

COMPUTATIONAL SOCIAL SCIENCE

Model supports storied social network theory

A new Bayesian analysis of remote work data supports one of the oldest theories in social networks, with fresh implications for the future of work environments.

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Weak ties describe the infrequent connections that we maintain with acquaintances, occasional colleagues, and periodic friends in our social networks¹. Despite their ‘weakness’, these ties often give rise to new ideas, opportunities, and advice in organizational settings^{1–4}. While this finding has largely stood the test of time, much remains unknown about its causal mechanisms⁴. What dynamically generates these ties? What maintains them? Can they withstand ‘exogenous’ shocks from the outside, such as changes in location motivated by the COVID-19 pandemic? This evolving landscape gives new urgency to calls for “insights into particular [social] processes at particular times” through fresh data, methods, and analytical rigor⁵. Now, an Article in *Nature Computational Science* answers this call, demonstrating that new computational methods can probe hard questions about organizational networks. In their piece, Daniel Carmody and colleagues⁶ use Bayesian time series analysis to provide evidence supporting an important, understudied theory in social networks called propinquity — which states that spatial proximity increases the odds of creating new connections and strengthening existing ones — in the context of COVID-19.

Weak tie formation often begins when familial, community, or organizational activities bring people together. Simply being in physical proximity to someone increases the likelihood of serendipitous interaction. In turn, these interactions give people the chance to explore shared qualities, interests, and behaviors with one another, and hence form ties. These steps describe the social process of propinquity — the closer we are physically to another person, the more likely we are to form a new tie or reify an existing one with them⁷ (Fig. 1a). Existing works have found that sharing socially significant qualities can amplify the effects of propinquity⁸ and that propinquity extends to virtual proximity^{9,10}. But the concept is often taken for granted even though it holds important implications for how we design

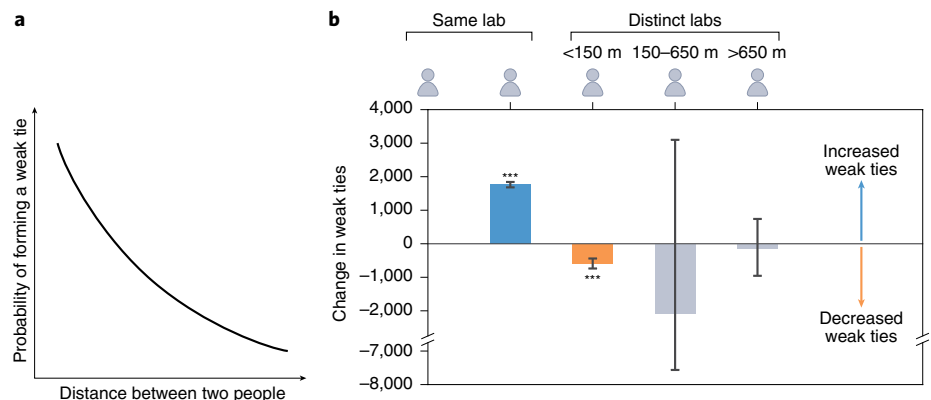


Fig. 1 | Loss of physical proximity due to remote work caused weak ties with nearby researchers to atrophy. a, Propinquity relates the distance between two people (horizontal axis) to the likelihood that those individuals will form a tie (vertical axis). People who are physically closer to one another are more likely to interact, and therefore to form ties with one another (the curve shown). The referenced study provided empirical evidence supporting this social science theory. **b**, The central finding from the referenced study, showing the change in the number of weak ties between researchers as a function of the distance between their labs from March 2020 to July 2021. The data was collected from the original study⁶. Statistically significant increases in weak ties are shown in blue; significant decreases are shown in orange; and non-significant changes appear in gray. Error bars represent 95% confidence intervals, and *** indicates a statistically significant finding with $p < 0.001$ (all other bars had $p > 0.1$). The graph shows that researchers who once worked nearby one another interacted with one another less throughout the COVID-19 pandemic, which caused the weak ties between those individuals to disappear. Meanwhile, researchers who worked in the same lab group (remotely) strengthened their existing relationships with those individuals and formed more weak ties than they would have if they shared physical lab space.

organizations and social gatherings. This leaves a surprising dearth of evidence showing this process as it happens, and so we lack knowledge of how the process might improve everything from technology dissemination to inequities⁴.

Carmody et al. provided an important empirical demonstration that shows weak ties as they form and degrade through propinquity. Most social network studies compare a few snapshots of social networks over some time interval because gathering granular temporal network data often proves quite difficult, both logistically and ethically. Ultimately, this prevents us from witnessing when and how most ties form. The authors overcome this obstacle by estimating the number of weak ties between researchers at the Massachusetts Institute

of Technology (MIT). Their e-mail dataset spans two dramatic changes in researchers’ work locations over a year and a half during the COVID-19 pandemic. The first transition took place on 23 March 2020, when MIT halted most in-person research activities. Researchers began working from home, hypothetically preventing weak ties from forming through propinquity. The second transition took place on 15 July 2021, when researchers began returning to campus, hypothetically increasing weak tie formation through propinquity. The authors examined the e-mail network spanning these real-world location transitions through a synthetic counterfactual e-mail network with these transitions absent to estimate how much propinquity affected weak tie formation.

Methodologically, the authors constructed their synthetic counterfactual through a Bayesian structural time series (BSTS) approach that separates out the effect of a treatment (here, remote work) from qualities unaffected by the treatment (such as linear trends and cyclical variations). This enabled them to construct a credible interval for the expected number of weak ties with and without remote work. Their analysis showed that remote work may have cost nearly 5,100 weak ties during the remote work period — about 1.8 ties per person — in exchange, of course, for important public health objectives due to the pandemic. Additionally, researchers were more likely to lose weak ties with people who worked in nearby labs than with those who worked in either the same or distant labs (Fig. 1b). Consequently, researchers were ‘stuck’ strengthening their existing ties instead. As a validation of this finding, they designed a generative network simulation to replicate several tie formation mechanisms (such as sharing a lab, mutual friends, and co-location). In doing so, they qualitatively show that a propinquity factor replicates the finding of their BSTS analysis.

Carmody and colleagues demonstrated the potential of modern computational techniques to support old social science theories and identify new phenomena. Their research could provide rigorous tools for verifying elusive causal hypotheses of social networks and information^{4,5}. Future studies should consider how other confounds might affect these results. For example, the authors note that having insufficient data from before the pandemic limited their ability to predict cyclic effects. This echoes the importance of appropriately constructing controls for quasi-experiments⁵. Building size and location, researcher demographics, university-required activities, and the kind of information exchanged (professional versus friendly¹¹) might confound the results, but might also reveal unexplored questions. A word of caution, though: the benefits of computation power become moot without appropriate framing from qualitative and theoretical social science⁵. Naïve computational studies risk drawing incorrect conclusions altogether. Interdisciplinary collaborations between scholars with computational and theoretical perspectives could begin to answer hard and

lingering questions, though — with patience and curiosity on all sides — in ways that may benefit how we design opportunities for social interaction in years to come. 

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Competing interests

The author declares no competing interests.