Journal of Applied Psychology

© 2021 American Psychological Association
ISSN: 0021-9010

2021, Vol. 106, No. 10, 1483–1492
https://doi.org/10.1037/apl0000969

Teamwork in the Time of COVID-19: Creating, Dissolving, and Reactivating Network Ties in Response to a Crisis

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The Coronavirus disease (COVID-19) pandemic has prompted an unprecedented shift to remote work. Workers across the globe have used digital technologies to connect with teammates and others in their organizations. In what ways did the COVID-19 crisis alter the frequency and balance of internal and external team interactions? During a crisis, networking offers a type of goal-directed behavior through which individuals source and provide information. We can understand how people use their network through the lens of network churn, changes in embeddedness brought on by the creation, dissolution, and/or reactivation of network ties. higher We posit that performing individuals exhibit distinct networking strategies as compared to lower performing employees during the pandemic. We present a field study conducted in a multinational industrial manufacturing company in China investigating network churn during the COVID-19 pandemic. Findings show that, during a crisis, job performance is positively related to the volume of inter-team tie creation and inter-team tie reactivation, but not intra-team tie creation and intra-team tie reactivation. Job performance is not related to the volume of intra- and inter-team tie dissolution. The study provides early, yet important insights into the interplay between crisis and organizational social networks.

Keywords: network churn, performance, team boundaries, dormant ties, uncertainty

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Organizations are continuously adapting to the "new normal" as the Coronavirus disease (COVID-19) pandemic threatens global health and contracts economies (Alter & Villa, 2020). Of all the disruptions brought on by the pandemic, one of the most pronounced was the sudden shift to remote work. Prior to COVID-19, many workers engaged in some degree of remote collaboration often centered around teams of people whose interaction is integral to the accomplishment of their shared goals. It entailed geographically separated workers interacting using digital technologies like Google Docs, Slack, Zoom, or Microsoft Teams.

As COVID-19 prompted organizations to direct employees to work from home, technologies facilitated interaction not just within their team but also outside their team. In what ways did the COVID-19 crisis influence the frequency and balance of internal and external team interactions? And did high and low performers leverage their internal and external networks *differently* in response to the crisis? Building on previous work on network churn, team boundary spanning, and cognitive resource allocation, we advance an integrated conceptual view of information processing and organizational networking behavior. In addition to this conceptual contribution, this study provides an important first look into how the sudden shift to remote work reshaped organizational networks, and how higher and lower performers differently rewired their networks in response to crisis. In doing so, the findings offer new insights into how employees may want to manage networks during crises.

During a crisis, networking offers a type of goal-directed behavior through which individuals source and provide information. We can understand how people use their network through the lens of *network churn*, changes in embeddedness brought on by the creation, dissolution, and/or reactivation of network ties (Monge & Contractor, 2003; Sasovova et al., 2010; Siciliano et al., 2018; Tanaka & Horvát, 2019). Network churn enables us to test extensions of team boundary-spanning theory which distinguishes internal and external team ties (Ancona & Caldwell, 1992; Caldwell & O'Reilly, 1982) and theories of group social capital (Oh et al., 2004).

Whereas intra-team ties allow team members to engage in requisite processes like planning, coordinating, and motivating (Marks et al., 2001) among a set of individuals working closely on shared goals, inter-team ties (also called bridging ties), provide individuals access to diverse information, a broader pool of resources, and the ability to "learn about developments within the organization faster (Oh et al., 2004, p. 864)." Network churn captures changes in how individuals derive value from their intra- and inter-team networks during a crisis.

While the experience of crisis prompts shifts in networks, high and low performers may well churn their networks differently. To understand how, we turn to resource allocation theory (Kanfer & Ackerman, 1989). COVID-19 caused a change in the nature of the work, making tasks more difficult and uncertain. The shift also

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We have no known conflict of interest to disclose. This research was supported by the National Science Foundation grants 2027572 and 2052366 and Fudan University's School of Management. Some of ideas in the manuscript were presented at the 2020 INGRoup conference and the North American Social Networks conference. We thank Yunjie Xu and Hui Li from Fudan University, Carmen Chan, and Feodora Kosasih for their help with the data collection. We are also immensely grateful to Sameer Srivastava and Michelle Shumate for their comments on an earlier version of the manuscript.

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required individuals to learn new skills in order to be effective in fully remote work (Trougakos et al., 2020). From a resource allocation perspective, this situational change would require more attention and effort, resources that can be more readily provided by high performers who have already mastered the work. They have advanced in skill acquisition to the point where many tasks are automatic, and no longer require attention. This freeing up of attention provides them mental resources needed for adapting to remote work. Churning one's network, by creating, dissolving, and reactivating ties, is one way they can adapt to remote work.

Theoretical Foundation

Network Churn as Adaptive Behavior

Social networks describe the embeddedness of individuals in a web of relationships (Balkundi et al., 2019). Though occupying a certain network position can be advantageous (e.g., brokers, Burt, 2004), individuals can also leverage their networks by shifting their attention and changing their ties over time. Changing one's network relations, or network churn, has three aspects: Creating new ties, dissolving previous ties, and reactivating ties that were once present and later dissolved (Kneeland, 2019; Sasovova et al., 2010; Vissa & Bhagavatula, 2012).

The first aspect of network churn is *creating new ties*. Prior research has identified multiple theories such as social exchange, balance, structural holes, and homophily to explain tie creation (Contractor et al., 2006; Monge & Contractor, 2003). Creating ties can proffer advantages from acquiring new skills to sourcing diverse information (Uzzi & Spiro, 2005).

The second aspect of network churn is *dissolving existing ties,* sometimes called tie decay (Burt, 2000; Kleinbaum, 2018). Given that ties take effort and attention to manage, there is a natural limit on how many ties one can manage (Dunbar, 1993). Viewed in this light, tie dissolution is not always an indicator of failed relationships (Powell et al., 2005), and in fact, it can have strategic advantages. Dissolving ties frees resources that can be redirected to cultivate new or reactivate dormant ties.

A third aspect of network churn is *reactivating old ties* (Kneeland, 2019). That is recreating ties with those previously in one's network, but later dissolved (Walter et al., 2015). Reactivated ties benefit from a shared history and once restored, can imbue novelty while benefiting from the fact that, because the relationship previously existed, these ties take less effort and attention to cultivate by relying on previous scripts for efficient communication, a basis for trust, and shared perspectives (Levin et al., 2011).

Churning Intra- and Inter-Team Ties

When working in teams, network churn provides a valuable way to understand individuals' changes in networks within and outside the team. Boundary spanning (Marrone, 2010), also called group social capital, distinguishes bonding and bridging ties (Oh et al., 2004). Bonding or *intra-team ties* are relations among team members that enable them to carry out taskwork and teamwork. Bridging or *inter-team ties* form between two individuals who are not teammates. They provide access to diverse information and perspectives, bringing resources back to the team (e.g., scouting; Ancona & Caldwell, 1988), or they can promote and advocate for the needs of the team (e.g., ambassadorial; Ancona & Caldwell, 1988).

Given the strategic value of inter-team ties, creating and reactivating these ties may render greater strategic advantage during a crisis. Inter-team ties offer access to more diverse information and broader resources, relative to creating or reactivating intra-team ties. To accommodate these new ties, there may be an advantage to dissolving intra-team ties. Oh et al. (2004) found a curvilinear relationship whereby a moderate degree of intra-team ties benefits performance, whereas high density of ties are redundant and can undermine performance. When working under major constraints, dissolving intra-team ties may be advantageous. Having identified patterns of churn that may proffer a strategic advantage, we return to the central question of how crisis shapes churn behavior.

Churning in Crisis: A Resource-Allocation Perspective

From the preceding discussion of churn and group social capital, we can see how individuals stand to gain a strategic advantage by creating and reactivating inter-team ties, and dissolving intra-team ties. Our central question is the degree to which the shift to remote work necessitated by COVID-19 may have prompted the use of strategic churn, and whether some workers were in a better position to leverage this strategy than others. A useful framework for understanding the effects of the shift to remote work is Kanfer and Ackerman's resource allocation theory (1989), which explains the role of ability and motivation in acquiring complex skills. Two especially informative elements of the theory for understanding work behavior in response to COVID-19 are attentional resources and attentional demands.

Attentional resources describe the amount of mental effort and attention available to an individual (e.g., from ability, or mastery), whereas *attentional demands* describe the amount of mental effort and attention required to successfully perform the task (i.e., as affected by difficulty or novelty). The shift to remote work increased attentional demands, requiring new modes of communicating, greater uncertainty, while simultaneously reducing attentional resources through the addition of anxiety and other ambient distractions. Notably, this theory illustrates why successful adaptation to the confluence of these attentional constraints is markedly easier for those individuals who are at an advanced mastery of their jobs.

High performers, through some combination of ability and motivation, have mastered their jobs to the point where some aspects of work are automatic. Knowing who to ask for information, or how to solve a complicated problem, for example, may require less rework and cognitive effort as the job is mastered. Thus, mastery frees up spare attentional resources that are available should the need arise. We propose the COVID-19 sudden shift to remote work presented employees with such a need. Workers had to adjust and learn new ways of coordinating and accomplishing their basic job functions. At the same time, attentional resources were taxed by the general anxiety and uncertainty caused by the pandemic. Accordingly, it follows from resource allocation theory that high performers, by virtue of their greater pool of attentional resources, would have been better positioned to their networks than lower performers. Networking behavior requires effort. Low performers would need to devote a greater share of their resources to adjusting to the altered task at a time when it was not yet well-learned, hence rendering them less discretionary effort to devote to network behaviors.

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Creating and reactivating inter-team ties, and dissolving intra-team ties, provide a source of strategic advantage, albeit one requiring attentional resources to realize. Based on this integration of network churn, group social capital, and resource allocation theory, we posit that high performers were better able to engage in strategic network churn during the COVID-19 crisis than were low performers. Realizing the strategic advantage of inter- relative to intra-team ties, higher performers, enabled by a greater pool of attentional resources, would respond to a crisis by creating and reactivating inter-team ties that provide access to novel information and enable them to advocate for the needs of their teams. At the same time, in order to open up opportunities for expanded inter-team networking, we would expect high performers to dissolve more intra-team ties than do low performers. Thus, we expect:

> *Hypothesis 1:* During a crisis, job performance is positively related to inter-team tie creation, but not intra-team tie creation.

> *Hypothesis 2:* During a crisis, job performance is positively related to intra-team tie dissolution, but not to inter-team tie dissolution.

> *Hypothesis 3:* During a crisis, job performance is positively related to inter-team tie reactivation, but not intra-team tie reactivation.

Method

We studied network churn in a field study in two departments (i.e., Human Resources, Career Improvement Professional Office) of a multinational industrial manufacturing company in the People's Republic of China (Northwestern University IRB STU00211072 "Leveraging digital trace data to predict survey data on social relationships"). The 200 employees in the sample constituted the full population of employees. These professionals worked in 18 teams within and across 17 cities in China. The average team size was 11.65 (ranging from 6 to 20). The sample was predominantly female (86.28%), with an average age of 37 years, and organizational tenure of 7.6 years. Eighteen were team leads. The sample is racially homogeneous (97.83% Chinese). We excluded 14 newly hired individuals who had not undergone a performance review, and two senior executives who were not members of a particular team. The sample size for our analysis was 184.

We obtained digital metadata from employees' use of a conferencing platform. The platform was officially adopted by the company and widely used for any type of video or audio call involving two or more participants. Any employee had the ability to set up a meeting with any other employee through the platform. The de-identified digital trace data and human resources data (e.g., gender, organizational rank) were obtained through a cooperation agreement between Fudan University and the company. A researcher at Fudan University went on-site to replace the names with anonymous IDs, linking the digital trace and HR data. Then researchers at Fudan shared the de-identified data with the research team to ensure that participants' identity was masked. The digital metadata, including participant IDs and duration of meetings, covered the period from October 2019 to mid-March 2020. Data predating the COVID-19 outbreak in China served as a baseline for studying changes in communication patterns on the platform when COVID-19 triggered a shift to fully remote work.

We partitioned the digital trace logs into four periods based on three major events that occurred during the crisis. The four periods were: *Pre-COVID-19*, *crisis looming*, *shift to remote work*, and *phased return* (Table 1). On January 11, 2020, when the government implemented public health response planning, employees still worked in the office with the awareness of the virus. The public holidays of Lunar New Year spanned from January 24 to February 4, 2020. However, given the spread of COVID-19, employees were required to work fully remotely, from January 24 to February 17, 2020. From February 17, the organization began a phased return to offices, and most employees returned to their offices by March 12, 2020.

Table 1
Description of the Four Time Periods Marking Shifts in Work Practices Triggered by the COVID-19 in China Between October 2019 and March 2020

Period name	Time period	Major events	Details
Pre-COVID-19	10/08/2019–01/10/2020		The research team was studying the use of digital platforms and did not realize that we were in the *Pre-COVID-19* period.
Crisis looming	01/11/2020–02/03/2020	01/11/2020—Media in China reported the first death due to the COVID-19 virus[a]	The public was increasingly aware of the spreading virus and thinking about how it may affect them. Lunar New Year, an event marked by travel and large gatherings, occurred from 1/24 to 2/4.
Shift to remote	02/04/2020–02/16/2020	02/04/2020—Employees did not come back to office as expected[b]	Public considered how it may affect them and started responding to the awareness. A lockdown began in China right after Lunar New Year holiday on 2/4.
Phased return	02/17/2020–03/12/2020	2/17/2020—Employees in the organization started phased return to offices	As virus transmission in China waned, the company began a partial return to in-person working.

Note. COVID-19 = Coronavirus disease.
[a] Source: Taylor, D. B. (2021, March 17). A timeline of the coronavirus pandemic. *The New York Times*. https://www.nytimes.com/. [b] Source: Devonshire-Ellis, C. (2020, February 21). Updated: China factory and offices reopening schedules after Lunar New Year. *China Debriefing*. https://www.china-briefing.com/.

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Measures

Job Performance

To capture individuals' mastery of their jobs before COVID-19, we obtained the 2019 annual evaluation data for all employees. Employees and their supervisors identified goals and objectives for the employee at the beginning of the evaluation year (e.g., processing all forms within three business days). At the end of the evaluation period, supervisors evaluate employees' performance based on these goals. Ratings were made on a 5-point scale (1 = *low*; 5 = *high*; $M = 3.46$, $SD = 0.57$). 2.5% received a rating of two, 46.5% of employees received a score of three, 43% received a score of four, and 1% received a rating of five.

Tie Creation

The first dependent network churn variable is tie creation. This variable was coded as follows: We counted the number of ties created in each employee's networks compared to all the prior periods (newly created ties). The first period served as the baseline, so we counted it only for the *crisis looming*, *shift to remote,* and *phased return* periods. We then summed the counts of tie creation for all three periods to obtain our measure of tie creation. We will describe how a "tie" is operationalized in the analysis section.

Tie Dissolution

The second dependent network churn variable, tie dissolution, is the number of ties dissolved relative to the preceding period. We summed the raw count of ties dissolved in the last three periods by each employee to operationalize tie dissolution.

Tie Reactivation

The third dependent network churn variable, tie reactivation, is the number of ties reactivated by each employee in either the *shift to remote* or *phased return* that did not exist in the preceding period but were present in the periods before the preceding period. We summed the raw count of ties reactivated in the last two periods for each employee to obtain our measure of tie reactivation. Table 2 illustrates how we count the number of tie creation, dissolution, and reactivation across the four periods.

Intra- and Inter-Team Ties

We further classified each tie as being either between two individuals in the same team (intra-team) or different teams (inter-team). To illustrate these operationalizations, Figure 1 depicts a high performer's network across the four periods.

Gender

We included gender as a control variable because previous research has shown it influences the structure of social networks due to homophily effects—people are more likely to develop ties with others of the same gender (McPherson et al., 2001). As it could influence network churn, it is important to control for it. We coded gender as 0 for males and 1 for females.

Organizational Tenure

Based on prior research, we also controlled organizational tenure. The longer an employee has worked in a company, the greater chance they have to develop ties (e.g., van de Bunt, 1999). Organizational tenure was coded as the number of years that an employee worked in the organization.

Organizational Rank

We controlled for organizational rank, because one's position in an organizational hierarchy influences their networking (Smith et al., 2012; Srivastava, 2015). Individuals of a higher rank are more likely to be sought out for advice and included in meetings at an organization (Loury, 2006), especially during times of organizational crisis (Diesner et al., 2005). We coded organizational rank as 1 for team leads and as 0 for other employees.

Team Size

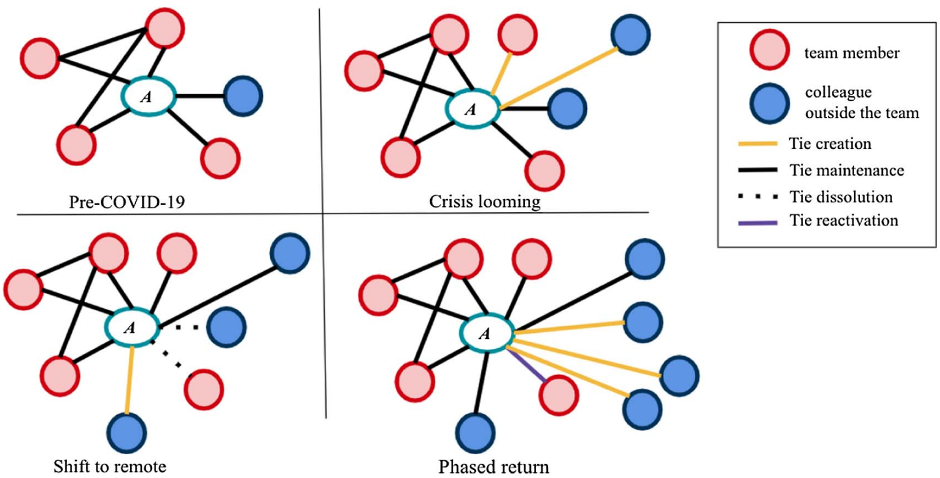
We controlled team size since individuals in larger teams may have more opportunities to develop ties within teams, and

Table 2
Patterns of Changes in Observed Ties That Indicate the Three Types of Churn (i.e., Tie Activation, Tie Dissolution, and Tie Reactivation)

Types of churn	Possible scenarios	Pre-COVID-19	Crisis looming	Shift to remote	Phased return
Tie creation	1	0	1		
	2	0	0	1	
	3	0	0	0	1
Tie dissolution	1	1	0		
	2		1	0	
	3			1	0
Tie reactivation	1	1	0	1	
	2		1	0	1
	3	1	0	0	1

Note. For a given dyad, 1 = tie present, 0 = tie absent. For each of the churn types (i.e., tie creation, tie dissolution, and tie reactivation), there are three possible scenarios for each dyad, represented under the "Possible scenarios" column. For example, for tie creation, in all three scenarios, no ties were present *pre-COVID-19*, and then a tie appeared in one of the three subsequent phases. For tie dissolution, we compared networks in two consecutive periods to check if the tie in one period became absent in the immediate subsequent period. Thus, if there was no tie during the *crisis looming* period then tie dissolution could not exist in the subsequent *shift to remote* period thus that column is blank for the first possible scenario in tie dissolution, and so on. For tie reactivation, we compared networks in one period with the networks in the previous two or three periods. COVID-19 = Coronavirus disease.

Figure 1
A Graphic Illustration of Higher Performer's Network Churn on Intra- and Inter-Team Ties



Note. During the *pre-COVID-19* period, Person A was connected with four team members and one colleague outside the team. During the period when the crisis was looming, Person A created a new tie with one team member and one colleague outside the team. During the *shift to the remote* period, Person A dissolved (indicated by a dotted line) one intra-team and one inter-team tie, and created one inter-team tie. Finally, during the phased return, Person A created three inter-team ties and reactivated one intra-team tie that had been dissolved during the shift to remote period. As Figure 1 shows, the size of Person A's network does not vary much, from 5, 7, 6, to 9, but tie creation, dissolution, and reactivation illustrate the changes in how one leverages their network over the four periods of the crisis. See the online article for the color version of this figure.

individuals in smaller teams may have more opportunities to develop ties outside their teams. Team size also has the potential to impact the extent to which individuals perform cross-team boundary spanning (connecting with individuals outside their team), although these potential effects have not been fully tested (Marrone, 2010).

We constructed communication networks using digital trace metadata on who held conferences with whom during each of the four time periods (Table 1). We excluded larger meetings from our analysis, in order to focus on meaningful interactions which typically occurred in groups of size seven or fewer (Miller, 1956). Larger meetings tended to be department- or company-wide informational sessions. The latter only accounted for 7.03% of all meetings. In addition, we excluded weekends or holidays (e.g., Lunar New Year) when there was little communication on the video-conferencing platform. Fourteen days of the Lunar New Year holidays were excluded. Though this constitutes much of the *crisis looming*, there was very little interaction on the platform due to the holiday and these dates were not comparable to workdays.

To define ties in the network, we looked at the number of times that two employees met in each of the four time periods. Since the periods each lasted a different number of workdays (66 workdays in *pre-COVID-19*, 9 workdays in *crisis looming*, 9 workdays in *shift to remote*, and 20 workdays in *phased return*), for each period we used a different count of meetings as the cutoff for determining whether a tie existed between two employees. The cutoffs were proportional to the number of workdays in each period: At least seven meetings during *pre-COVID-19*, at least one meeting during *crisis looming*, at least one meeting during *shift to remote*, and at least two meetings during *phased return*.

In order to assess the validity of digital trace data before and after the shift to remote work, we correlated survey-derived social networks with the trace data obtained in each period (see Table 6). The survey data was collected in the organization between December 15 and December 30, 2019, right before the outbreak of COVID-19 in China. This survey was planned and implemented without any anticipation of the impending COVID-19 pandemic. One of the survey questions asked, "In the past month, who have you interacted with in-person?" Our accompanying instructions noted that by "in person" we were asking about meaningful interactions and not brief encounters like greeting a colleague in passing. We constructed the perceptual in-person network based on the survey data and compared this network to the other virtual communication networks constructed using digital trace data. Then we computed the correlations between the networks across different periods, as shown in the table, and assessed their significance using the Quadratic Assignment Procedure (QAP). The results indicate that the extent to which digital trace data reflects the in-person network is moderate and consistent across the four periods.

Analytic Approach

Given that the response variables are counts (i.e., the number of intra- and inter-team ties created, dissolved, and reactivated), hypotheses were tested with negative binomial Generalized Linear Mixed Models (GLMM; Bono et al., 2021; Greene, 2003). The negative binomial model is a generalization of a Poisson model that accounts for overdispersion that is present in count data. In addition to fixed effects as in ordinary least squares regressions, GLMM also measures the random effects of the intercepts of the models and accounts for the count data as the response variables.

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We included the team affiliations as random intercepts, with no random slopes included. From likelihood ratio tests, models did not improve when we included random slopes for teams by performance. The dependent variables were the volume of tie creation (intra- and inter-team), dissolution (intra- and inter-team), and reactivation (intra- and inter-team) and the independent variable used to test hypotheses was job performance.

For each set of analysis, we constructed a base model that includes the control variables (e.g., gender, organizational tenure, organizational rank, and team size), and then conducted a likelihood ratio test to compare the base model with the full model with the performance variable. The glmer.nb function in the "lmer" package in R was used to construct the negative binomial GLMMs.

Results

Table 3, along with Figure 2, presents the descriptive statistics of daily meetings. The results show an increase of 21.64% in the average duration of meetings from *pre-COVID-19* to the *crisis looming* period, which further increased 17.01% during the *shift to remote* period and held almost constant during the *phased return* period. This is consistent with the idea that the crisis increased attentional demands. Likewise, the number of participants per meeting increased 17.21% during the *crisis looming* period and continued to grow 38% during the *shift to remote* period and reverted to the same size as during the *crisis looming* period once they entered the *phased return* period. Finally, the average number of daily meetings fell 12.40% during the *crisis looming* periods as compared to *pre-COVID-19* period but increased dramatically (52.77%) during the *phased return* period. The length of meetings and number of meetings may have been related such that as meetings were taking longer, employees were having fewer of them in total. In summary, the aggregate statistics indicate that the various periods associated with the COVID-19 crisis had discernable impacts on communication among employees.

Table 4 shows the descriptive statistics and intercorrelations among key variables. None of the control variables is significantly correlated with employee performance. We note, however, that there are generally high intercorrelations among the dependent variables (tie creation, dissolution, and reactivation). Whereas it is possible to create ties without necessarily later dissolving or reactivating them, it is not possible to dissolve a tie that wasn't first created or to reactivate a tie that hadn't previously been created and later dissolved. To address this issue, tie creation was included as an additional control in the models testing Hypothesis 2 (with tie dissolution as dependent variables), and both tie creation and tie dissolution were included as controls in the models testing Hypothesis 3 (with tie reactivation as dependent variables).

In order to examine the overall trend in intra- and inter-team ties over time, Figure 3 depicts the ties over the four periods. Though the total number of ties changed little as the crisis first unfolded (*pre-COVID-19* to *crisis looming*, to *shift to remote*), the balance of intra- and inter-team ties changed during the shift to remote work (intra- and inter-team ties were the most even during this time). We also see a marked increase in the total number of ties during the *phased return*. While these are the overall trends, the hypotheses posited differences based on employee job performance.

Table 3
Descriptive Statistics of Meetings in the Four Periods From October 2019 to Mid-March 2020

Time period	Period name	*N* (workdays)	Mean	*SD*	Min	Max
		Daily average duration of meetings (minutes)				
10/8–1/10	Pre-COVID-19	66	21.26	3.43	13.01	29.1
			21.64%	−5.25%	74.87%	15.53%
1/11–2/3	Crisis looming	9	25.86	3.25	22.75	33.62
			17.01%	12.92%	8.66%	8.27%
2/4–2/16	Shift to remote	9	30.26	3.67	24.72	36.4
			−3.64%	−30.52%	−1.01%	−3.76%
2/17–3/12	Phased return	20	29.16	2.55	24.47	35.03
		Daily average size of meetings				
10/8–1/10	Pre-COVID-19	66	3.66	1.14	2.31	8.78
			17.21%	25.44%	28.14%	−21.30%
1/11–2/3	Crisis looming	9	4.29	1.43	2.96	6.91
			38.00%	−16.78%	19.26%	9.70%
2/4–2/16	Shift to remote	9	5.92	1.19	3.53	7.58
			−16.89%	31.93%	−7.08%	37.60%
2/17–3/12	Phased return	20	4.92	1.57	3.28	10.43
		Daily average number of meetings				
10/8–1/10	Pre-COVID-19	66	194.35	35.92	77	253
			−12.40%	−20.57%	59.74%	−13.04%
1/11–2/3	Crisis looming	9	170.25	28.53	123	220
			2.53%	11.92%	4.07%	9.55%
2/4–2/16	Shift to remote	9	174.56	31.93	128	241
			52.77%	−3.54%	70.31%	39.00%
2/17–3/12	Phased return	20	266.68	30.80	218	335

Note. The percentages of parameters for each shift between periods are shown in between rows of periods. We compute the mean of the duration of meetings, size of meetings, and count the number of meetings for each day in each period. Across days within each period, we then computed the mean, standard deviation, minimum, and maximum. COVID-19 = Coronavirus disease.

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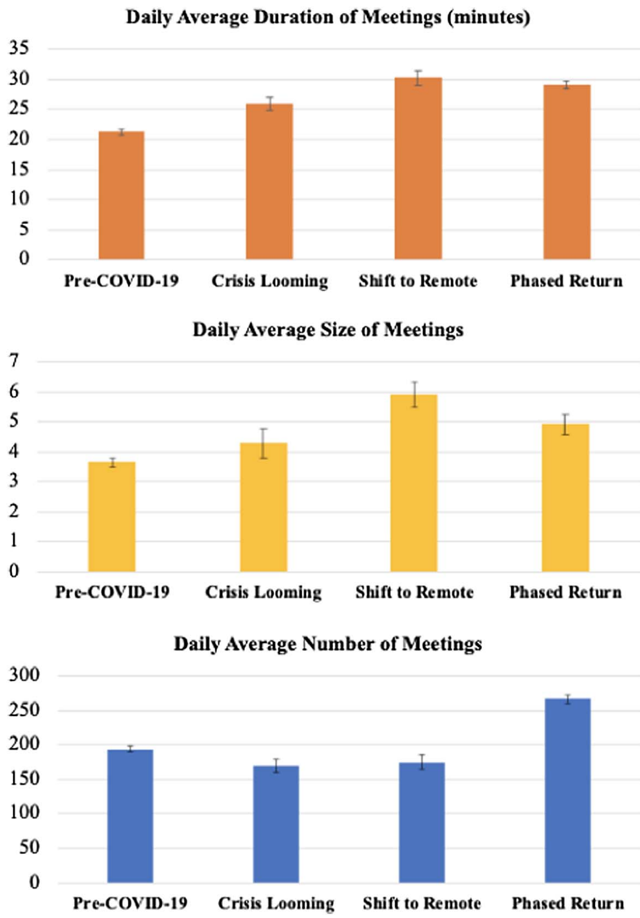
Figure 2
Descriptive Statistics of Meetings During the Four Periods From October 2019 to Mid-March 2020



Note. This bar plot maps the data presented on Table 3. Error bars represent standard errors. See the online article for the color version of this figure.

Table 5 summarizes the results from negative binomial GLMM analyses that test the hypotheses on how higher versus lower performers varied in their volume of network churn. We used the first set of models with the volume of tie creation as the dependent variable to test our first hypothesis. Job performance was positively related to inter-team tie creation ($\beta = 0.39$, $p < .01$), but not intra-team tie creation ($\beta = 0.16$, *n.s.*), during the postlockdown periods. Hypothesis 1 was supported. Among the control variables included employees with higher organizational rank (i.e., team leads) were more likely to create inter-team ties ($\beta = 0.60$, $p < .05$), but not intra-team ties ($\beta = 0.28$, *n.s.*). The significant improvement of the model fit from the likelihood ratio tests provides further evidence that job performance is positively associated with inter-team tie creation beyond what is explained by organizational rank.

Next, we examined tie dissolution, job performance was not significantly related to the dissolution of either inter-team ties ($\beta = 0.13$, *n.s.*) or intra-team ties ($\beta = 0.13$, *n.s.*). This pattern of results runs counter to Hypothesis 2 which posited job performance is positively related to intra- but not inter-team tie dissolution. Thus, Hypothesis 2 was not supported.

Table 4
Correlation Matrix and Descriptive Statistics[a]

Variables	Mean	*SD*	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1. Gender[b]	0.85	0.36	0	1												
2. Organizational tenure	8.17	6.13	0	33	0.00											
3. Organizational rank[c]	0.09	0.28	0	1	−0.14	0.26**										
4. Team size	12.12	3.63	6	20	0.01	0.12	−0.05									
5. Performance	3.45	0.57	2	5	−0.01	0.03	0.13	0.11								
6. Intra-team tie creation	1.75	1.77	0	8	0.00	−0.22**	0.09	−0.13	0.02							
7. Inter-team tie creation	4.45	4.30	0	21	0.03	0.01	0.20**	−0.16*	0.34**	0.16*						
8. Intra-team tie dissolution	2.10	2.16	0	9	0.10	−0.13	0.07	0.15*	0.10	0.09	0.16*					
9. Inter-team tie dissolution	4.88	5.20	0	27	0.01	−0.08	0.13	−0.12	0.32**	0.02	0.74**	0.25**				
10. Intra-team tie reactivation	0.80	1.23	0	6	0.08	−0.12	0.08	0.23**	0.19*	0.07	0.19**	0.74**	0.24**			
11. Inter-team tie reactivation	1.51	2.42	0	13	−0.07	−0.08	0.17*	−0.14	0.29**	0.04	0.60**	0.15*	0.73**	0.17*		
12. Tie creation (total)	6.20	4.90	0	22	0.02	−0.07	0.20**	−0.19*	0.31**	0.50**	0.93**	0.18*	0.66**	0.19**	0.54**	
13. Tie dissolution (total)	6.97	6.11	0	28	0.04	−0.11	0.13	−0.05	0.31**	0.05	0.69**	0.57**	0.94**	0.47**	0.67**	0.62**

[a] Number of participants = 184; number of teams = 18. [b] 0 = male; 1 = female. [c] 0 = employee; 1 = team lead.
* $p < .05$. ** $p < .01$, two-tailed tests.

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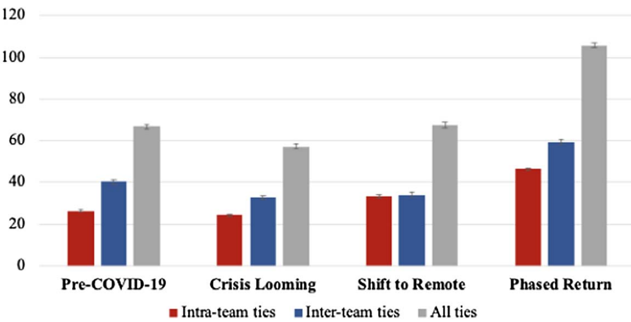
Figure 3

The Average Number of Intra- and Inter-Team Ties Per Day in Each of the Four Periods



Note. See the online article for the color version of this figure.

Finally, we examined tie reactivation as the dependent variable, finding job performance was positively associated with the inter-team tie reactivation (β = 0.34, $p < .05$), but not intra-team tie reactivation (β = 0.20, *n.s.*), in the postlockdown period, supporting Hypothesis 3.

The coefficient reported in the negative binomial GLMMs can be interpreted as the effect of a variable on the logarithm of the dependent variable. Therefore, controlling gender, organizational tenure, organizational rank, team size, a one-unit increase in the job performance score is related to around a 48% increase in inter-team tie creation. Adding controls for the total number of tie creation and dissolution, a one-unit increase in the job performance score is related to a 40% increase in the number of inter-team tie reactivation. We conducted likelihood ratio tests to assess the improvement of the goodness-of-fit of the models. Adding the performance variable to the base models with only control variables always resulted in a better model fit, though the improvement is significant in two models, inter-team tie creation ($\chi^2 = 9.17$, $p < .01$) and inter-team tie reactivation ($\chi^2 = 4.29$, $p < .05$).

Discussion

While remote work has grown in popularity for several decades, it has never been more critical than in the aftermath of COVID-19. Many countries were forced to order shelter-in-place to slow the spread of the disease, in turn forcing organizations to rapidly transition to remote work. This sudden shift was aided by the widespread adoption of digital collaboration technologies in work settings. Though all workers had access to these technologies, there was substantial discretion in the manner in which one churned their network over time as the crisis unfolded. We identify the creation and reactivation of inter-team ties, and dissolution of intra-team ties as a potential source of strategic advantage. Through the lens of resource allocation theory (Kanfer & Ackerman, 1989), we posited the crisis would trigger high performers to take greater advantage than lower performers of this network advantage. Findings from a large field study conducted before and during COVID-19 support this perspective with tie creation and reactivation. We did not find a relation between employee performance and the dissolution of intra-team ties.

Our results indicate that in the wake of a crisis employees change the patterns of their communication networks. Yet not all employees reacted similarly. When facing uncertainties, higher performers

Table 5

Parameter Estimates of Negative Binomial Generalized Linear Mixed Models Predicting Performance Differences in the Volume of Network Churn[a]

	Tie creation					
	Intra-team ties			Inter-team ties		
Variables	β	Odds ratio	Std err	β	Odds ratio	Std err
Intercept	0.02	1.02	0.70	0.44	1.55	0.60
Gender[b]	0.06	1.06	0.17	0.10	1.11	0.19
Organizational tenure	−0.01	0.99	0.01	0.00	1.00	0.01
Organizational rank[c]	0.28	1.32	0.20	0.60*	1.82	0.24
Team size	−0.02	0.98	0.05	−0.05	0.95	0.03
Tie creation (total)						
Tie dissolution (total)						
Performance	0.16	1.17	0.11	0.39**	1.48	0.13
AIC	598.98			928.04		
BIC	624.7			953.76		
Log-likelihood	−291.49			−456.02		
Pearson χ^2	156.12			164.67		
Likelihood ratio test	2.09			9.17**		

	Tie dissolution					
	Intra-team ties			Inter-team ties		
Variables	β	Odds ratio	Std err	β	Odds ratio	Std err
Intercept	−1.10	0.33	0.80	0.09	1.09	0.64
Gender[b]	0.21	1.23	0.22	0.08	1.08	0.18
Organizational tenure	−0.02	0.98	0.01	−0.03*	0.97	0.01
Organizational rank[c]	0.27	1.31	0.27	0.32	1.38	0.00
Team size	0.07	1.07	0.05	0.00	1.00	0.04
Tie creation (total)	0.03†	1.03	0.02	0.13***	1.14	0.01
Tie dissolution (total)						
Performance	0.13	1.14	0.14	0.13	1.14	0.12
AIC	690.67			886.71		
BIC	719.61			915.65		
Log-likelihood	−336.34			−434.36		
Pearson χ^2	156.14			160.06		
Likelihood ratio test	0.91			1.25		

	Tie reactivation					
	Intra-team ties			Inter-team ties		
Variables	β	Odds ratio	Std err	β	Odds ratio	Std err
Intercept	−3.35***	0.04	0.90	−2.01**	7.46	0.65
Gender[b]	0.32	1.38	0.31	−0.06	0.94	0.24
Organizational tenure	−0.04*	0.96	0.02	−0.01	0.99	0.02
Organizational rank[c]	0.61†	1.84	0.33	0.52*	1.68	0.26
Team size	0.12*	1.13	0.05	−0.03	0.97	0.02
Tie creation (total)	−0.02	0.98	0.03	0.06**	1.06	0.02
Tie dissolution (total)	0.10***	1.11	0.02	0.12***	1.13	0.02
Performance	0.20	1.22	0.19	0.34*	1.40	0.17
AIC	407.47			506.47		
BIC	439.62			538.62		
Log-likelihood	−193.73			−243.24		
Pearson χ^2	146.61			171.60		
Likelihood ratio test	1.12			4.29*		

[a] Number of participants = 184; number of teams = 18. Standard errors are in the parentheses. [b] 0 = male; 1 = female. [c] 0 = employee; 1 = team lead. [d] A likelihood ratio test compares the goodness-of-fit of models with the base models with the control variables (gender, organizational tenure, organizational rank, team size, tie creation, and tie dissolution).
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$, two-tailed test.

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focused on spanning boundaries or reaching out to other team members by creating and reactivating more inter-team ties than did lower performers. We interpret this behavior from the lens of resource allocation theory, whereby job mastery provides discretionary attentional resources to deploy strategically toward boundary-spanning networks. This pattern is consistent with prior work that finds general stability in job performance over time (Sturman et al., 2005). Insofar as bridging inter-team networks offer a strategic advantage, these findings offer an explanation for how higher performers were able to adapt in response to the crisis.

Contrary to Hypothesis 2, we did not find a performance effect for tie dissolution, either for intra- or inter-team ties. We posited based on Oh et al. (2004) that dissolving intra-team ties would free attentional resources in ways that were strategic, an alternative logic not inconsistent with the resource allocation perspective is that higher performers did not need to use dissolution as a way to free up attentional resources. Higher performers created and reactivated more inter-team ties than lower performers while showing no difference in tie dissolution behavior.

This study makes three theoretical and practical contributions. First, we offer an integrative framework for understanding the interplay of organizational networks and individual information processing. We examine how individuals churn their networks within and across teams, and we explain how attentional resources and attentional demands, concepts from the motivation literature (Kanfer & Ackerman, 1989), jointly explain how individuals adjust their networks in response to a crisis. This integration can spur future theorizing about network adaptation to other extreme and crisis-like events, or more generally, events that increase attentional demands. Likewise, understanding the effects of individual differences on behavior during crises may also be explained via cognitive resources.

Our second contribution is to provide an early look into how the shift to remote work brought on by the pandemic prompted changes in networking behavior. Indeed, we see notable churn in networks when it comes to inter-team networks. High performers created and reactivated more inter-team ties than did low performers. Interestingly, high performers did not show differences in creation, dissolution, or reactivation of intra-team networks, except during the phased return to work when we observed a positive relationship between employee performance and the reactivation of intra-team ties.

Finally, our study highlights for managers the differences in networking behaviors between lower and higher performers, and offers insights on how they can strategically position them in teams with functions that fit their networking behaviors in the wake of crises. This is particularly important during times of crisis when those employees who have not yet mastered their jobs will be especially affected. Providing additional training and support targeted at more novice workers could be integral to their adaptation to the crisis. Further, this attentional perspective may prove similarly fruitful in understanding behavior in response to other types of events exerting similar pressures on attentional resources such as natural disasters (e.g., flooding of the offices of developer Hello Games) or major corporate restructuring (e.g., mass layoffs, the Barings Bank collapse).

Limitations

There are three chief limitations to consider. First, these hypotheses were tested using digital trace data on only one channel—conferencing. There are certainly other important platforms for communication that can be used to network. This operationalization is necessarily limited, though we do note that this conferencing platform was the dominant mode of meeting and was widely used for "in-person meetings" that were conducted before COVID-19 so that employees from different work locations could join the meetings. In order to assess the validity of digital trace data in accurately reflecting the communication in the prelockdown periods, Table 6 suggests that the consistent magnitude of correlations over time somewhat mitigates this concern.

Second, tie creation, dissolution, and reactivation were highly correlated with one another raising concerns over multicollinearity. In order to account for their interrelation, we considered their dependencies and included appropriate controls. Though it is important to note that these networking behaviors are intertwined such that dissolving ties depends on first creating them and reactivating them requires that they were created and later dissolved.

Third, we defined performance as a single upper-level managerial evaluation of each individual and examined how higher performers engage in different network churn strategies than lower performers. Future research should consider the effect of network churn strategies on subsequent performance. Future research should also consider the impact of network churn on the performance of teams and multiteam systems. Arguably a network churn strategy that might serve the performance interests of an individual, could also simultaneously undermine the collective performance of the team and multiteam system.

Conclusion

Remote work has shaped a "new normal" for workplaces. We anticipate the "next normal," to occur when in-person work is once again possible. Insights about network churn during the crisis offer us critical insights of what changes will endure beyond the crisis. We are navigating seismic mutations in our work patterns and from these mutations, we are selecting some that are beneficial during the crisis. A robust program of research on network churn within and between teams can help us identify which mutations should be retained to maximize individual, team, and organizational returns.

To conclude, this article provides early insights into network churn during different periods of the COVID-19 pandemic as employees transitioned to working outside the office and later transitioned back. By leveraging the digital trace metadata and collating it with the human resource data, this study provides early but important empirical evidence to support the effect of job performance on networking strategies during crisis through a team-level lens, with a future eye to help us better envision the "next normal."

Table 6

Correlations Between Survey-Derived In-Person Network and Trace-Data-Based Networks

Virtual communication network (digital trace)	*Pre-COVID-19* in-person network (survey data)
Pre-COVID-19	0.31***
Crisis looming	0.29***
Shift to remote	0.28***
Phased return	0.39***

Note. COVID-19 = Coronavirus disease.
*** $p < .001$.

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Received January 31, 2021
Revision received August 11, 2021
Accepted August 13, 2021 ■

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