsilon_{it}, \quad (3)$$

where α_i is the employee fixed effect, Summer is a dummy variable that equals 1 if and only if t is a summer period, and η is a linear control for time trends. Effectively, these regressions compare the same employee in different periods, accounting for seasonal differences and time trends, using the variation in our network measures over time to estimate their effects.

[9] We define networks over six month periods as the WFH period is only six months. We don't use shorter periods as this would lead to very sparse networks, since innovation is an infrequent event.

5 Results

We start with descriptive statistics of innovator networks (Section 5.1) and then discuss the impact of network position on the quality of innovation (Section 5.2), the externalities of bridging (Section 5.3), the impact of past collaboration (Section 5.4), how networks change with remote work (Section 5.5), and last we discuss several extensions (Section 5.6).

5.1 Innovator Networks

In this subsection, we characterize innovator networks and highlight some typical patterns of the distribution of degree and bridging nodes. In each time period, the overall network of innovators will consist of many disconnected components; i.e., subsets of innovators within the overall network that are either directly or indirectly linked, while there are no links across components. As mentioned above, we refer to each such component as a "network."

Figure 4 illustrates different innovator networks. While a lot of innovator networks are small (e.g., only two innovators), the figure illustrates some mid-size and larger networks. Those latter networks tend to be characterized by relatively dense clusters of nodes, with some nodes bridging across such clusters. There is substantial heterogeneity in degree within each of these networks, with some nodes having only 1-2 neighbors, while others are linked to more than twenty neighbors.

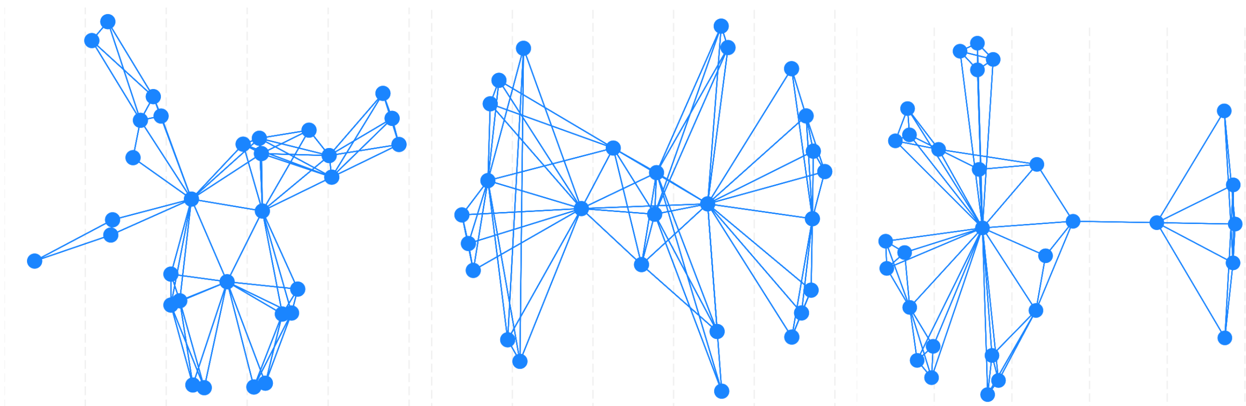

Figure 4: The figure illustrates three components of innovator networks in (left to right), winter 2018-2019, summer 2019, and summer 2020.

Figure 5 shows the distribution of our three main network characteristics of interest. Network size ranges from 1 (singleton networks omitted in the figure) to the largest network of 93 innovators. As can be seen in the figure, the vast majority of networks involve between 2-20 innovators. In line with the presence of homophily in network formation, the observed degree distribution is very unequal and resembles a power law. Most innovators have a degree between 1-10, but the most highly connected innovator has collaborated with 33 distinct colleagues (middle panel). The third panel shows the distribution of bridge centrality. Most mass here is concentrated between 0 and 2. The peak at a bridge centrality of 1 stems largely from small networks with only two innovators.

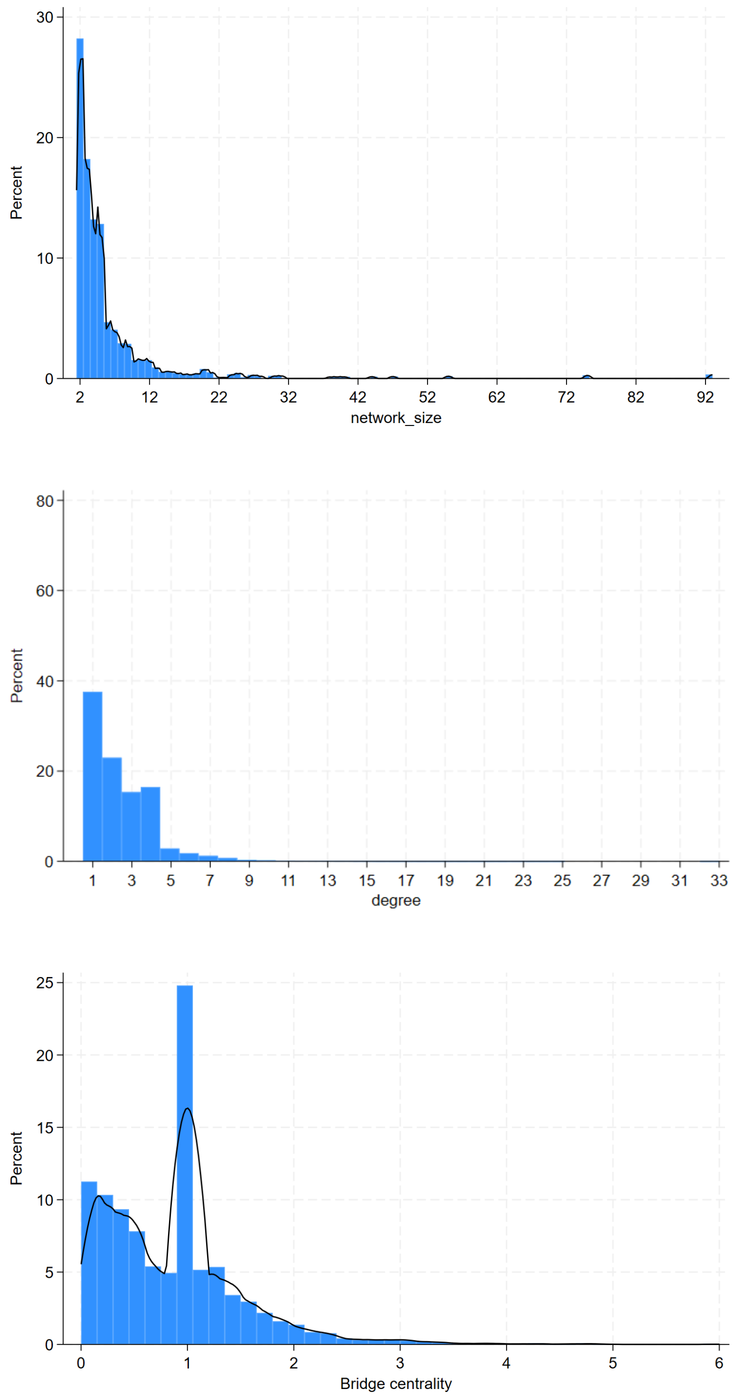

Figure 5: Distribution of network size (first panel), degree (second) and bridge centrality (third panel).

There are no substantial time trends. In the period between summer 2016 and winter 2019/20, average network size is very slightly increasing by 0.04 nodes per six-month period.[10] Average degree is slightly decreasing (0.01 nodes per half year) and average bridging increases by 0.001 every six months on average. There is some auto-correlation. Employees who had higher degree or bridging in the past are also more likely to have high degree or bridge centrality in the present (Appendix Table C.1).

Our main network characteristics of interest are pairwise strongly correlated. After dropping singleton nodes, the pairwise correlation between degree and network size is $\rho = 0.4354^{***}$. The correlation between degree and bridge centrality is $\rho = 0.5634^{***}$ and between network size and bridge centrality it is $\rho = 0.1630^{***}$.[11]

5.2 Individual Network Position and Innovation

In this section, we ask how network position affects the quality of innovation. We have two main measures of innovation quality: whether a suggested idea is accepted and implemented by the company, and whether the customer gives a good rating for the suggested idea.[12]

Table 2 displays the regression estimating equation (3). In columns (1) and (2), we clearly see a significantly positive effect of degree: The same individual, in a period with more coauthors, produces on average higher quality ideas, holding other features of the network structure (size, bridge centrality) constant. Moving from no co-innovators to four co-innovators increases the acceptance probability by almost ten percentage points. The effect size is almost identical for our second outcome variable: client approval. The direction of the effect is the same also in columns (3) and (4) where we do not hold bridge centrality constant, albeit with a slightly smaller effect size. A high degree contributes positively to innovation quality.

In columns (1) and (2), the effect of bridge centrality is significantly negative, holding constant the number of coauthors (degree) and network size. This may at first seem surprising, since the previous literature associates bridge centrality with benefits for innovation (Burt, 2004). In columns (5) and (6), where we do not condition on degree, the effect either reverses to be significantly positive or remains statistically zero.

According to our theoretical framework, bridging may have costs (arising from translation and coordination across teams) and benefits (such as knowledge transfer, fostering better innovation). Based on the results in Table 2, bridge centrality has a non-negative effect when

[10]The period 2020 onwards will be discussed in Section 5.5, where we analyze the impact of working from home and hybrid work on networks.

[11]If we include singletons (isolated nodes), these correlations are larger (degree and network size 0.5440^{***}; degree and bridge centrality 0.5460^{***}; bridge centrality and network size 0.2266^{***}). The reason is that, for all isolated nodes, all three measures equal zero, which somewhat inflates the correlation.

[12]In Section 5.6 we briefly discuss results with a third measure of idea quality.

Table 2: Predicting idea quality with network statistics

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Idea Accepted	Client Approval	Idea Accepted	Client Approval	Idea Accepted	Client Approval
Degree	0.024***	0.025***	0.017***	0.016***		
	(0.002)	(0.003)	(0.002)	(0.002)		
Bridge Centrality	-0.043***	-0.059***			0.013*	-0.000
	(0.009)	(0.010)			(0.007)	(0.008)
Network Size	0.000	0.001*	0.001	0.001**	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Summer	0.002	0.011**	0.002	0.011**	0.003	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
With singletons	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48510	48510	48510	48510	48510	48510
Clusters	28877	28877	28877	28877	28877	28877

Note: IdeaAccepted is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was accepted for implementation. ClientApproval is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was rated 3 or 4 out of 4 by the client. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

not conditioning on degree, confirming that there seem to be benefits from being in a bridging position. These benefits are partly due to the fact that bridging nodes have more co-authors; i.e., higher degree. It appears that when degree is held constant (as in columns (1) and (2)), the coefficient on bridge centrality reflects its costs more than its (short-term) benefits, thus turning negative, as the degree coefficient absorbs some of the positive effect of bridging.

Network size has either an effect that is not statistically different from zero, or a positive effect if degree is not held constant (columns (5) and (6)). This is also consistent with the idea that beneficial information or knowledge travels through the network, and so larger networks tend to be advantageous. The summer dummy tends to have a positive effect on client approval, reflecting some seasonality in innovation.

In Appendix Table C.2, we re-run the same regressions as in Table 2, without singletons (i.e., without employees who suggested ideas but did not collaborate in that period). Thus, the estimates in that appendix table reflect only the intensive margin of collaboration. All signs and qualitative results are the same: degree has an unambiguously positive effect, bridging has a negative effect conditional on degree, and a non-negative effect without conditioning on degree. Appendix Figure D.3 shows that the effect of both degree and bridging remains stable if we restrict to innovators who submitted at most x different ideas, while varying x. Hence, the average effects are not driven by outlier nodes with extremely few ideas, nor by those with extremely many ideas.

In Appendix Table C.3, we re-run the regressions in Table 2 without employee fixed effects. Those regressions compare different employees in different network positions. The qualitative results are the same: degree has an unambiguously positive effect, whereas bridging has a negative effect conditional on degree. Finally, in Table C.4 in the appendix, we show that replacing bridge centrality with betweenness centrality produces practically the same results, so these two network centrality measures are largely interchangeable in this setting.

One might wonder whether the lower idea quality when bridging is caused by translation and communication costs affecting the quality of "bridged" ideas, as suggested by our model (equation (2)), or whether those costs affect the quality of all ideas the employee produces in that period. To this end we distinguish periods where an employee with high bridge centrality (defined as the top 10% in bridge centrality distribution) produces ideas with other nodes who also have high bridge centrality, from periods where the employee has high bridge centrality themselves but does not innovate with others with high bridge centrality. We find that, indeed, idea quality is somewhat (1.6 percentage points) lower in the former periods, but the difference is not statistically significant.

5.3 Externalities of Bridging

Table 2 investigated how an individual's innovation quality is related to their network position. We next turn to the question of how individuals are affected by others in the network. Based on the theory, there are two reasons why we would expect that others' network positions should also matter. First, there is diffusion of insights (knowledge, perspectives) across the network (equation (1)). Second, there can be effort spillovers. To study these questions, we use the dummy variable, HighDegree-NW ('high degree node in network'), which takes value 1 if and only if at least one of the other employees in i's network is in the top 10% of the degree distribution in that period. Similarly, HighCentrality-NW takes value 1 if and only if at least one of the other employees in i's network is in the top 10% of the bridge centrality distribution in that period. Thus, we can investigate whether having employees in one's network who are characterized by strong network positions (measured by degree and bridge centrality) improves one's own idea quality. Note that these employees need not be neighbors (i.e., coauthors), or even neighbors of neighbors. They might be further away. Thus it is particularly important to control for network size.

Table 3: Externalities of high bridge centrality and degree

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Idea Accepted	Client Approval	Idea Accepted	Client Approval	Idea Accepted	Client Approval
HighDegree-NW	0.010	0.015	0.034***	0.034***		
	(0.012)	(0.013)	(0.010)	(0.010)		
HighCentrality-NW	0.034***	0.027***			0.039***	0.034***
	(0.010)	(0.010)			(0.008)	(0.009)
Network Size	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Summer	0.002	0.011**	0.003	0.012**	0.002	0.011**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
With singletons	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48510	48510	48510	48510	48510	48510
Clusters	28877	28877	28877	28877	28877	28877

Note: IdeaAccepted is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was accepted for implementation. ClientApproval is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was rated 3 or 4 out of 4 by the client. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table 3 displays these regressions. Columns (1) and (2) show that having a colleague in the network who bridges different clusters (i.e., someone with high bridge centrality) is positively associated with idea quality. The same is not true for degree. Having someone with high bridge centrality in the network increases the chance of getting an idea accepted by over 3 percentage points, and similarly increases the chance of getting a high rating from the client by almost 3 percentage points. These estimates are significantly positive for both outcome measures. Having a high degree individual in the network is associated with a smaller effect, which is not significantly different from zero. Columns (3)-(6) of Table 3 show that having a high degree or a high centrality individual in the network is beneficial, when not conditioning on the other. This is because having a high degree individual and a high centrality individual in the network are highly correlated ($\rho = 0.74^{***}$).

Is the positive bridging externality a coauthor effect, or is it present when the bridging individuals are farther away in the network? Table 4 uses dummy variables for whether there is a high degree or a high centrality individual in the network who is not a coauthor; i.e., is at distance of at least 2 to the individual in question, to predict idea quality. Similar to Table 3, a

Table 4: The network effects of bridging centrality and degree (not coauthors)

	(1)	(2)
Dependent variable	IdeaAccepted	ClientApproval
HighDegree-NW≥ 2	0.000	0.010
	(0.019)	(0.019)
HighCentrality-NW≥ 2	0.031**	0.029*
	(0.016)	(0.016)
Network Size	0.002***	0.002***
	(0.001)	(0.001)
Summer	0.003	0.012**
	(0.005)	(0.005)
Employee FE	Yes	Yes
Linear time trend	Yes	Yes
With singletons	Yes	Yes
Observations	48510	48510
Clusters	28877	28877

Note: IdeaAccepted is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was accepted for implementation. ClientApproval is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was rated 3 or 4 out of 4 by the client. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

high degree individual in the network (who is not a coauthor) does not have a significant effect on idea quality, with an estimated coefficient very close to zero. By contrast, having a high centrality individual in the network (who is not a coauthor) does have a positive and significant effect: it increases the odds that the idea is accepted by 3.1 percentage points, and the chance of a favorable client rating by 2.9 percentage points. These estimates are only slightly smaller than those for high centrality individuals in the network (see Table 3).

Unlike in the case of individual network characteristics, when looking at characteristics of others in the network, it appears that high centrality is more important than high degree. This suggests that bridging in an innovation network may have a positive externality. Based on our theory, the channel of this positive effect is the spreading of valuable information and insights from one cluster of individuals in the network to another, thus bridging a structural hole in the network.

One could imagine that highly innovative and highly connected people tend to be together in networks, in which case the effect of HighCentrality-NW might just be a reflection of individual characteristics. However, this is not the case. Table 5 displays regressions that include both

Table 5: Individual position vs network effects

	(1)	(2)
Dependent variable	IdeaAccepted	ClientApproval
Degree	0.023***	0.024***
	(0.003)	(0.003)
Bridge Centrality	-0.045***	-0.061***
	(0.009)	(0.010)
HighDegree-NW	-0.017	-0.013
	(0.013)	(0.013)
HighCentrality-NW	0.027***	0.022**
	(0.010)	(0.010)
Network Size	0.000	0.001
	(0.001)	(0.001)
Summer	0.001	0.010**
	(0.005)	(0.005)
Employee FE	Yes	Yes
Linear time trend	Yes	Yes
With singletons	Yes	Yes
Observations	48510	48510
Clusters	28877	28877

Note: IdeaAccepted is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was accepted for implementation. ClientApproval is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was rated 3 or 4 out of 4 by the client. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

the individual network position—degree and bridge centrality—and the two variables measuring whether there are high degree and high centrality individuals in the network. While the individual position variables retain their significant effects, it is still the case that having a high centrality individual in the network is beneficial for innovation quality, holding own degree and centrality constant. Thus, the network variables are not merely picking up the effects of the omitted individual position variables. Instead, having a high centrality individual in the network has a significant positive effect on top of the individual position effects. The positive externality of high bridging individuals appears to be quite robust.

Table 6: Effect of previous collaborations and bridging

	(1)	(2)	(3)	(4)
Dependent variable	IdeaAccepted	ClientApproval	IdeaAccepted	ClientApproval
Degree	0.024***	0.025***	0.023***	0.025***
	(0.002)	(0.003)	(0.002)	(0.003)
Bridge Centrality	-0.043***	-0.059***	-0.042***	-0.060***
	(0.009)	(0.010)	(0.009)	(0.010)
Network Size	0.000	0.001*	0.000	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Degree_{t-1}	0.002	-0.001		
	(0.002)	(0.002)		
$\text{Bridge Centrality}_{t-1}$			0.015*	-0.003
			(0.009)	(0.009)
Summer	0.002	0.011**	0.002	0.011**
	(0.005)	(0.005)	(0.005)	(0.005)
Employee FE	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
With singletons	Yes	Yes	Yes	Yes
Observations	48510	48510	48510	48510
Clusters	28877	28877	28877	28877

Note: IdeaAccepted is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was accepted for implementation. ClientApproval is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was rated 3 or 4 out of 4 by the client. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

5.4 Past Collaborations

We have already learned that more collaborations in the present, as measured by degree, increase average innovation quality. To learn more about the mechanisms by which network position impacts idea quality, we want to see if this positive effect lasts or just applies to the current period. For example, if the positive effect of degree is due to the effort provided by co-innovators in generating the current idea, then the positive effect might not last past the current collaboration or the current period. However, if the positive effect is due to knowledge or skill transfer, then—if the knowledge or skills do not become obsolete quickly—we might see the positive effects persist in future periods.

In Table 6, we first include the lagged degree (from 6 months ago) in the regression, in addition to the network characteristics we used before (degree, bridge centrality, and network size). Thus, we can answer whether more collaborations half a year ago increase current idea quality, as is the case for more current collaborations. We focus on the first lag, because that gives us the best chance to detect an effect if there is one, given that the effects would likely fade over time. Columns (1) and (2) show that a previous high degree does not increase idea quality: the lagged degree coefficient is not significantly different from zero, whereas the other network characteristics retain their signs and significances (compared to Table 2).

We also ran regressions (not displayed here) with two lags for degree, and none of the lagged terms have a significant effect. Similarly, we defined a dummy variable for whether there was collaboration in any of the previous periods—not just the last two—and again there is no significant effect on idea quality. Thus, it does not appear that a high degree has longer-lasting effects. Instead, the positive collaboration effect is instantaneous and short-lived. We interpret this as an indication that the impact of degree operates mainly via the effort channel in equation (2). Co-innovators contribute effort to the generation of an idea and this improves idea quality.

In similar analyses in columns (3) and (4) of Table 6, we investigate the effect of previous bridging activity, by including one lag of bridge centrality in the regression. For the first outcome measure, high bridge centrality in the previous period is associated with a larger acceptance probability of the suggested idea. While statistical significance is marginal, this is notable as the sign of the effect is opposite to that of current bridging. For the second outcome measure, the lagged bridge centrality term is not significantly different from zero. We also find this pattern if we include a second lag of bridge centrality, which itself is not significantly different from zero (not displayed here). Overall, a zero or positive effect of previous bridge centrality is consistent with our interpretation that bridging is costly (e.g., due to opportunity costs of time): high bridge centrality in the current period has a negative effect, whereas past bridging behavior—since the costs have been borne in the past—no longer negatively affects current idea quality. The positive coefficient on past bridging could be indicative of lasting gains in innovative potential through the knowledge and perspectives gained from past bridging.

5.5 Changes to Networks in Working From Home and Hybrid Work

In this section, we ask how working from home and hybrid work affect networks. One conjecture is that changes to network structure could explain observed drops in the quality of innovation during working from home (Brucks and Levav, 2022; Gibbs et al., 2024).

Table 7 shows how work from home (WFH) and hybrid work affect our three main network characteristics of interest. Compared to work from the office (WFO), network size, average degree and average bridge centrality are all slightly decreasing under WFH, with only the effect on degree being statistically significant at the 10 percent level. For hybrid work, the negative effects are much stronger and highly statistically significant. Average network size

Table 7: WFH disruption of networks.

	Network Size	Degree	Bridge Centrality
	(1)	(2)	(3)
WFH	-0.194	-0.075*	-0.000
	(0.151)	(0.041)	(0.009)
HY	-1.423***	-0.349***	-0.028***
	(0.181)	(0.045)	(0.009)
Summer	-0.626***	-0.024	-0.004
	(0.0845)	(0.0201)	(0.00478)
Employee FE	Yes	Yes	Yes
Linear Time Trend	Yes	Yes	Yes
With singletons	Yes	Yes	Yes
Observations	48,510	48,510	48,510
Clusters	28,877	28,877	28,877

Note: WFH is a dummy taking the value 1 in the WFH period summer 2020 and HY takes the value 1 in the hybrid phases winter 2020-21 and summer 2021. Summer is a dummy that takes the value 1 in all summer periods. Robust standard errors in parentheses. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

decreases by 1.4 people, and each innovator works with on average ≈ 0.35 fewer others than under WFO. Bridge centrality decreases by almost 30% percent during hybrid work. Appendix Table C.6 conducts the same analysis after dropping singletons. In this case, the effect sizes are all slightly bigger. In the case of degree, under WFH the effect is twice as large. Comparison of the two tables hence shows that the overall effect reported in Table 7 comes primarily from a reduction in degree, network size, and bridge centrality among connected nodes; i.e., from the intensive margin. There is only a small increase in the share of isolated nodes.

Why are the effects on network characteristics stronger under hybrid than under WFH? There are at least two possible explanations. First, some disruption to networks caused by WFH might take longer to realize, and as the hybrid period directly follows the WFH period, these longer-term changes might show up under hybrid only. Second, it is possible that hybrid work leads to more network disruption if people are mis-coordinated between office and home work (Yang et al., 2022; Carmody et al., 2022; Gibbs et al., 2024).

What is the impact of these network changes on the quality of innovation? As we saw in Section 5.2, a higher degree benefits innovation. Bridge centrality benefits innovation in the future and generates positive externalities for others in the network, but (conditional on degree) has a short term negative impact on the quality of ideas of the person who bridges. If these relationships are maintained under WFH and hybrid, this would then mean that the network disruption we see is likely to have detrimental effects on innovation.

Table 8: Is the effect of network characteristics different during WFH/Hybrid?

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Idea Accepted	Client Approval	Idea Accepted	Client Approval	Idea Accepted	Client Approval
Degree	0.023***	0.026***	0.016***	0.017***		
	(0.003)	(0.003)	(0.002)	(0.002)		
Bridge Centrality	-0.046***	-0.062***			0.008	0.002
	(0.010)	(0.011)			(0.008)	(0.008)
Network Size	0.000	0.001	0.000	0.001*	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Degree × WFH	-0.011*	-0.012*	-0.005	-0.007		
	(0.006)	(0.007)	(0.004)	(0.005)		
Bridge Centrality × WFH	0.047**	0.035			0.017	0.003
	(0.024)	(0.025)			(0.017)	(0.019)
Network Size × WFH	0.006***	0.005***	0.006***	0.005**	0.005***	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Degree × Hybrid	0.017**	-0.000	0.013**	-0.003		
	(0.007)	(0.007)	(0.006)	(0.005)		
Bridge Centrality × Hybrid	-0.024	-0.011			0.004	-0.021
	(0.024)	(0.026)			(0.020)	(0.021)
Network Size × Hybrid	-0.004	-0.002	-0.004	-0.002	0.002	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
WFH	0.060***	0.044***	0.058***	0.042***	0.051***	0.032***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Hybrid	0.028**	0.021*	0.029**	0.021*	0.023*	0.010
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
Summer	-0.012**	0.001	-0.012**	0.001	-0.011**	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
With singletons	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48510	48510	48510	48510	48510	48510
Clusters	28877	28877	28877	28877	28877	28877

Note: IdeaAccepted is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was accepted for implementation. ClientApproval is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was rated 3 or 4 out of 4 by the client. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table 8 shows that under hybrid work these relationships are largely the same, with the positive associations of degree and idea quality being even stronger for some measures of idea quality. Under WFH, by contrast, the impact of degree on idea quality is much weaker than under WFO, while bridge centrality now does not affect the probability that an idea is accepted (conditional on degree) and has a smaller negative effect on client approval. One possible reason could be that, as communication and coordination costs are increasing overall under WFH, they are no longer that different across collaborations with similar and dissimilar others. This means that—conditional on degree—bridging becomes comparatively less costly.

In summary, we have seen that remote work (full or hybrid) led to substantial disruption of innovator networks. People collaborated with fewer others and crucial bridges were falling away. These changes can possibly explain negative impacts of remote work on idea quality.[13]

5.6 Discussion and Extensions

This section contains a number of extensions and discussion of our main results.

Groundbreaking Innovation. We measure the quality of employee ideas by whether they are internally accepted by the company and, if appropriate, approved by the client. One might wonder what types of ideas are more likely to be accepted and what types of ideas are produced by those in "favorable" network positions: small and safe ideas, or big, bold, and potentially game-changing ideas? To answer this question, we analyze the projected monetary value of the idea to the firm, which idea proposers estimate at the time of submission. This measure has to be interpreted with caution, as this value may be estimated in a very ad hoc manner. It can nevertheless give us some hint as to whether accepted ideas tend to be "small" or "big." First, we find that idea acceptance and the projected value are positively related ($\rho = 0.0113^{**}$). The same is true for customer approval, but with a smaller correlation ($\rho = 0.0082^{*}$). Appendix Table C.7 then reruns our main regression but with the projected value as an outcome variable. The table shows that those with a higher degree tend to produce more high value innovation, while those with higher bridging—conditional on degree—tend to produce lower value innovation. The effect size is substantial. The mean projected value of those with a degree of two or more is more than three times as high as that of those with a degree of zero or one.

Bridging and Diversity of Innovation. We can also try to understand a bit better the differences between bridges and other innovators in terms of the diversity of ideas they produce. There are two variables we can exploit for this purpose. First, every idea is assigned to a customer team. This is the customer for which this idea is going to be most relevant. Many

[13]We do not estimate the effect of WFH/Hybrid work on innovation quality directly here, as we have already done this for a different sample of employees in Gibbs et al. (2024).

ideas are useful only to a specific customer; e.g., if the idea concerns airplane software, then it is most likely not relevant for a customer who manufactures soft-drinks or is in banking. One measure of diversity is the number of different customer teams to which an innovator has contributed. A second measure of diversity of ideas is the number of idea categories in which an employee suggests ideas. The categories are process improvement, cost optimization, cycle time reduction, technical solutions, tool development, and risk mitigation. Appendix Table C.8 shows that those with a high bridge centrality are indeed more likely to produce diverse ideas according to both measures. The same is true for degree but with a smaller effect size. This suggests that those with a high bridge centrality are indeed exposed to more different ideas and perspectives than others and hence able to innovate in more categories and for a larger set of customers.

Aggregate Impact of Bridging. We have seen that—conditional on degree—bridging has a negative impact on an employee's quality of innovation, but it does generate positive externalities. A natural question is what is the aggregate impact of bridging? A short back-of-the-envelope calculation shows that it is positive. Being a high bridge centrality individual lowers innovation quality by -0.036 percentage points, while it provides a positive externality of $+0.027$ percentage points to all nodes in the network on average (Table 5). The average size of a network with at least one high centrality employee is 6.19 and the average number of high centrality employees in such a network is 2.05. The aggregate effect is therefore $+0.093$ for the average network with a high centrality employee, an almost ten percentage point gain. The aggregate impact of bridging is positive.

Strategic Network Formation. Anecdotal evidence suggests that most links in our networks are formed spontaneously based on pre-existing social relationships as well as the organizational structure of the firm. For example, links are more likely between office mates than with employees at further away locations. However, one might wonder what we should expect if networks were formed strategically. If innovators strategically aim to obtain a network position that leads to high-quality innovation, then they should link to many others (strive for a high degree) as well as to others who bridge to benefit from the bridging externality. In the data, we do not see a lot of evidence for such behavior, with almost half of the nodes being singleton nodes; i.e., of degree zero. Note also that, as long as strategic innovators have a short horizon, they should not want to bridge themselves. As bridging provides positive externalities, though, taking a more strategic perspective on network formation could be useful for the company. In particular, our results show that explicitly rewarding individually costly but collectively beneficial bridging might be justified.

6 Conclusions

In this paper we exploit a rare opportunity, by analyzing a large sample of employee innovations within a firm. As a first step, we developed a simple model of network position and innovation to frame the empirical work. In the next step, we measured several elements of employee networks that have been considered important to innovation in the literature: degree, network size, and bridge centrality. The primary empirical analyses provide evidence on how these relate to each other, and most importantly to the quality of employee ideas. Finally, we analyzed how networks changed with full or partial use of remote work, which is currently of high practical interest as many employers seek to bring employees back to the office.

The evidence shows that certain important network measures are related to innovation. Because of our substantial sample size, we are able to disentangle their differential impacts despite the fact that different network measures are often strongly correlated with each other. First, network size is not associated with innovation, after controlling for degree and bridge centrality. These three measures are significantly pairwise correlated. Without controlling for either of those measures, network size has a positive effect on innovation.

Second, network degree is significantly and positively associated with the quality of employee ideas. That is consistent with prior literature. Lagged network degree does not affect current innovation and there don't seem to be positive externalities from high-degree individuals. These findings are evidence for the importance of direct collaboration to current (but not future) innovation.

The idea of bridging across structural holes has been prominent in the literature on networks and innovation. We measure each employee's bridge centrality in each period of time. Bridging has positive aggregate impacts on innovation, but the individual level effects are more subtle. The immediate effect of bridging on quality of innovation (holding degree constant) is negative, but in the medium run there are net benefits to the employee. This may seem surprising at first, but most likely reflects the fact that the costs of bridging (coordination, translation) outweigh the benefits in terms of improved perspective. In the medium run, however, the costs are largely in the past and net benefits appear. At the same time, having one or more colleagues with high bridge centrality is positively associated with the quality of the employee's ideas. Bridging presents a tradeoff. This is consistent with our model, which highlights that acting as a broker across structural holes has effort costs for the employee, but benefits that accrue to colleagues. Thus, bridging has positive externalities for others in the network. Even if it does not improve the employee's personal innovation in the short term, the medium and long term benefits may lead to better performance evaluations, higher rates of promotion, and other rewards, as has been found in prior work (Burt, 2004).

These findings have a number of interesting implications to contexts outside of the firm. The positive externality of bridges is consistent with the idea of "weak ties." This literature has shown that weak ties can be beneficial by providing information about, e.g., jobs (Granovetter, 1973; Rajkumar et al., 2022). A person who supports many such weak ties can be extremely useful to a community while they may not necessarily benefit themselves in the short run. The findings also raise some questions about how organizations can support bridges if (short-run) incentives to bridge are not there. To the extent that the results are transferable they suggest, for example, that interdisciplinary research, while not necessarily beneficial to the people conducting it, can be very fertile for the discipline. This raises a question for research funders on how to best motivate such interdisciplinary "bridging."

Currently CEOs are expressing concerns about reduced productivity and innovation due to the increased use of working from home or hybrid home-office work (Stewart, 2023; Smith, 2024). Many firms are mandating that employees return to the office, and seeking ways to coordinate days allowed for remote work. Several studies have provided good reasons to expect that remote work leads to reductions in important intangibles, such as mentoring, collaboration, coordination, social networks, and innovation (Teevan et al., 2020; DeFilippis et al., 2022; Yang et al., 2022; Gibbs et al., 2023; Emanuel and Harrington, 2024). It also seems likely that fostering a productive corporate culture will suffer. As a last step in this paper, we analyzed how our measures of network position differ in periods of working from home or hybrid mode, compared to working from the office.

Our evidence reinforces prior literature and concerns about the costs of remote work. The effects of network degree and bridging were similar in all three work modes. However, social networks suffered from WFH and hybrid work. Compared to working at the office, network degree declined during working from home. Hybrid work was associated with even more negative effects on network structures, reducing network size, degree, and bridge centrality. These findings suggest that coordination and communication is especially tricky when employees are in hybrid mode, and networks suffer as a result. They may also explain recent evidence that innovation suffers from remote work compared to WFO (Brucks and Levav, 2022; Gibbs et al., 2024). It is conceivable that our results might understate the challenges that remote work presents for innovation, especially WFH. Our period of working from home immediately followed that of working from the office. Thus existing social networks were in place, and probably declined gradually with WFH. It would be quite interesting for researchers to study how networks change with remote work long term.

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Online Supplementary Material

For Online Publication

Contents

A Additional Theory

In this section we provide additional details on the theoretical impact of degree, network size and bridging on innovation quality. To start, optimal effort e^* solves

$$B\frac{\partial q(Q_z)}{\partial Q_z}\rho = c(e^*)\frac{\partial c(e^*)}{\partial e^*},$$

where we note that $\frac{\partial q(Q_z)}{\partial Q_z}$ is constant as $q(Q_z)$ is assumed linear.

Impact of Degree To understand the impact of degree on the quality of an innovation z which is co-authored by i, we consider the impact of adding one additional neighbor i' of equal similarity to i as the average of i's existing neighbors. The following is true

Claim: *If i' is not a neighbor of any other co-authors on idea z (other than i), then the quality of idea i is strictly increasing with this increase in degree if either (i) i' is a co-author of z or (ii) if $\delta > 0$ and $\exists k$ s.t. $f_{ik} \neq f_{i'k}$.*

To see this note that the impact on κ_i is always non-negative. It is strictly positive whenever (i) $\delta > 0$ and (ii) $\exists k$ s.t. $f_{ik} \neq f_{i'k}$. i's optimal effort e_i^* is unchanged as we have assumed that i' of equal similarity to i as the average of i's existing neighbors, which means i's costs are not increasing. i' provides positive effort in equilibrium if they are a co-author and no other co-authors equilibrium effort is changing as they are not neighbors of i'.

Corollary: *An extensive margin increase from a single-authored to a co-authored idea always has a strictly positive impact on quality.*

This corollary follows from the claim above for the special case where where there are no other co-authors on idea z; Also note that the conditions identified in the claim are sufficient conditions. In cases not covered by the claim, whether the impact of an additional neighbor is positive or negative depends on assumptions on the functional form $c(e)$ as well as the relative importance of ρ and δ.

Impact of Network Size To understand the impact of network size (conditional on degree) we engage in the following thought experiment. We are adding an innovator i' to i's network who is *not* a neighbor of i.

Claim: *If $d(i, i') > 2$, then the quality of idea i is strictly increasing with this increase in network size if $\delta > 0$ and $\exists k$ s.t. $f_{ik} \neq f_{i'k}$.*

To see this note that if $d(i, i') > 2$ then there is no impact on effort of any of the co-authors as none of them is linked to i'. If further $\delta > 0$ and $\exists k$ s.t. $f_{ik} \neq f_{i'k}$ then this additional person in the network has a strictly positive impact on i's innovation potential leading to an overall positive effect.

Again it should be noted that these are sufficient conditions. In general whenever i is not a neighbor of any co-authors on idea z (and if $\delta > 0$ and $\exists k$ s.t. $f_{ik} \neq f_{i'k}$ for at least one co-author i on the idea z), then there is a strictly positive impact of this additional neighbor on idea quality.

Impact of Bridge Centrality To understand the impact of bridge centrality conditional on degree the thought experiment is to rewire one of i's links in such a way that betweenness is increased. Figure A.1 shows two example of such rewiring.

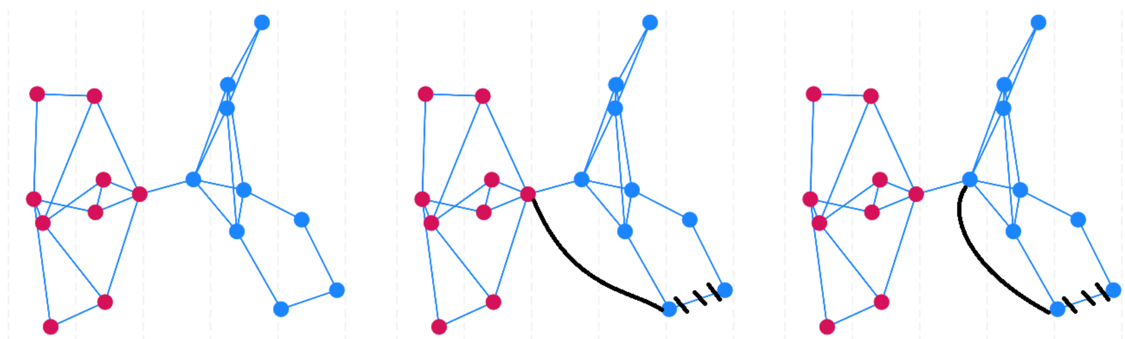


Figure A.1: An example of rewiring starting from left panel. Simulated network with $N = 18$ and two types $(0, 1)$ and $(1, 0)$ identified by red and blue nodes. Node i is the bottom-most blue node. Their link to the right with the second-most bottom blue node is cut and rewired (black link). Degree is held constant but betweenness increases in both middle and right panel.

The impact of bridging will depend on whether the new neighbor is more or less similar to i compared to the previous neighbor. If the new neighbor is less similar (as in the middle panel of Figure A.1) then there will be a negative impact on effort as i now has increased effort costs as well as a positive impact on κ_i (as long as $\delta > 0$). The overall effect in this case depends on parameters such as δ and ρ. If the new neighbor is equally or more similar (as in the right panel of Figure A.1) the impact on κ_i as well as on i's effort would be non-negative. The overall impact would depend on parameters such as δ and ρ and on the impact on the effort of other co-authors on z.

B Additional Information: Background and Setting

We list some examples of implemented and rejected ideas. Because of the sensitivity of the information we only include the idea gist and have replaced names (of products, teams etc by XXX).

- Examples of Implemented Ideas
  - Developing a XXX utility to setup the batching end-to-end scenario on a single click.
  - XXX Analysts take over the work of XXX support team employed for converting these XXX.
  - Enable all apps to be accessed on smart phones like iPhone.
  - Automation of the process of result entry from Lab machines to XXX system without changing the XXX.
  - Creating an online engagement dashboard/portal which showcases all relevant live XXX.
  - To create a tool that can be used as XXX control and has capability to trace changes back to XXX.
  - Provide XXX frame work for developers to write and execute their test cases in XXX, XXX and XXX.
  - Make a web application that will give the reservation XXX page to the user who wants XXX.
- Examples of Rejected Ideas
  - Automate Script or Procedure to update the XXX queries in XXX Database.
  - Color the XXX plots and plot output.
  - Develop a single reliable model to monitor various critical processes that are running in XXX.
  - Automation of the Process Flow with XXX.
  - Create an XXX that can be used to modify or add to XXX and has ability to connect to XXX.
  - Create a version control tool which would provide XXX for the XXX project.
  - Automated Tool to create the XXX template at a single click.
  - Integration of XXX support to the existing XXX system.

C Additional Tables

Table C.1: Are past network characteristics predictive of future network characteristics?

	(1)	(2)	(3)
Dependent variable	Degree_t	$\text{Bridge Centrality}_t$	Network Size_t
Degree_{t-1}	0.555***		
	(0.017)		
$\text{Bridge Centrality}_{t-1}$		0.294***	
		(0.023)	
$\text{Network Size}_{t-1}$			0.353***
			(0.028)
Summer	0.088**	0.003	-0.294**
	(0.039)	(0.008)	(0.131)
Employee FE	No	No	No
Linear time trend	Yes	Yes	Yes
With singletons	Yes	Yes	Yes
Observations	10706	10706	10706
Clusters	6309	6309	6309

Note: The regressions predict this period's network characteristic based on last period's network characteristic, a summer dummy for this period, and a linear time trend. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table C.2: Predicting idea quality with network statistics (without singletons)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Idea Accepted	Client Approval	Idea Accepted	Client Approval	Idea Accepted	Client Approval
Degree	0.013***	0.011***	0.009***	0.005**		
	(0.003)	(0.003)	(0.002)	(0.002)		
Bridge Centrality	-0.021**	-0.032***			0.007	-0.008
	(0.009)	(0.011)			(0.007)	(0.008)
Network Size	0.000	0.001	0.000	0.001	0.001**	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Summer	-0.002	0.007	-0.002	0.007	-0.002	0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
With singletons	No	No	No	No	No	No
Observations	28166	28166	28166	28166	28166	28166
Clusters	18297	18297	18297	18297	18297	18297

Note: IdeaAccepted is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was accepted for implementation. ClientApproval is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was rated 3 or 4 out of 4 by the client. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table C.3: Predicting idea quality with network statistics (no employee FE)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Idea Accepted	Client Approval	Idea Accepted	Client Approval	Idea Accepted	Client Approval
Degree	0.041***	0.049***	0.034***	0.040***		
	(0.002)	(0.002)	(0.001)	(0.002)		
Bridge Centrality	-0.069***	-0.088***			0.041***	0.042***
	(0.007)	(0.009)			(0.006)	(0.007)
Network Size	0.000	0.000	0.001*	0.001**	0.005***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Summer	0.005	0.014***	0.005	0.014***	0.007*	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Employee FE	No	No	No	No	No	No
Linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
With singletons	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48510	48510	48510	48510	48510	48510
Clusters	28877	28877	28877	28877	28877	28877

Note: IdeaAccepted is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was accepted for implementation. ClientApproval is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was rated 3 or 4 out of 4 by the client. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table C.4: Predicting idea quality with network statistics

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Idea Accepted	Client Approval	Idea Accepted	Client Approval	Idea Accepted	Client Approval
Degree	0.019***	0.019***	0.017***	0.016***		
	(0.002)	(0.002)	(0.002)	(0.002)		
Betweenness Centrality	-0.038**	-0.057***			0.019	-0.000
	(0.015)	(0.017)			(0.014)	(0.015)
Network Size	0.000	0.001**	0.001	0.001**	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Summer	0.002	0.011**	0.002	0.011**	0.003	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
With singletons	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48510	48510	48510	48510	48510	48510
Clusters	28877	28877	28877	28877	28877	28877

Note: IdeaAccepted is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was accepted for implementation. ClientApproval is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was rated 3 or 4 out of 4 by the client. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table C.5: Effect of having well connected colleagues in the network in the past

	(1)	(2)	(3)	(4)
Dependent variable	IdeaAccepted	ClientApproval	IdeaAccepted	ClientApproval
HighDegree-NW	0.011	0.014	0.009	0.015
	(0.012)	(0.013)	(0.012)	(0.013)
HighCentrality-NW	0.034***	0.027***	0.037***	0.028***
	(0.010)	(0.010)	(0.010)	(0.011)
Network Size	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
HighDegree-NW$_{t-1}$	0.009	-0.014		
	(0.011)	(0.011)		
HighCentrality-NW$_{t-1}$			0.018**	0.004
			(0.009)	(0.009)
Summer	0.002	0.012**	0.002	0.011**
	(0.005)	(0.005)	(0.005)	(0.005)
Employee FE	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
With singletons	Yes	Yes	Yes	Yes
Observations	48510	48510	48510	48510
Clusters	28877	28877	28877	28877

Note: IdeaAccepted is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was accepted for implementation. ClientApproval is the mean over all of an employee's ideas in a 6-month period of an indicator whether an idea was rated 3 or 4 out of 4 by the client. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table C.6: WFH disruption of networks without singleton nodes

	Network Size	Degree	Bridge Centrality
	(1)	(2)	(3)
WFH	-0.052	-0.144**	-0.003
	(0.262)	(0.063)	(0.016)
HY	-1.872***	-0.378***	-0.039**
	(0.336)	(0.069)	(0.017)
Summer	-1.145***	-0.042	-0.009
	(0.148)	(0.031)	(0.008)
Employee FE	Yes	Yes	Yes
Linear Time Trend	Yes	Yes	Yes
With singletons	Yes	Yes	Yes
Observations	28,166	28,166	28,166
Clusters	18,297	18,297	18,297

Note: WFH is a dummy taking the value 1 in the WFH period summer 2020 and HY takes the value 1 in the hybrid phases winter 2020-21 and summer 2021. Summer is a dummy that takes the value 1 in all summer periods. Robust standard errors in parentheses. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table C.7: Predicting idea value with network statistics

	(1)	(2)	(3)
Dependent variable	Log(IdeaValue)	Log(IdeaValue)	Log(IdeaValue)
Degree	0.223***	0.166***	
	(0.016)	(0.014)	
Bridge Centrality	-0.391***		0.142***
	(0.060)		(0.049)
Network Size	-0.004	-0.002	0.017***
	(0.003)	(0.003)	(0.003)
Summer	0.030	0.032	0.040
	(0.027)	(0.027)	(0.027)
Employee FE	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes
With singletons	Yes	Yes	Yes
Observations	48510	48510	48510
Clusters	28877	28877	28877

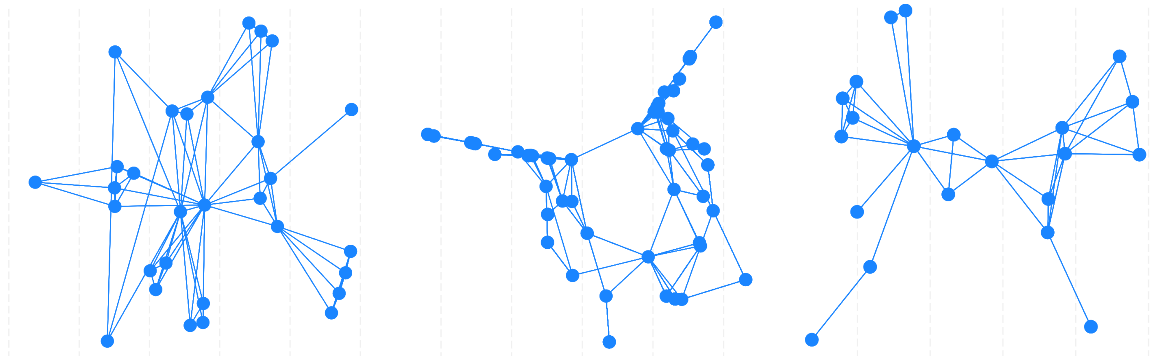
Note: Log(IdeaValue) is the natural logarithm of the mean of the projected idea value to the firm over all of an employee's ideas in a 6-month period. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table C.8: Diversity of Ideas

	(1)	(2)	(3)
Dependent variable	NumTeams	MoreThanOneTeam	NumIdeaCategories
Degree	0.014***	0.004***	0.057***
	(0.004)	(0.002)	(0.005)
Bridge Centrality	0.063***	0.030***	0.374***
	(0.015)	(0.007)	(0.022)
Network Size	-0.001***	-0.000*	0.001
	(0.000)	(0.000)	(0.001)
Summer	0.023***	0.012***	-0.010
	(0.004)	(0.002)	(0.007)
Employee FE	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes
With singletons	Yes	Yes	Yes
Observations	48510	48510	48510
Clusters	28877	28877	28877

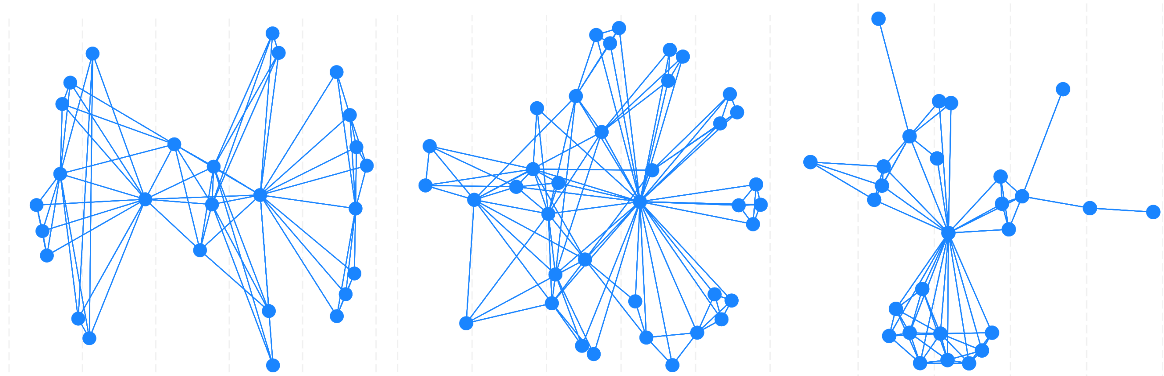
Note: NumTeams is the number of teams for which the employee submitted ideas in that period. MoreThanOneTeam is an indicator equal to 1 if the number of teams for which the employee submitted ideas in that period exceeds 1. NumIdeaCategories is the number of different kinds of ideas the employee submitted in that period. The unit of observation is the employee-period, where a period is 6 months. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

D Additional Figures



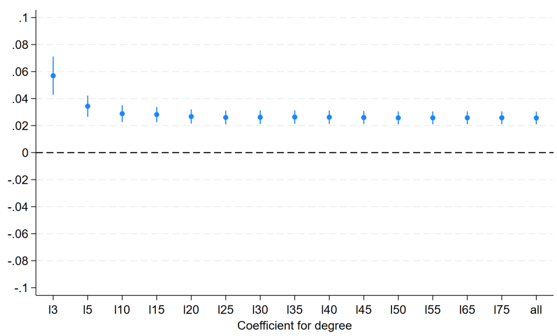
(a) Winter 2018-19 (b) Winter 2019-20 (c) Winter 2020-21

Figure D.1: The largest component in two winter networks before (Panels (a) and (b)) and one after WFH (Panel (c)).

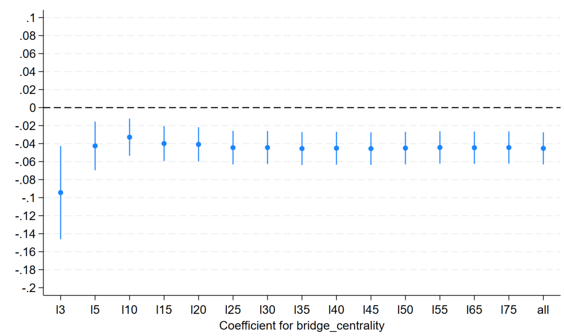


(a) Summer 2019 (b) Summer 2020 (c) Summer 2021

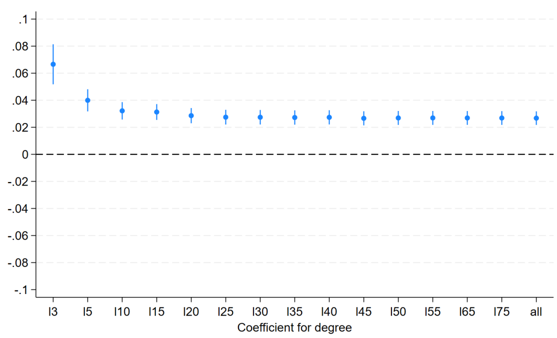
Figure D.2: The largest component in one summer network before (Panel (a)) one during WFH (Panel (b)) and one during HY (Panel (c)).



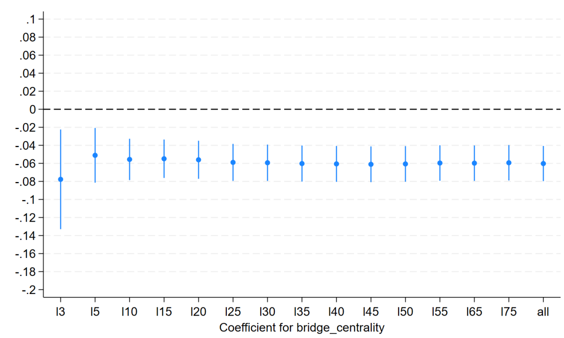
(a) IdeaAccepted



(b) IdeaAccepted



(c) CustomerApproval



(d) CustomerApproval

Figure D.3: Coefficient Plots showing the coefficients for degree (left panel) and bridge centrality (right panel) for regressions restricted to nodes with a weighted degree of at most x.