Efforts undertaken to try to minimize the spread of COVID-19 have dramatically altered social life. Beginning in the middle of March of 2020, most U.S. residents were under “stay at home” orders and advised to shelter in place. More than 40 percent of U.S. workers were still working from home full-time in June, the vast majority of students were sent home from school, and travel came to a virtual standstill (Baker et al. 2020; Education Week 2020; Oxford and Osborne 2020). The majority of institutions that structure our social lives were disrupted (Feld 1981; Small 2017; Small, Deeds Pamphile, and McMahan 2015). As state-mandated lockdown orders began to lift at varying rates in early June, considerable restrictions on social interaction remained. As of November 2020, people were still advised to wear masks, social distance, and keep six feet apart.

While existing research has examined the network characteristics associated with loneliness during periods of social stability, the extent to which network size, structure, or composition helps protect against loneliness during periods of prolonged isolation remains understudied. Moreover, very little research in the social sciences has examined changes in networks in response to large-scale exogenous shocks (Romero, Uzzi, and Kleinberg 2016). While research has found an increase in network cohesion and network shrinkage in response to natural disasters (Forgets et al. 2009; Phan and Airoldi 2015), as well as a tendency to “turtle up” or an intensification of strong-tie interactions and clustering following price shocks (Romero et al. 2016), further research is needed to understand how networks have changed during COVID-19. We utilize longitudinal social network data collected pre–COVID-19 (June 2019) and compare them with data collected in June of 2020 to examine changes in social networks following a period of intense social isolation. We also report on factors that do not moderate the effect of social isolation on perceived loneliness, such as gender, age, or overall social network size.

Our study found a significant increase in loneliness between June 2019 and June 2020. During this period, which coincided with the COVID-19 epidemic, we found significant decreases in network density and global network size. While there is an overall increase in loneliness during this era, certain social network characteristics of individuals are associated with smaller increases in loneliness. Specifically, we find that people with fewer than five “very close” relationships report increases in loneliness. We further find that face-to-face interactions, as well as the duration and frequency of interactions with very close ties, are associated with smaller increases in loneliness during the pandemic. We also report on factors that do not moderate the effect of social isolation on perceived loneliness, such as gender, age, or overall social network size.
Social Networks and Loneliness

Early studies have documented an increase in loneliness during COVID-19 (Gauthier et al. 2020; Killgore et al. 2020; Krendl and Perry 2020; van Tilburg et al. 2020). Loneliness is “a discrepancy between an individual’s preferred and actual social relations” that leads to distressing negative feelings of social isolation even when one is among family and friends (Peplau and Perlman 1982). Loneliness is a subjective experience, not simply a condition of being physically isolated. According to Cacioppo et al., “feeling alone or lonely does not necessarily mean being alone nor does being alone necessarily mean feeling alone” (Cacioppo et al. 2015:239). Put differently, while a lack of social interaction and time spent alone are correlated with loneliness, they are distinct psychological constructs (Russell, Peplau, and Cutrona 1980).

A study of 1,013 U.S. adults conducted three weeks after stay-at-home orders were enacted in most states using the UCLA Loneliness Scale found significantly elevated rates of loneliness. Forty-three percent of respondents exceeded the cutoff for high loneliness compared with a baseline of 38 percent reported in prior work (Killgore et al. 2020). A study of a large population of older Dutch adults found that loss of social contact, loss of work, and needing but not receiving social support were associated with emotional loneliness during the pandemic (van Tilburg et al. 2020).

Since the time of Durkheim, sociologists have been keenly aware of the negative consequences of social isolation (Durkheim 2014). A growing body of research at the intersection of social networks and loneliness has found that the quality and quantity of social connections, as well as their structure, are associated with loneliness. In general, the literature on network structure and loneliness has focused on four dimensions: network size, the number of close or intimate ties one has, density, and network composition (particularly, familial ties).

Overall network size, or the number of contacts the respondent frequently interacts with, has not been found to be a consistently significant predictor of loneliness in cross-sectional analyses (Stokes 1985). Yet, network size may be important during crises. Prior work has found that Katrina survivors embedded in larger social networks experienced fewer financial, physical, and health disturbances as a result of the disaster (Forgette et al. 2009). However, survivors’ networks decayed substantially (by more than 25 percent) postcrisis, suggesting that networks themselves are not particularly resilient to negative shocks (Forgette et al. 2009).

Having more confidants or very close ties in one’s network is generally associated with lower levels of loneliness (Hawkley et al. 2008; van Tilburg 1990). The marginal effect of an additional very close tie is especially large for the four closest ties, while additional close ties beyond the first four continue to be associated with lower levels of loneliness but are not as protective (Gierveld, Tilburg, and Dykstra 2006). The composition of these intimate ties also seems to matter, with people whose networks are composed primarily of familial ties being at higher risk of loneliness than those with more heterogenous networks (Dykstra 1990; Silverstein, Chen, and Heller 1996). Finally, network density has been shown to help guard against loneliness. In a study that simultaneously examined network size, closeness, and density, as well as individual and personality characteristics, network density was found to be the strongest predictor of loneliness (Stokes 1985). While density can help protect against loneliness during periods of stability, research has found that network density can have negative effects during periods of change, such as divorce, widowhood, and transitioning to college (Cacioppo, Fowler, and Christakis 2009; Hirsch 1980; Wilcox 1981).

Beyond the frequency and structure of interactions, modes of communication may also be associated with loneliness. Recent research suggests that smartphone usage increased during the pandemic. A study of Flemish adults found that on average, users were spending more time on their phones, roughly 45 more minutes than prior to the outbreak. The increase arose from an increased duration of calls, texts, and media use rather than more frequent use (Ohme et al. 2020). While more frequent and longer face-to-face social interactions have been associated with lower rates of loneliness outside of the pandemic in some studies (Lee and Ko 2018; Roberts and Dunbar 2011; Russell et al. 1980), there is mixed evidence of the extent to which communication via phone, videoconferencing, text, or email reduces loneliness. Randomized control trials examining modality of communication remain fairly limited (Noone et al. 2020) but are necessary to deal with the selection issues endemic to studies in this area. Given the restrictions on face-to-face interactions during COVID-19, the pandemic presents an unusual opportunity to study whether technologically mediated communication can act as an effective substitute for face-to-face interaction while avoiding some of the selection issues common in this line of research. Early research on older adults has found that the strength of social relationships, but not how frequently they engaged with social contacts, was associated with depression during COVID-19 (Krendl and Perry 2020). This suggests that technologically mediated communication may not have been an effective substitute for other forms of social interaction during the pandemic.

Existing research has documented the key role that social networks play in guarding against loneliness (Gierveld et al. 2006; Hawkley et al. 2008; Stokes 1985) as well as the role of external shocks in shaping networks (Phan and Airolidi 2015; Romero et al. 2016). COVID-19 is likely to be a particularly disruptive shock to networks since many of the foci for social activities that structure our daily social interactions from schools to workplaces (Feld 1981; Hsung, Lin, and Breiger 2010; Small 2017) were closed during the lockdown. We bring together these two streams of research and build on a growing literature examining how individuals’ networks change over time (Burt 2000; Sasovova et al. 2010; Small et al. 2015). We do so by examining how networks have changed during the social isolation brought about by the COVID-19 pandemic as well as the relationship between these changes and loneliness. In doing so, we contribute to...
research at the intersection of social networks and mental health by highlighting how exogenous events can shape networks and, in turn, mental health (Kawachi and Berkman 2001; Liu, King, and Bearman 2010; Perry and Pescosolido 2015) and answer calls for more research on how COVID-19 has disrupted networks (Gauthier et al. 2020). The context also affords an important opportunity to examine exogenously induced social isolation, networks, and loneliness. Moreover, this study provides insight into one of the most profoundly impactful social experiences of our time.

Data

We recruited survey participants from a Yale University local participant research pool. Surveys were completed for a small monetary payment, and the survey questions and design were deemed exempt by the Yale Institutional Review Board. The surveys were administered online. We collected our data in two waves. The first wave was collected in mid-June 2019. The second wave was collected in mid-June of 2020, just before the state entered its second stage of reopening. In both waves, we conducted a detailed survey with participants answering questions about their perceptions of loneliness, detailed information on their social networks, frequency and mode of communication, and demographic characteristics, such as gender, age, and race-ethnicity.

Because our sample is drawn from a specific state and county, participants in our sample are exposed to the same quarantine requirements (e.g., closure of major foci for social activity, such as restaurants, bars, hair salons, and schools). Of the respondents, 50.1 percent were employed, 4.7 percent were living alone, 38 percent were female, 81 percent were white, and their average age was 27.6 years. Only a small proportion (two people, 0.8 percent of the sample in the second wave) were recently laid off or unemployed due to COVID. The sample is a convenience sample (whomever signed up to the local university’s participant pool) and is admittedly not representative of the larger U.S. population.

The first wave of the survey was completed by 418 participants. A year later, we contacted the same participants through the email address they provided and asked them to do a follow-up survey. The follow-up survey included the same questions asked during the first wave; in addition, it contained a few questions about the respondents’ communication patterns, employment status, and household living situation during the COVID-19 quarantine. (See the appendix for all questions and instruments used in the survey.) Out of the 418 original participants, 189 participants completed the second wave of the survey. Because our main aim is to compare the change in loneliness pre- and postquarantine, we report results using these 189 participants. Additional analyses show that even though there is some self-selection bias into the second wave such that African Americans, Latinx people, and people with more social ties or a higher level of loneliness are less likely to repeat the survey, additional analyses show that our results hold even after controlling for the self-selection bias statistically with a Heckman correction (see Table A1 in the appendix).

Loneliness Scale

We used the UCLA Loneliness Scale (Version 3; Russell 1996), an established scale in the psychology literature that has been applied in more than 3,000 studies. We asked the participants 20 items of the loneliness scale, about half positively worded (“I have people to talk to”) and half negatively worded (“I feel lonely”). People responded on a 4-point Likert scale. The questions were displayed in a randomized order. We reverse-coded the responses to positively worded statements, so that higher values correspond to higher loneliness, and took the average of the responses to create a composite loneliness scale. The Cronbach’s alpha test value was .89, confirming that the question items can be combined into a single scale.

Network Survey

The network survey was conducted using the Assess Your Network survey platform (www.assessyournetwork.com). Participants were asked to name up to seven people with whom they have discussed important matters, up to seven people in their organization (workplace, school, etc.) who are important for them to get decisions done, and up to seven people with whom they spend social time with. Using an ego-network approach, the survey also asked participants about relationships among their alters. Participants were then asked about the gender, age, and occupation of these people and their relationship with them (family/work/friend, how close they are to each other, how often they communicate). From the survey answers, we calculated aggregate ego-network measures to characterize each respondent’s social networks in terms of overall composition, closeness, frequency of communication, and density. (See Figures A1 to A6 in the appendix for the actual questions in the survey.) Density was calculated as the total number of observed edges divided by the total number of possible edges. Edges between alters were defined by asking whether alters knew one another (see Appendix Figure A4).

Global network size, or the estimated size of the respondents’ extended acquaintance network, was calculated using the network scale-up method, which allowed us to estimate the overall size of a respondent’s networks beyond their ego network (Zheng, Salganik, and Gelman 2006). Following McCarty et al. (2001), in this context, “knowing” someone was defined as (1) recognizing them by sight or name, (2) being able to contact them without searching online for their email address or connecting through social media, and (3) having been in contact with them by phone, snail mail, or face-to-face in the past two years. To estimate network size, we asked respondents how many people they know named Alan, Adam, Bruce, Emily, and Rachel. The names for the network size estimate are taken from McCormick, Salganik, and Zheng (2010) since they tend to generate less biased estimates across age groups. (See Appendix Figure A2 for
questions.) For each of these names, we calculated global network size by scaling up responses based on how frequently the names occur in the United States and then took the average across all five names.

**Mode of Communication**

To assess how frequently respondents used various modes of communication (phone, text, face-to-face, email, video calling, etc.) to interact with members of their network of varying tie strengths, we used a modified version of the Rochester Interaction Record (Cohen et al. 2015; Reis and Wheeler 1991). This work has established that a 10-minute minimum duration improves respondents’ accuracy at recalling interactions and provides a well-established definition of what constitutes an interaction. While doing a full time-diary analysis was beyond the scope of this study, previous work has found that recollection of interactions within 24 hours is accurate (Cohen et al. 2015; Reis and Wheeler 1991). Accuracy is likely to be increased in our study since most interactions happened over media that has digital records (phone, email, video-calling logs). Participants were asked to draw on these logs when answering questions about the duration and frequency of interactions.

**Method**

Our primary goal is to explore what social network patterns are associated with changes in levels of loneliness from June 2019 to June 2020. We first report on simple mean comparisons of the key variables in June 2019 and June 2020. We then turn to a regression framework and use 2019 levels of the key variables to predict change in loneliness from 2019 to 2020.

We explicitly note that for our independent variables, the count and strength of network ties and network density, we are estimating the effect of the level of the relevant variables. We do so because this statistical modeling approach is closer to the spirit of our argument. We are interested in how social networks may buffer against increases in loneliness during COVID-19 lockdowns. This is an argument about a moderation effect, specifically, how network ties moderate the effect of the lockdown. Because it is a moderation argument, the level of variables should be used.1

Because there are significant changes in individuals’ reported social networks, the next question is then to decide whether we want to explore the effects of the 2019 or the 2020 network characteristics. Arguments could be made for and against either of the network time snapshots, so we present results using both alternatives. Finally, we examine associations between the frequency, duration, and modality of interaction and loneliness.

All models control for loneliness in 2019 as well as employment status, whether the respondent lived alone, gender, race-ethnicity, and age, which have been shown in previous studies to be associated with loneliness. We first report models for very close or close ties, network density, and network size separately before reporting the full combined model. We take this modeling approach since network variables are frequently highly correlated. Theoretically, given time and cognitive constraints, there are often trade-offs between the number and strength of ties someone can maintain. Moreover, density is likely to be higher in networks composed of strong ties. By first examining these variables separately, we can assess their independent associations with loneliness.

**Results**

We first report on simple mean comparisons of the key variables in June 2019 and June 2020. Table 1 shows the results. Loneliness increased significantly during COVID-19: The average loneliness score in 2019 was 2.69 versus 2.82 in 2020 ($t = −3.96, p < .001$), corresponding to a 0.29-standard-deviation increase in loneliness.

This period was also accompanied by considerable shifts in network composition and structure. We find that the global estimated network size of respondents decreased from 1,503 people in June 2019 to 1,098 individuals in June 2020 ($t = 3.51, p < .001$). Interestingly, we observed statistically significant differences for men and women. Men’s networks experienced significantly more shrinkage than women’s networks ($t = −2.75, p < .001$).2

The overall count of very close and close ties in core networks did not significantly change during this period. While the overall count of very close ties does not change, the composition of very close ties changes: We see a decrease in the count of very close friends ($1.51$ vs. $1.21$, $t = 2.80, p < .01$) and very close colleagues ($0.26$ vs. $0.20$, $t = 1.645, p = .051$) but an increase in the count of very close family members in individuals’ core networks ($1.20$ vs. $1.52$, $t = 3.589, p < .001$). Finally, the density of the reported network decreases from 0.69 to 0.64 ($t = 3.43, p < .001$).

Table 2 reports regression results that explore network factors associated with the change in reported loneliness between 2019 and 2020. The eight model specifications are all linear regressions predicting a change in the person’s reported loneliness. Models 1 through 4 use the respondents’ 2019 network information to predict the change in their reported loneliness

---

1If we were to use the change variable, we would be answering the question “does the change in social ties lead to a change in perceived loneliness?” – this is a valid question but it is somewhat different from what we are asking.

2In these calculations, participants who reported zero contacts to all names were coded as missing. A more conservative way of calculating changes in network size is to include these respondents. Using this lower bound estimation method, we observe a reduction in network size of roughly 16%. Again, we observe significant differences by gender with men’s networks shrinking significantly more than women’s networks. All of our results are robust to both measures of global network size.
Table 1. Comparison of the June 2019 and June 2020 Values of Key Variables.

| Variable       | 2019    | 2020    | Difference |
|----------------|---------|---------|------------|
|                | M  | SD    | 95% CI     | M  | SD    | 95% CI     | p   |
| Loneliness     | 2.69| 0.49  | [2.62, 2.76]| 2.82| 0.38  | [2.77, 2.88]| .00 |
| Very close     | 3.34| 2.22  | [3.03, 3.66]| 3.25| 2.34  | [2.91, 3.58]| .25 |
| Close          | 2.07| 1.81  | [1.81, 2.33]| 2.11| 2.02  | [1.82, 2.40]| .38 |
| Very close family| 1.20| 1.28  | [1.01, 1.38]| 1.52| 1.46  | [1.31, 1.73]| .00 |
| Very close friends| 1.51| 1.94  | [1.23, 1.79]| 1.21| 1.66  | [0.98, 1.46]| .00 |
| Very close colleague| 0.26| 0.63  | [0.17, 0.36]| 0.20| 0.60  | [0.11, 0.28]| .05 |
| Network sizea | 1503.33| 1119.86 | [1329, 1677]| 1098.49| 838.97 | [967, 1229]| .00 |
| Density        | 0.69| 0.23  | [0.66, 0.73]| 0.64| 0.18  | [0.61, 0.66]| .00 |

Note: N = 189. CI = confidence interval.
*aFor this question, N = 161 because not all participants answered the network scale-up questions, based on which this variable is calculated.

Table 2. Linear Regressions Predicting a Person’s Change in Level of Loneliness from 2019 to 2020.

| Variable       | Change in Loneliness, Network Covariates Measured in 2019 | Change in Loneliness, Network Covariates Measured in 2020 |
|----------------|----------------------------------------------------------|----------------------------------------------------------|
|                | (1)           | (2)           | (3)           | (4)           | (5)           | (6)           | (7)           | (8)           |
| Very close     | −.04** (.01)  | −.04** (.02)  | −.06** (.01)  | −.06** (.01)  |
| Close          | −.03 (.01)    | −.03 (.02)    | −.03* (.01)   | −.02 (.01)    |
| Density        | .33** (.12)   | .00 (.14)     | .35* (.14)    | −.00 (.12)    |
| Network size   | −.00 (.02)    | .01 (.03)     | −.08** (.02)  | −.06 (.02)    |
| Loneliness     | −.69** (.06)  | −.63** (.06)  | −.64** (.07)  | −.73** (.07)  |
| Live alone     | .11 (.06)     | .08 (.07)     | .14* (.07)    | .10 (.06)     |
| Employed       | .00 (.05)     | .02 (.05)     | −.01 (.05)    | −.02 (.05)    |
| Female         | −.02 (.05)    | −.09 (.05)    | −.03 (.05)    | .00 −.07 −.10*|
| African American| −.41** (.09) | −.39** (.10)  | −.45** (.10)  | −.49** (.10)  |
| Latinx         | −.10 (.08)    | −.14 (.09)    | −.08 (.08)    | −.12 (.09)    |
| Age            | .00 (.00)     | .00 (.00)     | .00 (.00)     | .00 (.00)     |
| Constant       | 2.24** (.19)  | 1.69** (.18)  | 2.11** (.25)  | 2.39** (.22)  |
| N              | 189 189       | 167* 167*     | 167* 167*     | 189 189       |
| R²             | .54 .52       | .54 .52       | .54 .59       | .60 .52       |

Note: Dependent variable is change in loneliness (loneliness 2020 – loneliness 2019). Robust standard errors shown in parentheses.
aThe number of observations is smaller in these models because not all participants answered the network scale-up question, based on which the network size variable is calculated.
*p < .05. **p < .01.

from 2019 to 2020. Models 5 through 8 use the respondent’s 2020 network information to predict the change in their reported loneliness from 2019 to 2020. In each model, we control for the respondent’s level of loneliness in 2019. The results across the models show that while global network size in 2019, or the number of people the respondent recalls knowing, is not associated significantly with the change in loneliness, there is a negative and significant association between...
the number of people the respondent recalled knowing in 2020 and change in loneliness.

Participants with a larger number of very close and close ties reported lower increase in loneliness during COVID-19 than those with lower counts of very close and close ties. Across models, we also see that very close contacts are associated with lower increases in loneliness than close contacts. Based on the 2019 network data, each additional very close tie, on average, is associated with an 11 percent standard deviation lower increase in loneliness. In models without the full set of network controls, denser networks are associated with higher rates of self-reported loneliness, though this effect disappears when controls for the number of close ties and network size are included.

Gender, age, employment status, or living alone does not affect significantly whether the respondent reported an increased loneliness level in 2020. In terms of race, we find that blacks and/or African Americans report lower increases in loneliness than non–African Americans, but given the very low number of African Americans in our sample (n = 6), we would refrain from making any substantial interpretation of this finding.

Because the count of very close contacts seems to be the most strongly associated with low increases in loneliness during the social isolation, we further explore this effect by replacing the linear term of “count of very close contacts” in Table 2’s Model 1 with dummy variables for each level of count of contacts and then plot the marginal effect of each level of very close contacts on change in loneliness. Figure 1 plots the results. We see that for respondents who did not report any very close contacts in 2019, there is no significant increase in loneliness during the social isolation—presumably because they did not have very close contacts before and already had higher levels of reported loneliness, so the social isolation and quarantine did not change this significantly. Respondents with one to four very close ties reported in 2019 did report significantly higher loneliness in June 2020 than in June 2019. Respondents with five or more very close contacts did not report increased loneliness.

Next, we disaggregate the count of very close ties from type of tie (family, friends, colleagues, contacts from social organizations, contacts from professional organizations). Table 3 shows the results. Family, friends, and fellow members of professional organizations account for the reduction in loneliness associated with close ties. Similarly, tests for differences in coefficients for each of the categories across the two periods were also not significant. Collectively, these results suggest that family, friends, and fellow members of professional organizations had a stable association with loneliness irrespective of the pandemic.

Finally, Tables 4 and 5 report results exploring whether the frequency, duration, and mode of communication between respondents and their social ties are related to respondents’ change in reported loneliness from June 2019 to June 2020. Table 4 analyzes answers given to the questions “How many people did you interact with for at least 10 minutes in the previous 24 hours?” and “How many hours did you spend interacting with individuals during the past 24 hours?” Each answer was broken down by ties of different relationship length (see the appendix for the exact prompts). Table 4 shows that both more frequent and longer interactions with very close ties were associated with lower levels of increase in loneliness. Specifically, on basis of estimates in Model 3, we find that interaction with an additional very close tie, on average, is associated with a 13 percent standard deviation lower increase in loneliness, while each additional hour of interaction with a very close tie is associated with a 5 percent standard deviation lower increase in loneliness.

Table 5 explores how the mode of communication with social ties is associated with the change in loneliness (based on the question shown in Figure A4 in the appendix). The only mode of communication for very close ties that was statistically significant was in-person communication. The effect is quite sizable: People who reported to have interacted with a very close tie in person reported a 31 percent standard deviation lower increase in loneliness than those who did not have an in-person interaction with a very close tie. Interestingly, emailing with strangers (people previously not known to the participant) was also associated with lower levels of increase in self-reported loneliness.

---

3 Of course, because of the relatively small sample size, we cannot be confident that these factors do not have any effect on the change in loneliness due to the social isolation during COVID. We acknowledge this as a limitation to our paper. We note that as a robustness check, we have re-run our models without these controls, and our results hold.

4 Another explanation for this non-significant result could be the low count of respondents (N=7) who reported that they had no very close social ties.

5 The non-significant change in loneliness holds even if we combine the “five or more very close counts” categories.
Table 3. Composition of Very Close Ties Predicting a Person’s Change in Level of Loneliness from 2019 to 2020.

| Variable                      | Ties in 2019 (1) | Ties in 2020 (2) |
|-------------------------------|-----------------|-----------------|
| Type of very close tie        |                 |                 |
| Family                        | −.05* (0.02)    | −.06** (0.02)   |
| Friend                        | −.03* (0.01)    | −.06** (0.02)   |
| Colleague                     | .00 (0.03)      | .01 (0.03)      |
| Social organization           | −.07** (0.02)   | −.08 (0.06)     |
| Professional organization     | −.28* (0.11)    | −.18* (0.09)    |
| Multiplex                     | −.07 (0.04)     | −.05 (0.03)     |
| Constant                      | 2.21** (0.19)   | 2.27** (0.18)   |
| \(R^2\)                       | .56             | .63             |

Note: \(N=189\). Models include controls for self-reported loneliness in 2019, close ties, employment status, whether the respondent lived alone, gender, race-ethnicity, and age. Coefficient estimates for the controls are not shown here. Comparisons of coefficients for tie composition in 2019 and 2020 did not find statistically significant differences. Robust standard errors shown in parentheses.

* \(p < .05\). ** \(p < .01\).

Table 4. Interaction Frequency and Duration Predicting a Person’s Change in Level of Loneliness from 2019 to 2020.

| Variable                      | (Loneliness 2020 – Loneliness 2019) |
|-------------------------------|------------------------------------|
| Dependent Variable:          | (1)                                |
| Very close frequency         | \(-.06^{**}\) (0.01)               |
| Close frequency              | \(-.01\) (0.02)                    |
| Friendly acquaintance        | \(.01\) (0.02)                     |
| Distant frequency            | \(.00\) (0.01)                     |
| Stranger frequency           | \(-.02\) (0.01)                    |
| Very close duration (hours)  | \(-.02^{**}\) (0.01)               |
| Close duration (hours)       | \(-.02\) (0.02)                    |
| Friendly acquaintance duration (hours) | \(-.01\) (0.02) |
| Distant duration (hours)     | \(.01\) (0.02)                     |
| Stranger duration (hours)    | \(-.02\) (0.04)                    |
| Constant                     | 2.02^{**} (0.18)                   |
| \(R^2\)                      | .56                               |

Note: \(N=189\). Includes controls for self-reported loneliness in 2019, employment status, whether the respondent lived alone, gender, race, and age. Coefficient estimates for the controls are not shown here. Robust standard errors shown in parentheses.

* \(p < .05\). ** \(p < .01\).

Discussion, Limitations, and Future Work

We utilize longitudinal social network data collected pre-COVID-19 in June 2019 and compare them with data collected in June 2020. We found significant decreases in the size of respondents’ acquaintance networks during COVID-19 but a strengthening of their closest ties. This is consistent with prior work that has found that crises, negative affect, and stressful external shocks lead networks to “turtle up” or focus on stronger ties (Romero et al. 2016) and shrink (Forgette et al., 2009; Shea et al., 2015). While the network shrinkage we observe may arise from a smaller part of one’s acquaintance network being activated and mobilized (Menon and Smith 2014; Shea et al. 2015), social disruption and a lack of social interaction are also likely contributors to shrinkage (Gauthier et al. 2020). After two months without face-to-face contact, feelings of closeness between friends and family members drop by more than 30 percent, according to a study by Roberts and Dunbar (2011). For friends, feelings of closeness continue to decline, dropping by close to 80 percent after five months. Thus, a lack of contact with friends and acquaintances may also help explain network shrinkage.

The gender differences in network shrinkage we observe are somewhat revealing in this regard. Given that we observe strong gender differences, it is unlikely that this finding is an artifact or arises from measurement error. However, the differences still do not provide a clear indication which mechanism may be driving this finding, since women tend to have more accurate network recall (Brashears, Hoagland, and Quintaine 2016) and also tend to rely more heavily on conversation to maintain ties (Roberts and Dunbar 2015). In contrast, men are more likely to rely on shared activities, which are more likely than conversation to be interrupted by COVID. Future research examining what accounts for the observed network shrinkage, as well as the observed gender differences, is needed.

The increased focus on close ties during COVID was associated with a lower increase in loneliness. We examine changes in perceived loneliness and changes in social networks following a period of intense social isolation. We find that while there was an overall increase in loneliness during the social isolation of March to June 2020, certain social network characteristics of individuals are associated with lower increases in loneliness. Specifically, we find that people with fewer than five close ties reported a higher increase in loneliness. It is worth noting that research estimating the size of
core networks generally finds that most Americans have far fewer than five ties (Brashears 2011; Marsden 1987; McPherson, Smith-Lovin, and Brashears 2006). We show that both more frequent and longer interactions with very close ties were associated with a lower increase in loneliness, especially when the interaction was face-to-face. We also report on factors that do not moderate the effect of social isolation on change in perceived loneliness, such as gender, age, and overall social network size. Our work contributes to the literature on social networks and mental health by highlighting how exogenous events and social isolation can shape networks and, in turn, mental health (Kawachi and Berkman 2001; Liu et al. 2010; Perry and Pescosolido 2015).

One major advantage of our research design is that it utilizes an external shock of social isolation and therefore suffers to a lesser extent from endogeneity bias. That is, in theory, the arrow of causality can move both from perceptions of loneliness to social networks (people who feel lonely are less likely to make friends) and from social networks to loneliness (people with fewer social ties feel lonelier). Because the quarantine orders in the state directly influenced the opportunities to meet with one’s network, this external shock to social isolation provides evidence for the social network–to–loneliness pathway. While our statistical identification strategy cannot directly prove causality because it is not a randomized trial (it would be hard to do a randomize trial on people’s core social networks), our design utilizes an unanticipated external shock to help understand the network paths of loneliness.

**Limitations**

Of course, our paper is not without limitation. One limitation is sample size. Only 189 people completed both rounds of the survey, and this sample size limits the extent to which we can confidently report null results (such that age does not matter) or test other effects for which we do not have enough variability (for example, only 19 percent of respondents are nonwhite, and this translates to 37 people, making it impossible to earnestly study the effect of race and ethnicity). Also, the sample is a convenience sample and comprises individuals who signed up to our study through our university’s participant pool. We make no claims, therefore, about the representativeness of the participant pool to the general U.S. population.

Another related limitation of our sample is that it was collected in a limited geographical area—most respondents are from a single county. While this limits the generalizability of our sample to other geographical areas, our research design keeps constant the quarantine regulations our participants experienced. That is, because they all live in the same area, they were all subject to the same government regulations, workplace limitations, restaurant and movie theater closings, and so on.

Finally, our data allow us to compare two waves of data, one well before the social isolation started and one that was collected before the quarantine regulations were about to be eased. In the future, researchers could collect a third wave to see if the loneliness levels go back to pre-COVID times after the quarantine is over.

**Implications**

Our results document an association between social isolation due to the COVID-19 outbreak and increased loneliness. While loneliness in itself is an important phenomenon to study, social isolation–induced loneliness could have indirect health effects as well because loneliness is also associated with wide-ranging health problems such as high blood pressure, obesity, anxiety, depression, cognitive decline, Alzheimer’s disease, and suicide (Holt-Lunstad et al., 2015). We call for future research to study how these health

---

Table 5. Interaction Mode Predicting a Person’s Change in Level of Loneliness from 2019 to 2020.

| Variable                          | In Person | Audio | Video | Text | Email |
|----------------------------------|-----------|-------|-------|------|-------|
| Very close                       | −.15**    | −.10  | −.05  | −.13 | .03   |
|                                  | (.05)     | (.06) | (.08) | (.07) | (.14) |
| Close                            | .07       | −.03  | .00   | −.05 | −.10  |
|                                  | (.07)     | (.05) | (.06) | (.06) | (.10) |
| Friendly acquaintance            | .05       | .06   | −.07  | −.08 | .03   |
|                                  | (.07)     | (.06) | (.05) | (.05) | (.07) |
| Distant                          | .11       | .07   | .01   | .02  | .01   |
|                                  | (.11)     | (.09) | (.08) | (.07) | (.08) |
| Stranger (have not interacted before) | −.12     | .02   | .01   | −.01 | −.21*** |
|                                  | (.09)     | (.10) | (.08) | (.13) | (.08) |

Note: N= 189. Based on a regression that included controls for 2019 level of loneliness, employment status, and demographic characteristics (gender, age, race). Coefficient estimates for the controls are not shown here. Robust standard errors shown in parentheses.

*p < .05. **p < .01.
indicators have changed during and after the period of social isolation and to study the extent to which these changes can be explained by increases in loneliness or moderated by social networks.

Our results also show that the increase in loneliness during the pandemic did not affect all people equally: People with more very close social ties and people with less dense networks were less likely to report increased loneliness during social isolation. Having many less close connections, however, did not seem to be associated with lower increase in loneliness. These patterns indicate that the lockdown had a heterogenous effect on the population. For individuals, our work suggests that focusing efforts on maintaining relationships with close ties through frequent, in-person communication may be an important way to curtail loneliness during periods of social isolation. We find little evidence that non-face-to-face modalities of communication, such as videoconferencing or text-based exchanges, are associated with a lower increase in loneliness, suggesting that alternative media are not an effective substitute for face-to-face interaction. The social isolation–induced increase in loneliness is, of course, just one of the aspects to be considered, but our results indicate that this is an important aspect to consider, especially given the secondary health effects of increased loneliness.

**Appendix**

| Basic Information | Employment Information | Your Network | Network Member Details | Who Knows Who? | Additional Questions |
|-------------------|------------------------|--------------|------------------------|----------------|----------------------|

*Figure A1.* Screenshot from the AssessYourNetwork survey: Listing social ties.
Figure A2. Screenshot from the AssessYourNetwork survey: For each social tie listed in the previous step, participants are asked to detail the nature of the relationship.

Figure A3. Global network size estimation question based on McCarty et al. (2001) and McCormick, Salganik, and Zheng (2010).
Figure A4. Edge construction used in the density measure.
Think about the interactions you have had that have lasted longer than 10 minutes during the past 24 hours. An interaction is "a situation involving two or more people in which the behavior of each person is in response to the behavior of another person. A conversation is the most obvious example of an interaction, but there are many other sorts of interactions. Merely being in the presence of another is not enough by itself."

For instance watching TV or passively being on a video call with someone is not an interaction unless you were actively conversing or engaging with them. A 10-minute phone call or spending more than 10 minutes total reading/receiving and writing/sending texts with a particular person would count as an interaction. Interactivity is key.

In thinking about the interactions you have had over the last 24 hours, it may be helpful to check your calendar and phone.

Of the people you have interacted with during the last 24 hours, how many people fall into each relationship category? (e.g., if you have conversed with five immediate family members and two strangers you would, enter “5” in the box for “Very Close” and “2” in the box for “Stranger/Have Not Interacted Before”)

0 Very Close
0 Close
0 Friendly Acquaintance
0 Distant
0 Stranger/Have Not Interacted Before

Approximately how many hours did you spend interacting with individuals in each relationship category during the past 24 hours? (Note: If one hour, input 1 into the box. For 30 minutes, input 0.5 hours)

0 Very Close
0 Close
0 Friendly Acquaintance
0 Distant
0 Stranger/Have Not Interacted Before

Figure A5. Screenshot from the 2020 Qualtrics survey, highlighting the question asked about the frequency and duration of social interactions.
**Figure A6.** Screenshot from the 2020 Qualtrics survey, highlighting the question asked about the mode of social interactions.

**Table A1.** Heckman Selection Model Predicting the Change in the Person’s Level of Loneliness from 2019 to 2020.

| Variable                  | Response Equation | Selection Equation |
|---------------------------|-------------------|--------------------|
| Very close 2019           | −.03*             | −.05               |
|                           | (.01)             | (.03)              |
| Close 2019                | −.02              | −.11**             |
|                           | (.02)             | (.04)              |
| Density 2019              | .17               | −.14               |
|                           | (.13)             | (.36)              |
| Network size 2019         | −.05              | −.02               |
|                           | (.03)             | (.07)              |
| Loneliness 2019           | .34**             | −.10               |
|                           | (.06)             | (.18)              |
| Live alone 2020           | .11               |                    |
|                           | (.08)             |                    |
| Employed 2020             | .02               | .11                |
|                           | (.05)             | (.13)              |
| Female                    | −.05              |                    |
|                           | (.05)             |                    |
| African American          | .03               | −.58*              |
|                           | (.11)             | (.24)              |
| Latinx                    | −.02              | −.36*              |
|                           | (.07)             | (.15)              |
| Age                       | −.00              | .02***             |
|                           | (.00)             | (.01)              |
| Burnout 2019              |                    | −.26*              |
|                           |                   | (.12)              |
| Constant                  | 2.38**            | 1.04               |
|                           | (0.25)            | (0.79)             |
| N                         | 189               | 417                |

Note: Robust standard errors shown in parentheses. Compare with Table 2’s Model 4. As an exclusion criterion, we use the respondent’s self-reported burnout level, which was collected in Wave 1 only and is based on the six-question Copenhagen Burnout Inventory (Kristensen et al., 2005).

*p < .05, **p < .01.
Table A2. Distribution of the Count of “Very Close” Ties in 2019 (on the Subsample of Participants Who Completed Both Waves of the Survey).

| Count of “Very Close” Ties | Frequency |
|----------------------------|-----------|
| 0                          | 7         |
| 1                          | 35        |
| 2                          | 44        |
| 3                          | 43        |
| 4                          | 16        |
| 5                          | 14        |
| 6                          | 13        |
| 7                          | 9         |
| 8                          | 3         |
| 10                         | 2         |
| 11                         | 1         |

Acknowledgments

We are grateful for the research support of Jess Halten and Rob Bartholomew, and for the detailed feedback at a Yale internal seminar where we presented our results. We have no conflicts of interest to disclose.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Data collection was sponsored by Yale University SOM’s Faculty Research Funds and its Behavioral Lab.

ORCID iD

Balazs Kovacs https://orcid.org/0000-0001-6916-6357

References

Baker, Scott, Nicholas Bloom, Stephen Davis, and Stephen Terry. 2020. COVID-Induced Economic Uncertainty. Cambridge, MA: NBER.

Brashears, Matthew E. 2011. “Small Networks and High Isolation? A Reexamination of American Discussion Networks.” Social Networks 33(4):331–41.

Brashears, Matthew E., Emily Hoagland, and Eric Quintane. 2016. “Sex and Network Recall Accuracy.” Social Networks 44:74–84.

Burt, Ronald S. 2000. “Decay Functions.” Social Networks 22:1–28.

Cacioppo, John T., James H. Fowler, and Nicholas A. Christakis. 2009. “Alone in the Crowd: The Structure and Spread of Loneliness in a Large Social Network.” Journal of Personality and Social Psychology 97(6):977–91.

Cacioppo, Stephanie, Angela J. Grippo, Sarah London, Luc Goossens, and John T. Cacioppo. 2015. “Loneliness: Clinical Import and Interventions.” Perspectives on Psychological Science 10(2):238–49.

Cacioppo, John T., James H. Fowler, and Nicholas A. Christakis. 2008. “Sex and Network Recall Accuracy.” Social Networks 33(3):331–41.

Acknowledgments

We are grateful for the research support of Jess Halten and Rob Bartholomew, and for the detailed feedback at a Yale internal seminar where we presented our results. We have no conflicts of interest to disclose.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Data collection was sponsored by Yale University SOM’s Faculty Research Funds and its Behavioral Lab.

ORCID iD

Balazs Kovacs https://orcid.org/0000-0001-6916-6357

References

Baker, Scott, Nicholas Bloom, Stephen Davis, and Stephen Terry. 2020. COVID-Induced Economic Uncertainty. Cambridge, MA: NBER.

Brashears, Matthew E. 2011. “Small Networks and High Isolation? A Reexamination of American Discussion Networks.” Social Networks 33(4):331–41.

Brashears, Matthew E., Emily Hoagland, and Eric Quintane. 2016. “Sex and Network Recall Accuracy.” Social Networks 44:74–84.

Burt, Ronald S. 2000. “Decay Functions.” Social Networks 22:1–28.

Cacioppo, John T., James H. Fowler, and Nicholas A. Christakis. 2009. “Alone in the Crowd: The Structure and Spread of Loneliness in a Large Social Network.” Journal of Personality and Social Psychology 97(6):977–91.

Cacioppo, Stephanie, Angela J. Grippo, Sarah London, Luc Goossens, and John T. Cacioppo. 2015. “Loneliness: Clinical Import and Interventions.” Perspectives on Psychological Science 10(2):238–49.

Cohen, Sheldon, Denise Janicki-Deverts, Ronald B. Turner, and William J. Doyle. 2015. “Does Hugging Provide Stress-Buffering Social Support? A Study of Susceptibility to Upper Respiratory Infection and Illness.” Psychological Science 26(2):135–47.

Durkheim, Emile. 2014. The Division of Labor in Society. New York: Free Press.

Dykstra, Pearl A. 1990. Next of Non-Kin. The Importance of Primary Relationships for Older Adults’ Well-Being. Amsterdam: Swets & Zeitlinger.

Education Week. 2020. “Coronavirus and School Closures.” Retrieved May 15, 2020 (https://www.edweek.org/ew/section-multimedia/map-coronavirus-and-school-closures.html).

Feld, Scott. 1981. “The Focused Organization of Social Ties.” American Journal of Sociology 86(5):1015–36.

Forgo, Richard, Bryan Dettrey, Mark Van Boening, and David A. Swanson. 2009. “Before, Now, and After: Assessing Hurricane Katrina Relief.” Population Research and Policy Review 28(1):31–44.

Gauthier, Gertrude R., Jeffrey A. Smith, Catherine García, Marc A. Garcia, and Patricia A. Thomas. 2020. “Exacerbating Inequalities: Social Networks, Racial/Ethnic Disparities, and the COVID-19 Pandemic in the United States.” Journals of Gerontology: Series B. https://doi.org/10.1093/geronb/gbaa117.

Hawkley, Louise C., Mary Elizabeth Hughes, Linda J. Waite, Christopher M. Masl, Ronald A. Thisted, and John T. Cacioppo. 2008. “From Social Structural Factors to Perceptions of Relationship Quality and Loneliness: The Chicago Health, Aging, and Social Relations Study.” Journals of Gerontology: Series B 63(6).

Hirsch, Barton J. 1980. “Natural Support Systems and Coping with Major Life Changes.” American Journal of Community Psychology 8(2):159–72.

Holt-Lunstad, Julianne, Timothy B. Smith, Mark Baker, Tyler Harris, and David Stephenson. 2015. “Loneliness and Social Isolation as Risk Factors for Mortality.” Perspectives on Psychological Science 10(2):227–37.

Hsung, Ray-May, Nan Lin, and Ronald L. Breiger, eds. 2010. Contexts of Social Capital: Social Networks in Markets, Communities and Families. Vol. 43. Routledge.

Gierveld, Jenny de Jong, Theo G. van Tilburg, and Pearl A. Dykstra. 2006. “Loneliness and Social Isolation.” Pp. 485–500 in The Cambridge Handbook of Personal Relationship, edited by A. Vangelisti, D. Perlman. Cambridge, UK: Cambridge University Press.

Kawachi, I., and L. F. Berkman. 2001. “Social Ties and Mental Health.” Journal of Urban Health: Bulletin of the New York Academy of Medicine 78(3):458–67.

Killgore, William D. S., Sara A. Cloonan, Emily C. Taylor, and Natalie S. Dailey. 2020. “Exacerbating Inequalities: Social Networks, Racial/Ethnic Disparities, and the COVID-19 Pandemic in the United States.” Journals of Gerontology: Series B. https://doi.org/10.1093/geronb/gbaa117.

Krendl, Anne C., and Brea L. Perry. 2020. “The Impact of Sheltering in Place During the COVID-19 Pandemic on Older Adults’ Social and Mental Well-Being.” Journals of Gerontology: Series B. https://doi.org/10.1093/geronb/gbaa110.

Kristensen, Tage S., Marianne Borritz, Ebbe Villadsen, and Karl B. Christensen. 2005. “The Copenhagen Burnout Inventory:
A New Tool for the Assessment of Burnout.” Work & Stress 19(3):192–207.

Lee, Yeun, and Young-gun Ko. 2018. “Feeling Lonely When Not Socially Isolated.” Journal of Social and Personal Relationships 35(10):1340–55.

Liu, K. Y., M. King, and P. S. Bearman. 2010. “Social Influence and the Autism Epidemic.” American Journal of Sociology 115(5):1387–1434.

Marsden, Peter V. 1987. “Core Discussion Networks of Americans.” American Sociological Review 52(1):122.

McCarty, Christopher, Peter D. Killworth, H. Russell Bernard, Eugene C. Johnsen, and Gene A. Shelley. 2001. “Comparing Two Methods for Estimating Network Size.” Human Organization 60(1):28.

McCormick, Tyler H., Matthew J. Salganick, and Tian Zheng. 2010. “How Many People Do You Know? Efficiently Estimating Personal Network Size.” Journal of the American Statistical Association 105(489):59–70.

McPherson, Miller, Lynn Smith-Lovin, and Matthew E. Brashears. 2006. “Social Isolation in America: Changes in Core Discussion Networks over Two Decades.” American Sociological Review 71(3):353–75.

Menon, Tanya, and Edward Bishop Smith. 2014. “Identities in Flux: Cognitive Network Activation in Times of Change.” Social Science Research 45:117–30.

Noone, Chris, Jenny McSharry, Mike Smallie, Annette Burns, Kerry Dwan, Declan Devane, and Eimear C. Morrissey. 2020. “Video Calls for Reducing Social Isolation and Loneliness in Older People: A Rapid Review.” Cochrane Database of Systematic Reviews 5(5):1–40.

Ohme, Jakob, Mariok M. P. Vanden Abee, Kyle Van Gaeveren, Wouter Durnez, and Lieven De Marez. 2020. “‘Staying Informed and Bridging ‘Social Distance’: Smartphone News Use and Mobile Messaging Behaviors of Flemish Adults During the First Weeks of the COVID-19 Pandemic.” Socius: Sociological Research for a Dynamic World 6:237802312095019. Oxford, Nick, and Janie Osborne. 2020. “The Future of Travel: How the Industry Will Change after the Pandemic.” New York Times, May 6.

Peplau, Letitia Ann, and Daniel Perlman. 1982. “Perspectives on Loneliness.” Pp. 1–18 in Loneliness: A Sourcebook of Current Theory, Research and Therapy, edited by L. A. Peplau and D. Perlman. New York: Wiley.

Perry, Brea L., and Bernice A. Pescosolido. 2015. “Social Network Activation: The Role of Health Discussion Partners in Recovery from Mental Illness.” Social Science and Medicine 125:116–28.

Phan, Tuan Q., and Edoardio M. Airoldi. 2015. “A Natural Experiment of Social Network Formation and Dynamics.” Proceedings of the National Academy of Sciences of the United States of America 112(21):6595–6600.

Reis, Harry T., and Ladd Wheeler. 1991. “Studying Social Interaction with the Rochester Interaction Record.” Advances in Experimental Social Psychology 24(C):269–318.

Roberts, Sam B. G., and Robin I. M. Dunbar. 2015. “Managing Relationship Decay.” Human Nature 26(4):426–50.

Roberts, Sam G. B., and Robin I. M. Dunbar. 2011. “Communication in Social Networks: Effects of Kinship, Network Size, and Emotional Closeness.” Personal Relationships 18(3):439–52.

Romero, Daniel M., Brian Uzzi, and Jon Kleinberg. 2016. “Social Networks under Stress.” Pp. 9–20 in Proceedings of the 25th International Conference on World Wide Web. Republic and Canton of Geneva, CH: International World Wide Web Conferences Steering Committee.

Russell, Daniel W. 1996. “UCLA Loneliness Scale (Version 3): Reliability, Validity, and Factor Structure.” Journal of Personality Assessment 66(1):20–40.

Russell, Dan, Letitia A. Peplau, and Carolyn E. Cutrona. 1980. “The Revised UCLA Loneliness Scale: Concurrent and Discriminant Validity Evidence.” Journal of Personality and Social Psychology 39(3):472–80.

Sasovova, Zuzana, Ajay Mehra, Stephen P. Borgatti, and Michäela C. Schippers. 2010. “Network Chunr: The Effects of Self-Monitoring Personality on Brokerage Dynamics.” Administrative Science Quarterly 55(4):639–70.

Shea, Catherine T., Tanya Menon, Edward B. Smith, and Kyle Emich. 2015. “The Affective Antecedents of Cognitive Social Network Activation.” Social Networks 43:91–99.

Silverstein, Merrill, Xuan Chen, and Kenneth Heller. 1996. “Too Much of a Good Thing? Intergenerational Social Support and the Psychological Well-Being of Older Parents.” Journal of Marriage and the Family 58(4):970.

Small, Mario Luis. 2017. Someone to Talk to. Oxford, UK: Oxford University Press.

Small, Mario Luis, Vontrese Deeds Pamphile, and Peter McMahan. 2015. “How Stable Is the Core Discussion Network?” Social Networks 40:90–102.

Stokes, Joseph P. 1985. “The Relation of Social Network and Individual Difference Variables to Loneliness.” Journal of Personality and Social Psychology 48(4):981–90.

van Tilburg, Theo G. 1990. “The Size of the Supportive Network in Association with the Degree of Loneliness.” Pp. 137–50 in Social Network Research: Substantive Issues and Methodological Questions, edited by C. P. M. Knipscheer and T. C. Antonucci. Lisse: Swets & Zeitlinger.

van Tilburg, Theo G., Stephanie Steinmetz, Elske Stolte, Henriëtte van der Roest, and Daniel H. de Vries. 2020. “Loneliness and Mental Health During the COVID-19 Pandemic: A Study among Dutch Older Adults.” The Journals of Gerontology: Series B. https://doi.org/10.1093/geronb/gbaa111.

Wilcox, B. L. 1981. “Social Support in Adjusting to Marital Disruption: A Network Analysis.” Pp. 97–115 in Social Networks and Social Support, edited by B. H. Gottlieb. Beverly Hills, CA: Sage.

Zheng, Tian, Matthew J. Salganik, and Andrew Gelman. 2006. “How Many People Do You Know in Prison? Using Overdispersion in Count Data to Estimate Social Structure in Networks.” Journal of the American Statistical Association 101(474):409–23.

Author Biographies

Balazs Kovacs is an associate professor of management at the Yale School of Management and in the Department of Sociology (courtesy). He studies various topics in organization theory, including social networks, authenticity, learning, diffusion, identity, and status. His current work investigates the effects of category spanning and innovation in technological and cultural domains.
Nicholas Caplan is a principal at TDV Capital Partners and a partner at Team Good, LLC. He has developed tools to allow individuals to assess and maintain their social networks.

Samuel Grob is an undergraduate at Yale University studying psychology and education.

Marissa King is a professor of organizational behavior at the Yale School of Management. Her research examines social networks, social influence, and team dynamics. Her most recent line of work analyzes how to effectively leverage networks to treat opioid-use disorders and address the loneliness epidemic.