Social Networks Shape Beliefs and Behavior: Evidence From Social Distancing During the Covid-19 Pandemic*

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Abstract

We use de-identified data from Facebook to study how social connections affect beliefs and behaviors in high-stakes settings. During the Covid-19 pandemic, individuals with friends in areas currently experiencing worse disease outbreaks reduced their mobility substantially more than their otherwise similar neighbors with friends in less affected areas. To explore the mechanisms through which social connections shape behaviors, we show that individuals with higher friend exposure to Covid-19 are more likely to publicly post in support of social distancing measures and less likely to be members of groups seeking to "reopen" the economy. These findings suggest that friends influence individuals' behaviors in part through their beliefs, even in the presence of ubiquitous information from expert sources.

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In the United States and many other countries, there is substantial public disagreement about important elements of established scientific consensus such as global warming and the safety and efficacy of vaccines (Weber and Stern, 2011; Jacobson, Sauver and Rutten, 2015; Peretti-Watel et al., 2020). As a result, policy makers often struggle to achieve outcomes that rely on people's willingness to adjust their behaviors based on the acceptance of such scientific facts. The recent Covid-19 pandemic has highlighted some of these challenges: despite the ubiquity of high-quality public information about the virus,[1] beliefs about its risks varied widely across individuals, affecting their willingness to follow public health guidance and engage in social distancing behavior to reduce their risk of exposure.

But why did people with similar exposure to information from public health experts hold such divergent beliefs about the risks from Covid-19? In this project, we explore the role of individuals' social networks—their friends, families, and acquaintances—in shaping beliefs and behaviors during the Covid-19 pandemic. We first analyze the effects of friend exposure to Covid-19 cases on individuals' social distancing behavior. We document that individuals who have friends in locations with more severe outbreaks disproportionately reduce their mobility. We then study the mechanisms underlying this effect, showing that friend exposure to Covid-19 increases individuals' willingness to reduce mobility at least in part by influencing their beliefs about Covid-19. As such, information acquired through social networks shifted beliefs and behaviors even when information on the same topic had been prominently communicated by domain experts. This finding has important implications both for the design of policy as well as the development of new models of information acquisition.

We work with de-identified data from Facebook, a large online social networking service. The data provides information on individuals' movement patterns and the location of their friends, allowing us to measure the effects of friend exposure to Covid-19 on social distancing behavior.[2] The data also includes information on public posts on the platform and membership in public Facebook groups, allowing us to study individuals' perceptions of the Covid-19 pandemic. Relative to the cell phone location data used in much of the existing research on social distancing behavior, our unique ability to link individual-level data on mobility to information on demographics, social networks, and proxies for perceptions allows us to generate novel insights into the determinants of behaviors and beliefs.

We begin by documenting time-series patterns in mobility and show that—consistent with prior work—U.S. Facebook users in our sample drastically reduced their mobility after the outbreak of the pandemic. In mid-February 2020, the probability of staying home averaged around 18% on a given day; by late March, this probability had increased to about 30%.

We then explore the role of friendship networks in shaping social distancing behavior. To illustrate our results in the raw data, we first focus on the early onset of the pandemic. We classify each individual as being either above or below the median of friend exposure *within their zip code* based on the exposure

[1] A poll by the Pew Research Center (2020) between March 10-16, 2020 found that 89% of respondents had been following news related to Covid-19 'very closely' or 'fairly closely', with only 2% saying they had been following the news 'not at all closely'.

[2] We observe measures of mobility only for Facebook users who consented to sharing and storing their location information. We proxy for staying at home with staying within a single level-16 Bing tile, an area of about 600m x 600m (see Section 1.1). We use Facebook friendship links as a proxy for an individual's real-world social network, and believe that it provides a high-quality measure of the peers that an individual would interact with both online and in the offline world. Overall, Facebook users are highly representative of the U.S. population, and friendship links largely represent real-world friends and acquaintances (Jones et al., 2013). Indeed, prior work has shown that in the U.S., Facebook friendship links provide a reliable representation of real-world friendship links (e.g. Bailey et al., 2018*a*, 2019, 2022*a*,*b*; Chetty et al., 2022*a*,*b*).

of their social network to Covid-19 as of March 15, 2020, right after President Trump declared a national emergency. Prior to the pandemic, movement patterns of the two groups look strikingly similar. In contrast, after the outbreak, users with above-median friend exposure—that is, those who have relatively more friends living in areas highly affected by the virus—were more likely to stay home compared to others in the same zip code with lower friend exposure. Quantitatively, a one standard deviation higher friend exposure to Covid-19 cases was associated with an 8.8% larger increase in the probability of staying home by April 2020. These differences remain large and significant when we include controls for time-varying effects of various demographics and other characteristics of an individual's social network.

A potential concern with interpreting these cross-sectional findings is that the location of individuals' friends in the U.S. may be associated with other factors that could impact social distancing behaviors during the pandemic. For instance, people with friends in early hotspots such as NYC and Seattle might be more politically liberal and, as a result, independently engage in more social distancing than their neighbors. To address concerns like these, our main specification uses a dynamic approach which estimates the effects of *changes* in friend exposure to Covid-19 over a given month on *changes* in social distancing during that month as the pandemic evolves. We demonstrate that individuals with friends in the early hot spots like Seattle disproportionately reduced their mobility in the early pandemic compared to their otherwise-similar neighbors with friends in different parts of the country. But by June 2020, it was individuals with friends in the newly emerging hotspots like Oklahoma, Texas, and Arizona that disproportionately increased their social distancing. To interpret our results as driven by unobservables rather than as evidence for a causal effect of friend experiences on social distancing, one would need to argue that in every month, individuals with friends regions with the largest outbreaks happened to reduce their mobility for reasons other than their friend exposure. Since a plausible version of this story is difficult to tell, we conclude that higher friend exposure to Covid-19 likely induces social distancing. We also find that the effects of friend exposure to Covid-19 on mobility patterns are virtually identical for weekends and weekdays, suggesting that the reduced mobility associated with friend exposure to Covid-19 is by choice and not due to differences in individuals' ability to work from home.

We then explore the mechanisms through which social networks affect high-stakes decisions such as whether to reduce mobility during a pandemic. In our context, a direct effect could exist if individuals in current virus hotspots schedule fewer in-person social interactions with their friends. Alternatively, a preference effect might arise if those in more affected areas engage in more home-bound activities such as cooking, leading their friends to become more engaged in these activities. Finally, friend experiences might affect individuals' beliefs about the benefits of social distancing by providing information about the severity of the virus in a way that particularly resonates with the individuals.

To understand the role of these possible explanations in our setting, we first show that changes in the Covid-19 exposure of friends living more than 100 miles away still have very sizeable effects on an individual's social distancing. This suggests that a large part of our results is not driven by a direct effect of friend exposure to Covid-19 limiting visits and interactions with the affected friends.

Next, we explore whether friend experiences shape behavior by affecting individuals' beliefs. We use data from public user posts and group memberships to construct a measure of individuals' stated *beliefs* about Covid-19 and their *attitudes* towards social distancing. Friend exposure to Covid-19 cases increases an individual's propensity to post about Covid-19 and the probability that such posts voice support for restrictions on public life. Similarly, greater friend exposure to Covid-19 cases lowers the likelihood that an individual joins public Facebook groups advocating for a reopening of the economy.

It is noteworthy that we find this effect of friend experiences on individuals' beliefs and behaviors even in a context where high-quality expert information about the risks of Covid-19 and the need for social distancing was ubiquitous and intensely covered in the media. It is thus unlikely that friends conveyed content that individuals had not already received through other channels. Instead, it is more likely that the information provided by friends—even if not necessarily new *per se*—resonated more with individuals and thus had a large effect on their beliefs and behaviors. Our findings therefore suggest that policy makers may have more success at shifting beliefs and behavior when relevant information is conveyed by people who resonate with the relevant target communities.

Our work speaks to a large literature on how individuals form beliefs and the extent to which these beliefs translate into actions (e.g., Rothwell et al., 2021; Roth and Wohlfart, 2020; Bakkensen and Barrage, 2021; Bordalo et al., 2022; Kuchler and Zafar, 2019; D'Acunto et al., 2022; Armona, Fuster and Zafar, 2019; Armantier et al., 2015; Bachmann, Berg and Sims, 2015; Giglio et al., 2021*a*,*b*; Malmendier and Nagel, 2011). Most closely related is work that documents the possible role of social interactions—and in particular the experience of friends—on belief formation and behavior. In this literature, Bailey et al. (2018*a*, 2019) show that friends' house price experience can influence a person's own house price expectations. Similarly, Ratnadiwakara (2021), Hu (2022), Mayer (2023), and Xu and Box-Couillard (2023) use county-level social network data from Bailey et al. (2018*a*) to conclude that when an individuals' friends experience extreme weather events such as hurricanes and floods, this can affect a person's own beliefs about climate change. Relative to this literature, our work uses individual-level data on social networks to highlight that friend experiences shape beliefs, opinions, and behaviors even in settings where high-quality information from domain experts is ubiquitous. This suggests that the role of friends in shaping beliefs and behaviors goes beyond those friends being a low-cost source of information, as in Banerjee et al. (2019). Instead, the evidence provides support for models of learning in which the identity of the person conveying the information matters for how much weight the information receives in the belief-formation process. Malmendier and Veldkamp (2022) propose such a model in which "abstractly learned statistics and other information tends to be weighted significantly less than information gathered from [. . .] the experiences of others whom we care about, identify with or empathize with."

This paper also contributes to a growing literature on the determinants of social distancing during the Covid-19 pandemic, surveyed by Giuliano and Rasul (2020*b*) and Brodeur et al. (2021),[3] as well as work on the effect of social networks on health behaviors more generally (see Christakis and Fowler, 2007, 2008; Huang et al., 2014; Fletcher and Ross, 2018; Sato and Takasaki, 2019). In related work, Tian, Caballero and Kovak (2022) argue that international migration networks helped to convey information about the disease. Similarly, Charoenwong, Kwan and Pursiainen (2020) use county-level social network

[3]In this literature, civic capital (Giuliano and Rasul, 2020*a*; Barrios et al., 2021; Chetty et al., 2022*a*), trust in scientific knowledge (Brzezinski et al., 2021), trust in policy makers (Bargain and Aminjonov, 2020), general trust (Brodeur, Grigoryeva and Kattan, 2021), news consumption (Simonov et al., 2022; Bursztyn et al., 2022), political affiliation (Allcott et al., 2020*b*; Barrios and Hochberg, 2021), policy decisions (Allcott et al., 2020*a*), and potential spillover effects of policy across states (Holtz et al., 2020) have all been shown to affect social distancing.

data from Bailey et al. (2018*b*) to show that individuals living in U.S. counties with more connections to China and Italy—two early hotspots of the Covid-19 pandemic—reduce their mobility more. Makridis and Wang (2020) show that consumption decreases more in counties with higher friend exposure to Covid-19 cases. Relative to this work, our individual-level analysis allows us to absorb any direct effects of local conditions likely correlated with friend exposure (see Kuchler, Russel and Stroebel, 2022) and our data on posts and group memberships allows us to establish individuals' beliefs about Covid-19 as an important mechanism through which friend exposure affects mobility.

1 Data and Descriptive Statistics

We work with de-identified data from the global online social networking site Facebook to measure individual-level social networks and social distancing behavior. As of December 2019, Facebook had 248 million monthly active users and 190 million daily active users in the U.S. and Canada (Facebook, 2020). Duggan, Greenwood and Perrin (2016) found that, among U.S. adults, usage rates were relatively constant across income groups, education levels, and race; usage rates were slightly declining in age.

Establishing a connection on Facebook requires the consent of both individuals, and a person can have at most 5,000 connections. As a result, Facebook connections are primarily between real-world friends, acquaintances, and family members and Facebook networks resemble real-world social networks more closely than networks on other online platforms where uni-directional links to non-acquaintances, such as celebrities are common. Indeed, prior studies show that Facebook networks predict many important real-world economic and social interactions, including patterns of trade (Bailey et al., 2021), patent citations (Bailey et al., 2018*b*), travel flows (Bailey et al., 2020*a*,*b*), housing choices (Bailey et al., 2018*a*, 2019), bank lending (Rehbein, Rother et al., 2020), social program participation (Wilson, 2022), product adoption decisions (Bailey et al., 2022*a*), investment decisions (Kuchler et al., 2022), disease transmission (Kuchler, Russel and Stroebel, 2022), and upward income mobility (Chetty et al., 2022*a*,*b*).

1.1 Sample Restrictions and Summary Statistics

Our analyses of mobility behavior are limited to a sub-population of Facebook users who have consented to sharing and storing their location,[4] have active accounts, are 18 or older, live in the 50 U.S. States or the District of Columbia, and have between 100 and 1,500 U.S.-based Facebook friends. We restrict the analysis to ZIP Code Tabulation Areas (ZCTAs) with 50 or more users who meet all previous requirements. Overall, the sample of users that meet the above criteria includes 12.8 million individuals. The average ZCTA has 592 users, the median has 319, and the 10th percentile has 72 users. We do not require users to have location information in every week (for example, if their mobile device was turned off) and thus observe information for about 7.2 million users per week.

Table 1 provides summary statistics on the users in our mobility sample. Age ranges from 26 years at the 10th percentile to 63 years at the 90th percentile. 53% of the sample is female, and just over half

[4]Users consented to having their location stored if they used a feature that required high-frequency location data to function. We do not see a shift in usage patterns around the onset of the pandemic, though usage of these features had been slowly declining. To address possible concerns that the sample of users sharing their location is biased, we confirm that our core results are similar when re-weighting users sharing their location so that their observable characteristics match those of our broader sample of Facebook users. We also show that our baseline patterns replicate at the zip-code level using an independent source of movement data provided by Safegraph.

the users have listed a college.[5] We also observe whether a user primarily accesses Facebook from an iPhone or from an Android phone, with about 25% of the sample using an iPhone. Finally, we observe that about half the sample sometimes also accesses Facebook from a tablet (e.g., an iPad) in addition to accessing it from a smartphone, which is a requirement to enter our mobility sample.

Table 1: Summary Characteristics - Mobility Sample

	Mean	SD	P10	P25	P50	P75	P90
Age	43.58	14.93	26	32	42	54	63
Female	0.53	0.50	0	0	1	1	1
Has College	0.53	0.50	0	0	1	1	1
Has iPhone	0.25	0.43	0	0	0	0	1
Has Tablet	0.53	0.50	0	0	1	1	1
Zip Code Income	$58,792	$21,961	$36,160	$43,648	$54,000	$69,203	$88,096
Number of Friends	532.80	326.61	193	276	441	718	1047
Friend Exposure to Cases	10.35	19.34	0.74	1.77	4.49	11.12	26.31
Staying at home (Feb)							
- All	18.33	29.35	0	0	0	28.57	66.67
- Weekend	19.39	34.44	0	0	0	50.00	100.00
- Weekday	16.83	29.80	0	0	0	20.00	66.67
Bing tiles visited (Feb)							
- All	10.96	9.07	1.57	3.43	9.00	15.86	23.43
- Weekend	10.57	9.79	1.00	3.00	7.50	15.50	24.50
- Weekday	11.34	9.77	1.50	3.40	9.00	16.20	24.60

Note: Table presents summary statistics describing individuals analyzed in our mobility sample of users. Individual-level characteristics include age, gender, whether the user has a college listed on Facebook, whether the user primarily accesses Facebook mobile from an iPhone, whether the individual has accessed Facebook from a tablet, number of friends, friend-exposure to Covid cases on March 15th, and patterns of mobility during the week of February 25th to March 2nd. The table also includes information on the users' home ZCTA 2018 median household income.

After mapping users to their presumed ZCTA of residence, we supplement our individual-level data with public data on median household income from the 2014-2018 American Community Survey (ACS). The median user in our sample lives in a ZCTA with a median household income of $54,000, not far from the true U.s. median household income of $53,958. The 10th and 90th percentiles are $36,160 and $88,096, respectively, numbers that are also close to their U.S. population equivalents of $34,658 and $89,355. For comparison, Table A1 provides summary statistics for a broader population of Facebook users without the requirement for location information. This broader sample and the mobility sample are largely similar, though users in the mobility sample are slightly less likely to have attended college, less likely to use an iPhone, and are from slightly lower-income ZCTAs on average.

To measure an individual's exposure to Covid-19 cases, we use data from Dong, Du and Gardner (2020) on Covid-19 cases at the county-by-day level. We map each user to a county by crosswalking their ZCTA of residence to the county in which the largest fraction of its population resides.[6]

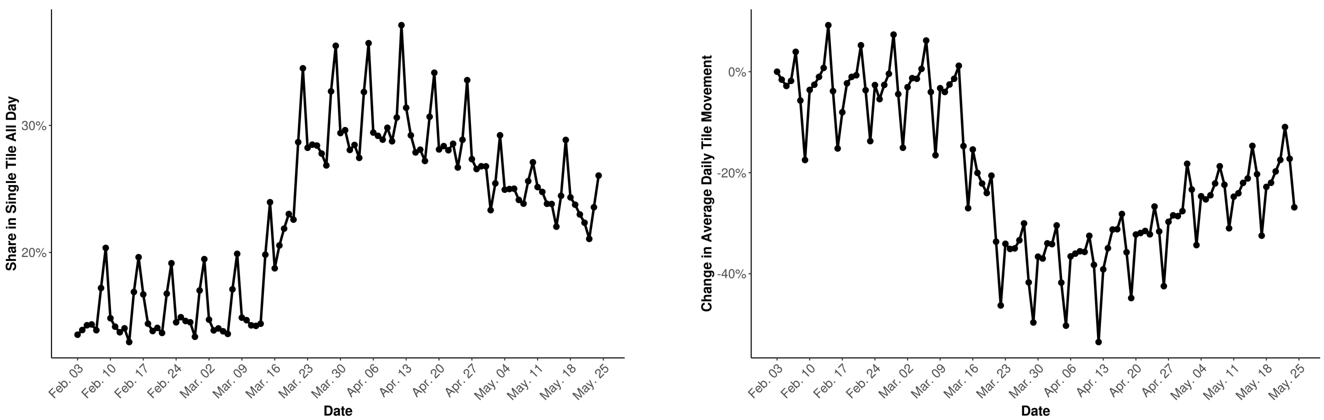
[5] This measure captures college *attendance* better than college *degree attainment*, with the former much higher than the latter in the in the general population.

[6] We use Covid-19 cases rather than deaths. The average friend exposure in our sample in March is 10 cases as shown in Table 1 so regressions using death instead of cases would be underpowered given the still relatively low mortality rates.

Measuring Mobility and Social Distancing. We measure mobility using user-level GPS data for individuals who have consented to sharing and storing their location information. This location data is recorded at high frequency: in Iyer et al. (2020), researchers noted that 54% of users globally who opted in to this feature record a location 'ping' in at least half of the 5-minute intervals during each day.[7] Location data is aggregated using the Bing Maps Tile System, which defines a series of grids at different resolution levels over a rectangular projection of the world (Schwartz, 2018). We use level-16 Bing tiles, which are 600 meters $\times$ 600 meters at the equator. We construct two mobility indices: (i) whether a user remains in the same level-16 Bing tile throughout the day (which we will refer to as "staying at home"), and (ii) the total number of distinct level-16 Bing tiles visited on a given day.

Figure 1: Mobility Over Time

(a) Probability of Staying at Home **(b)** Change in Average Number of Tiles Visited



Note: Figures show average mobility patterns according to two metrics described in Section 1.1. Panel (a) shows the probability of staying at home. Panel (b) shows the percent change in average number of tiles visited from February 3rd.

Figure 1 shows daily values of our two mobility measures between early February and late May 2020.[8] In Figure 1a, we see that in February and early March, between 15% and 20% of users stayed at home on a given day, with recurring spikes on weekends (see also Table 1). Starting the week of March 16—the first week after Covid-19 had been declared a national emergency and when a large number of schools and offices were closed in response to the emerging pandemic—the probability of staying at home jumped to well over 30% by March 23. It rarely fell below 30% throughout April. In May, as social distancing restrictions were eased across parts of the U.S., the series decreased steadily, though the probability of staying at home remained elevated relative to the baseline period and never fell below 20%. Figure 1b shows that the average number of tiles visited follows the same patterns over time. Thus, in our main analysis, we focus on the probability that a user stays at home as our primary mobility metric.

[7]These data are similar to those described in Maas et al. (2019) and used to create the Facebook Data for Good Mobility Dashboard, available at https://www.Covid19mobility.org/dashboards/facebook-data-for-good/.

[8]In all graphs in this section, we control for the possible effects of a technical change in the methodology of location data collection near the end of February. Specifically, we assume that the relationship between the levels of our metrics in early February and the levels in the week of February 24th matches the relationship over the same time periods in the SafeGraph data described in the Appendix. Such an adjustment is not necessary in any other analysis in the paper, where we either use only data after the technical methodology change or estimate results using a difference-in-difference approach (where the methodology change had quasi-random effects across groups).

We also briefly explore how the extent of social distancing varies with individual characteristics—something our individual-level data is uniquely suited to examine. Appendix Tables A2 and A3 show that while older individuals already spent more time at home prior to the pandemic, they changed their behavior more during the pandemic, consistent with the fact that Covid-19 poses a greater risk to that demographic. Similarly, female users increased their rate of staying home by 4.5 percentage points more than men did, consistent with an increased childcare burden being borne by women during the pandemic (see Alekseev et al., 2022). We also find that users who list a college education increased their probability of staying home by more than users without college education. This finding is consistent with the conclusions from Dingel and Neiman (2020), who note that jobs requiring high levels of educational attainment are less likely to be deemed "essential" and can more often be done from home (though we find that individuals listing a college degree were also more likely to stay at home on weekends).[9]

2 Effects of Friend Exposure to Covid-19 Cases on Social Distancing

We next explore the relationship between friend exposure to Covid-19 cases and social distancing behavior. We first study behavior at the onset of the pandemic, allowing us to illustrate our results in the raw data. In our primary specification, we estimate the effect of *changes* in friend exposure on *changes* in social distancing as the pandemic progresses allowing us to rule out possible concerns about persistent unobservable differences correlated with friend exposure to Covid-19.

2.1 Friend Exposure and Social Distancing Behavior at Onset of Covid-19 Pandemic

We measure friend exposure to Covid-19 cases at the onset of the pandemic for each user as:

$$FriendExposure_i^{Mar15} = \sum_{j=1}^{J} FracFriends_{ij}^{Mar15} \times Covid19Cases_j^{Mar15}. \tag{1}$$

$FracFriends_{ij}^{Mar15}$ is the share of U.S.-based friends of person i in county j on March 15. $Covid19Cases_j^{Mar15}$ is the cumulative number of Covid-19 cases reported in county j before March 15. The mean number of cases across counties is 0.95 and the standard deviation is 9.33.[10]

Table 1 shows substantial variation in this measure of friend exposure across individuals, with a mean of 10.4 friend-weighted cases and a standard deviation of 19.3. For the first few weeks of the pandemic, the correlation of $FriendExposure_i$ measured at different points in time is high, as similar U.S. locations had the highest cumulative case counts. This finding also suggests that strategic friendship formation after the discovery of Covid-19 does not drive our results (see Appendix Figure A4 for details).

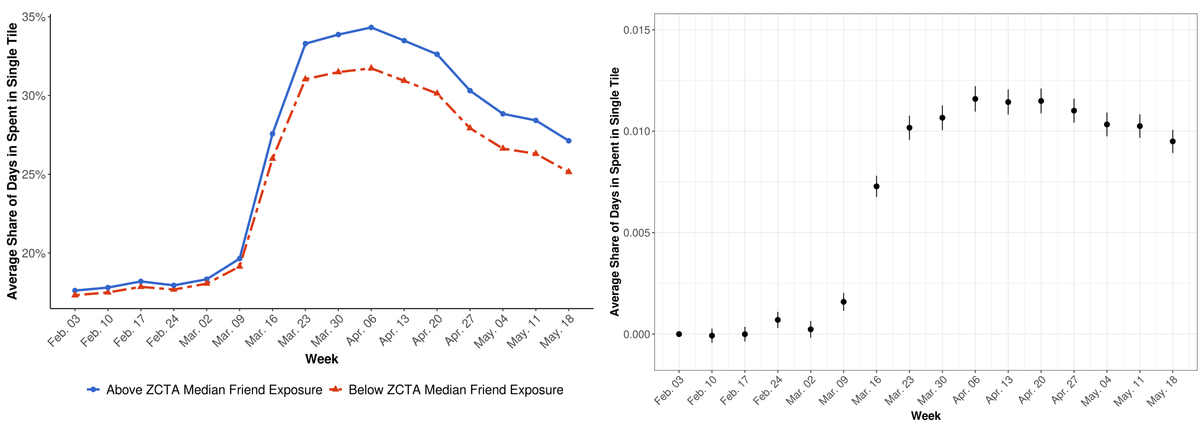
[9] We present time series versions of these results in Appendix Figures A1 and A2. These figures highlight that the demographic differences in social distancing behavior discussed above arise in mid-March 2020, and persist through the end of May.

[10] Appendix Figure A3 maps the number of cases by county. In this section, we primarily use measures of Covid-19 cases that do not normalize cases by the county populations. In the early stages of the pandemic, when measured case counts were low, the raw number of cases was likely a more salient measure of Covid-19 exposure than a normalized measure. For example, the areas with highest case exposures on March 15th were King County and New York City, each widely covered as early pandemic hot spots. By contrast, the areas with highest per capita infection rates were Pitkin and Eagle counties in Colorado. The outbreaks in these small counties received relatively little attention. In column 3 of Appendix Table A9 we show that our primary results hold when normalizing case counts by population. In Section 2.2 we use normalized measures of exposure when exploring later stages of the pandemic.

Friend Exposure and Social Distancing Behavior at the Onset of Covid-19 Pandemic — Raw Data. We first focus on users within the same ZCTA and compare the social distancing behavior of those with high and low levels of friend exposure. Concretely, for every ZCTA k, we calculate the median friend exposure to Covid-19 cases as of March 15. We then define $HighExp_i$ for user i as an indicator of whether their friend exposure is higher or lower than the median in their home ZCTA. This measure of relative exposure allows us to show variation in social distancing by friend exposure in the raw data.

Figure 2: Effects of Friend Exposure to Covid-19 on Probability of Staying at Home

(a) Times Series **(b)** Diff-In-Diff



Note: Figures show the relationship between friend exposure to Covid-19 on March 15th and mobility behavior. We measure the latter as the weekly averages of the probability of staying at home from the week of February 3rd to the week of May 18th, separately for individuals above and below the median level of friend-exposure in their ZCTA. Panel (a) shows raw means, while Panel (b) shows coefficients estimated using the difference-in-differences setup specified in equation 2. The specification includes fixed effects for each individual, and fixed effects for the following groups, interacted with dummies for each week: ZCTA; age group; gender; has college listed on Facebook; has iPhone; has tablet; and percentiles of friend-exposures (as in equation 3) for median household income, population density and the share of the population living in urban areas. Standard errors are clustered by ZCTA. See Appendix Figure A5 for a corresponding analysis of the average number of tiles visited.

Figure 2a presents a time-series plot for the probability of staying at home split by $HighExp_i$. Before the onset of the pandemic, there are no differences in movement patterns between users in the same ZCTA with high and low levels of friend exposure. In February the probability of staying at home for both groups was between 17% and 20%, with any differences always less than half of a percentage point. Starting in mid-March, however, users with high friend exposure to Covid-19 became substantially more likely to stay home. By early April, individuals with high friend exposure have a probability of staying at home of close to 35% compared to less than 32% for users with lower levels of friend exposure.

Difference-in-Differences Analysis. While the raw data shows identical mobility patterns between individuals with high and low friend exposure to Covid-19 prior to the pandemic, both in levels and in changes, it is important to acknowledge that friend exposure is likely non-random even within ZCTA: given the geographic concentration of U.S. Covid-19 cases in mid-March, friend exposure likely correlates with individual characteristics that might also affect behavior during a pandemic (but not before).[11]

[11] We present summary statistics of the high- and low-exposure samples in Appendix Table A4. To understand the relationship between friend exposure to Covid-19 and individual and ZCTA-level characteristics, we regress a set of control variables on the log of $FriendExposure_i^{Mar15}$ in Appendix Table A5. We find that certain demographics are indeed correlated with friend exposure on March 15. For example, older users and those reporting college attendance had higher levels of friend exposure.

We next show the importance of controlling for such observable differences before introducing our main specification, which uses a dynamic approach to also address concerns about unobservable factors. Figure 2b shows estimates of β_t from the following difference-in-differences specification:[12]

$$Y_{it} = \mu_i + \sum_{t=1}^{15} \beta_t \left(HighExp_i \times week_t \right) + \sum_{t=1}^{15} \delta_t' \left(X_i \times week_t \right) + \epsilon_{it}. \tag{2}$$

Y_{it} is individual i's mobility during week t. We include data for the week of February 3rd as $t = 0$, but omit a coefficient for this reference time period. μ_i is an individual-level fixed effect. $HighExp_i$ is an indicator equal to one if user i has friend exposure greater than their ZCTA median on March 15. $week_t$ is an indicator for the week of the outcome. The vector X_i includes fixed effects for the individual's location (ZCTA), college attendance, ownership of iPhone and tablet, age group, and gender. It also includes fixed effects for percentiles of friend-weighted median household income, population density, and share urban, each calculated analogous to our friend-based Covid-19 exposure as:[13]

$$FriendMetric_i = \sum_{j=1}^{J} FracFriends_{ij} \times Metric_j. \tag{3}$$

Relative to the simple comparison of means in Figure 2a, Figure 2b allows for time-varying differences across individuals with different demographics and different distributions of friendship networks across measures such as the average income or population density where friends live. Consistent with Figure 2a, the two groups' movements look nearly identical prior to the pandemic. Users with higher friend exposure are substantially less mobile after the outbreak begins, though the inclusion of the rich set of control variables in equation 2 somewhat reduces the estimated magnitude of the difference.[14]

Finally, to benchmark the magnitude of this effect, we use a multivariate analysis to compare the relative magnitudes of changes in friend exposure to Covid-19 on social distancing against the differences in social distancing across demographic groups (see Appendix A.1). We find that a one-standard-deviation increase in friend exposure to Covid-19 corresponds to an increase in social distancing that is more than two-thirds as large as the effect of being age 55 or older (relative to being below age 35), and roughly half of the effect of reporting a college.

2.2 Dynamics of Friend Exposure to Covid-19 and Social Distancing Behavior Over Time

We now turn to our primary specification to estimate the effect of friend exposure to Covid-19 cases on social distancing behavior. Rather than focusing on the effects of friend exposure at the onset of the pandemic, we now study the effects of *changes* in friend exposure as the pandemic evolves on *changes*

[12] Since "treatment timing" does not vary, this simplifies our specification relative to that estimated in Goodman-Bacon (2021).

[13] The data on median household income and population density come from the 5-year ACS from 2014-2018 and the share of the population living in urban areas comes from the 2010 Census.

[14] In Appendix Figures A6 and A7 we estimate equation 2 separately for weekdays and weekends. We find that individuals with high friend-exposure tend to reduce their mobility by a similar amount on both weekends and weekdays, which is consistent with a mechanism in which voluntary social distancing drives our results, as opposed to mechanisms related to one's industry of employment or ability to work from home. These two Appendix figures also show specifications that include college-by-week fixed effects (i.e., a week-specific mobility effect for everyone who attended the University of Michigan), further demonstrating the robustness of our results.

in social distancing. As the pandemic progressed, the changing geography of Covid-19 outbreaks led different individuals to experience increases in friend exposure at different points in time. With fixed individual characteristics differenced out, the dynamic approach therefore alleviates important concerns that correlations between our friend exposure measure and unobservable individual characteristics could be driving our earlier results.

Measuring Changes in Friend Exposure to Covid-19. For each month, we define changes in an individual's friend exposure to Covid-19 cases as follows:[15]

$$ChangeFriendExposure_{it} = \log(1 + FriendExposure100k_{it}) - \log(1 + FriendExposure100k_{it-1}) \quad (4)$$

with $FriendExposure100k_{it} = \sum_{j=1}^{J} FracFriends_{ijt} \times \frac{Covid19Cases_{jt}}{Residents100k_{j}}$. Figure 3 shows the locations with the largest changes in per capita Covid-19 cases in each month in the sample, with brighter colors corresponding to larger increases. In March, case growth was highest in New York, Seattle, Denver, and Louisiana. By April, the highest case growth was in the Midwest; in May, hotspots appear in Minnesota, Iowa, and North Carolina, while in June the location of hotspots moved to Texas, Oklahoma, and Arizona. In July, southern Texas and the north western Moutain states see new hotspots emerge. This geographic variation in case growth throughout our sample means that, in each month, it is different individuals who happen to be most exposed to Covid-19 case growth through their friendship networks. Indeed, Appendix Table A6 shows that the correlation between changes in friend exposure to Covid-19 and demographic characteristics changes over time. For example, with a listed college were more exposed to Covid-19 case growth through their friends at the beginning of the pandemic; in later months, as the pandemic spread across the United States, the relationship reverses.

Effect of Changes in Friend Exposure to Covid-19 on Changes in Social Distancing Behavior. To analyze the effects of *changes* in friend exposure over time on *changes* in social distancing behavior, we estimate the following equation:

$$\Delta Y_{i,t} = \sigma_0 + \sigma_1 ChangeFriendExposure_{i,t} + \sigma_{2,t}' X_{i,t} + \epsilon_{i,t}. \quad (5)$$

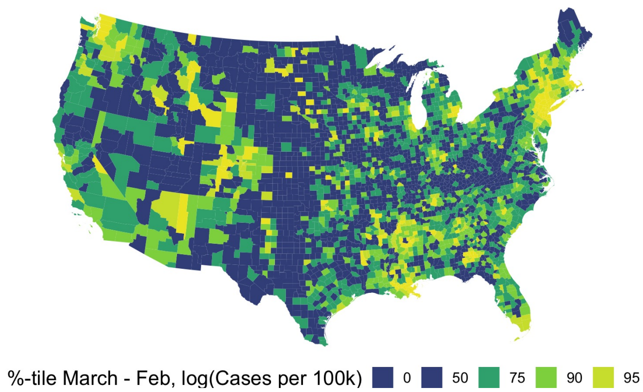
$X_{i,t}$ captures a range of characteristics of individual i at time t. In our baseline specification, $X_{i,t}$ includes fully interacted Month × ZCTA × Age Group × Gender × Has College × Has Tablet × Has iPhone fixed effects. This interaction captures any changes in (or varying effects of) local conditions and lets their effects co-vary with characteristics. We also include percentiles of friend-weighted urbanity, population density, and median household income as defined in equation 3, each interacted with month fixed effects to allow the effects of those network characteristics on changes in social distancing to vary over time.[16]

[15] In our dynamic analysis, we normalize cases by population, since, as the pandemic progressed, coverage of hotspots shifted from talking about "total cases" to "total cases per population;" see also footnote 10. Using the difference of logs gives a higher weight to the same absolute increase of cases per population in places with relatively fewer prior cases per population. While we believe that this is a useful specification to capture salient changes in Covid-19 exposure, we have verified that our results and conclusions are robust to a wide variety of ways of measuring "changes in friend exposure to Covid-19."

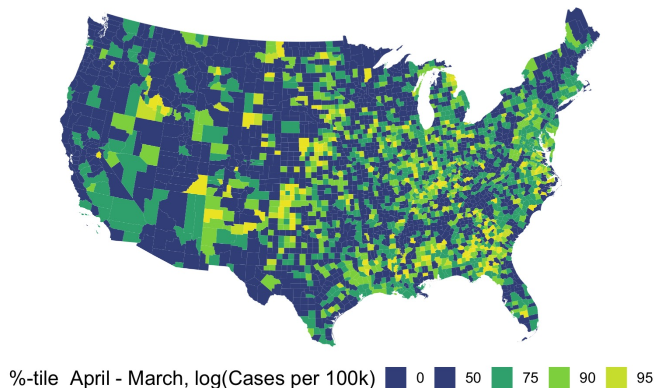
[16] Note that these measures are calculated using the friend network as of March 15. The network is relatively constant over the sample period and re-calculating the measure using alternative exposure dates does not change our results.

Figure 3: Variation in Δ Covid-19 Cases Per Capita

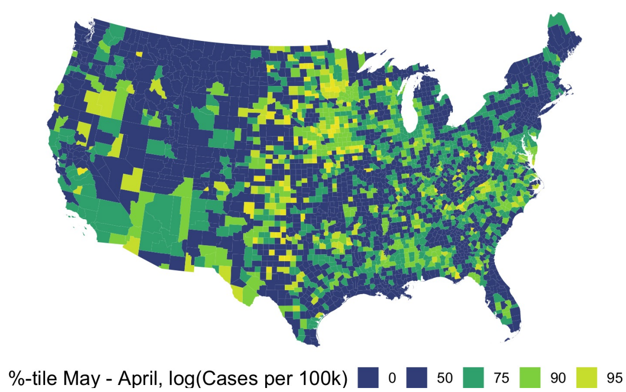
(a) March



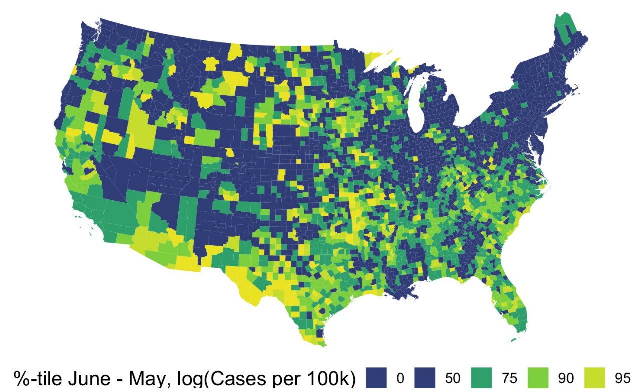
(b) April



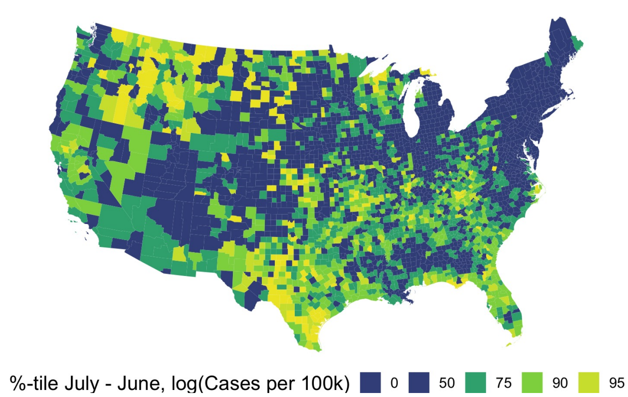
(c) May



(d) June



(e) July



Note: Figures show percentiles of the change in log(Covid-19 cases per 100k residents + 1) by county for the continental U.S. Cases are measured on the last Friday of each month: panel (a) shows that change from February to March, panel (b) shows the change from March to April, panel (c) shows the change from April to May, panel (d) shows the change from May to June and panel (e) shows the change from June to July. Darker blue indicates a smaller increase and brighter green and yellow indicate a larger increase.

Column 1 of Table 2 presents the estimate of σ_1 from equation 5, pooling across all months in our sample. Appendix Figure A10 presents the corresponding binned scatter plot. The results show that doubling the increase in friend exposure is associated with a 9% higher change in the likelihood that a person stays at at home in a given month.

We also explore the relationship between changes in social distancing behavior and changes in friend exposure to Covid-19 for each month separately. This allows us to explore whether the effects in the pooled regression in column 1 were primarily driven by individuals' social distancing behavior in a given month. Concretely, we estimate equation 5 separately for each month and include all past changes in friend as explanatory variables. Columns 2-6 of Table 2 present the results of this analysis. In March—consistent with our earlier results for the onset of the pandemic—higher increases in friend exposure significantly increase the probability of staying at home. Importantly, in subsequent months, changes in social distancing behavior are driven primarily by changes in the friend exposure in the corresponding months. That is, individuals with friends in early hotspots, such as New York City, Seattle, Denver and Louisiana, stay home more in March than their otherwise-similar neighbors with friends in the Midwest. As the pandemic progresses, their neighbors with friends in the Midwest experience large increases in friend exposure in April and, accordingly, increase their probability of staying at home. In May, hotspots appear in Minnesota, Iowa, and North Carolina, and again, individuals with friends in those areas start social distancing more than their otherwise similar neighbors with friends in other parts of the country. Across all months, we find that the most recent changes in the rate of friend exposure are the most important, though our results in April are not statistically significant. These findings support our hypothesis that friend exposure to Covid-19 has a sizeable effect on social distancing behavior.

As shown above, characteristics of users with high friend exposure to changes in Covid-19 cases varies substantially over time. As a result, the *dynamic* relationship between changes in friend exposure and changes in social distancing behavior allows us to establish this relationship without the concern for bias from unobservable characteristics and to overcome several of the shortcomings of the cross-sectional specification studied before. In particular, any individual characteristics with a constant effect on the level of mobility are differenced out.[17] In addition, the effects of observable characteristics on social distancing are controlled for, even if the relationship between characteristics and the change in social distancing behavior varies across months. Similarly, the specification allows the effects of all local conditions on social distancing to vary by characteristics and over time. To obtain unbiased estimates of the causal effect of friend exposure on social distancing with specification 5, we need to assume that any time-varying effect of unobservable characteristics on social distancing is not systematically correlated with the changes in friend exposure—a very plausible assumption.

We conduct several robustness checks to the analysis presented in Table 2. Appendix Table A10 shows that our results are very similar when focusing only on users for which a complete panel is available. Similarly, including an individual fixed effect to capture possible individual-level trends in mobility over time does not affect the results. Appendix Table A11 shows that this relationship holds using number of tiles visited as the outcome and using a Poisson functional form. In Appendix Table

[17] Instead of an individual mobility affect, one could assume an individual level *social distancing* effect which only affects mobility after the onset of the pandemic. To difference out such an effect, we can exclude the first month of pre-pandemic data in the estimation. Appendix Table A10 shows the results are very similar.

Table 2: Effects of Friend-Exposure by Month: Δ Probability of Staying at Home

	Monthly Change in Prob. Stay at Home					
	All months	March	April	May	June	July
Change Friend Exposure, Same Month	0.208***					
	(0.029)					
Change Friend Exposure, March		0.207***	0.006	-0.076**	0.097	0.037
		(0.046)	(0.040)	(0.048)	(0.054)	(0.064)
Change Friend Exposure, April			0.035	0.096	0.329***	0.069**
			(0.052)	(0.056)	(0.061)	(0.071)
Change Friend Exposure, May				0.379***	0.044	-0.057
				(0.082)	(0.078)	(0.094)
Change Friend Exposure, June					0.854***	-0.329*
					(0.114)	(0.127)
Change Friend Exposure, July						0.323**
						(0.138)
Other Network Exposure FE	Y x Month	Y	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y x Month	Y	Y	Y	Y	Y
R-Squared	0.211	0.174	0.141	0.150	0.146	0.145
Sample Mean	1.611	14.214	-0.923	-5.989	-1.068	0.679
N	30,742,008	6,688,448	6,579,359	6,169,176	5,848,722	5,456,303

Note: The first column of this table reports the results of regression 5 with one observation per user per month between March 2020 and July 2020. Change in friend exposure is defined in equation 4. In the following five columns, we subset the data to observations from the months up to and including the one listed in the header. Here, each observation is an individual. In all columns, the outcome variable is the change in the probability of staying home between the final week of a given month and the final week of the previous month. We define the final weeks to be the last Friday to Thursday period in a month. The last weeks are then: February 25-March 2, March 24-March 30, April 21-April 27, May 26-June 1, June 23-June 29, and July 21-July 28. The sample of users is restricted to those for whom location can be observed at the end of each of the two relevant months. In all columns we control for interactions of ZCTA fixed effects, age groups, gender, whether the individual has a college listed on Facebook, whether the individual primarily accesses mobile Facebook from an iPhone, and whether the individual has accessed Facebook from a tablet. All columns also include fixed effects for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

A12, we show that we obtain similar patterns when regressing changes in mobility only on changes in friend exposure for the same month (without also including changes in prior months).

2.3 Heterogeneity of Friend Exposure Effects

We next explore heterogeneity in the effect of friend exposure on social distancing behavior along an individual's own characteristics. To avoid capturing heterogeneity in the *ability* to work from home rather than the *desire* to stay home, we focus on weekend movements. Specifically, we modify equation 5 to interact our measure of changes in friend exposure with indicators for various demographic characteristics. Table 3 shows that changes in friend exposure have a larger effect on the social distancing behavior of younger users: the effect for those aged 35-55 is only about one-third the size of the effect for those aged 18-34. The effects of friend exposure on mobility is also substantailly larger for females than for males and, similarly, larger for users with a listed college than for users without a listed college. In addition, the effect is increasing in the average income of an area, as well as the prevalence of Covid-19 in the user's own county. Interestingly, despite these heterogeneities, for nearly all of the various groups we consider, we find that increases in friend exposure lead to increases in social distancing.

Table 3: Heterogeneity of Monthly Friend-Exposure Effects, Weekends

	Monthly Change in Prob. Stay at Home, Weekends						
Change Friend Exposure x I(Age < 35)	0.745***						
	(0.069)						
Change Friend Exposure x I(Age 35-55)	0.229***						
	(0.055)						
Change Friend Exposure x I(Age > 55)	0.066						
	(0.072)						
Change Friend Exposure x Female		0.505***					
		(0.055)					
Change Friend Exposure x Male		0.109**					
		(0.054)					
Change Friend Exposure x College			0.516***				
			(0.054)				
Change Friend Exposure x No College			0.101*				
			(0.055)				
Change Friend Exposure x Zip Income First Tertile				0.016			
				(0.064)			
Change Friend Exposure x Zip Income Second Tertile				0.252***			
				(0.063)			
Change Friend Exposure x Zip Income Third Tertile				0.776***			
				(0.072)			
Change Friend Exposure x County Cases First Tertile					0.099*		
					(0.055)		
Change Friend Exposure x County Cases Second Tertile					0.415***		
					(0.079)		
Change Friend Exposure x County Cases Third Tertile					0.687***		
					(0.074)		
Change Friend Exposure, Friends Ranked 1 - 25						0.289***	
						(0.039)	
Change Friend Exposure, Friends Ranked 26 - 50						0.105***	
						(0.041)	
Change Friend Exposure, Friends Ranked 51 - 75						0.016	
						(0.040)	
Change Friend Exposure, Friends Ranked 76 - 100						-0.067*	
						(0.039)	
Change Friend Exposure, Friends <100mi Away							0.387***
							(0.085)
Change Friend Exposure, Friends >100mi Away							0.321***
							(0.058)
Other Network Exposure FE	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month
R-Squared	0.189	0.189	0.189	0.189	0.189	0.189	0.246
Sample Mean	1.436	1.436	1.436	1.436	1.436	1.436	1.615
F Test (Rank 1-25 = Rank 76-100)						34.593***	
N	27,821,521	27,821,521	27,821,521	27,821,521	27,821,521	27,797,612	10,656,616

Note: Table shows results from versions of regression 5. The variable $ChangeFriendExpsoure_{it}$ is interacted with age groups in rows 1-3; gender in rows 4-5; whether the individual has a college listed in Facebook in rows 6-7; ZCTA median household income in rows 8-10; and county-level cases of Covid-19 in rows 11-13. Rows 14-17 show measures of change in friend exposure constructed using friends of certain ranks (i.e. a measure for how close friends are). Rows 18-19 show measures of change in friend exposure constructed using friends who live within (outside) 100 miles. The final column is restricted to users that have at least 100 friends <100 miles away and >100 miles away. All columns include controls for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas, each interacted with month. All columns include monthly fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01). In Appendix Table A13 we repeat these analyses studying mobility on all days, not just on weekends. In Appendix Tables A15 and A16 we conduct related heterogeneity analyses using versions of the specification in equation A1 that focuses on exposure at the onset of the pandemic. In Appendix Figures A8 and A9 we show heterogeneity results in the event-study framework described in Section 2.1.

We also study heterogeneity in the effects of friend exposure to Covid-19 by the strength of the underlying friendships. Friendships are ranked by 'closeness' based on the extent of various interactions between users on Facebook. Our specification amends equation 5 by replacing $ChangeFriendExposure_{it}$ among all friends with four variables that measure changes in friend exposure among friends with different friend ranks: 1-25, 26-50, 51-75, and 76-100. Column 6 of Table 3 shows that the effects of friend exposure tend to be strongest for the closest friends, with effect size falling off among more marginal friends. The effect of friend exposure among a person's 25 closest friends is nearly three times stronger than the effect of friend exposure among the person's *next* 25 closest friends (those ranked 26-50). The effect size is smaller, and no longer statistically significant, for the two more distant friend groups. The decrease in the effect size of friend exposure as we move toward more 'distant' friends is consistent with our hypothesis that the observed effects on health behavior are indeed driven by friend exposure to Covid-19 cases rather than omitted variables.

3 Mechanisms

So far we have shown that friend exposure to Covid-19 cases induces individuals to engage in more social distancing. In this section, we explore possible mechanisms behind these findings. First, there might be a direct effect of friend exposure on one's own movement, for example if individuals cut back on meeting up with friends in areas with high Covid-19 caseloads. Second, it is possible that the effect operates through a preference channel. This could occur, for instance, if home-bound friends in highly exposed areas begin to bake or garden, and share tips that make these activities more appealing relative to alternative activities taking place outside one's home. Finally, friend exposure might change people's beliefs or attitudes towards the risks of Covid-19. We combine several pieces of information from users' activity on Facebook to conclude that a key part of the mechanism through which friend exposure to Covid-19 affects social distancing is through influencing individuals' beliefs about Covid-19.

3.1 Direct Effects of Friend Exposure to Covid-19

We first consider the possibility that the effects of friend exposure operate largely through a direct channel, where higher Covid-19 rates in friends' locations directly reduce visits to and movements together with these friends. To do this, we perform variants of regression 5, splitting friends according to their physical distance from the person: closer or further than 100 miles. For this analysis, we restrict to users who have at least 100 friends both close and more than 100 miles away. The rightmost column of Table 3 shows that higher exposure to Covid-19 cases among all types of friends is associated with a higher likelihood that the user stays home on a given day. In addition, the impact of far-away friends relative to nearby ones is only slightly smaller in magnitude. Since trips to visit far-away friends are uncommon, our finding that Covid-19 cases in the locations of these friends have a substantial effect on an individual's mobility patterns suggests that the effects we observe are not primarily explained by a decreased likelihood of travel to visit friends in affected areas.[18]

[18]Friends who live further away are generally less close. At the same time, users with substantial numbers of far away friends may have fewer close local friends, for instance, because they only recently moved to the area. To address these concerns, we additionally divide the groups according to the ranking of friend strength used in Table 3, allowing us to compare friends who are similarly socially close but live different distances away from the user. The results of these regressions are presented in Table A14 and support the notion that far away friends have substantial effects on social distancing behavior.

3.2 The Role of Beliefs

We next explore whether friend exposure to Covid-19 cases affects social distancing behavior through shaping beliefs about the risks from Covid-19. To do this, we examine whether proxies for individuals' beliefs react to friend exposure to Covid-19.

3.2.1 Posting Behavior

We begin by analyzing users' public Facebook posts, which can be viewed by any other user on the platform. We use these public posts to construct two measures. First, we use regular expression searches to measure the percentage of a user's public posts that mention the coronavirus; this measure captures the user's level of general engagement in discussions about Covid-19. Second, we identify common phrases used to support or oppose social distancing measures to quantify a user's level of opposition to these measures. Specifically, we measure the number of posts opposed to social distancing as a fraction of all 'signed' posts, that is, all posts identified as either supporting or opposing these measures. Appendix C provides details on these classifications.

We estimate the effect of friend exposure to Covid-19, as well as other individual- and ZCTA-level characteristics, on these public posting behavior outcomes using the following regression:

$$Y_i = \delta_0 + \delta_1 \log(FriendExposure_i^{Mar15}) + \delta_2 X_i + \epsilon_i. \tag{6}$$

Y_i corresponds to one of the posting outcomes described above. $FriendExposure_i^{Mar15}$ is defined as in equation 1. We control for fully interacted ZCTA $\times$ Age Group $\times$ Gender $\times$ Has College $\times$ Has Table $\times$ Has iPhone fixed effects. For this analysis of users' beliefs about Covid-19, we require that users have posted publicly at least once in February, March, or April of 2020. Since we do not limit the sample to users with location sharing and storage permissions, our sample size increases substantially compared with the prior analysis.[19] Summary statistics for this sample are shown in Appendix Table A18.

Table 4 presents estimates of the coefficient of interest, δ_1.[20] In column 1, we explore the effect of friend exposure to Covid-19 on the share of public posts between February and April 2020 that are about the coronavirus. Friend exposure to Covid-19 cases has substantial effects on posting behavior: a doubling in friend exposure corresponds to an increase in the share of posts about the coronavirus of about 0.17 percentage points, a 10% increase relative to the average, even with our tight controls for ZCTA interacted with individual characteristics.[21]

This first analysis suggests that users with higher levels of friend exposure to Covid-19 are generally more likely to talk about the coronavirus, but does not capture the nature of individuals' posts.

[19] We still observe an assumed ZCTA of residence based on IP address, profile information, and other factors, allowing us to include ZCTA-level controls in our regressions.

[20] In Appendix Table A17 we also measure the general sentiment of public posts relating to Covid-19 using the VADER algorithm described in Hutto and Gilbert (2014). We replace Y_i in equation 6 with the change in average post sentiment between February 3-23 and April 6-26. We find that users with higher levels of friend exposure to Covid-19 cases have significantly larger decreases in post sentiment, suggesting the overall sentiment in their posts becomes more negative. While this result is consistent with friend exposure affecting beliefs about Covid-19 risks (e.g., as captured by posts like "I really hate Covid"), our measure can also pick up a wide variety of beliefs. For instance, posts critical of Covid-19 related policies (e.g., "I really hate Covid lockdowns") also display negative sentiment, complicating interpretation.

[21] Appendix Figure A11a shows a binned scatter plot that corresponds to our analysis in column 1. The relationship between the percentage of posts about Covid-19 and friend exposure is strong, with a functional form that is close to linear.

Table 4: Posting Behavior and Group Membership

	DV: Share Posts about Covid-19 (Feb - Apr)	DV: Share "Signed Posts" Opposed to Distancing (Feb - Apr)	DV: Member "Reopen Group" by June 28, 2020	
log(Friend Exposure March 15)	0.249*** (0.006)	-1.929*** (0.245)	-0.129*** (0.007)	
log(Friend Exposure End of June)				-0.122*** (0.009)
Percentiles of Total Number of Groups (Feb 2020)			Y	Y
Other Network Exposure FE	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y
Sample	People With Any Posts Feb - April	People With "Signed Posts" Feb - April	People With Group Memberships	
R-Squared	0.060	0.445	0.074	0.074
Sample Mean	1.755	35.979	1.216	1.216
N	34,528,373	277,776	119,145,833	119,153,786

Note: Table shows results from regressions 6 and 7. Each observation is an individual. The outcome in column 1 is the percentage of individual posts that are about Covid-19; in column 2 it is the percentage of pro- or anti-distancing posts that are anti-distancing; in columns 3-4 it is whether the individual was a member of a 'Reopen' Facebook group as of June 28th. For ease of interpretation and because of small magnitudes, we rescale coefficients and standard errors by 100, so that they correspond to percentages. Post classification is based on the regex in Appendix C. Group classification is determined by the regular expression described in Appendix C. All columns control for percentiles of friend-exposures (as described in equation 3) of median household income, population density, and the share of the population living in urban areas. All columns include fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. The group-based analyses in columns 3-4 also include fixed effects for the percentile of the number of groups an individual was in as of February 2020. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Specifically, our measure includes both posts supportive of the notion that the virus poses a great threat to public health and endorsing measures to contain the risk, as well as posts that downplay the threat of the virus or that call for an end to restrictions. In column 2 of Table 4, we thus explore the share of 'signed' posts which oppose social distancing requirements and shutdowns. For this analysis, we concentrate on those users who share at least one 'signed' post in February, March, or April of 2020. Friend exposure to Covid-19 decreases the likelihood that users oppose social distancing measures in their posts (Appendix Figure A11b shows the corresponding binned scatter plot): a doubling in friend exposure corresponds to a 1.3 percentage point reduction in the share of signed posts opposing distancing. This implies a 4% reduction given a baseline average of 36%.[22]

3.2.2 Group Membership

We next explore the effects of friend exposure to Covid-19 cases on a user's decisions to join various Facebook groups advocating to "reopen" the economy. Facebook users can create and join groups to chat, meet, and otherwise engage with others. For our analysis, we focus on membership in public groups, which any Facebook user can access without additional restrictions. Since no restrictions on posting behavior and/or location settings are necessary for this part of the analysis, we focus on all ac-

[22]It is possible that some of the observed effect is driven by users changing what they decide to share in the face of anticipated backlash or support from friends in hard-hit areas. However, the fact that changes in friend exposure also induce real changes in behavior that are not visible to friends in far-away locations suggests that observed effects on stated beliefs and opinions likely correspond with true changes in beliefs.

tive users who meet the non-mobility sample requirements described in Section 1. We present summary statistics for this group of users in Appendix Table A1.

To measure beliefs about the risks of Covid-19, we focus on groups created between March 1 and June 28, 2020 with names that suggest support for an early reopening of the economy. Appendix C provides details on how we identify these groups. We then estimate:

$$ReopenGroup_i = \gamma_0 + \gamma_1 \log(FriendExposure_i) + \gamma_2 X_i + \epsilon_i \quad (7)$$

where $ReopenGroup_i$ is an indicator equal to one if, on June 28, user i is a member of at least one group advocating for the lifting of Covid-19 related restrictions. $FriendExposure_i$ and X_i are defined as above. In addition to the control variables used in the previous specifications, we include fixed effects for percentiles of the number of groups the user is a member of as of February 2020, allowing us to control for potential differences in usage of the groups feature on Facebook. Table 4 presents estimates of γ_1 using friend exposure on March 15 (column 3) as well as cumulative friend exposure to Covid-19 cases through June (column 4).[23]

About 1.2% of all users are a member of at least one Reopen Group. Column 3 shows that a doubling in friend exposure to Covid-19 on March 15 decreases the probability of being a member of such a group by about 0.09 percentage points, or 7.5%. Column 4 shows that these results are similar when using cumulative friend exposure by the end of June.[24]

3.3 Mechanisms: Summary and Discussion

Taken together, the results in this section suggest that the exposure of one's friends to Covid-19 cases is an important determinant of how an individual perceives the risks from Covid-19 as well as the policy responses to address the virus. This adds an important insights for the mechanisms driving our findings in Section 2 and, more broadly, the mechanisms that drive social network effects on behavior documented in previous works. Indeed, friend exposure shapes individuals' beliefs about Covid-19 and the need for public health-motivated restrictions on public life, providing evidence for an important beliefs-based channel that in turn affects mobility behavior.

It is noteworthy that we find these effects in a setting where publicly available information from domain experts was ubiquitous. This suggests that the effects on beliefs are not primarily the result of friends conveying information that is hard to access otherwise. It is instead more consistent with a mechanism whereby information resonates more with individuals when it is communicated by friends. For instance, Malmendier and Veldkamp (2022) propose a model of learning in which people process the same information differently depending on who delivers it. In this model, "abstractly learned statistics and other information tends to be weighted significantly less than information gathered from [...] the experiences of others whom we care about, identify with or empathize with."

[23]In Appendix Table A17 we use a looser set of controls and also present estimates of γ_2. Appendix Table A19 uses a normalized measure of exposure at the end of each month in our sample period. The table shows a negative, though not always statistically significant, effect in each month.

[24]In addition to the results presented in this Section, in Appendix Tables A20, A21, A22, we study heterogeneities in the observed effects of friend exposure to Covid-19, finding results largely consistent with those presented in Section 2.3.

4 Evidence on Friend-Exposure Effects from Public Data

In this final section, we briefly describe analyses that confirm our main results using publicly available ZCTA-level data. Appendix B provides more details and the complete set of results.

For this analysis, we combine public data on mobility from Safegraph with the Social Connectedness Index (SCI) data from Facebook (see Bailey et al., 2018*b*). We find that social distancing in a ZCTA increases when Covid-19 exposure increases in other locations with many social links to the target ZCTA. While this analysis does not allow us to control for many individual-level characteristics that are correlated with changes in social distancing behavior and exposure to Covid-19, it has the advantage that the Safegraph mobility data are based on a different and larger set of individuals, thus mitigating concerns that the results discussed in the main body are merely an artifact of the somewhat selected sample of Facebook users who have consented to sharing and storing their location information.

We also disaggregate the Safegraph mobility data by point-of-interest and merchant type to understand which types of establishments are visited less often by individuals with high friend exposure to Covid-19. Using a difference-in-differences analysis similar to Section 2, we document that individuals living in places that are socially connected to highly-exposed places tend to disproportionately reduce discretionary visits to places requiring social interaction with others. There are smaller and insignificant effects on less discretionary visits, such as those to food and beverage stores and healthcare providers.

5 Conclusion

We use de-identified data from Facebook to show that personal connections to Covid-19 hotspots significantly affected individuals' social distancing behavior during the Covid-19 pandemic. At the onset of the pandemic, individuals whose friends lived in areas with worse coronavirus outbreaks reduced their mobility more than their otherwise similar neighbors with fewer friends in affected areas. As the pandemic spread across the U.S., users with more friends in emerging hotspots in one month continued to reduce their mobility in that month relative to their neighbors with friends in other parts of the country. Analyzing mobility at the individual level in such a changes-on-changes specification allows us to rule out various confounds when establishing the effect of friend experiences on social distancing behavior.

We then use data on public Facebook posts and group memberships, to show that friend exposure to Covid-19 cases affects individuals' stated beliefs about the risks of Covid-19 and the benefits of mitigating public health behavior. Specifically, users with higher friend exposure to Covid-19 cases are more likely to post about the coronavirus and are less likely to oppose distancing in these posts. These users are also less likely to join Facebook groups advocating for a reopening of the economy.

A key conclusion of our work is that friend experiences affected beliefs about the Covid-19 pandemic at a time when information from many expert sources was ubiquitous, and when Covid-19 received unparalleled press coverage and public messaging. It is thus unlikely that the main reason why friend experiences were so influential is that they provided a low-cost source of information. Instead, it is more likely that information received from friends resonates particularly with people, and thus receives a substantial weight in the belief formation process. Our results therefore add new insight into the general mechanism underlying the important role of social networks in shaping individuals' beliefs and subsequent actions. We believe that studying both the empirical and theoretical properties of such an "information resonance" channel is a very promising area for future research. It is also important to highlight that under such mechanisms, friend experiences are likely to influence beliefs and behavior in both desirable and undesirable ways—consistent, for example, with the role of social interactions in spreading conspiracy theories—with a limited role of providing expert information as a countervailing force. This insight can play an important role in helping policy makers design more effective public information campaigns across a range of settings, from public health to consumer protection.

References

Alekseev, Georgij, Safaa Amer, Manasa Gopal, Theresa Kuchler, John W Schneider, Johannes Stroebel, and Nils Wernerfelt. 2022. "The Effects of COVID-19 on US small businesses: Evidence from owners, managers, and employees." *Management Science*.

Allcott, Hunt, Levi Boxell, Jacob C Conway, Billy A Ferguson, Matthew Gentzkow, and Benny Goldman. 2020*a*. "What explains temporal and geographic variation in the early US coronavirus pandemic?" National Bureau of Economic Research.

Allcott, Hunt, Levi Boxell, Jacob Conway, Matthew Gentzkow, Michael Thaler, and David Yang. 2020*b*. "Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic." *Journal of Public Economics*, 191: 104254.

Armantier, Olivier, Wändi Bruine de Bruin, Giorgio Topa, Wilbert Van Der Klaauw, and Basit Zafar. 2015. "Inflation expectations and behavior: Do survey respondents act on their beliefs?" *International Economic Review*, 56(2): 505–536.

Armona, Luis, Andreas Fuster, and Basit Zafar. 2019. "Home price expectations and behaviour: Evidence from a randomized information experiment." *The Review of Economic Studies*, 86(4): 1371–1410.

Bachmann, Rüdiger, Tim O Berg, and Eric R Sims. 2015. "Inflation expectations and readiness to spend: Cross-sectional evidence." *American Economic Journal: Economic Policy*, 7(1): 1–35.

Bailey, Michael, Abhinav Gupta, Sebastian Hillenbrand, Theresa Kuchler, Robert Richmond, and Johannes Stroebel. 2021. "International trade and social connectedness." *Journal of International Economics*, 129: 103418.

Bailey, Michael, Drew Johnston, Theresa Kuchler, Dominic Russel, Johannes Stroebel, and Bogdan State. 2020*a*. "The determinants of social connectedness in Europe." 1–14, Springer.

Bailey, Michael, Drew Johnston, Theresa Kuchler, Johannes Stroebel, and Arlene Wong. 2022*a*. "Peer Effects in Product Adoption." *American Economic Journal: Applied Economics*, 14(3): 488–526.

Bailey, Michael, Drew M Johnston, Martin Koenen, Theresa Kuchler, Dominic Russel, and Johannes Stroebel. 2022*b*. "The social integration of international migrants: evidence from the networks of Syrians in Germany." National Bureau of Economic Research.

Bailey, Michael, Eduardo Dávila, Theresa Kuchler, and Johannes Stroebel. 2019. "House price beliefs and mortgage leverage choice." *The Review of Economic Studies*, 86(6): 2403–2452.

Bailey, Michael, Patrick Farrell, Theresa Kuchler, and Johannes Stroebel. 2020*b*. "Social connectedness in urban areas." *Journal of Urban Economics*, 118: 103264.

Bailey, Michael, Rachel Cao, Theresa Kuchler, and Johannes Stroebel. 2018*a*. "The economic effects of social networks: Evidence from the housing market." *Journal of Political Economy*, 126(6): 2224–2276.

Bailey, Michael, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong. 2018*b*. "Social connectedness: Measurements, determinants, and effects." *Journal of Economic Perspectives*, 32(3): 259–80.

Bakkensen, Laura A, and Lint Barrage. 2021. "Going underwater? Flood risk belief heterogeneity and coastal home price dynamics." *The Review of Financial Studies*.

Banerjee, Abhijit, Arun G Chandrasekhar, Esther Duflo, and Matthew O Jackson. 2019. "Using gossips to spread information: Theory and evidence from two randomized controlled trials." *The Review of Economic Studies*, 86(6): 2453–2490.

Bargain, Olivier, and Ulugbek Aminjonov. 2020. "Trust and compliance to public health policies in times of COVID-19." *Journal of Public Economics*, 192: 104316.

Barrios, John M., and Yael V. Hochberg. 2021. "Risk perceptions and politics: Evidence from the COVID-19 pandemic." *Journal of Financial Economics*, 142(2): 862–879.

Barrios, John M, Efraim Benmelech, Yael V Hochberg, Paola Sapienza, and Luigi Zingales. 2021. "Civic capital and social distancing during the Covid-19 pandemic." *Journal of Public Economics*, 193: 104310.

Bordalo, Pedro, Giovanni Burro, Katherine B Coffman, Nicola Gennaioli, and Andrei Shleifer. 2022. "Imagining the future: memory, simulation and beliefs about COVID." National Bureau of Economic Research.

Brodeur, Abel, David Gray, Anik Islam, and Suraiya Bhuiyan. 2021. "A literature review of the economics of COVID-19." *Journal of Economic Surveys*, 35(4): 1007–1044.

Brodeur, Abel, Idaliya Grigoryeva, and Lamis Kattan. 2021. "Stay-at-home orders, social distancing, and trust." *Journal of Population Economics*, 34(4): 1321–1354.

Brzezinski, Adam, Valentin Kecht, David Van Dijcke, and Austin L Wright. 2021. "Science skepticism reduced compliance with COVID-19 shelter-in-place policies in the United States." *Nature Human Behaviour*, 5(11): 1519–1527.

Bursztyn, Leonardo, Aakaash Rao, Christopher Roth, and David Yanagizawa-Drott. 2022. "Opinions as Facts." *The Review of Economic Studies*. rdac065.

Charoenwong, Ben, Alan Kwan, and Vesa Pursiainen. 2020. "Social connections with COVID-19–affected areas increase compliance with mobility restrictions." *Science advances*, 6(47): eabc3054.

Chetty, Raj, Matthew O Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B Fluegge, Sara Gong, Federico Gonzalez, Armelle Grondin, Matthew Jacob, et al. 2022*a*. "Social capital I: measurement and associations with economic mobility." *Nature*, 608(7921): 108–121.

Chetty, Raj, Matthew O Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B Fluegge, Sara Gong, Federico Gonzalez, Armelle Grondin, Matthew Jacob, et al. 2022*b*. "Social capital II: determinants of economic connectedness." *Nature*, 608(7921): 122–134.

Christakis, Nicholas A., and James H. Fowler. 2007. "The Spread of Obesity in a Large Social Network over 32 Years." *New England Journal of Medicine*, 357(4): 370–379. PMID: 17652652.

Christakis, Nicholas A., and James H. Fowler. 2008. "The Collective Dynamics of Smoking in a Large Social Network." *New England Journal of Medicine*, 358(21): 2249–2258. PMID: 18499567.

Dingel, Jonathan I, and Brent Neiman. 2020. "How many jobs can be done at home?" *Journal of Public Economics*, 189: 104235.

Dong, Ensheng, Hongru Du, and Lauren Gardner. 2020. "An interactive web-based dashboard to track COVID-19 in real time." *The Lancet infectious diseases*, 20(5): 533–534.

Duggan, Maeve, Shannon Greenwood, and Andrew Perrin. 2016. "Social Media Update 2016." Pew Research Center Report.

D'Acunto, Francesco, Daniel Hoang, Maritta Paloviita, and Michael Weber. 2022. "IQ, expectations, and choice." *Review of Economic Studies*.

Facebook. 2020. "Facebook Form 10-K, 2019 Annual Report."

Fletcher, Jason M, and Stephen L Ross. 2018. "Estimating the effects of friends on health behaviors of adolescents." *Health economics*, 27(10): 1450–1483.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus. 2021*a*. "Five facts about beliefs and portfolios." *American Economic Review*, 111(5): 1481–1522.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus. 2021*b*. "The joint dynamics of investor beliefs and trading during the COVID-19 crash." *Proceedings of the National Academy of Sciences*, 118(4): e2010316118.

Giuliano, Paola, and Imran Rasul. 2020*a*. "Civic capital and social distancing: Evidence from Italians' response to COVID-19." Vox.

Giuliano, Paola, and Imran Rasul. 2020*b*. "Compliance with social distancing during the Covid-19 crisis." Vox.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277.

Holtz, David, Michael Zhao, Seth G. Benzell, Cathy Y. Cao, Mohammad Amin Rahimian, Jeremy Yang, Jennifer Allen, Avinash Collis, Alex Moehring, Tara Sowrirajan, Dipayan Ghosh, Yunhao Zhang, Paramveer S. Dhillon, Christos Nicolaides, Dean Eckles, and Sinan Aral. 2020. "Interdependence and the cost of uncoordinated responses to COVID-19." *Proceedings of the National Academy of Sciences*, 117(33): 19837–19843.

Huang, Grace C, Jennifer B Unger, Daniel Soto, Kayo Fujimoto, Mary Ann Pentz, Maryalice Jordan-Marsh, and Thomas W Valente. 2014. "Peer influences: the impact of online and offline friendship networks on adolescent smoking and alcohol use." *Journal of Adolescent Health*, 54(5): 508–514.

Hutto, Clayton J, and Eric Gilbert. 2014. "Vader: A parsimonious rule-based model for sentiment analysis of social media text."

Hu, Zhongchen. 2022. "Social interactions and households' flood insurance decisions." *Journal of Financial Economics*, 144(2): 414–432.

Iyer, Shankar, Brian Karrer, Daniel Citron, Farshad Kooti, Paige Maas, Zeyu Wang, Eugenia Giraudy, P Alex Dow, and Alex Pompe. 2020. "Large-Scale Measurement of Aggregate Human Colocation Patterns for Epidemiological Modeling." *medRxiv*.

Jacobson, Robert M, Jennifer L St Sauver, and Lila J Finney Rutten. 2015. "Vaccine hesitancy." Vol. 90, 1562–1568, Elsevier.

Jones, Jason J, Jaime E Settle, Robert M Bond, Christopher J Fariss, Cameron Marlow, and James H Fowler. 2013. "Inferring tie strength from online directed behavior." *PloS ONE*, 8(1): e52168.

Kuchler, Theresa, and Basit Zafar. 2019. "Personal experiences and expectations about aggregate outcomes." *The Journal of Finance*, 74(5): 2491–2542.

Kuchler, Theresa, Dominic Russel, and Johannes Stroebel. 2022. "JUE Insight: The geographic spread of COVID-19 correlates with the structure of social networks as measured by Facebook." *Journal of Urban Economics*, 127: 103314.

Kuchler, Theresa, Yan Li, Lin Peng, Johannes Stroebel, and Dexin Zhou. 2022. "Social proximity to capital: Implications for investors and firms." *The Review of Financial Studies*, 35(6): 2743–2789.

Maas, Paige, Shankar Iyer, Andreas Gros, Wonhee Park, Laura McGorman, Chaya Nayak, and P Alex Dow. 2019. "Facebook Disaster Maps: Aggregate Insights for Crisis Response and Recovery." *Proceedings of the 16th International Conference on Information Systems for Crisis Response and Management (ISCRAM)*.

Makridis, Christos, and Tao Wang. 2020. "Learning from Friends in a Pandemic: Social Networks and the Macroeconomic Response of Consumption." *Available at SSRN 3601500*.

Malmendier, Ulrike, and Laura Veldkamp. 2022. "Information resonance." Working Paper.

Malmendier, Ulrike, and Stefan Nagel. 2011. "Depression babies: Do macroeconomic experiences affect risk taking?" *The Quarterly Journal of Economics*, 126(1): 373–416.

Mayer, Maximilian. 2023. "Climate change concerns and information spillovers from socially-connected friends." IWH Discussion Papers.

Peretti-Watel, Patrick, Valérie Seror, Sébastien Cortaredona, Odile Launay, Jocelyn Raude, Pierrea Verger, Lisa Fressard, François Beck, Stéphane Legleye, Olivier l'Haridon, et al. 2020. "A future vaccination campaign against COVID-19 at risk of vaccine hesitancy and politicisation." *The Lancet Infectious Diseases*, 20(7): 769–770.

Pew Research Center. 2020. "U.S. Public Sees Multiple Threats From the Coronavirus – and Concerns Are Growing." Pew Research Center Report.

Ratnadiwakara, Dimuthu. 2021. "Flooded Social Connections." *The Quarterly Journal of Finance*, 11(04): 2150018.

Rehbein, Oliver, Simon Rother, et al. 2020. "Distance in bank lending: The role of social networks." University of Bonn and University of Mannheim, Germany.

Roth, Christopher, and Johannes Wohlfart. 2020. "How do expectations about the macroeconomy affect personal expectations and behavior?" *Review of Economics and Statistics*, 102(4): 731–748.

Rothwell, Jonathan T, Christos Makridis, Christina Ramirez, and Sonal Desai. 2021. "COVID-19 Information Treatments Shift Related Policy Preferences and Plans for Consumer Behavior." *Available at SSRN 3859751*.

Sato, Ryoko, and Yoshito Takasaki. 2019. "Peer Effects on Vaccination Behavior: Experimental Evidence from Rural Nigeria." *Economic Development and Cultural Change*, 68(1): 93–129.

Schwartz, Joe. 2018. "Bing Maps Tile System." Microsoft Report.

Simonov, Andrey, Szymon Sacher, Jean-Pierre Dubé, and Shirsho Biswas. 2022. "Frontiers: The persuasive effect of Fox News: Noncompliance with social distancing during the COVID-19 pandemic." *Marketing Science*, 41(2): 230–242.

Tian, Yuan, Maria Esther Caballero, and Brian K Kovak. 2022. "Social learning along international migrant networks." *Journal of Economic Behavior & Organization*, 195: 103–121.

Weber, Elke U, and Paul C Stern. 2011. "Public understanding of climate change in the United States." *American Psychologist*, 66(4): 315.

Wilson, Riley. 2022. "The impact of social networks on eitc claiming behavior." *Review of Economics and Statistics*, 104(5): 929–945.

Xu, Yilan, and Sebastien Box-Couillard. 2023. "Social Learning about Climate Change Risk." *Working Paper*.

Appendices

A Additional Results

A.1 Effects of Friend Exposure on Social Distancing Behavior: Magnitude

In this section, we compare the magnitudes of the effects of friend exposure on social distancing in the early pandemic with the effects of demographic characteristics on social distancing. Our analysis is based on the following multivariate specification:

$$\Delta Y_i = \alpha_1 \log(FriendExposure_i^{Mar15}) + \alpha_2 X_i + \epsilon_i. \quad \text{(A1)}$$

ΔY_i is individual i's change in the average probability of staying home between February 2020 (before the pandemic) and April 2020 (during the height of the first U.S. pandemic wave). $FriendExposure_i^{Mar15}$ is defined as in equation 1 in the main paper. X_i is a vector consisting of dummies for age, gender, educational attainment, ownership of iPhone and tablet, and tertiles of ZCTA-level income and local exposure to Covid-19 (county-level Covid-19 cases per resident as of March 15). Depending on the specifications, we include additional controls in X_i.

Table A8 presents the results, while Appendix Table A23 shows corresponding results using the percentage change in tiles visited as the dependent variable. Columns 1 and 2 of Table A8 show that older users, female users, and users who reported a college increase their probabilities of staying home more than others. Columns 3-5 add controls for friend exposure to Covid-19 cases, as well as fixed effects for friend-weighted network characteristics as described in the discussion of equation 3. Column 3 includes ZCTA fixed effects but omits all other individual-level characteristics of columns 1 and 2. Given a standard deviation in $\log(FriendExposure_i^{Mar15})$ of 1.35, the coefficient estimate on friend exposure of 0.92 indicates that a one standard deviation increase in friend exposure is associated with an increase in the probability of staying at home of about 1.2 percentage points, an 8.8% increase relative to the sample mean of 13.7%. Adding additional individual-level characteristics to the regression in column 4 decreases the coefficient estimate for α_1 only slightly to 0.85.

Comparing the coefficient estimates for friend exposure to Covid-19 to those for other individual-level characteristics highlights that friend exposure is an important determinant of social distancing. An increase in friend exposure by one standard deviation corresponds to an increase in social distancing that is more than two thirds as large as being age 55 or older, and hence belonging to a group that is considered most vulnerable to the health risks of Covid-19. In column 5 of Table A8, we include the full interaction of individual-level controls with ZCTA fixed effects. This has no additional impact on the estimated coefficient estimate for α_1.[1] Columns 6-8 show that α_1 remains relatively stable when focusing on weekend/weekday movement and when controlling for particular college fixed effects.

[1] Our sample size is about 5% smaller in this regression, due to combinations of ZCTA- and individual-level characteristics for which we have only a single observation. In Appendix Figure A12, we present a binned scatter plot corresponding to this specification. Appendix Figure A13 presents the corresponding binned scatter plot for the percentage change in average tiles visited. These figures confirm the linear relationship between the change in mobility and the log of friend exposure.

A.2 Friendship Links to Other Countries

In our baseline specifications, we focused on exposure to Covid-19 cases among individuals' U.S.-based social networks. But many of the early Covid-19 hotspots around the world were outside of the United States. To test whether friend exposure to these foreign hotspots also affected social distancing behavior, Appendix Table A9 adds controls for the fraction of friends living in China, South Korea, Italy, and Spain, all of which were early hotspots of the Covid-19 pandemic. Interestingly, just like exposure to early U.S.-based Covid-19 hotspots was associated with a larger propensity to reduce mobility, stronger friendship links with foreign countries with early Covid-19 outbreaks was similarly associated with an increased propensity to stay at home.

B Public Data Analyses and Results

In this Appendix, we reproduce some of our key results using aggregated information on social networks and movement patterns.

B.1 Safegraph Data

In light of the Covid-19 pandemic, Safegraph Inc. released several data products to researchers that allow for a detailed understanding of consumer spending and of mobility patterns across time and space. We use two data products from Safegraph: social distancing data and point of interest (POI) visit data, both of which are widely used by contemporaneous research on the Covid-19 pandemic.

The Safegraph Social Distancing data contains location data obtained from a number of smartphone applications. Safegraph uses each user's location history to impute their Census block group of residence, and provides aggregated data for each block group from January 1, 2020. We use data through July 28, 2020 to construct the number of devices that are assigned to a Census block group on a given day, the number of devices that do not leave their home location during a given day,[2] and the average distance traveled.[3] The average number of devices observed on a given day in our sample period is about 19 million. Using these metrics, we calculate (a) the fraction of devices that remain at home over the course of a day and (b) the average distance traveled in kilometers. These two ZCTA-level measures of social distancing correspond roughly to the Facebook measures of the probability of staying at home and average daily tile movement, respectively. As before, we construct weekly averages.

Safegraph's POI data aggregates cellphone GPS pings to measure the number of visits by residents of an area to particular establishments. We use these data through July 28, 2020 to construct a weekly measure of the total POI visits by ZCTA, both overall and by industry.[4] With the objective of distinguishing between 'essential' and 'nonessential' places, we focus on the following categories: (i) Arts, Entertainment, and Recreation (NAICS code 71), (ii) Food Services and Drinking Places (NAICS code 722), (iii) Retail Trade Excl. Food and Beverage Stores (NAICS codes 44 and 45, excluding 445), (iv) Food and Beverage Stores (NAICS code 445), (v) Parks (NAICS code 712190); and (vi) Health Care and Social Assistance (NAICS code: 62). We think of (i)-(iii) as less essential places that can be avoided in order to reduce physical interaction. By contrast, (iv)-(vi) are either more essential or entail very limited physical interaction.

B.2 ZCTA-Level Friend-Exposure to Covid-19

To construct a measure of friend-exposure to Covid-19, we combine data from Facebook on social connectedness and data from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. The Social Connectedness Index (SCI) (Bailey et al., 2018*b*) is a scaled metric of relative connectedness of different ZCTAs across the U.S., defined as:

$$SCI_{ij} \propto \frac{FBConnections_{ij}}{FBUsers_i \times FBUsers_j}. \tag{A2}$$

[2] Home location corresponds to the geohash-7 in which home is located. A geohash-7 is a region about 500 feet on each side.

[3] We construct the average distance traveled based on the number of devices per bin of travel distance. Where possible, we use the mean of highest and lowest value of the bin. For the open ended top bin (> 50km) we assign a value of 75km.

[4] For the sample period, there are on average 27.5 million POI visits each day, distributed over roughly 5.4 million POIs.

$FBConnections_{ij}$ is the scaled number of connections between ZCTA i and ZCTA j, and $FBUsers_i$ and $FBUsers_j$ are the respective numbers of users for ZCTA i and j. To create our measure of friend-exposure, we begin by calculating per-user connections between ZCTA i and county k:

$$PerUserConnect_{ik} = \sum_{j \in k} SCI_{ij} * Pop_j \tag{A3}$$

Pop_j is the population of ZCTA j that is in county k. Note that in the absence of public data on user counts, we use population counts rather than user counts. In constructing this measure we have two objectives. First, since the data on Covid-19 cases is only available at the county level this measure moves us from zips to counties. Second, this measure of per-user connections helps to construct a measure of friend exposure that is independent of the number of users or friends on Facebook (which might systematically differ with the way Facebook is used across regions). Next, for each ZCTA i, we calculate the fraction of per-user connections from county k relative to all counties:

$$FracConnect_{ik} = \frac{PerUserConnect_{ik}}{\sum_{k \in K} PerUserConnect_{ik}} \tag{A4}$$

We can loosely think of this measure as the fraction of all friends a representative user in ZCTA i has in county k. As a final step, we multiply this metric with the number of Covid-19 cases in county k and sum over all counties in order to create our measure of friend-exposure to Covid-19. Since the number of cases varies over time, this metric is also time-variant (in our case, by week).

$$FriendExpCOVID_{it} = \sum_{k \in K} FracConnect_{ik} \times Cases_{kt} \tag{A5}$$

B.3 Replication at ZCTA Level

To validate the findings presented in Section 2, we estimate the effect of having high social exposure to Covid-19 cases at the zip level on social distancing behavior at the zip level:

$$Y_{it} = \mu_i + \sum_{t=1}^{29} \beta_t \left(HighExp_i \times week_t\right) + \sum_{t=1}^{29} \delta_t' \left(X_i \times week_t\right) + \epsilon_{it} \tag{A6}$$

Y_{it} is our measure of social distancing for ZCTA i during week t constructed from Safegraph data, i.e. either (a) the average fraction of devices at home full-time for a given ZCTA or (b) the percentage change in the average distance traveled relative to January 2020.[5] The variable μ_i represents ZCTA fixed effects. $HighExp_i$ is an indicator equal to one if ZCTA i has friend-exposure to Covid-19 higher than the median for the county it is located in, based on the number of Covid-19 cases as of March 15. As before, $week_t$ is an indicator for the week of the outcome. Here we include data for the week of January 1st as $t = 0$, but omit a coefficient for this reference time period. We include a rich set of controls: in addition to county-time fixed effects, we control for various zip-level covariates interacted with time fixed effects.

[5] More precisely, based on our measure of average distance traveled for ZCTA i during week t, i.e. $AvgDist_{it}$, we calculate $\%\Delta Dist_{it} = \frac{AvgDist_{it} - AvgDist_{iJan20}}{AvgDist_{iJan20}} * 100$.

These are the median household income of the area, as well as the fraction of individuals in in each of the following demographic groups: male, Asian, black, white, service employee, manager, art or science employee, high-speed internet user, high-school educated, some college completion, college educated. We also control for the fraction of individuals in several age buckets: between 18 and 24, between 25-34, between 35-44, between 45-54, between 55-64, between 65-74 and above 75. All these control variables are obtained from the most recent 5-year ACS (2014-2018). Finally, as described in depth in Section 2, we control for national ventiles of friend-exposure to other factors, i.e. median household income, population density and urbanity.[6] In Table A24, we show the differences between high and low friend-exposure places with respect to these characteristics.

While high and low friend-exposure places appear balanced on many demographic characteristics, a few differences are noticeable. In particular, high exposure places are slightly more racially diverse, have a somewhat lower median household income, and include individuals more likely to have a college degree. High exposure places also have larger populations, are more densely populated, and have more POIs. While none of these differences is very large, they might affect the the average ability or willingness of residents to engage in social distancing in a way that is independent of friend-exposure. We therefore control for all the above-mentioned set of covariates and allow for the value of these controls to vary over time. Together, these control variables help to alleviate concerns that any observed effects are merely driven by differences in demographic, socio-economic or other work-related variables that are correlated with social distancing behavior. Figure A14 depicts the corresponding β_t estimates from Equation A6. These coefficients capture the effect of having a level of (ZCTA-level) friend-exposure to Covid-19 that is above the county mean. Standard errors are clustered at the ZCTA-level.

Figure A14 shows changes in mobility as a result of friend-exposure to Covid-19 that are qualitatively very consistent with the results presented in Section 2. As is in apparent both in Figure A14a and in Figure A14b, in January and February—before the outbreak of the pandemic in the U.S.—changes in mobility between high and low-exposure places are always very close to zero. Beginning in the week of March 4, these coefficients begin to shift, indicating that groups with more friend-exposure have begun to stay home more and travel less. For the fraction of devices at home, coefficients continue to rise, reaching levels of around 0.025 in late March and early April. Thereafter, coefficients slowly return to values closer to zero, yet they remain statistically significant for several more weeks, until the middle of May. In line with these patterns, for the percentage change in the average distance traveled, coefficients continue to fall during late March and stay low, i.e. around -1.5, for much of April before they gradually return to around zero. Together, these estimates highlight that as the Covid-19 pandemic hits the U.S., places with greater friend-exposure to Covid-19 reduce their mobility more than places with lower friend-exposure. These effects are persistent over time and cannot entirely be explained by our measures of differential ability and/or willingness to engage in social distancing. In spite of the different data source, the different level of analysis and the different sample, these results are thus consistent with the evidence presented in Section 2: friend-exposure to Covid-19 matters when trying to explain differences in social distancing behavior across individuals and across places.

[6] These friend-exposure variables are constructed as $FriendExpMetric_i = \sum_{k \in K} FracConnect_{ik} \times Metric_k$ where $Metric_k$ is one of population density, median household income (both from ACS 2014-2018) and the fraction of the population residing in urban settings (from 2010 Census).

B.4 Additional Detail on Mobility Effects By Type of Establishment

We continue our analysis by disaggregating our mobility measures, honing in on the types of visits that seem to change in places with high levels of friend exposure. We continue to estimate equation A6, with Y_{it} now corresponding to the log of one plus the number of POIs visited in a given ZCTA i per week t, split by the type of establishment. Again, we control for county $\times$ time fixed effects together with ZCTA fixed effects and ZCTA-level covariates interacted with time fixed effects. The covariates are the same as in Section B.3. We cluster standard errors at the ZCTA-level.

Figure A15 shows coefficient estimates for β_t, with each panel corresponding to a different type of destination. For reference, we include results for all POIs aggregated in the gray series. The patterns are consistent with the hypothesis that people in places with high friend exposure to Covid-19 disproportionately reduce their mobility to avoid unnecessary physical interactions. While differential responses in POI visits are negative for nonessential POIs in Panels (a)-(c), they are close to zero and insignificant for essential POIs in Panels (d)-(f). More concretely, the coefficient estimates for arts, recreation, and entertainment locations (Figure A15a) show that the difference in the change of visits between high and low exposure places can be as large as 0.05 log points (in absolute magnitude). Similar effects can be observed for retail destinations (Figure A15b), and restaurants and bars (Figure A15c). Although coefficient estimates return to zero well before the end of the sample period, they are negative and highly significant for the period from mid-March to mid-April. In contrast, coefficient estimates for visits of food and beverage stores (Figure A15d), health care and social assistance (Figure A15e) and parks (Figure A15f) are insignificant and substantially smaller, suggesting that there is no differential reduction in these types of visits among individuals with differential friend exposure to Covid-19. Reassuringly, all coefficient estimates in every panel are very close to zero prior to March, indicating no differential behavior before the outbreak of the pandemic. Note that since friend exposure is defined within counties—and distancing policies were nearly always administered at the federal, state, or county level—differences in business closures across places are unlikely to drive our results.

C Post and Group Classifications

To classify posts and groups in certain analyses, we use regular expression searches. Posts or groups are flagged if they match one more of the regular expressions described.

We classify public Facebook posts made between February 3rd and May 3rd according to the regular expressions in Table A25. Posts that match any of "neutral lockdown", "pro-lockdown", or "anti-lockdown" are classified as Covid-19 posts.

We classify public Facebook groups as a 'Reopen Group' if it was created between March 1st and June 28th, 2020 and has a (case-insensitive) name that matches one of the following regular expressions, with "%" corresponding to a wildcard that can capture any number of characters (including 0): "%reopen%", "%liberate%", "%end%shutdown%", "%end%lockdown%", "%against%quarantine%."

D Additional Tables

Table A1: Summary Characteristics - Group Membership Sample

	Mean	SD	P10	P25	P50	P75	P90
Age	41.97	16.01	24	29	39	53	64
Female	0.57	0.50	0	0	1	1	1
Has College	0.59	0.49	0	0	1	1	1
Zip Code Income	$63,798	$26,081	$36,954	$45,848	$57,600	$76,544	$99,328
Has iPhone	0.61	0.49	0	0	1	1	1
Has Tablet	0.43	0.50	0	0	0	1	1
Number of Friends	502.52	319.56	177	252	410	676	1003
Friend Exposure to Cases	12.42	22.17	0.91	2.23	5.64	13.77	31.75
Number Groups (Feb)	33.03	57.89	3	8	18	38	73
Has Any Groups (Feb)	0.98	0.13	1	1	1	1	1
Number Anti-Lockdown Groups (April)	0.014	0.133	0	0	0	0	0
Has Anti-Lockdown Group (April)	0.012	0.110	0	0	0	0	0

Note: Table presents summary statistics describing users in our sample underlying the analysis of group memberships. Individual-level characteristics include age, gender, whether the user has a college listed on Facebook, whether the user primarily accesses Facebook mobile from an iPhone, whether the individual has accessed Facebook from a tablet, number of friends, friend-exposure to Covid-19 cases on March 15th, and patterns of mobility during the week of February 25th to March 2nd. The table also includes information on the users' home ZCTA 2018 median household income.

Table A2: Change in Probability of Staying at Home

	Stay at Home					
	All		Weekdays		Weekends	
	Level Feb	ΔFeb-Apr	Level Feb	ΔFeb-Apr	Level Feb	ΔFeb-Apr
Overall	18.33	13.68	16.83	13.58	19.39	14.29
By Age Group						
18-34	14.49	13.17	13.23	13.30	14.54	13.12
35-54	16.57	13.22	14.95	13.13	17.98	13.79
55+	25.68	14.99	24.10	14.64	27.04	16.29
By Gender						
Female	20.15	15.68	18.72	15.76	21.19	15.89
Male	16.21	11.33	14.62	11.02	17.26	12.39
By College						
Has College	17.66	15.27	16.11	15.33	18.94	15.48
No College	19.10	11.84	17.66	11.56	19.90	12.89
By Zip Code Income						
Bottom Tertile	19.27	11.54	17.84	11.29	19.96	12.50
Middle Tertile	18.19	12.78	16.69	12.65	19.33	13.43
Top Tertile	17.55	16.69	15.98	16.76	18.88	16.85
By County Total Cases/Population						
Bottom Tertile	18.62	10.86	17.15	10.65	19.75	11.66
Middle Tertile	17.97	15.17	16.56	15.07	18.71	15.84
Top Tertile	18.15	16.75	16.55	16.80	19.30	17.02
By Exposure through Friends						
High Exposure	18.46	14.82	16.97	14.77	19.45	15.34
Low Exposure	18.21	12.55	16.70	12.40	19.33	13.23

Note: Table describes changes in social distancing across different user characteristics. Social distancing is measured as the average probability of staying home. Characteristic splits include age group, gender, whether the user has a college listed on Facebook, the tertile of home ZCTA median household income, the tertile of county-level cases per resident as of March 15th, and whether the log of friend-exposure to Covid cases on March 15th is above (high exposure) or below (low exposure) the user's home ZCTA median. Columns 1, 3, and 5 show the levels for the week of February 25th to March 2nd (prior to the pandemic). Columns 2, 4, 6 show the difference between the week of April 14th to 20th (during the early stages of the pandemic) and this baseline. Columns 1 and 2 include movement on all days; 3 and 4 include weekdays only; and 5 and 6 include weekends only.

Table A3: Change in Average Tiles Visited

	Bing Tile Visited					
	All		Weekdays		Weekends	
	Level Feb	ΔFeb-Apr	Level Feb	ΔFeb-Apr	Level Feb	ΔFeb-Apr
Overall	10.957	-3.590	11.339	-3.632	10.570	-3.714
By Age Group						
18-34	11.590	-3.593	11.883	-3.587	11.555	-3.843
35-54	11.507	-3.753	11.952	-3.818	10.975	-3.834
55+	9.287	-3.307	9.656	-3.358	8.804	-3.381
By Gender						
Female	9.729	-3.641	9.937	-3.697	9.694	-3.711
Male	12.398	-3.530	12.985	-3.555	11.602	-3.717
By College						
Has College	11.041	-3.945	11.395	-4.012	10.714	-4.014
No College	10.862	-3.179	11.275	-3.193	10.405	-3.362
By Zip Code Income						
Bottom Tertile	10.735	-3.146	11.110	-3.147	10.392	-3.372
Middle Tertile	10.899	-3.367	11.265	-3.386	10.530	-3.525
Top Tertile	11.238	-4.247	11.642	-4.353	10.787	-4.228
By County Total Cases/Population						
Bottom Tertile	10.670	-2.916	11.006	-2.883	10.358	-3.186
Middle Tertile	11.317	-4.066	11.713	-4.129	10.939	-4.174
Top Tertile	11.140	-4.246	11.579	-4.382	10.643	-4.174
By Exposure through Friends						
High Exposure	10.959	-3.849	11.333	-3.900	10.599	-3.968
Low Exposure	10.956	-3.331	11.345	-3.365	10.542	-3.460

Note: Table describes changes in social distancing across different user characteristics. Social distancing is measured as the average number of daily Bing tiles visited. Characteristic splits include age group, gender, whether the individual has college information in Facebook, the tercile of ZCTA-level median household income, the tercile of county-level cases per resident as of March 15th, and whether the log of friend-exposure to Covid-19 cases on March 15th is above (high exposure) or below (low exposure) the users' home ZCTA median. Columns 1, 3, and 5 show the levels for the week of February 25th to March 2nd (prior to the pandemic). Columns 2, 4, 6 show the difference between the week of April 14th to 20th (during the early stages of the pandemic) and this baseline. Columns 1 and 2 include all days; 3 and 4 include weekdays only; and 5 and 6 include weekends only.

Table A4: Summary Characteristics - Mobility Sample, by Exposure

Panel A: Above Median ZCTA Friend Exposure

	Mean	SD	P10	P25	P50	P75	P90
Age	43.47	14.84	26	32	41	53	63
Female	0.52	0.50	0	0	1	1	1
Has College	0.57	0.49	0	0	1	1	1
Has iPhone	0.25	0.43	0	0	0	1	1
Has Tablet	0.54	0.50	0	0	1	1	1
Zip Code Income	$58,791	$21,958	$36,160	$43,648	$53,992	$69,216	$88,128
Number of Friends	557.66	333.32	202	293	469	757	1083
Friend Exposure to Cases	14.49	23.98	1.89	3.50	7.41	16.12	35.75

Panel B: Below Median ZCTA Friend Exposure

	Mean	SD	P10	P25	P50	P75	P90
Age	43.68	15.01	25	32	42	54	63
Female	0.55	0.50	0	0	1	1	1
Has College	0.49	0.50	0	0	0	1	1
Has iPhone	0.24	0.43	0	0	0	0	1
Has Tablet	0.52	0.50	0	0	1	1	1
Zip Code Income	$58,794	$21,963	$36,168	$43,656	$53,988	$69,216	$88,096
Number of Friends	507.97	317.84	186	262	414	677	1007
Friend Exposure to Cases	6.21	11.81	0.45	0.95	2.42	6.11	15.03

Note: Table presents summary statistics describing individuals analyzed in our mobility sample of users, as in Table 1. The top and bottom panels present summaries for individuals above and below their ZCTA median friend-exposure, respectively.

Table A5: Relationship Between Friend-Exposure and Individual Characteristics

	DV: log(Friend Exposure)				
Age Group					
35-54	-0.005***			0.017***	
	(0.002)			(0.001)	
55+	-0.055***			0.022***	
	(0.004)			(0.001)	
Female	-0.100***			-0.015***	
	(0.001)			(0.001)	
Has College	0.185***			0.052***	
	(0.003)			(0.001)	
Has iPhone	0.090***			0.004***	
	(0.002)			(0.001)	
Has Tablet	0.045***			0.014***	
	(0.001)			(0.000)	
Zip Code Income					
Middle Tertile	0.120***				
	(0.019)				
Top Tertile	0.415***				
	(0.019)				
County Cases/Pop					
Middle tertile	1.030***				
	(0.015)				
Top Tertile	1.676***				
	(0.020)				
Zip Code FE		Y	Y	Y	
Other network exposure FE			Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone					Y
R-Squared	0.377	0.671	0.851	0.851	0.873
Sample Mean	1.458	1.458	1.458	1.458	1.487
N	6,803,762	6,803,761	6,803,761	6,803,761	6,400,738

Note: Table shows results from regressing various measures on the log of friend-exposure to Covid-19 cases on March 15th. Each observation is an individual. Column 1 includes controls for age groups, gender, whether the individual has a college listed on Facebook, whether the individual primarily accesses mobile Facebook from an iPhone, whether the individual has accessed Facebook from a tablet, the tertile of home ZCTA median household income, and the tertile of home county cases per resident as of March 15th. Column 2 includes only ZCTA fixed effects. Column 3 adds percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. Column 4 adds back the individual-level controls from column 1. Column 5 adds fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A6: Determinants of Change in Friend Exposure to Covid-19 by Month

	Monthly Change Friend Exposure									
	March	April	May	June	July	March	April	May	June	July
Age Group										
35-54	0.040***	0.014***	-0.013***	-0.008***	-0.001**	0.015***	0.005***	-0.004***	-0.003***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
55+	0.076***	0.015***	-0.026***	-0.018***	-0.004***	0.024***	0.007***	-0.006***	-0.006***	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.021***	0.006***	0.003***	0.006***	0.004***	-0.004***	0.002***	0.001***	0.000**	-0.000***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Has College	0.039***	-0.031***	-0.007***	-0.008***	-0.004***	0.003***	-0.013***	-0.003***	0.002***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Has iPhone	0.011***	0.005***	-0.007***	0.008***	0.013***	0.002***	-0.002***	-0.000	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Has Tablet	0.005***	-0.009***	-0.008***	-0.001***	0.002***	0.003***	-0.002***	-0.002***	-0.000***	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network-Exposure Median HH Income ($k)	0.015***	-0.004***	0.001***	-0.009***	-0.013***					
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)					
Network-Exposure Population Density	349.495***	-34.302***	-65.142***	-71.383***	-88.601***					
(residents/meter^2)	(5.622)	(1.527)	(1.280)	(1.582)	(1.764)					
Network-Exposure Fraction of Pop. Urban	1.112***	-0.076**	-0.263***	0.319***	0.456***					
	(0.035)	(0.019)	(0.016)	(0.014)	(0.016)					
Zip Code Income										
Middle Tertile	-0.034***	-0.017**	0.007	-0.011**	-0.004					
	(0.011)	(0.008)	(0.006)	(0.005)	(0.006)					
Top Tertile	0.002	-0.026***	-0.008	-0.006	0.005					
	(0.011)	(0.008)	(0.005)	(0.005)	(0.006)					
Zip Code FE						Y	Y	Y	Y	Y
Other Network Exposure FE						Y	Y	Y	Y	Y
R-Squared	0.560	0.044	0.117	0.215	0.281	0.877	0.680	0.728	0.781	0.822
Sample Mean	2.800	2.303	0.810	0.476	0.615	2.800	2.303	0.810	0.476	0.615
N	7,090,255	6,981,142	6,571,618	6,251,614	5,859,728	7,090,254	6,981,141	6,571,617	6,251,614	5,859,728

Note: Table shows results from regressing various measures on the change in log of friend-exposure to Covid cases per 100k residents between the last Fridays of each month (e.g. February to March in column 1). Columns 1-5 include age groups; gender; whether the individual has a college listed on Facebook; whether the individual primarily accesses the Facebook app from an iPhone; whether the individual has accessed Facebook from a tablet; friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas; and the tercile of ZCTA-level median household income. Columns 6-10 control for ZCTA fixed effects and percentiles of the friend weighted exposure metrics. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A7: Mobility Sample Summary by Month

	February	March	April	May	June	July	August
Age	44.83	45.01	45.06	45.20	45.32	45.41	45.49
	(14.87)	(14.92)	(14.92)	(14.91)	(14.91)	(14.91)	(14.92)
Female	0.54	0.54	0.54	0.54	0.54	0.54	0.54
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Has College	0.53	0.53	0.53	0.53	0.53	0.53	0.53
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Has iPhone	0.18	0.18	0.17	0.16	0.16	0.15	0.15
	(0.39)	(0.39)	(0.38)	(0.37)	(0.36)	(0.36)	(0.35)
Has Tablet	0.53	0.53	0.53	0.53	0.53	0.53	0.53
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Zip Code Income	$58,651.00	$58,597.00	$58,509.00	$58,571.00	$58,624.00	$58,656.00	$58,681.00
	(21689)	(21674)	(21641)	(21659)	(21669)	(21673)	(21692)
Number of Friends	519.92	520.00	519.22	517.86	517.21	516.05	515.40
	(321.70)	(322.10)	(321.76)	(321.11)	(320.79)	(320.42)	(320.25)
Friend Exposure to Cases	10.05	10.00	9.98	10.01	10.01	10.01	10.01
	(18.94)	(18.87)	(18.85)	(18.88)	(18.89)	(18.90)	(18.91)
N	8,306,154	7,985,569	7,788,454	7,327,655	6,865,099	6,440,827	6,036,002

Note: Table shows averages and standard deviations (in parenthesis) of observable demographics for users in the mobility sample by month. A user is only included if their mobility data (described in Section 1.1) is available for that particular month.

Table A8: Social Distancing by Demographics: Probability of Staying at Home

	DV: Δ Stay at Home (Feb - Apr)							
Age Group								
35-54	-0.394***	-0.360***		-0.347***				
	(0.036)	(0.032)		(0.032)				
55+	1.381***	1.544***		1.589***				
	(0.045)	(0.038)		(0.037)				
Female	4.404***	4.718***		4.852***				
	(0.031)	(0.030)		(0.029)				
Has College	2.876***	2.538***		2.228***				
	(0.029)	(0.026)		(0.025)				
Has iPhone	0.147***	-0.332***		-0.465***				
	(0.035)	(0.032)		(0.032)				
Has Tablet	0.936***	0.900***		0.851***				
	(0.024)	(0.023)		(0.023)				
Zip Code Income								
Middle Tertile	1.001***							
	(0.109)							
Top Tertile	3.671***							
	(0.109)							
County Cases/Pop								
Middle tertile	3.816***							
	(0.089)							
Top Tertile	5.105***							
	(0.120)							
log(Friend Exposure)			0.923***	0.849***	0.878***	0.825***	0.919***	0.961***
			(0.026)	(0.026)	(0.028)	(0.037)	(0.030)	(0.045)
Zip Code FE		Y	Y	Y				
Other Network Exposure FE			Y	Y	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone					Y	Y	Y	Y
College FE								Y
Sample						Weekend	Weekday	College
R-Squared	0.021	0.041	0.035	0.044	0.175	0.159	0.174	0.193
Sample Mean	13.683	13.683	13.683	13.683	13.800	14.415	13.704	15.852
N	6,804,168	6,804,167	6,803,761	6,803,761	6,400,738	5,808,187	6,309,820	2,616,959

Note: Table shows results from regression A1. Each observation is an individual. The outcome in all columns is the change in probability of staying at home from the week of February 25-March 2, 2020 (prior to the pandemic) to April 14-20, 2020. Column 1 includes controls for age groups, gender, whether the individual has a college listed on Facebook, whether the individual primarily accesses Facebook mobile from an iPhone, whether the individual has accessed Facebook from a tablet, the tertile of home ZCTA median household income, and the tertile of home county cases per resident as of March 15th. Column 2 adds ZCTA fixed effects, but maintains the individual level controls. Column 3 includes only the log of friend-exposure to Covid cases on March 15th; ZCTA fixed effects; and percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. Column 4 adds back the individual-level controls from column 1. Column 5 adds fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. In Column 6 the outcome is measured using weekend movement and in column 7 using weekday movement. Column 8 limits to individuals that attended a college, limiting to colleges with more than 100 individuals, and adds a fixed effect for each individual college. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A9: Social Distancing and Other Exposure

	DV: Δ Stay at Home (Feb - Apr)							
log(Friend Exposure)	0.878***	0.521***		0.872***	0.875***	0.876***	0.872***	0.861***
	(0.028)	(0.043)		(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
log(Friend Exposure, Cases per 100k)			0.778***					
			(0.029)					
Share Friends China				1.116***				1.075***
				(0.090)				(0.089)
Share Friends South Korea					0.215***			0.207***
					(0.022)			(0.021)
Share Friends Italy						0.068***		0.053***
						(0.014)		(0.014)
Share Friends Spain							0.209***	0.200***
							(0.022)	(0.022)
Sample		Friends >100mi						
Other Network Exposure FE	Y	Y	Y	Y	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y	Y	Y	Y	Y
R-Squared	0.175	0.229	0.175	0.175	0.175	0.175	0.175	0.175
Sample Mean	13.800	14.876	13.800	13.800	13.800	13.800	13.800	13.800
N	6,400,738	2,479,352	6,400,738	6,400,738	6,400,738	6,400,738	6,400,738	6,400,738

Note: Table shows results from regression A1, using alternative measures of friend-exposure to Covid-19. Each observation is an individual. The outcome in all columns is the percent reduction in average number of Bing tiles visited from the week of February 25th to March 2nd (prior to the pandemic) to April 14th to 20th. Column 1 is the same specification as column 5 of Table A8. Column 2 limits exposure to only friendships with individuals in counties more than 100 miles away. The sample size falls as we restrict to individuals with more than 100 such friends (as described in Section 1.1, we use a similar friend count including *all* friends in our primary sample). Column 3 uses cases per 100k residents (instead of cases) to calculate friend-exposure. Columns 4, 5, 6, and 7 add controls for the share of friends individuals have in China, South Korea, Italy, and Spain respectively. Column 8 adds all four of these country controls at once. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A10: Effects of Friend-Exposure by Month: Δ Probability of Staying at Home, Robustness

	Monthly Change in Prob. Stay at Home								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Change Friend Exposure, Same Month	4.753***	1.479***	1.465***	0.208***	0.263***	0.207***	0.183***	0.203***	0.236***
	(0.004)	(0.023)	(0.024)	(0.029)	(0.036)	(0.033)	(0.049)	(0.034)	(0.039)
Sample						Excl. March	Excl. March	Full Panel	Full Panel
Zip Code		Y X Month							
Other Network Exposure FE				Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone			Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month
User FE					Y		Y		Y
R-Squared	0.037	0.081	0.210	0.211	0.287	0.154	0.272	0.239	0.275
Sample Mean	1.582	1.582	1.611	1.611	1.456	-1.894	-1.974	1.308	1.308
N	32,754,357	32,754,354	30,742,008	30,742,008	29,777,929	24,053,560	22,902,553	21,812,115	21,812,115

Note: Table shows results from robustness versions of regression 5. Columns 4 is the same as column 1 of Table 2. In Column 1 we drop all controls. In columns 2 and 3 we include only ZCTA-by-month and only ZCTA-by-month-by-observable group fixed effects, respectively. In columns 6-7 we exclude the first month, March. In columns 8-9 we only include users for which every month of data is available. Columns 5, 7, and 9 include fixed effects for each user. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A11: Effects of Friend-Exposure by Month: Number of Tiles Visited

	% Change in Bing Tiles Visited		# of Bing Tiles Visited	
Change Friend Exposure, Same Month	-0.568***	-0.934***	-0.038***	-0.003***
	(0.117)	(0.123)	(0.005)	(0.001)
Specification	OLS	OLS	OLS	Poisson
Other Network Exposure FE	Y x Month	Y X Month	Y X Month	Y X Month
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y x Month	Y X Month	Y X Month	Y X Month
User FE		Y	Y	Y
(Pseudo) R-Squared	0.016	0.035	0.261	0.565
Sample Mean	20.81	20.76	8.86	8.86
N	30,742,008	29,777,929	29,777,929	29,777,929

Note: Table reports results of versions of regression 5 with different outcomes and functional forms. As in columns 1-2 of Table 2, there is one observation per user per month between March 2020 and July 2020. In columns 1-2 the outcome is the percentage change in the number of Bing tiles visited from last week of the prior month to the last week of the current month. In columns 3-4 the outcome is the number of Bing tiles visited. Columns 2-4 include user fixed effects. All columns include the ZCTA-by-demographic controls and percentiles of friend exposure controls described in Table 2. In column 4 we show results of analogous Poisson Pseudo-Maximum Likelihood regression model. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A12: Effects of Friend-Exposure by Month: Δ Probability of Staying at Home

	Monthly Change in Prob. Stay at Home				
	March	April	May	June	July
Change Friend Exposure, March	0.207***				
	(0.046)				
Change Friend Exposure, April		0.032			
		(0.048)			
Change Friend Exposure, May			0.460***		
			(0.073)		
Change Friend Exposure, June				0.577***	
				(0.089)	
Change Friend Exposure, July					0.076
					(0.089)
Other Network Exposure FE	Y	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y	Y
R-Squared	0.174	0.141	0.150	0.146	0.145
Sample Mean	14.214	-0.923	-5.989	-1.068	0.679
N	6,688,448	6,579,359	6,169,176	5,848,722	5,456,303

Note: Table shows results from a regression similar to Equation 5, splitting out the changes in friend exposure and probability of staying at home by month. Each observation is an individual. The outcome variable is the change in the probability of staying home between the final weeks of a given month and the previous months' final week: February 25-March 2 for February; March 24-March 30 for March; April 21-April 27 for April; May 26-June 1; June 23-June 29; July 21-July 28. We consider changes by month. In all columns we control for interactions of age groups, gender, whether the individual has a college listed on Facebook, whether the individual primarily accesses mobile Facebook from an iPhone, and whether the individual has accessed Facebook from a tablet. We also control for fixed effects for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. In column 2, we include user fixed effects. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A13: Heterogeneity of Monthly Friend-Exposure Effects, All Days

	Monthly Change in Prob. Stay at Home, Weekends						
Change Friend Exposure x I(Age < 35)	0.208***						
	(0.020)						
Change Friend Exposure x I(Age 35-55)	0.098***						
	(0.015)						
Change Friend Exposure x I(Age > 55)	-0.034*						
	(0.020)						
Change Friend Exposure x Female		0.125***					
		(0.015)					
Change Friend Exposure x Male		0.055***					
		(0.015)					
Change Friend Exposure x College			0.162***				
			(0.014)				
Change Friend Exposure x No College			0.016				
			(0.015)				
Change Friend Exposure x Zip Income First Tertile				0.003			
				(0.018)			
Change Friend Exposure x Zip Income Second Tertile				0.048***			
				(0.017)			
Change Friend Exposure x Zip Income Third Tertile				0.268***			
				(0.020)			
Change Friend Exposure x County Cases First Tertile					0.027*		
					(0.014)		
Change Friend Exposure x County Cases Second Tertile					0.107***		
					(0.023)		
Change Friend Exposure x County Cases Third Tertile					0.219***		
					(0.022)		
Change Friend Exposure, Friends Ranked 1 - 25						0.067***	
						(0.011)	
Change Friend Exposure, Friends Ranked 26 - 50						0.024**	
						(0.011)	
Change Friend Exposure, Friends Ranked 51 - 75						0.004	
						(0.011)	
Change Friend Exposure, Friends Ranked 76 - 100						0.002	
						(0.011)	
Change Friend Exposure, Friends <100mi Away							0.543***
							(0.054)
Change Friend Exposure, Friends >100mi Away							0.171***
							(0.039)
Other Network Exposure FE	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month	Y X Month
R-Squared	0.211	0.211	0.211	0.211	0.211	0.211	0.268
Sample Mean	1.611	1.611	1.611	1.611	1.611	1.611	1.805
F Test (Rank 1-25 = Rank 76-100)						15.187***	
N	30,742,008	30,742,008	30,742,008	30,742,008	30,742,008	30,742,008	30,742,008

Note: Table results from the same regressions as Table 3, but with the outcome variable as the change in movement on *all days*, rather than on the weekend only. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A14: Monthly Friend-Exposure Effects: Close vs. Far Friends

	Monthly Change in Prob. Stay at Home	
	All Days	Weekends
Change Friend Exposure, Friends Ranked 1-50, <100mi	0.240***	0.201**
	(0.059)	(0.093)
Change Friend Exposure, Friends Ranked 51-100, <100mi	0.310***	0.190**
	(0.055)	(0.086)
Change Friend Exposure, Friends Ranked 1-50, >100mi	0.140***	0.214***
	(0.030)	(0.046)
Change Friend Exposure, Friends Ranked 51-100, >100mi	0.093***	0.135***
	(0.031)	(0.047)
Other Network Exposure FE X Month, All Dist	Y	Y
Other Network Exposure FE X Month, >100mi	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y
R-Squared	0.273	0.250
Sample Mean	1.817	1.624
N	11,235,194	10,165,136

Note: Table shows results from versions of regression 5, similar to column 1 of Table 2. Here, we amend regression 5 by replacing $ChangeFriendExposure_{it}$ with four analogous variables constructed using exposure from individuals who live within (outside) 100 miles and are in user's the closest 50 (51-100) friends. Both columns are restricted to users that have at least 100 friends <100 miles away and >100 miles away (the same minimum restriction used for *overall* friends elsewhere). In column 1 the outcome variable is the change in the probability of staying home using data from all days. Column 3 uses data on weekend movement. In both columns we control for interactions of ZCTA fixed effects, age groups, gender, whether the individual has a college listed on Facebook, whether the individual primarily accesses mobile Facebook from an iPhone, and whether the individual has accessed Facebook from a tablet. Both columns also include fixed effects for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. We control for this measure both among all friends and friends >100mi away. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A15: Heterogeneity of Early Friend-Exposure Effects: Probability of Staying at Home

	%Δ Stay at Home					
log(Friend Exposure) x I(Age < 35)	1.241***					
	(0.042)					
log(Friend Exposure) x I(Age 35-55)	0.960***					
	(0.033)					
log(Friend Exposure) x I(Age > 55)	0.412***					
	(0.038)					
log(Friend Exposure) x Female		0.949***				
		(0.032)				
log(Friend Exposure) x Male		0.796***				
		(0.033)				
log(Friend Exposure) x College			1.321***			
			(0.034)			
log(Friend Exposure) x No College			0.443***			
			(0.031)			
log(Friend Exposure) x Zip Income First Tertile				0.386***		
				(0.037)		
log(Friend Exposure) x Zip Income Second Tertile				0.794***		
				(0.036)		
log(Friend Exposure) x Zip Income Third Tertile				1.608***		
				(0.045)		
log(Friend Exposure) x County Cases First Tertile					0.676***	
					(0.030)	
log(Friend Exposure) x County Cases Second Tertile					1.384***	
					(0.058)	
log(Friend Exposure) x County Cases Third Tertile					1.245***	
					(0.055)	
log(Friend Exposure - Rank 1 - 25)						0.204***
						(0.017)
log(Friend Exposure - Rank 26 - 50)						0.112***
						(0.017)
log(Friend Exposure - Rank 51 - 75)						0.082***
						(0.017)
log(Friend Exposure - Rank 76 - 100)						0.098***
						(0.017)
Other Network Exposure FE	Y	Y	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y	Y	Y
R-Squared	0.175	0.175	0.175	0.175	0.175	0.177
Sample Mean	13.800	13.800	13.800	13.800	13.800	14.488
F Test (Rank 1-25 = Rank 76-100)						17.328***
N	6,400,738	6,400,738	6,400,738	6,400,738	6,400,738	5,684,469

Note: Table shows results from regressions of friend-exposure to Covid-19 on March 15th, interacted with individual characteristics, on the percentage change in the probability of staying at home. Friend-exposure is interacted with age groups in rows 1-3; gender in rows 4-5; whether the individual has a college listed in Facebook in rows 6-7; ZCTA median household income in rows 8-10; county-level cases of Covid-19 in rows 11-13; and friend rank (i.e. a measure for how close friends are) in rows 14-16. All columns include controls for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. All columns include fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A16: Heterogeneity of Early Friend-Exposure Effects: Average Daily Tiles Visited

	%Δ Bing Tiles Visited					
log(Friend Exposure) x I(Age < 35)	1.942***					
	(0.146)					
log(Friend Exposure) x I(Age 35-55)	1.860***					
	(0.114)					
log(Friend Exposure) x I(Age > 55)	0.535***					
	(0.123)					
log(Friend Exposure) x Female		1.125***				
		(0.100)				
log(Friend Exposure) x Male		1.971***				
		(0.123)				
log(Friend Exposure) x College			2.030***			
			(0.107)			
log(Friend Exposure) x No College			1.006***			
			(0.114)			
log(Friend Exposure) x Zip Income First Tertile				0.576***		
				(0.136)		
log(Friend Exposure) x Zip Income Second Tertile				1.289***		
				(0.122)		
log(Friend Exposure) x Zip Income Third Tertile				2.990***		
				(0.135)		
log(Friend Exposure) x County Cases First Tertile					0.926***	
					(0.104)	
log(Friend Exposure) x County Cases Second Tertile					2.429***	
					(0.183)	
log(Friend Exposure) x County Cases Third Tertile					3.087***	
					(0.168)	
log(Friend Exposure - Rank 1 - 25)						0.463***
						(0.058)
log(Friend Exposure - Rank 26 - 50)						0.097
						(0.060)
log(Friend Exposure - Rank 51 - 75)						-0.062
						(0.059)
log(Friend Exposure - Rank 76 - 100)						0.139**
						(0.059)
Other Network Exposure FE	Y	Y	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y	Y	Y
R-Squared	0.154	0.154	0.154	0.154	0.154	0.156
Sample Mean	15.801	15.801	15.801	15.801	15.801	17.436
F Test (Rank 1-25 = Rank 76-100)						13.393***
N	6,400,738	6,400,738	6,400,738	6,400,738	6,400,738	5,684,469

Note: Table shows results from regressions of friend-exposure to Covid-19 on March 15th, interacted with individual characteristics, on the percentage change in average tile movement. Each observation is an individual. Friend-exposure is interacted with age groups in rows 1-3; gender in rows 4-5; whether the individual has a college listed in Facebook in rows 6-7; zip-level median household income in rows 8-10; county-level cases of Covid-19 in rows 11-13; and friend rank (i.e. a measure for how close friends are) in rows 14-16. All columns include controls for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. All columns include fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A17: Posting Behavior and Group Membership, Additional Results

	DV: Share Posts about Covid-19 (Feb - Apr)	DV: Share "Signed Posts" Opposed to Distancing (Feb - Apr)	DV: Member "Reopen Group" by June 28, 2020	DV: Δ Sentiment (Feb - Apr) All Posts	
log(Friend Exposure)	0.324***	-1.659***	-0.003	-0.109***	-0.094***
	(0.006)	(0.107)	(0.018)	(0.016)	(0.025)
Age Group					
35-54	0.579***	-2.196***	0.767***	-0.480***	
	(0.005)	(0.168)	(0.011)	(0.026)	
55+	0.351***	4.667***	0.851***	-0.031	
	(0.005)	(0.194)	(0.012)	(0.030)	
Female	-0.266***	-17.713***	-0.582***	0.942***	
	(0.003)	(0.142)	(0.010)	(0.024)	
Has College	0.637***	-2.392***	-0.188***	-0.283***	
	(0.004)	(0.141)	(0.006)	(0.023)	
Has iPhone	0.137***	-7.215***	0.019***	-0.150***	
	(0.003)	(0.135)	(0.006)	(0.023)	
Has Tablet	0.028***	-1.997***	-0.048***	0.039*	
	(0.003)	(0.125)	(0.003)	(0.023)	
Zip Code Income					
Middle Tertile	0.069***	-0.886***	0.211***	-0.075*	
	(0.013)	(0.229)	(0.041)	(0.031)	
Top Tertile	0.269***	-1.946***	0.379***	-0.121***	
	(0.016)	(0.250)	(0.044)	(0.035)	
County Cases/Pop					
Middle tertile	-0.064***	1.458***	0.219***	0.027	
	(0.014)	(0.256)	(0.049)	(0.037)	
Top Tertile	-0.097***	1.049***	0.204***	0.034	
	(0.013)	(0.240)	(0.048)	(0.036)	
Percentiles of Total Number of Groups (Feb 2020)			Y		
Other Network Exposure FE	Y	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone					Y
Sample	People With Any Posts Feb - April	People With "Signed Posts" Feb - April	People With Group Memberships	People With Posts between Feb 3 and May 3	
R-Squared	0.013	0.087	0.013	0.000	0.118
Sample Mean	1.750	39.806	1.217	-1.817	-1.823
N	34,828,054	546,499	119,384,394	11,209,068	10,777,790

Note: Table shows results from regressions 6 and 7, similar to Table 4. Each observation is an individual. The outcome in column 1 is the percentage of individual posts that are about Covid-19; in column 2 it is the percentage of pro- or anti-distancing posts that are anti-distancing; in column 3 it is whether the individual was a member of a 'Reopen' Facebook group as of June 28th; in columns 4-5 it is the change in the average sentiment of the posts from February 3rd through 23rd to April 6th through 26th. For ease of interpretation and because of small magnitudes, we rescale coefficients and standard errors by 100, so that they correspond to percentages. Post classification is based on the regex in Appendix C. Group classification is determined by the regular expression described in Appendix C. Sentiment is measured on a scale from -100 to 100 using the VADER algorithm described in Hutto and Gilbert (2014). Columns 1-4 include controls for the log of friend-exposure to Covid-19 on March 15th; age groups; gender; whether the individual has a college listed on Facebook; whether the individual primarily accesses Facebook mobile from an iPhone; whether the individual has accessed Facebook from a tablet; the tertile of home ZCTA median household income; the tertile of home county cases per resident as of March 15th; and percentiles of friend-exposures (as described in equation 3) for median household income, population density, and the share of the population living in urban areas. Column 5 adds fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. The group-based analyses in columns 3-4 also include fixed effects for the percentile of the number of groups an individual was in as of February 2020. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A18: Summary Characteristics - Posting Behavior Sample

	Mean	SD	P10	P25	P50	P75	P90
Age	42.40	15.96	24	29	40	53	64
Female	0.58	0.49	0	0	1	1	1
Has College	0.60	0.49	0	0	1	1	1
Zip Code Income	$61,284	$23,993	$36,729	$44,902	$55,662	$72,704	$94,000
Has iPhone	0.59	0.49	0	0	1	1	1
Has Tablet	0.47	0.50	0	0	0	1	1
Number of Friends	564.85	341.16	196	289	477	776	1103
Friend Exposure to Cases	10.31	19.68	0.78	1.84	4.55	10.83	25.16
Number of Posts Feb	16.12	64.85	0	0	1	8	34
Average Sentiment (Feb)	31.89	35.26	-3.41	3.50	29.91	58.00	83.00
Number of Posts April	20.83	74.95	0	0	2	13	47
Average Sentiment (April)	29.94	34.21	-4.75	3.86	27.80	53.84	79.47
Number Posts about Corona	0.724	4.687	0	0	0	0	2
Average Sentiment Corona Posts	21.46	52.79	-52.75	-10.13	21.09	66.71	93.37
Number Posts Support Lockdown	0.013	0.238	0	0	0	0	0
Number Posts Oppose Lockdown	0.008	0.118	0	0	0	0	0

Note: Table presents summary statistics describing users in our sample underlying the analysis of public posts. Individual-level characteristics include age, gender, whether the user has a college listed on Facebook, whether the user primarily accesses Facebook mobile from an iPhone, whether the individual has accessed Facebook from a tablet, number of friends, friend-exposure to Covid-19 cases on March 15th, and patterns of mobility during the week of February 25th to March 2nd. The table also includes information on the 2018 median household income of users' home ZCTA.

Table A19: Monthly Exposure and Group Membership - Cases per 100k

	Member "Reopen Group" by June 28, 2020				
log (Friend Exposure March 15, Cases per 100k)	-0.069***				
	(0.007)				
log (Friend Exposure End of March, Cases per 100k)		-0.015			
		(0.011)			
log (Friend Exposure End of April, Cases per 100k)			-0.005		
			(0.011)		
log (Friend Exposure End of May, Cases per 100k)				-0.049***	
				(0.011)	
log (Friend Exposure End of June, Cases per 100k)					-0.148***
					(0.015)
R-Squared	0.074	0.074	0.074	0.074	0.074
Sample Mean	1.216	1.216	1.216	1.216	1.216
N	119,145,833	119,153,784	119,153,786	119,153,786	119,153,786

Note: Table presents results from versions of regression 7. The outcome in all columns is whether the individual was a member of a 'Reopen' Facebook group as of June 28th. In row 1 we use $FriendExposure100k_{it}$ as of March 15th 2020. In rows 2-5 we use analogous exposure measures at the end of March, April, May, and June, respectively. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A20: Heterogeneity of Friend Exposure Effects - Own Age / Gender / College

	% Posts about Covid-19	% "Signed Posts" Opp. Distancing	Sentiment All Posts	Member "Reopen Group"
log(Friend Exposure) x I(Age < 35)	0.209***	-1.650***	-0.075**	-0.034***
	(0.007)	(0.416)	(0.033)	(0.006)
log(Friend Exposure) x I(Age 35-55)	0.307***	-2.185***	-0.081**	-0.210***
	(0.007)	(0.287)	(0.033)	(0.009)
log(Friend Exposure) x I(Age > 55)	0.213***	-1.572***	-0.143***	-0.127***
	(0.006)	(0.384)	(0.039)	(0.007)
Other Network Exposure FE	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y
R-Squared	0.060	0.445	0.118	0.074
Sample Mean	1.755	35.979	-1.823	1.216
N	34,528,373	277,776	10,777,790	119,145,833

	% Posts about Covid-19	% "Signed Posts" Opp. Distancing	Sentiment All Posts	Member "Reopen Group"
log(Friend Exposure) x Female	0.197***	-1.536***	-0.174***	-0.060***
	(0.006)	(0.262)	(0.028)	(0.006)
log(Friend Exposure) x Male	0.319***	-3.074***	0.034	-0.216***
	(0.007)	(0.388)	(0.034)	(0.008)
Other Network Exposure FE	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y
R-Squared	0.060	0.445	0.118	0.074
Sample Mean	1.755	35.979	-1.823	1.216
N	34,528,373	277,776	10,777,790	119,145,833

	% Posts about Covid-19	% "Signed Posts" Opp. Distancing	Sentiment All Posts	Member "Reopen Group"
log(Friend Exposure) x College	0.352***	-2.281***	-0.122***	-0.171***
	(0.007)	(0.258)	(0.030)	(0.007)
log(Friend Exposure) x No College	0.124***	-0.838**	-0.058*	-0.082***
	(0.005)	(0.399)	(0.031)	(0.000)
Other Network Exposure FE	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y
R-Squared	0.060	0.445	0.118	0.074
Sample Mean	1.755	35.979	-1.823	1.216
N	34,528,373	277,776	10,777,790	119,145,833

Note: Table shows results from regressions of friend-exposure to Covid-19 on March 15th, interacted with individual characteristics, on a number of outcomes. Each observation is an individual. Friend-exposure is interacted with age groups in rows 1-3; gender in rows 4-5; and whether the individual has a college listed in Facebook in rows 6-7. The outcomes in columns 1-2 are the change in probability of staying at home and the percent reduction in the average number of tiles visited, respectively, from the week of February 25 - March 2 (prior to the pandemic) to April 14 - 20. The outcome in column 3 is the percentage of individual posts that are about Covid-19. In column 4 it is the percentage of pro- or anti-distancing posts that are anti-distancing. In column 5 it is the change in the average sentiment of the posts from February 3 - 23 to April 6 - 26. In column 6 it is whether the individual, as of June 28, was a member of a 'Reopen' Facebook group. Post and group classifications are defined in Appendix C. All columns include controls for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. All columns include fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A21: Heterogeneity of Friend-Exposure Effects - Own Income / Local Cases

	% Posts about Covid-19	% "Signed Posts" Opp. Distancing	Sentiment All Posts	Member "Reopen Group"
log(Friend Exposure) x Zip Income First Tertile	0.163***	-2.155***	-0.034	-0.080***
	(0.007)	(0.377)	(0.033)	(0.011)
log(Friend Exposure) x Zip Income Second Tertile	0.216***	-1.792***	-0.101***	-0.136***
	(0.007)	(0.335)	(0.034)	(0.012)
log(Friend Exposure) x Zip Income Third Tertile	0.404***	-1.884***	-0.172***	-0.185***
	(0.010)	(0.338)	(0.040)	(0.014)
Other Network Exposure FE	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y
R-Squared	0.060	0.445	0.118	0.074
Sample Mean	1.755	35.979	-1.823	1.216
N	34,528,373	277,776	10,777,790	119,145,833

	% Posts about Covid-19	% "Signed Posts" Opp. Distancing	Sentiment All Posts	Member "Reopen Group"
log(Friend Exposure) x County Cases First Tertile	0.190***	-1.904***	-0.086***	-0.065***
	(0.006)	(0.294)	(0.028)	(0.012)
log(Friend Exposure) x County Cases Second Tertile	0.392***	-2.084***	-0.047	-0.183***
	(0.013)	(0.422)	(0.050)	(0.012)
log(Friend Exposure) x County Cases Third Tertile	0.356***	-1.855***	-0.168***	-0.123***
	(0.012)	(0.399)	(0.046)	(0.011)
Other Network Exposure FE	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y
R-Squared	0.060	0.445	0.118	0.074
Sample Mean	1.755	35.979	-1.823	1.216
N	34,528,373	277,776	10,777,790	119,145,833

Note: Table shows results from regressions of friend-exposure to Covid-19 on March 15th interacted with various ZCTA-level characteristics on a number of outcomes. Each observation is an individual. Friend-exposure is interacted with tertiles of ZCTA median household income in rows 1-3; and tertiles of county cases per resident as of March 15th in rows 4-6. The outcomes in columns 1-2 are the change in probability of staying at home and the percent reduction in the average number of tiles visited, respectively, from the week of February 25 - March 2 (prior to the pandemic) to April 14 - 20. The outcome in column 3 is the percentage of individual posts that are about Covid-19. In column 4 it is the percentage of pro- or anti-distancing posts that are anti-distancing. In column 5 it is the change in the average sentiment of the posts from February 3 - 23 to April 6 - 26. In column 6 it is whether the individual, as of June 28, was a member of a 'Reopen' Facebook group. Post and group classifications are defined in Appendix C. All columns include controls for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. All columns include fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A22: Heterogeneity of Friend-Exposure Effects - Friend Characteristics

	Share Posts about Covid-19 (Feb - Apr)	Share "Signed Posts" Opposed to Distancing (Feb - Apr)	Δ Sentiment (Feb - Apr) All Posts	Member "Reopen Group" by May 24, 2020
log(Friend Exposure - Rank 1 - 25)	0.061***	-0.360***	-0.032**	-0.053***
	(0.002)	(0.149)	(0.016)	(0.002)
log(Friend Exposure - Rank 26 - 50)	0.046***	-0.299*	0.013	-0.036***
	(0.002)	(0.160)	(0.016)	(0.002)
log(Friend Exposure - Rank 51 - 75)	0.033***	-0.433**	0.008	-0.053***
	(0.002)	(0.158)	(0.017)	(0.002)
log(Friend Exposure - Rank 76 - 100)	0.022***	-0.016	-0.037**	-0.051***
	(0.002)	(0.159)	(0.017)	(0.002)
Percentiles of Total Number of Groups (Feb 2020)				Y
Other Network Exposure FE	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y	Y	Y	Y
R-Squared	0.060	0.446	0.122	0.074
Sample Mean	1.869	35.319	-1.869	0.012
F Test (Rank 1-25 = Rank 76-100)	184.345***	2.180	0.045	1.352
N	30,814,578	255,095	9,482,790	108,911,020

Note: Table shows results from regressions of friend-exposure to Covid-19 on March 15th, calculated using limited friend sets, on a number of outcomes. Each observation is an individual. Friend-exposure is calculated using only subsets friends based on the strength of friendship connections. The outcomes in columns 1 and 2 are the change in probability of staying at home and the percent reduction in the average number of tiles visited, respectively, from the week of February 25th to March 2nd (prior to the pandemic) to April 14th to 20th. The outcome in column 3 is the percentage of individual posts that are about Covid-19. In column 4 it is the percentage of pro- or anti-lockdown posts that are anti-distancing. In column 5 it is the change in the average sentiment of the posts from February 3rd through 23rd to April 6th through 26th. In column 6 it is whether the individual, as of June 28th, was a member of a 'Reopen' Facebook group. Post and group classifications are defined in Appendix C. All columns include controls for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. All columns also include fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A23: Social Distancing by Demographics: Percent Reduction in Number of Tiles Visited

	DV: % Reduction - Bing Tiles Visited (Feb - Apr)							
Age Group								
35-54	1.073***	0.986***		1.012***				
	(0.104)	(0.101)		(0.101)				
55+	3.534***	3.702***		3.842***				
	(0.119)	(0.112)		(0.112)				
Female	9.577***	10.036***		10.285***				
	(0.084)	(0.082)		(0.082)				
Has College	7.347***	6.825***		6.233***				
	(0.085)	(0.081)		(0.081)				
Has iPhone	5.847***	4.934***		4.635***				
	(0.099)	(0.098)		(0.098)				
Has Tablet	0.141*	0.041		-0.057				
	(0.079)	(0.078)		(0.078)				
Zip Code Income								
Middle Tertile	3.467***							
	(0.229)							
Top Tertile	9.432***							
	(0.226)							
County Cases/Pop								
Middle tertile	8.387***							
	(0.204)							
Top Tertile	9.892***							
	(0.227)							
log(Friend Exposure)			1.802***	1.585***	1.514***	1.455***	1.481***	1.473***
			(0.083)	(0.083)	(0.092)	(0.155)	(0.103)	(0.144)
Zip Code FE		Y	Y	Y				
Other Network Exposure FE			Y	Y	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone					Y	Y	Y	Y
College FE								Y
Sample						Weekend	Weekday	College
R-Squared	0.009	0.018	0.015	0.020	0.154	0.155	0.156	0.172
Sample Mean	15.640	15.640	15.641	15.641	15.801	-1.943	12.668	20.942
N	6,804,168	6,804,167	6,803,761	6,803,761	6,400,738	5,808,187	6,309,820	2,616,959

Note: Table shows results from regression A1. Each observation is an individual. The outcome in all columns is the percent reduction in average number of Bing tiles visited from the week of February 25th to March 2nd (prior to the pandemic) to April 14th to 20th. Column 1 includes controls for age groups, gender, whether the individual has college information in Facebook, whether the individual primarily accesses mobile Facebook from an iPhone, whether the individual has accessed Facebook from a tablet, the tercile of ZCTA-level median household income, and the tercile of county-level cases per resident as of March 15th. Column 2 adds ZCTA fixed effects, but maintains the individual level controls. Column 3 includes only the log of friend-exposure to Covid-19 cases on March 15th; ZCTA fixed effects; and percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. Column 4 adds back the individual-level controls from column 1. Column 5 adds fixed effects for every group constructed from interacting ZCTA, age group, gender, has college, has tablet, and has iPhone. In Column 6 the outcome is weekend movement and in column 7 the outcome is weekday movement. Column 8 limits to individuals that attended a college, limiting to colleges with more than 100 individuals, and adds a fixed effect for each individual college. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table A24: Summary Statistics of ZCTAs with High and Low Friend-Exposure to Covid-19

	Low Friend-Exposure		High Friend-Exposure	
	Mean	SD	Mean	SD
Fraction Male	0.49	0.03	0.49	0.03
Fraction White	0.74	0.23	0.72	0.21
Fraction Black	0.12	0.18	0.13	0.18
Fraction Asian	0.05	0.08	0.06	0.09
Median HH Inc.	$65426.94	$24643.08	$64707.44	$28886.90
Management, Business, Science, Arts	0.17	0.08	0.18	0.08
Service Occupations	0.08	0.02	0.08	0.03
Production + Transportation	0.07	0.03	0.06	0.03
Fraction Age <18	0.23	0.05	0.22	0.05
Fraction Age 18-24	0.09	0.03	0.10	0.07
Fraction Age 25-34	0.14	0.04	0.14	0.05
Fraction Age 35-44	0.13	0.02	0.13	0.02
Fraction Age 45-54	0.14	0.02	0.13	0.02
Fraction Age 55-64	0.13	0.03	0.13	0.03
Fraction Age 65-74	0.09	0.03	0.09	0.03
Fraction Age >= 75	0.06	0.03	0.07	0.03
Fraction High School / GED	0.20	0.07	0.17	0.07
Fraction Some College	0.20	0.05	0.19	0.05
Fraction College Degree	0.19	0.11	0.23	0.13
Population Density	1606.18	4122.32	1531.22	3490.32
Fraction High-Speed Internet	0.80	0.11	0.80	0.11
Population	30175.11	21494.15	32923.65	20222.50
Mean Number of POIs	435.91	372.62	538.79	376.59
Number of ZCTAs	14079		11880	

Note: Table presents ZCTA-level summary statistics for the sample used in Section 4. Definitions of high- and low-exposure areas are based on friend-exposure to Covid-19 as defined in equation A5. High-exposure ZCTAs are ZCTAs with friend-exposure to Covid-19 above the median for corresponding county. Similarly, low-exposure ZCTAs are places with friend-exposure below that median. Medians are defined based on the number of Covid-19 cases as of March 15. Data on covariates is obtained from the 2014-2018 ACS data.

Table A25: Posts Regular Expression Classification

Neutral Lockdown		
%corona%	%covid%	%pandemic%
%sars%	%#socialdistancing%	%lockdown%
%stay at home%		

Pro Lockdown		
%#staysafe%	%#stayhome%	%#bendthecurve%
%bend the curve%	%#flattenthecurve%	%flatten the curve%
%#crushthecurve%	%crush the curve%	%#safeathome%

Anti Lockdown		
%#liberate%	%#endtheshutdown%	%#endthelockdown%
%#reopen%	%#openamerica%	%#stoptheshutdown%
%#stopthelockdown%	%against%quarantine%	%end the lockdown%
%end the shutdown%	%open now%	%hysteria%
%open the states%	%openthestates%	%lockdown%dictator%
%lockdown%oppress%	%lockdown%tyranny%	%lockdown%liberty%
%lockdown%freedom%	%shutdown%dictator%	%shutdown%oppress%
%shutdown%tyranny%	%shutdown%liberty%	%shutdown%freedom%
%dictator%lockdown%	%oppress%lockdown%	%tyranny%lockdown%
%liberty%lockdown%	%freedom%lockdown%	%dictator%shutdown%
%oppress%shutdown%	%tyranny%shutdown%	%liberty%shutdown%
%freedom%shutdown%		

Note: Table presents the regular expressions used to flag posts about Covid-19. % is a wildcard capturing any number of characters (including 0).

Table A26: Reweighted Movement Sample Summary

	N	Avg. Age	% Female	% College	Avg. ZCTA Income	% iPhone	% Has Tablet	Avg. Friends
Movement Sample	12,991,476	43.6	0.53	0.53	$58,736	0.24	0.53	532
Full Sample	119,468,019	42.0	0.57	0.59	$63,791	0.61	0.43	503
Reweighted Movement Sample	12,991,476	42.0	0.57	0.59	$63,296	0.61	0.43	507

Note: Table shows summary statistics about three groups of users considered in the analyses in this paper. In the first row is the movement sample, consisting of all the users that at some point have Location History enabled, allowing us to observe their movement patterns. This sample is constructed as described in Section 1.1. The sample in the second row includes all those used in the groups analyses in Section 3.2.2, a broader sample that does not restrict to users with Location History enabled. In the third row, we present (weighted) summary statistics, after we apply the observation weights used in the regressions presented in Table A27. These weights are calculated using a raking methodology, attempting to equalize the average age, gender balance, college attendance, ZCTA income, iPhone share, tablet share, and average number of friends across the two samples.

Table A27: Effects of Friend Exposure on Probability of Staying Home, Reweighted Sample

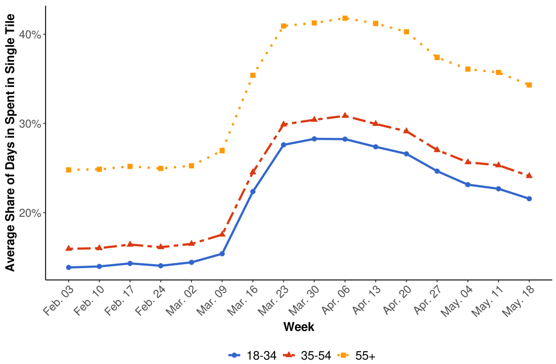
	Monthly Change in Prob. Stay at Home					
	All months	March	April	May	June	July
Change Friend Exposure, Same Month	0.255***					
	(0.040)					
Change Friend Exposure, March		0.222***	0.003	-0.113*	0.127*	0.012
		(0.061)	(0.056)	(0.064)	(0.071)	(0.082)
Change Friend Exposure, April			0.115	0.102	0.354***	-0.012
			(0.070)	(0.075)	(0.079)	(0.089)
Change Friend Exposure, May				0.483***	0.104	-0.159
				(0.107)	(0.103)	(0.118)
Change Friend Exposure, June					0.914***	-0.236
					(0.149)	(0.157)
Change Friend Exposure, July						0.156
						(0.177)
Weighted to Match Full Sample	Y	Y	Y	Y	Y	Y
Other Network Exposure FE	Y x Month	Y	Y	Y	Y	Y
Zip Code x Age Group x Gender x Has College x Has Tablet x Has iPhone	Y x Month	Y	Y	Y	Y	Y
R-Squared	0.272	0.224	0.190	0.201	0.196	0.194
Sample Mean	1.881	15.112	-1.081	-6.131	-1.056	0.695
N	30,742,008	6,688,448	6,579,359	6,169,176	5,848,722	5,456,303

Note: This table presents the results found in Table 2, applying sample weights to make the observable features of the movement sample resemble those of the larger sample used in the groups analyses. This reweighted sample is summarized in Table A26. Standard errors are clustered by ZCTA. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

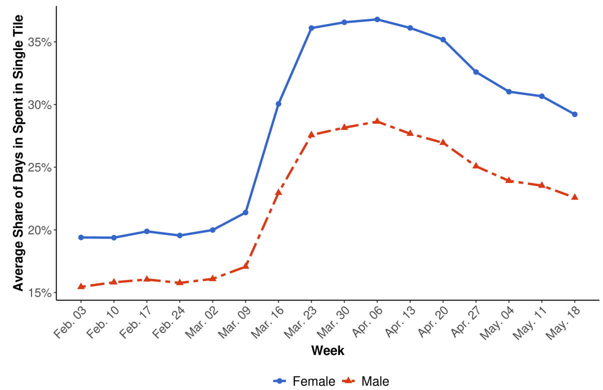
E Additional Figures

Figure A1: Heterogeneity in Probability of Staying at Home

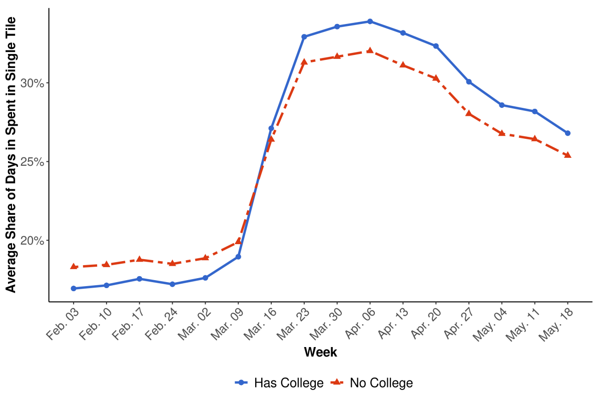
(a) Age



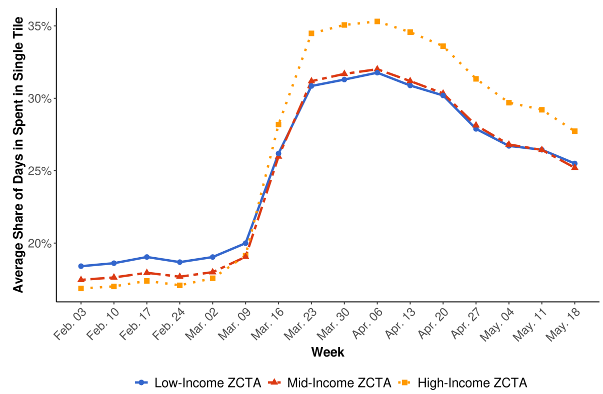
(b) Gender



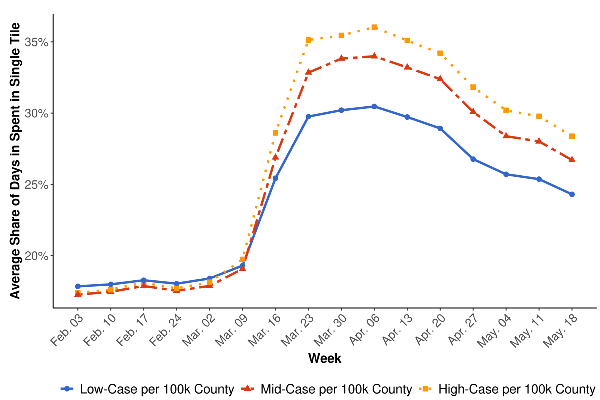
(c) Educational Attainment



(d) Income



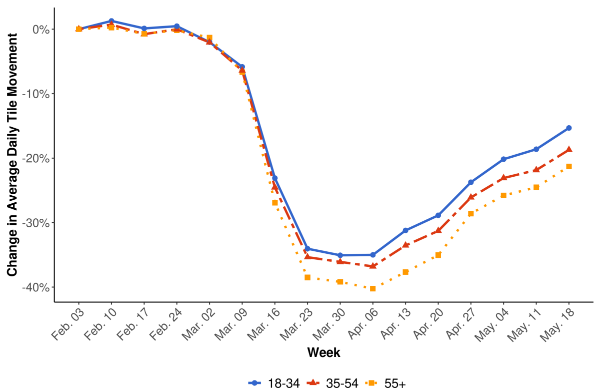
(e) Local Exposure to Covid-19



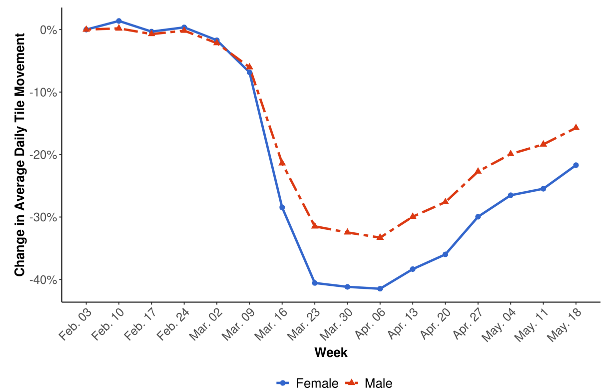
Note: Figures show weekly averages of the probability of staying at home from the week of February 3rd to the week of May 18th across certain characteristics. Panel (a) shows age; panel (b) shows gender; panel (c) shows whether the user has a college listed on Facebook; panel (d) shows the tertile of home ZCTA median household income; and panel (e) shows the tertile of county-level cases per resident as of March 15th.

Figure A2: Heterogeneity in Change in Average Tiles Visited

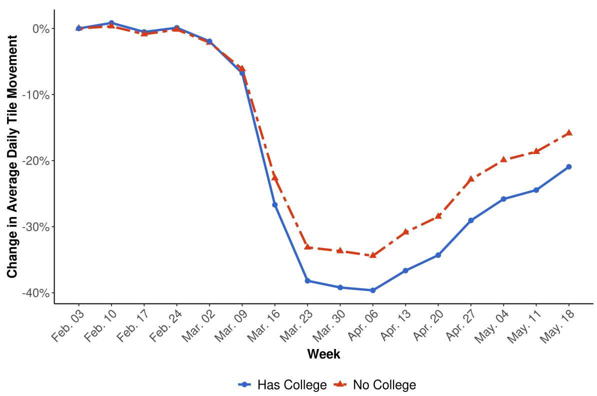
(a) Age



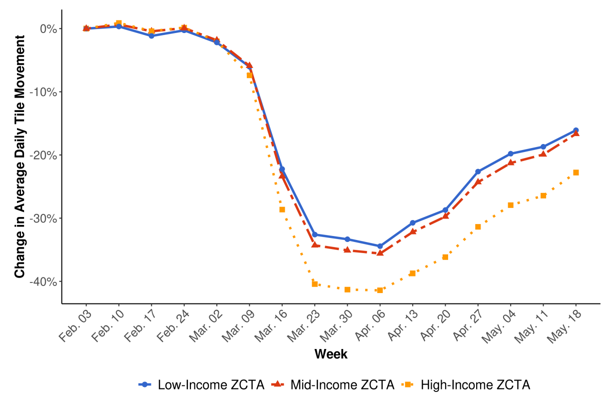
(b) Gender



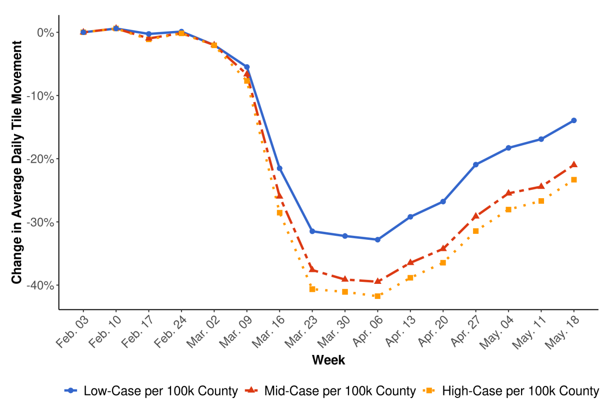
(c) Educational Attainment



(d) Income

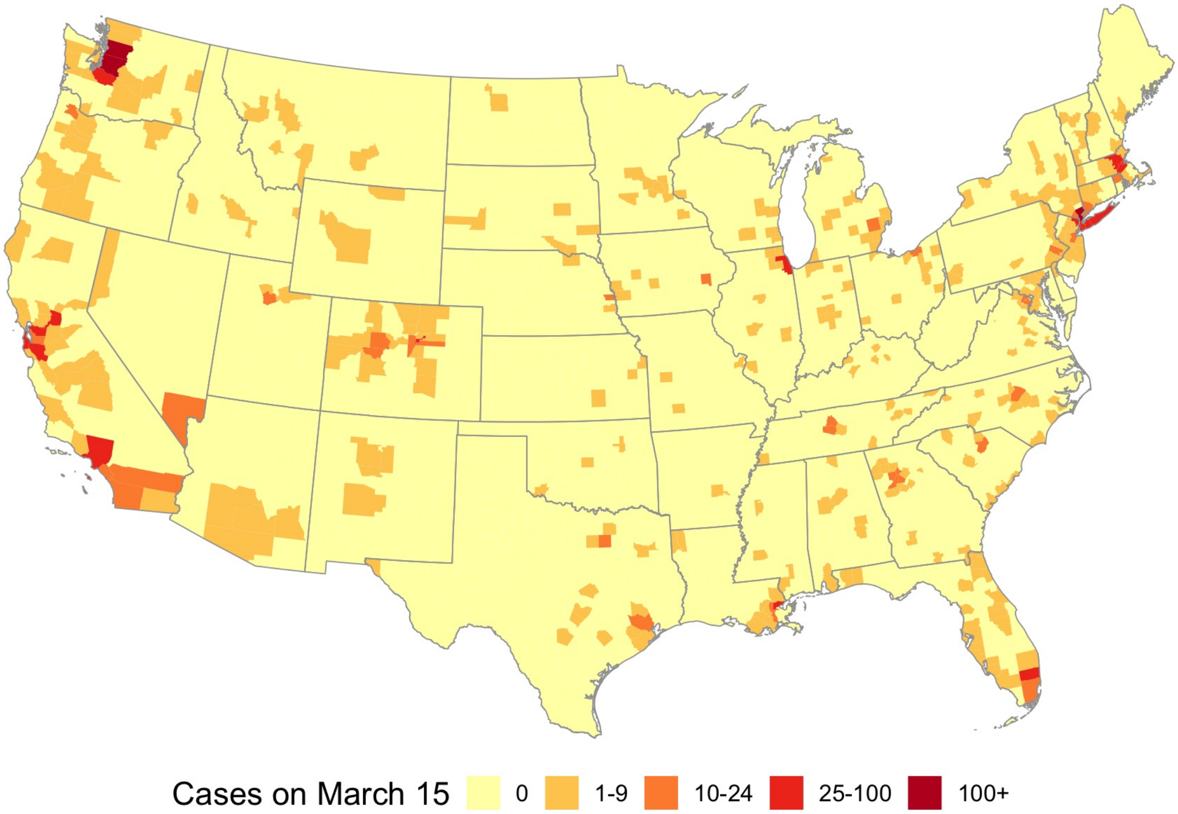


(e) Local Exposure to Covid-19



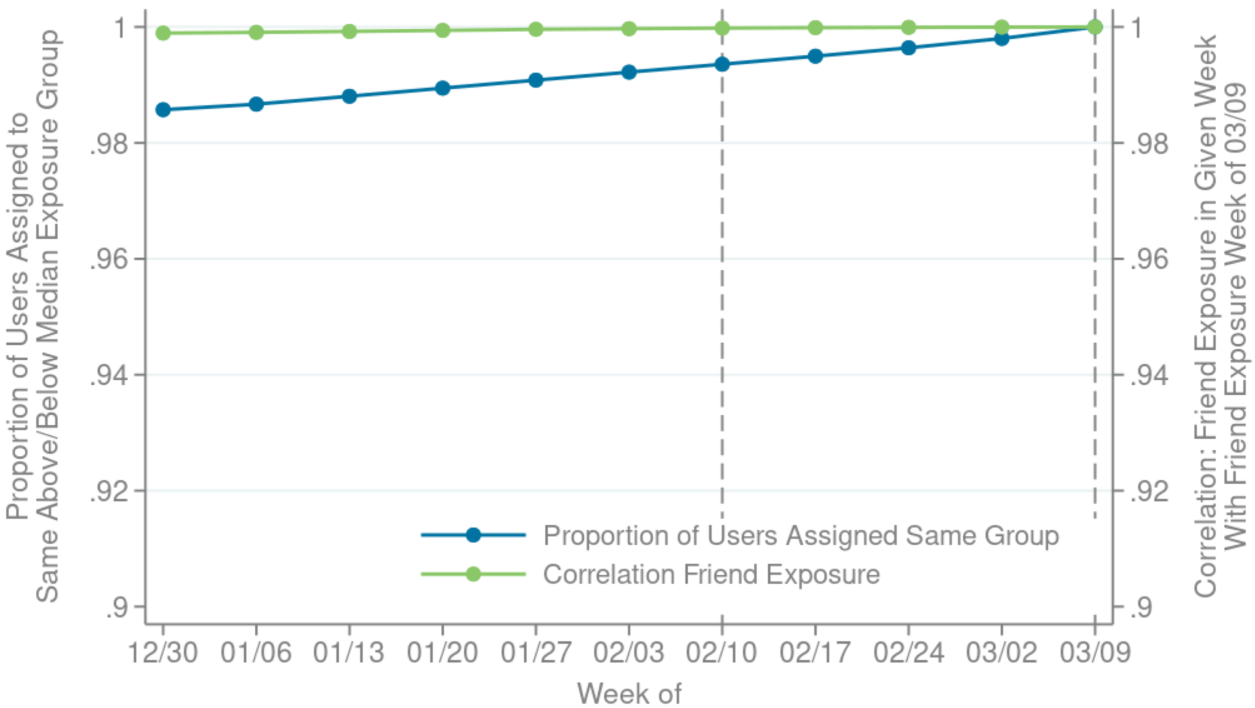
Note: Figures show the percent change in the weekly average of daily tiles visited from the week of February 3rd to the week of May 18th across certain characteristics. Panel (a) shows age; panel (b) shows gender; panel (c) shows whether the individual has college information in Facebook; panel (d) shows the tercile of ZCTA-level median household income; and panel (e) shows the tercile of county-level cases per resident as of March 15th.

Figure A3: Covid-19 Cases as of March 15, 2020



Note: Figure shows the cumulative number of reported Covid-19 cases by county as of March 15, 2020. Darker red colors correspond to higher Covid-19 prevalence.

Figure A4: Network Evolution Robustness

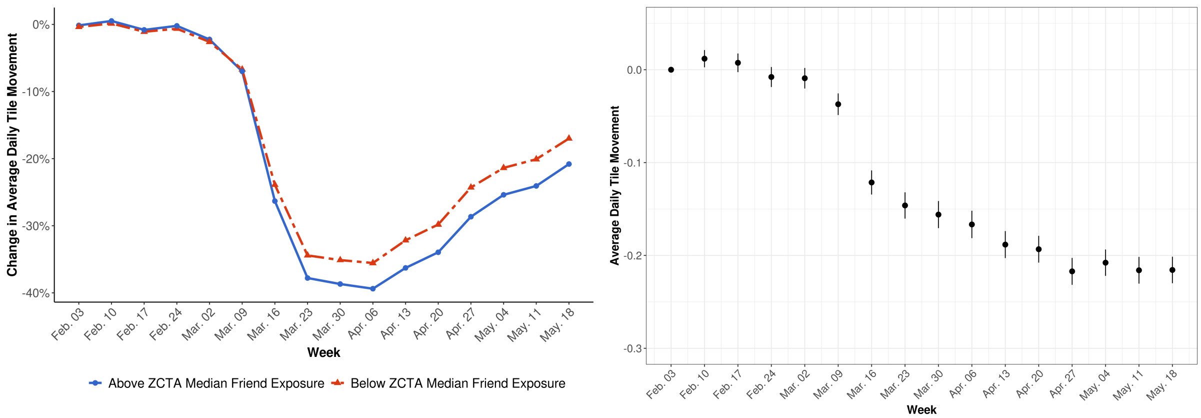


Note: This figure presents two figures illustrating the insensitivity of our measures of friend exposure to changes in users' social networks over time in our baseline sample. The green line correlates users' realized friend exposure to Covid-19 (constructed using Equation 1) on March 15 with the exposure that they would have had on March 15 had their network then been the same as it had been in each week since the start of the year. The blue line captures the fraction of users that would have been assigned to the same high- or low-exposure group in Equation 2, had friendship networks been frozen at a given date in the past. These two series indicate that patterns of exposure among individuals' networks have remained largely unchanged since the discovery of Covid-19.

Figure A5: Effects of Friend-Exposure to Covid-19 on Mobility Behavior

(a) Time Series: Average Tiles Visited

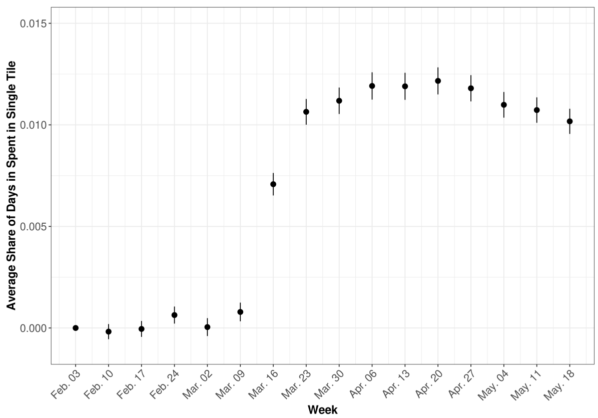
(b) Diff-In-Diff: Average Tiles Visited



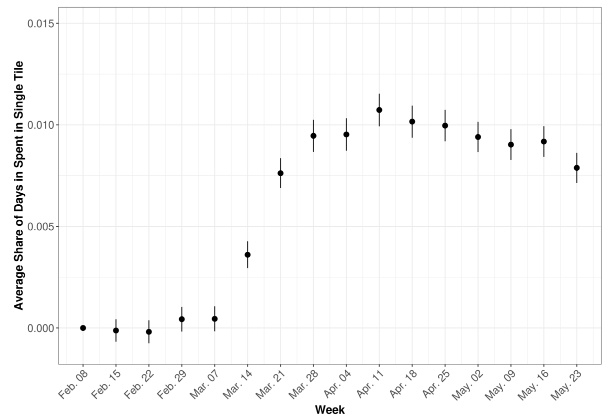
Note: Figures show the relationship between friend-exposure to Covid-19 on March 15th cases and mobility behavior measured as the average number of tiles visited from the week of February 3rd to the week of May 18th, separately for individuals above and below the median level of friend-exposure in their ZCTA. Panel (a) shows raw means, while Panel (b) shows coefficients estimated using the difference-in-differences setup specified in equation 2. The specification includes fixed effects at the individual level as well as the following groups interacted with week: ZCTA, age group; gender; has college listed on Facebook; has iPhone; has tablet; and percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. Standard errors are clustered by ZCTA.

Figure A6: Robustness: Effects of Friend-Exposure to Covid-19 on Prob. of Staying Home

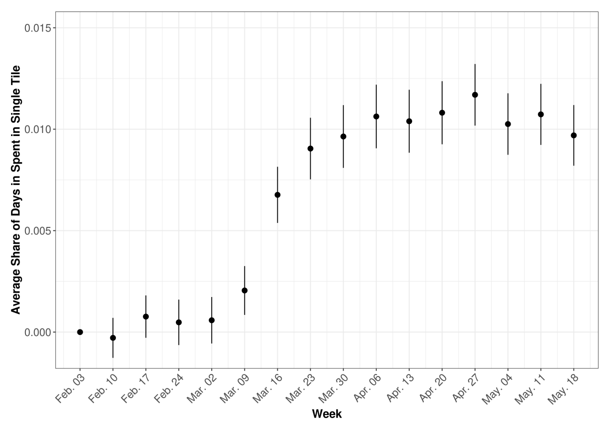
(a) Weekdays



(b) Weekends



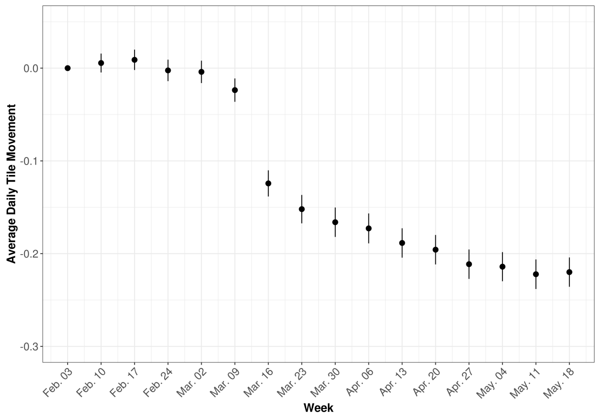
(c) Controlling for Exact College



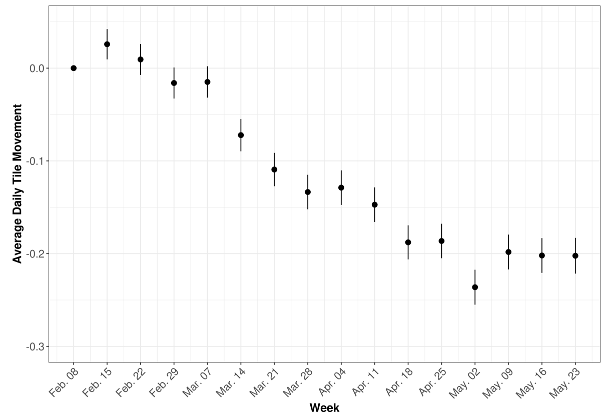
Note: Figures show coefficients estimated using the difference-in-differences setup specified in equation 2 with the outcome variable as the probability of staying at home. The outcome is measured on weekdays in panel (a) and weekends in panel (b). Panel (c) limits to individuals that attended college, limiting to colleges with more than 100 individuals, and adds a fixed effect for each individual college interacted with week. All specifications include fixed effects at the individual level as well as the following groups interacted with week: ZCTA; age group; gender; has college information in Facebook; has iPhone; has tablet; and percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. Standard errors are clustered by ZCTA.

Figure A7: Robustness: Effects of Friend-Exposure to Covid-19 on Daily Tiles Visited

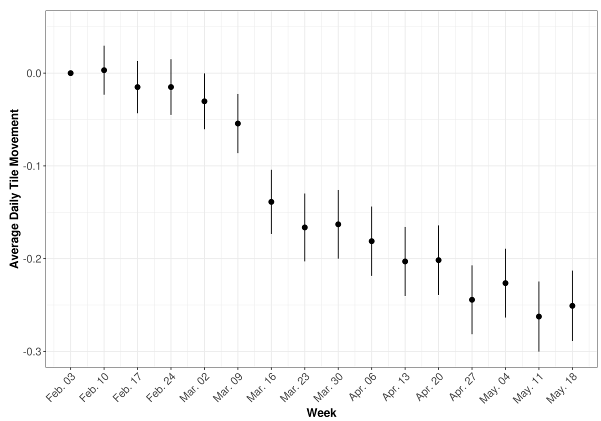
(a) Weekdays



(b) Weekends



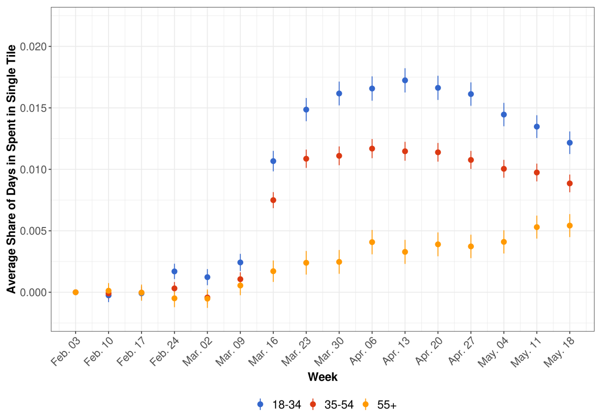
(c) Controlling for Exact College



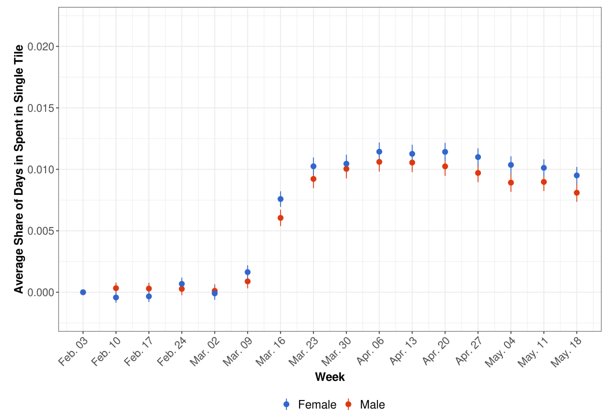
Note: Figures show coefficients estimated using the difference-in-differences setup specified in equation 2 with the outcome variable as the average number of Bing tiles visited. The outcome is measured on weekdays in panel (a) and weekends in panel (b). Panel (c) limits to individuals that attended college, limiting to colleges with more than 100 individuals, and adds a fixed effect for each individual college interacted with week. All specifications include fixed effects at the individual level as well as the following groups interacted with week: ZCTA; age group; gender; has college information in Facebook; has iPhone; has tablet; and percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. Standard errors are clustered by ZCTA.

Figure A8: Heterogeneity of Friend Effect: Probability of Staying at Home

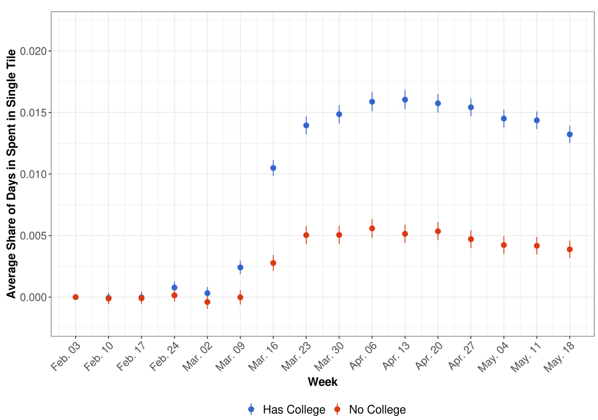
(a) Age



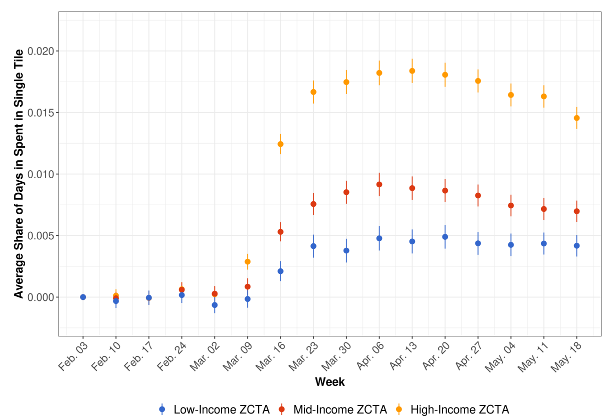
(b) Gender



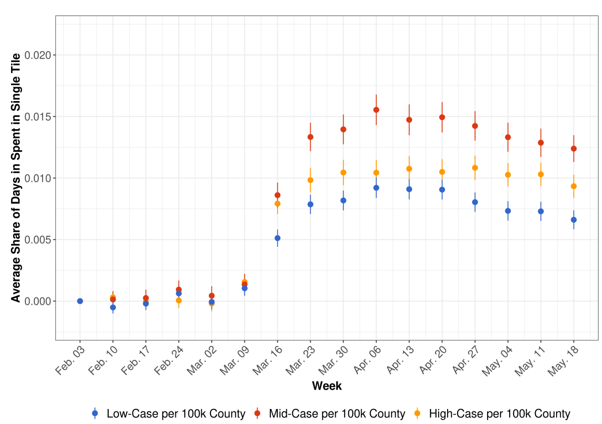
(c) Educational Attainment



(d) Income



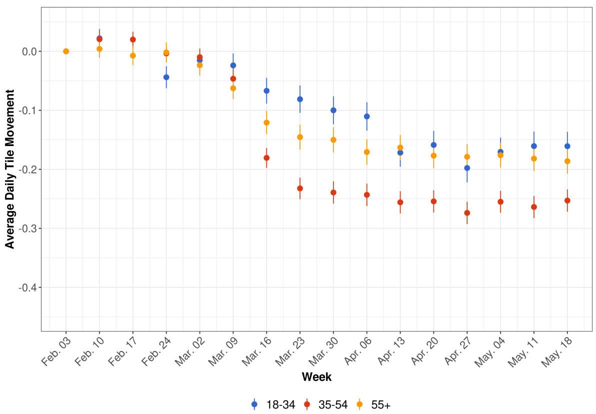
(e) Local Exposure to Covid-19



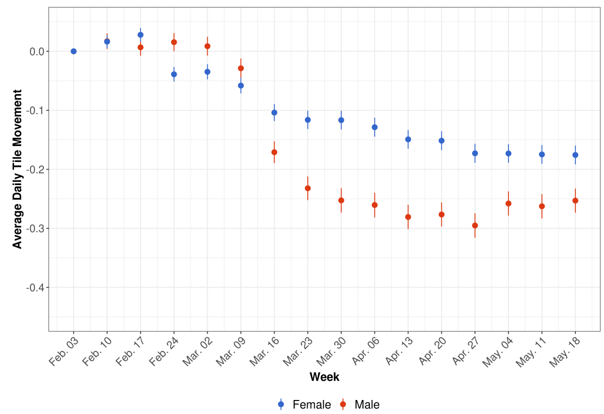
Note: Figures show coefficients estimated using versions of the difference-in-differences described in equation 2 with the outcome variable as the probability of staying at home. The heterogeneities interacted with exposure are: age in panel (a), gender in panel (b), whether the individual has a college listed on Facebook in panel (c); the tertile of home ZCTA median household income in panel (d); and the tertile of home county cases per resident as of March 15th in panel (e). All specifications include fixed effects at the individual level as well as the following groups interacted with week: ZCTA; age group; gender; has college; has iPhone; has tablet; and percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. Standard errors are clustered by ZCTA.

Figure A9: Heterogeneity of Friend Effect: Average Daily Tiles Visited

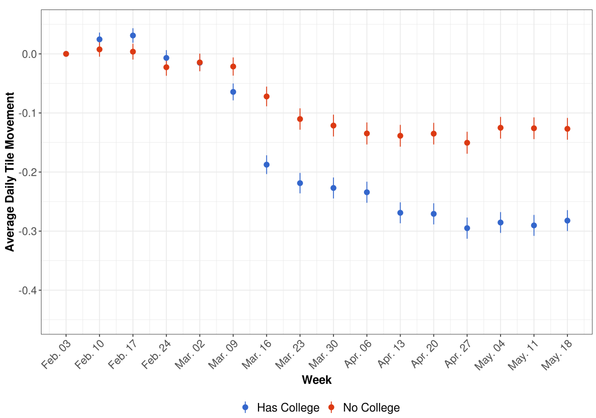
(a) Age



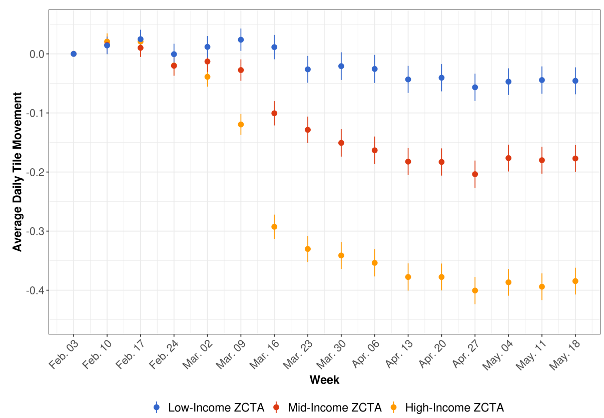
(b) Gender



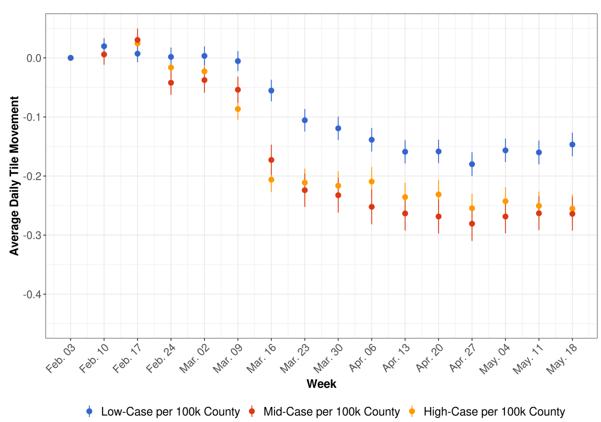
(c) Educational Attainment



(d) Income



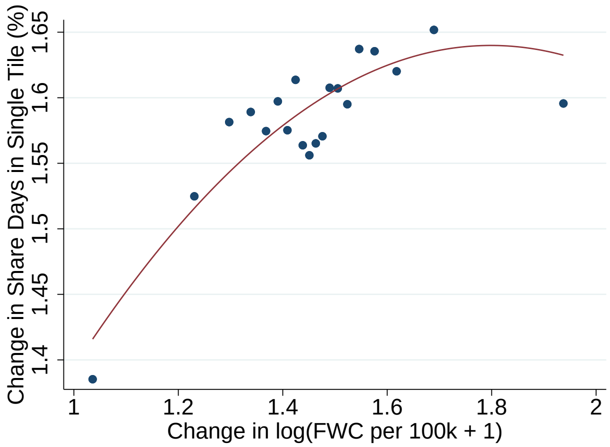
(e) Local Exposure to Covid-19



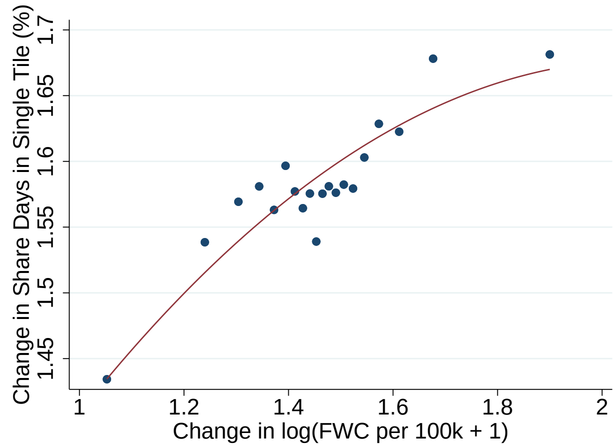
Note: Figures show coefficients estimated using versions of the difference-in-differences described in equation 2 with the outcome variable as the average daily tiles visited. The heterogeneities interacted with exposure are: age in panel (a), gender in panel (b), whether the individual has a college listed on Facebook in panel (c); the tertile of home ZCTA median household income in panel (d); and the tertile of home county cases per resident as of March 15th in panel (e). All specifications include fixed effects at the individual level as well as the following groups interacted with week: ZCTA; age group; gender; has college; has iPhone; has tablet; and percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. Standard errors are clustered by ZCTA.

Figure A10: Δ Probability of Staying at Home vs. Δ Friend-Exposure to Covid-19

(a) Without User Fixed-Effects



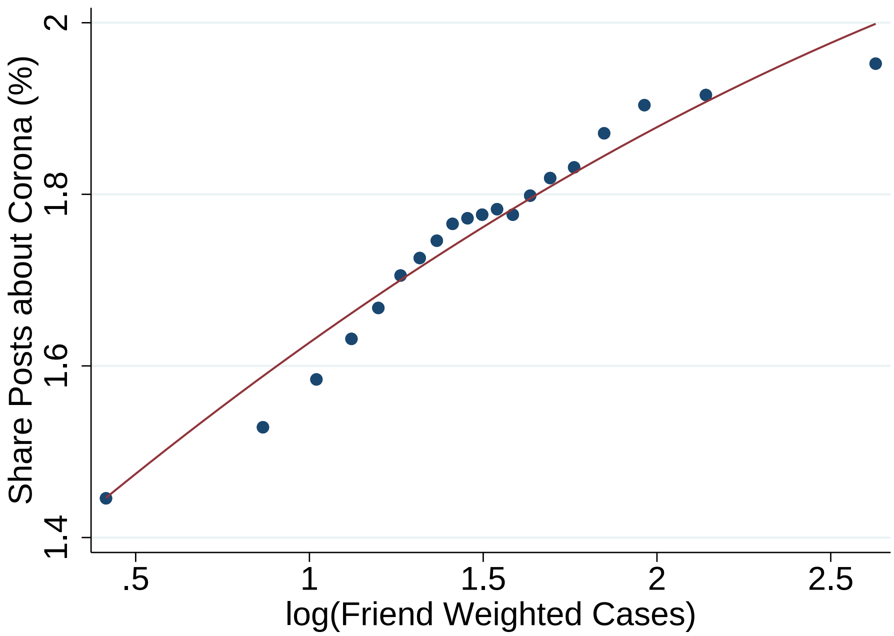
(b) With User Fixed-Effects



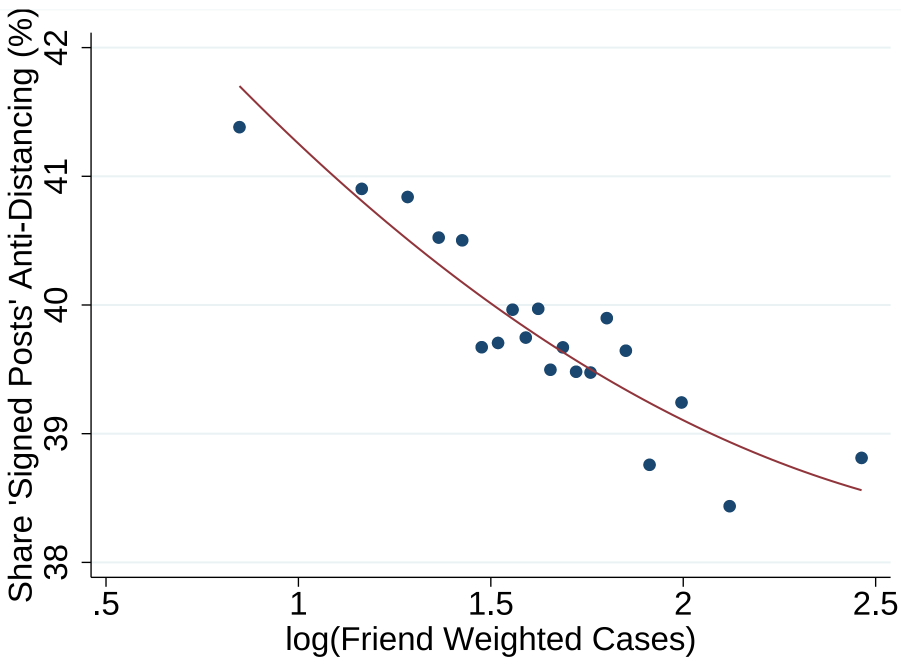
Note: Figure shows a binned scatter of the change in log friend-exposure to Covid-19 cases per 100k residents and the change in the probability of staying home. The underlying regressions are equation 5. Panel (a) corresponds to the first column of Table 2. Panel (b) adds user fixed-effects. Each observation is a unique individual and month for the months of March, April, May, June and July. Change in exposure is measured as of the last Friday of each month. Change in movement patterns is measured using the Tuesday to Monday week that includes each of these Fridays. Panel (a) includes fixed effects constructed by interacting dummies for the user's month, ZCTA, age group, gender, college background, and iPhone and tablet ownership. It also controls for month interacted with percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas. Panel (b) includes the same controls and also adds user fixed effects.

Figure A11: Posting Behavior vs. Friend-Exposure to Covid-19

(a) Share of Posts About Covid-19

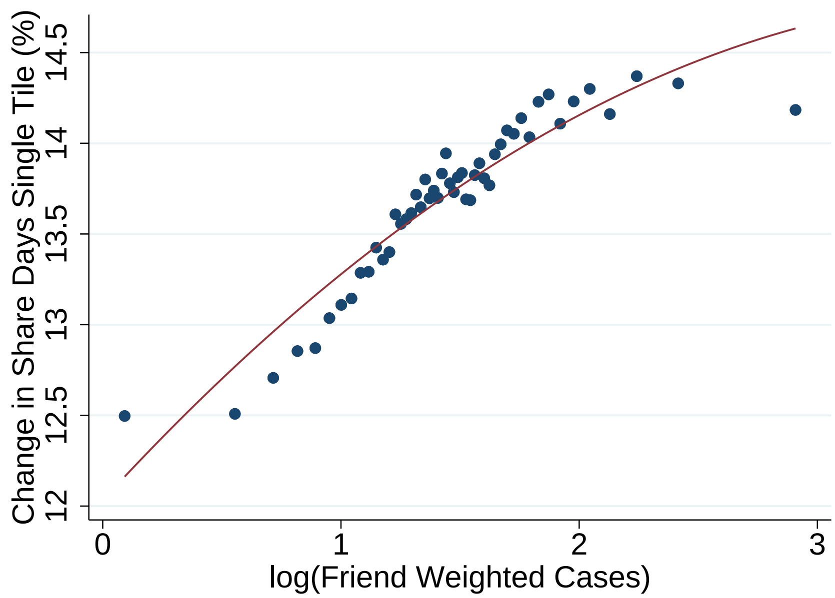


(b) Share of Signed Posts Opposing Distancing



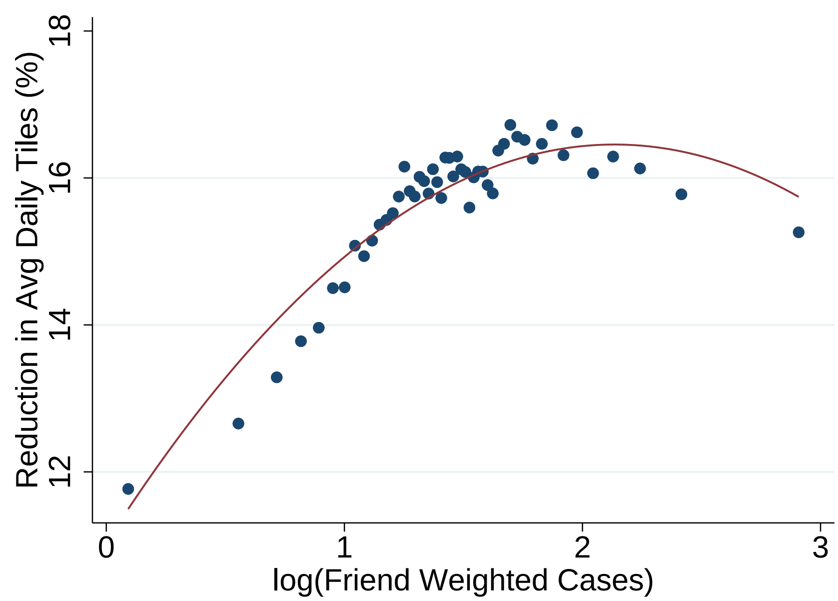
Note: Figures show binned scatter plots of the log of friend-exposure to Covid-19 on March 15th and Facebook post based measures. The outcome variable in panel (a) is the percentage of individual posts that are about Covid-19 and in panel (b) it is the percentage of pro- or anti-lockdown posts that are anti-distancing. Post classification is based on the regex in Appendix C. The plots control for fixed effects constructed from interacting dummies for one's ZCTA, age group, gender, college background, iPhone usage, and tablet usage. They also control for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas.

Figure A12: Probability of Staying at Home vs. Friend-Exposure to Covid-19



Note: Figure shows a binned scatter plot of the log of friend weighted friend-exposure to Covid-19 on March 15th and the change in probability of staying at home from the week of February 25-March 2, 2020 (prior to the pandemic) to April 14-20, 2020. The plot controls for fixed effects constructed from interacting the user's ZCTA, age group, gender, has a college listed on Facebook, and iPhone and tablet ownership. It also controls for percentiles of friend-exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas.

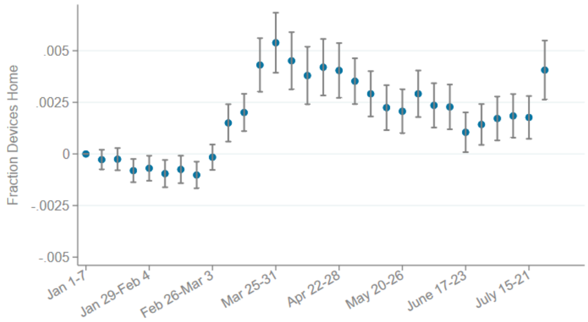
Figure A13: Percent Reduction in Average Number of Tiles Visited vs. Friend-Exposure



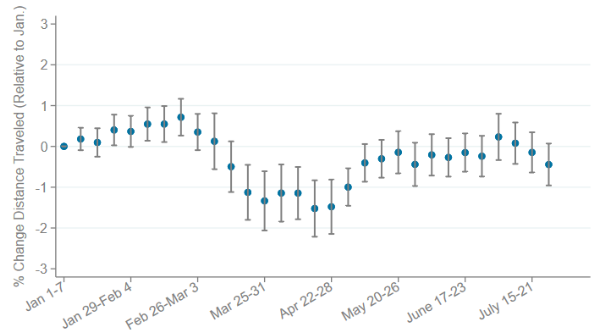
Note: Figure shows a binned scatter plot of the log of friend weighted friend-exposure to Covid-19 on March 15th and the percent reduction in average number of tiles visited from the week of February 25th to March 2nd (prior to the pandemic) to April 14th to 20th. The plot controls for fixed effects constructed from interacting the user's ZCTA, age group, gender, has college information in Facebook, and iPhone and tablet ownership. It also controls for percentiles of friend exposures (as described in equation 3) for median household income, population density and the share of the population living in urban areas.

Figure A14: Coefficient Estimates for β_t Equation A6

(a) Fraction of Devices Home



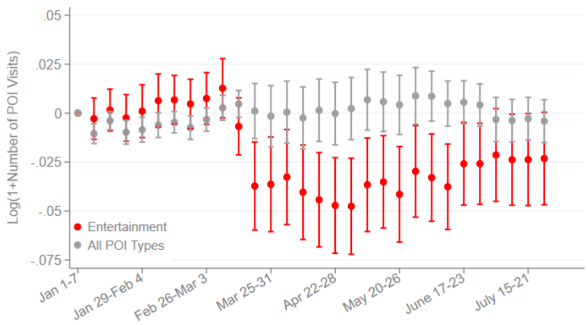
(b) Percentage Change Avg. Distance Traveled



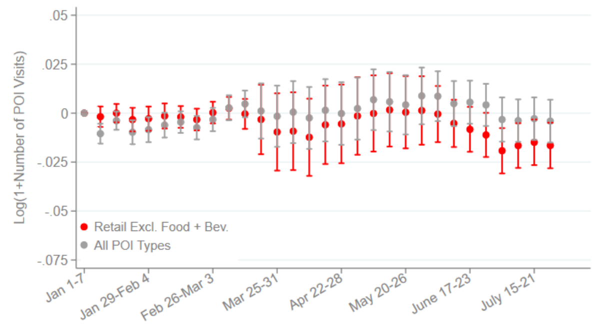
Note: Figures show coefficient estimates based on equation A6. In Panel (a), the dependent variable is the fraction of devices at home, while in Panel (b), the dependent variable is the percentage change in average distance traveled relative to the month of January 2020. The unit of observation is ZCTA by week. Regressions include a rich set of controls: in addition to ZCTA fixed effects and county fixed effects interacted with week indicators, we additionally control for a rich set of covariates interacted with week indicators. These covariates are the fraction of people being male, the fraction of Asian/black/white people, median household income, the fraction of individuals working in service occupations, the fraction of individuals working in production or transportation, the fraction of individuals working in management, arts or science, the fraction of individuals with a high school degree, some college education and a college degree as well as the fraction of households with high speed internet. We also include various age-related controls, i.e. the fraction of individuals 18 or younger, between 18 and 24, between 25-34, between 35-44, between 45-54, between 55-64, between 65-74 and above 75. All these control variables are obtained from the most recent 5-year ACS (2014-2018). In addition, we also control for ventiles of friend-exposure to other characteristics, namely income, population density (both from 2014-2018 ACS) and urbanity (from 2010 Census), again interacted with week indicators. Standard errors are clustered at the ZCTA-level.

Figure A15: Coefficient Estimates for Different Types of POI Places

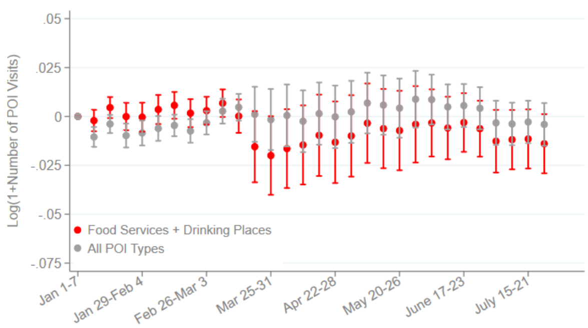
(a) Arts, Entertainment & Recreation



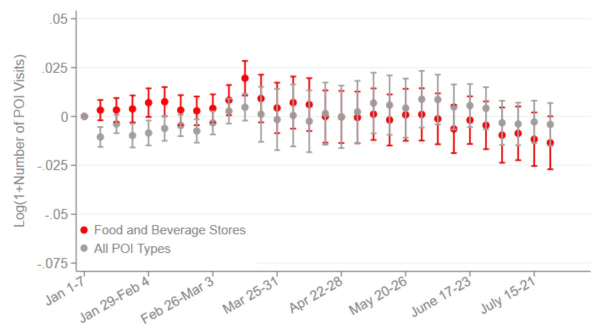
(b) Retail Trade, excl. Food & Beverage Stores



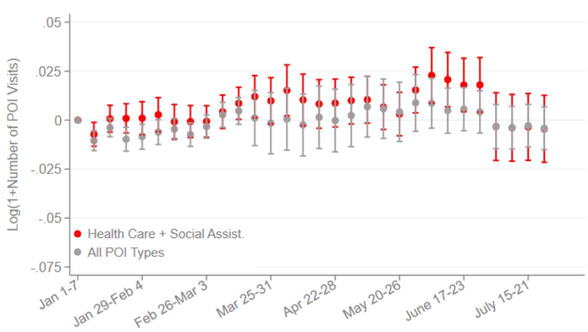
(c) Food Services & Drinking Places



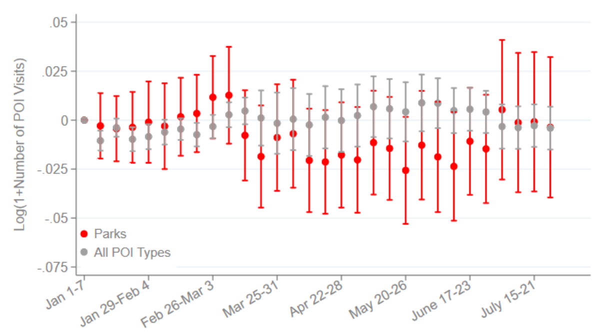
(d) Food & Beverage Stores



(e) Health Care & Social Assistance



(f) Parks



Note: Figures show coefficient estimates based on equation A6 for various types of POIs. For reference, we include estimates aggregating across all types of POIs in gray in all panels. We control for ZCTA fixed effects, county fixed effects interacted with week indicators as well as a rich set of covariates interacted with week indicators. These covariates are the fraction of people being male, the fraction of Asian/black/white people, median household income, the fraction of individuals working in service occupations, the fraction of individuals working in production or transportation, the fraction of individuals working in management, arts or science, the fraction of individuals with a high school degree, some college education and a college degree as well as the fraction of households with high speed internet. We also include various age-related controls, i.e. the fraction of individuals 18 or younger, between 18 and 24, between 25-34, between 35-44, between 45-54, between 55-64, between 65-74 and above 75. All these control variables are obtained from the most recent 5-year ACS (2014-2018). In addition, we also control for ventiles of friend-exposure to other characteristics, namely income, population density (both from 2014-2018 ACS) and urbanity (from 2010 Census), again interacted with week indicators. Standard errors are clustered at the ZCTA level.