Keep Your Distance! Modeling the Relationship Between Social Ecology and Changes in Geographic Mobility During the COVID-19 Pandemic

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ABSTRACT

In this paper, we examine whether relational mobility and historical pathogen prevalence on a country level relates to an individual's willingness or ability to restrict movement in response to the onset of the COVID-19 pandemic, both together an individually. We use data on geographic mobility compiled from geolocation data on mobile phones to examine aggregate changes in geographic mobility at the country-level at the onset of the COVID-19 pandemic, compared with a pre-pandemic baseline. We find that countries high in relational mobility showed a greater decrease in geographic mobility than countries low in relational mobility following the onset of the COVID-19 pandemic and stay-at-home orders. We also find that low pathogen prevalence at the country level was associated with increased case growth as well as decreased geographic mobility in response to the onset of the pandemic. These effects can be shown to work in tandem, with nations both high in relational mobility and low in pathogen prevalence being particularly able to reduce geographic mobility in response to pandemic conditions. These results suggest that increased flexibility in social relationships in high relational mobility nations may have enabled individuals to decrease geographic mobility in response to worsening pandemic conditions. This relational flexibility may be particularly important in environments low in pathogen prevalence when responding to pandemic viruses.

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Chapter 1

Introduction

The onset of the 2019 Coronavirus Disease (COVID-19) pandemic, precipitated in the early months of 2020 by the spread of a novel coronavirus (SARS-CoV-2) around the world, led to unprecedented changes in human behavior in a relatively short time frame. Faced with the prospect of a rapid spread of infections once this new virus was introduced, and lacking proven treatments or preventative vaccines, leaders around the globe made broad appeals to the general public to limit their geographic mobility through “social distancing”. However, the degree to which individuals were able to limit their geographic mobility when asked varied widely between countries, along with the efficacy of these pleas in reducing the spread of new COVID-19 cases when the virus was introduced. Given the prominent role limiting individual geographic mobility played in attempts to limit the spread of this infectious disease, it is vitally important to understand the varying cultural and socio-ecological factors which drive adherence to demands to limit geographic mobility.

While it is still somewhat unclear at this point why certain countries were more successful than others at limiting infections from spreading early on, researchers have examined a number of variables. As the pandemic progressed internationally, individual nations experienced varying levels of success in motivating the public to adhere to these NPIs over the long term. Some of this difference in mobility reduction may be explained by the timing of the imposition of different NPIs, which often varied both between (Lu et al., 2021) and within countries (Lasry et al., 2020). Outside of direct government orders to reduce mobility, there are important social-ecological factors that influence an individual's ability or motivation to reduce geographic mobility and practice "social distancing". Research has shown that factors including socioeconomic status (Ossimetha et al., 2021), general trust (Siegrist, Luchsinger, & Bearth, 2021), and personality differences (Chan et al., 2020) all play a role in determining an individual's motivation to decrease geographic mobility during the COVID-19 pandemic. Research has not yet considered the role of relational mobility, a social-ecological factor linked with an individual's ability to form relationships, in influencing overall ability to socially distance. Studies haven't yet explored the potential role of historical pathogen prevalence, a social-ecological factor linked to differences in behavioral change to avoid pathogens, in country-level differences in compliance with social distancing.

In considering compliance with social distancing during the pandemic, we conceptualized individuals as responding to two major exogenous "shocks" in propelling them towards a decision to reduce geographic mobility. The first of which is the discrete demands from politicians and public health officials to reduce geographic mobility through the imposition of stay-at-home (SAH) orders. Indeed, as one might expect, the imposition of these orders along with related business closures has been shown to drive decreases in geographic mobility

(Lasry et al., 2020). However, the decision to implement said SAH orders were not made in a vacuum, and we must therefore consider conditions brought about by the pandemic which individuals may respond to independently. In this way, analyses of the efficacy of SAH orders have been complicated by individuals responding to the conditions of the pandemic before the imposition of such orders (Chin et al., 2021; Berry et al., 2021). For this reason, we also consider the potential role of rising cases as a driver of decreases in geographic mobility early in the pandemic period.

Chapter 2

Study 1: Relational Mobility

Relational mobility is defined by how able individuals are in a given culture to form new relationships and terminate old ones (Schug, Yuki, Horikawa, & Takemura, 2007). In cultures high in relational mobility, individuals tend to have abundant opportunities to form new relationships and leave relationships that no longer suit their needs. In low relational mobility environments, individuals tend to have much fewer opportunities to form relationships, and there is less ease in terminating and leaving current relationships for new ones (Yuki & Schug, 2012). Thus, individuals in high relational mobility societies (e.g. the United States), being less constrained by current relationships, can more easily utilize opportunities to form new, more desirable interpersonal relationships. Individuals from societies low in relational mobility (e.g., Japan), however, being relatively less able to change relationships, are more invested in maintaining harmony within those long-lasting and difficult to change relationships with others.

Considering the relative ease in which individuals in high relational mobility environments can form and discard relationships relative to their low relational mobility peers, we may consider how this allows an individual to exert control over their existing relationships. Research has shown that individuals in low relational mobility contexts harbor an external locus of control and make more external attributions for their behavior (San Martin, Schug, & Maddux, 2019). That is, individuals in high relational mobility contexts make fewer external attributions for their behavior and may feel more empowered to exert control over their social relationships than do individuals in low relational mobility contexts. Furthermore, individuals in high relational mobility contexts display behavior more reflective of personal desires rather than avoiding negative reputation (e.g., Yamagishi, Hashimoto, & Schug, 2009; Yamagishi, Hashimoto, Li, & Schug, 2012) and are less sensitive to social rejection (Lou & Li, 2017). Therefore, they may be better able to forsake pre-existing social obligations to respond independently to fear of rising COVID-19 cases, recommendations from public health officials to reduce social contacts, or orders from government officials to stay home. As relational mobility is so closely related to one's ability to make and maintain friendships, and calls to limit mobility were targeted at reducing contacts outside of one's home, it stands to reason that relational mobility would play an important role in compliance with social distancing paradigms.

Methods

Geographic Mobility

To measure geographic mobility we utilized anonymized, aggregated data provided by Google's COVID-19 Community Mobility Reports (Google, LLC) at the country level. This data set maps geographic mobility by utilizing GPS data from individual smartphones of all users of Google Maps who have chosen to turn on anonymized data reporting. Mobility data is presented daily in the form of an average percent change compared with the median average mobility from the same day of the week in a pre-pandemic baseline (January 3rd, 2020 – February 6th, 2020). Geographic mobility is presented across a total of six distinct location categories: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and home/residential. For the home/residential category, geographic mobility was quantified by the change in *total time spent* to a home or residence, while all other categories were coded as the percent change in *total daily visits* to outlets Google Maps recognizes as belonging to a given category. For example, a value of "-20" in *grocery and pharmacy* on Sunday, March 3rd, 2020, would indicate that, on that date, total visits to locations coded on Google Maps as being grocery stores or pharmacies were down 20% compared to the median Sunday between January 3rd and February 6th, 2020. Data from COVID-19 Community Mobility Reports are available starting from February 15, 2020.

Similar to Chan et al. (2020), we used a Principal Components Analysis (PCA) with varimax rotation to create an aggregated measure of geographic mobility incorporating all six location categories from Google's Community Mobility Reports. This PCA yielded a single factor with an eigenvalue of 4.46, explaining 74.3% of the variance in mobility between the six categories. The extracted eigenvectors of this factor were 0.949 (*retail and recreation*), 0.870 (*grocery and pharmacy*), 0.620 (*parks)*, 0.925 (*transit stations*), 0.822 (*workplaces*), and -0.941 (*home/residential*). An overall geographic mobility measure was then computed daily for each country of interest by weighting the value of a given mobility category by its respective eigenvector and averaging across all five categories (excluding *parks*). The *parks* category was excluded due to its overall low factor loading and general variability between countries as to whether or not parks were included in politician's pleas with the public as places to avoid (Jacobsen & Jacobsen, 2020).

Relational Mobility

To quantify relational mobility, we used previously collected country-level relational mobility scores from Thomson and colleagues (2015) study. In this study, participants were recruited using Facebook advertisements and were then invited to complete a brief 'quiz' about their personal relationships. As part of this quiz, participants completed the relational mobility scale, a 12-item measure previously developed by Yuki and colleagues (2007). This instrument asks participants questions regarding how often other people in their prevailing social environment, and they individually, have opportunities to voluntarily enter new relationships and exit existing ones. Sample questions include: "They are able to choose, according to their own preferences, the people whom they interact with in their daily life" and "It is easy for them to meet new people". Thomson and colleagues collated these responses into country-level relational mobility scores, which were shown to correlate highly with similar constructs to relational mobility.

Control Variables

To quantify dates and strength of stay-at-home orders at the country level, values from Oxford University's Coronavirus Government Response Tracker (OxCGRT) (Hale et al., 2020) were used. On a daily basis, a value indicating the strength of a country's stay-at-home order was available, along with a separate value indicating the presence or lack of a stay-at-home order. This value was tracked on an ordinal scale ranging from a value of 0 ("no measures") to 3 ("require not leaving the house with minimal exceptions").

To control for differences in mobility which may be present on weekends as opposed to weekdays, which have been found to be endemic in other phone mobility samples (Yuan & Raubal, 2012), a variable indicating if a given day is a weekend or a weekday was included in our analysis. Each data point was dummy-coded as falling on a weekend (1) or a weekday (1). As the length of the workweek varies cross-nationally, Sunday - Thursday were considered "weekdays" for majority Muslim nations and Hong Kong was coded to have a 6-day working week (Wong & Ko, 2008).

Following Salvador and colleagues (2020), several demographic variables which may relate to the country-level spread of COVID-19 and therefore social distancing were included. Total population was included as larger groups would have more coronavirus cases, and population density was added as it is conceivable that infectious disease may spread more easily in dense environments where humans come into contact with one another more often. Net migration (number of individuals entering versus exiting country per 1,000) was included to control for overall population-level movement which could influence measures of geographic mobility. Median age was added as COVID-19 shows a sharp age gradient wherein older populations are more vulnerable to serious illness. To control for overall urban development at the country level GDP per capita was included, along with the percent of the overall population which resides in urban environments (percent urban).

Study 1 - Results

Changes in geographic mobility following the issuance of Stay-At-Home order

First, we sought to determine if cross-cultural differences in relational mobility would predict responsiveness to measures put in place by government agencies to curb the spread of COVID-19, such as stay-at-home (SAH) orders. We suspected that the issuance of a SAH order would be a clear cue altering individuals to modify their behavior and patterns of socialization, potentially leading to behavior change.

As countries differed considerably in the time of the first issuance of a SAH order in response to the COVID-19 pandemic, data in these analyses were centered on the day that the first SAH order was enacted in a given country. For example, some countries implemented SAH policies much later than others (e.g. Japan) or did not issue SAH orders at all (e.g. Sweden). To center this variable, the first day a country issued a SAH order was coded as “day zero”. For instance, Australia first enacted a SAH order on March 24th, and Japan declared a SAH order on April 4th -- both of these dates would be input as ‘day zero’ into the model. As Sweden never initiated SAH orders, this country is omitted from the analysis. Furthermore, Hong Kong had implemented SAH orders before February 15th, the first date for which geographic mobility data were available. Thus, data for Hong Kong begin on day 7.

Countries also varied in how long SAH orders were initially issued for, and whether or not SAH orders were re-issued during the study period. For these analyses, we only examined data corresponding with the issuance of a nation’s first SAH order, excluding data relating to any subsequent reissued SAH orders. Thus, we examined only the first 30 days after the issuance of the first SAH order in a given country.

The strength of what constituted a SAH order varied considerably at the country level. In some cases governments only recommended individuals stay home whenever possible, while other nations had mandates with strict enforcement requiring individuals to only leave home in special circumstances. Thus, we used OxCGRT data to create a dummy variable indicating whether a given country’s SAH orders were mandatory (“require not leaving house with exceptions for daily exercise, grocery shopping, and ‘essential’ trips” and “require not leaving house with minimal exceptions”) or recommended (“recommend not leaving house”).

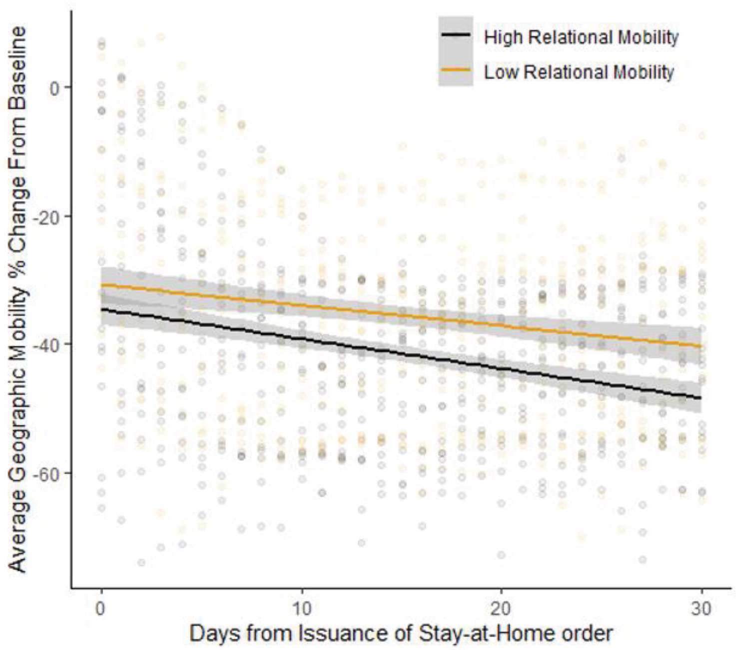
Table 1.
The impact of relational mobility on geographic mobility following the issuance of Stay-at-Home orders in each country

	Model 1				Model 2			
Predictors	Estimate	*(SE)*	95 % CI	*p*	Estimate	*(SE)*	95 % CI	*p*
(Intercept)	-32.27	2.71	-37.59 – -26.95	<.001	-40.88	(19.53)	-79.16 – -2.60	.036
Relational Mobility (RM)	-1.78	11.84	-24.97 – 21.42	.881	5.64	(11.46)	-16.82 – 28.09	.623
Day from Stay-at-home order	-0.42	0.08	-0.57 – -0.27	<.001	-0.62	(0.08)	-0.78 – -0.46	<.001
RM × Day from Stay-at-home order	-0.36	0.14	-0.63 – -0.08	.011	-0.78	(0.21)	-1.20 – -0.37	<.001
Stay-at-Home (SAH) Order Mandatory					-19.81	(1.19)	-22.13 – -17.48	<.001
RM × SAH Order Mandatory					-2.76	(6.68)	-15.85 – 10.33	.68
Day × SAH Order Mandatory					0.46	(0.06)	0.33 – 0.58	<.001
RM × Day × SAH Order Mandatory					0.21	(0.28)	-0.33 – 0.75	.45
Weekend					0.58	(0.51)	-0.41 – 1.57	.254
Population Density					0.30	(1.11)	-1.88 – 2.48	.789
Population (Thousands)					5.54	(3.60)	-1.51 – 12.59	.124
Median Age					0.15	(0.43)	-0.69 – 0.99	.727
Net Migration					-0.22	(0.46)	-1.12 – 0.68	.631
GDP per capita					1.45	(3.49)	-5.39 – 8.29	.678
% Urban Population					0.13	(0.17)	-0.20 – 0.45	.443
Random Effects								
σ2	65.15				50.86			
τ00 Country	184.6				127.82			
τ00 Day from Stay-at-home order	12.32				9.25			
ICC	0.75				0.73			
N Countries	33				33			
N Day from Stay-at-home order	31				31			
Total N	1016				1016			
Marginal R2 / Conditional R2	0.060 / 0.766				0.337 / 0.821			

The results are presented in Table 1. The results show a significant negative effect of day (estimate= -.42, p <.001) and a significant day × relational mobility interaction (estimate= -.36, p<.011). This indicates that, while geographic mobility tended to decrease over time from the start of an issued SAH order, it decreased to a greater extent in nations higher in relational mobility (Figure 1). These results suggest that individuals in countries with higher relational mobility were more likely than individuals in countries with lower relational mobility to decrease their geographic mobility in response to the issuance of SAH orders. These results remained significant when control variables, and an additional variable indicating if a SAH order was mandatory (1) or not (0), were added to our second model. Further, there was not a significant relationship between the strength of a nation's SAH order and level of relational mobility, indicating that these results cannot be explained by higher relational mobility nations having stronger SAH measures on average.

Figure 1

The impact of high vs. low relational mobility on geographic mobility following the issuance of Stay-at-Home orders



This analysis offers some support for the theory that individuals in high relational mobility environments are better able to exert control over social contacts and comply with SAH orders. In case of our first "shock" aimed at motivating behavior change, discrete SAH orders from government officials, it appears as though individuals with greater relational mobility were more able or willing to comply with such orders by reducing visits to entertainment venues and other areas frequented by social groups. As these analyses considered strength of SAH orders, it is not simply the case that low relational mobility nations more strongly urged their citizens to stay home. Next, we consider if this result will replicate with mere awareness of rising COVID-19 cases outside of discrete SAH orders.

Changes in geographic mobility at the onset of the COVID-19 pandemic

Next, we sought to examine whether or not changes in geographic mobility could be found in response to growth in COVID-19 cases during the initial onset of the pandemic, as opposed to individuals responding to discrete orders to limit geographic mobility as seen in the case of SAH orders. We propose that increasing case levels in the surrounding community should correspond with decreases in geographic mobility as individuals react to increasing infection risk by altering their behavior. Further, we expected that individuals from nations high in relational mobility would experience a greater decrease in geographic mobility, as they are more readily able to exert control over their social relationships outside the home.

To examine this possibility, we utilized a series of linear mixed-effects models to determine if relational mobility at the country-level predicted differences in change in geographic mobility during the initial onset of the COVID-19 pandemic. In these models, we utilized the same time periods examined by Salvador and colleagues (2020), who defined the onset of the pandemic as beginning when a country reached 100 COVID-19 cases and extending for 30 days.

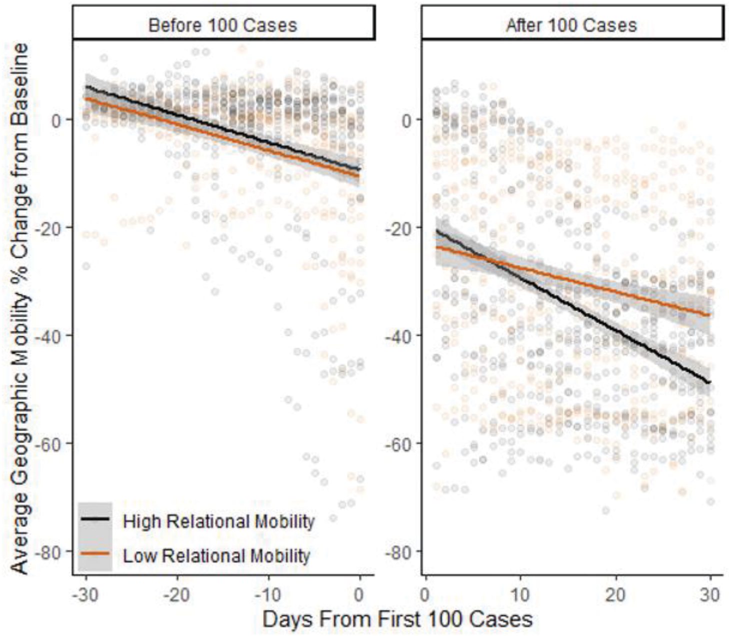
Table 2.
The impact of relational mobility on geographic mobility following the first 100 cases of COVID-19 in each country

Predictors	Estimate	*(SE)*	95 % CI	*p*	Estimate	*(SE)*	95 % CI	*p*
(Intercept)	-20.6	(2.88)	-26.24 – -14.96	<.001	-51.97	(20.28)	-91.71 – -12.23	.01
Relational Mobility (RM)	13.57	(13.71)	-13.31 – 40.44	.322	-4.09	(11.60)	-26.83 – 18.66	.725
Days from 100 cases	-0.77	(0.05)	-0.88 – -0.67	<.001	-0.41	(0.04)	-0.49 – -0.34	<.001
RM × Days from 100 cases	-1.27	(0.17)	-1.60 – -0.94	<.001	-0.70	(0.16)	-1.01 – -0.39	<.001
Stay-at-Home order in effect					-9.34	(0.55)	-10.41 – -8.27	<.001
Weekend					-0.75	(0.63)	-1.99 – 0.50	.239
Population Density					0.24	(1.16)	-2.04 – 2.52	.836
Population (Thousands)					6.16	(3.76)	-1.20 – 13.53	.101
Median Age					0.09	(0.45)	-0.78 – 0.97	.834
Net Migration					-0.08	(0.48)	-1.02 – 0.87	.875
GDP per capita					4.95	(3.65)	-2.21 – 12.10	.176
% Urban Population					0.23	(0.17)	-0.11 – 0.57	.191
Random Effects								
σ2	100.69				82.27			
τ00 Country	252.89				139.24			
τ00 Days from 100 cases	3.91				0.18			
ICC	0.72				0.63			
N Countries	34				33			
N Days from 100 cases	31				31			
Total N	1054				1023			
Marginal R2 / Conditional R2	0.132 / 0.756				0.503 / 0.816			

In this analysis we examined an initial model predicting decreases in geographic mobility from relational mobility, day, and a relational mobility × day interaction term to capture whether or not relational mobility would influence decreases in geographic mobility over time, with intercepts for country and day acting as random effects. We then repeated this same model with the addition of control variables previously described. As shown in Table 2, a significant effect of day (estimate= -.77, p <.001) and an interaction between day and relational mobility (estimate= -1.27, p <.001) was found. This indicates that geographic mobility decreased over time, with this decrease being influenced by country-level relational mobility.

Figure 2

The impact of high vs. low relational mobility on geographic mobility before and after the first 100 cases of COVID-19



As shown in Figure 2, individuals in countries with higher levels of relational mobility showed a relatively greater decrease in their geographic mobility over time when compared with countries low in relational mobility. This same relationship was not found before the onset of the COVID-19 outbreak period, suggesting that this difference is likely due to the awareness of exponential growth in cases rather than other factors unrelated to the pandemic.

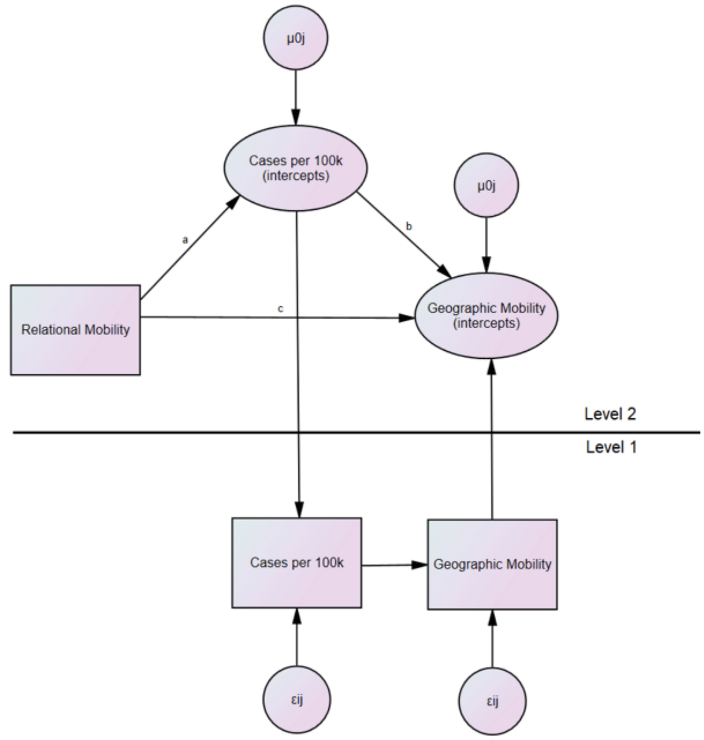
These results are similar to the findings in our previous SAH analysis, supporting the idea that high relational mobility allowed individuals more flexibility in their relationships to respond to the threat of COVID-19 by reducing their geographic mobility. Lack of a difference in mobility pre-outbreak indicates it is unlikely that this difference is simply due to lower geographic mobility in general amongst high RM nations, and is instead a response to pandemic conditions.

There are, however, alternative hypotheses that may be deployed to explain this phenomenon. For example, as high relational mobility is associated with faster case growth (Salvador et al., 2020), some may argue that this effect may be simply an artifact of aggregate differences in case growth. To address this possibility, we use a series of lagged analyses and a mediation model.

Relationship between case growth and geographic mobility decrease

Earlier analyses cannot exclude the possibility that changes in case levels brought about by differences in relational mobility (as in Salvador et al., 2020) are leading to downstream changes in geographic mobility. That is, there is not necessarily a direct relationship between relational mobility and changes in geographic mobility, the previously observed relationship is a spurious result of the relationship between COVID-19 case growth and relational mobility. To determine if this is the case, we constructed a multi-level mediation model using the Lavaan package (Rosseel, 2012) for the R statistical software package, as well as a series of linear mixed-effects models, similar to our previous analyses, utilizing 7-day lagged variables to establish temporal precedence and probe the previously described moderation effect.

Figure 3
Multi-level mediation model

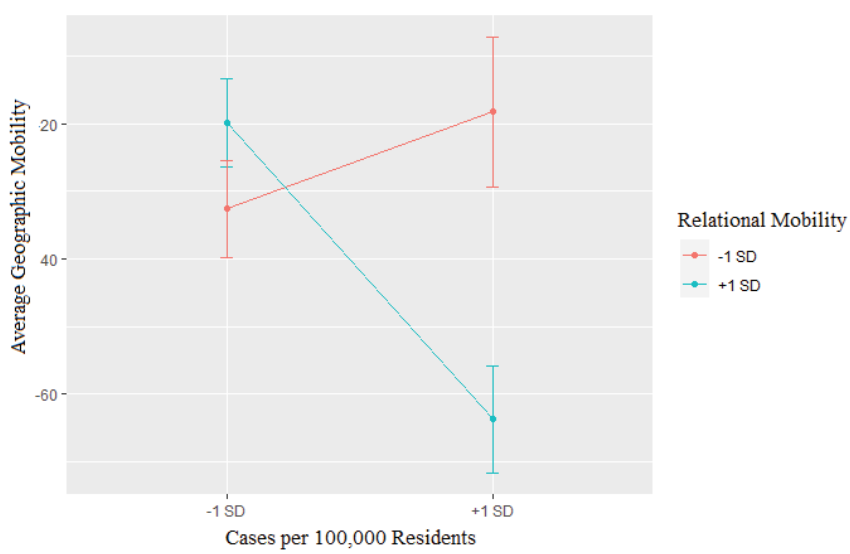


To determine if the relationship between relational mobility and geographic mobility is mediated by growth in COVID-19 cases, a multi-level mediation model (see: Figure 3) with geographic mobility predicted by relational mobility, as mediated by cases per 100,000 population. In this analysis relational mobility is a level 2 variable while cases and geographic mobility are level 1 variables. The indirect effect of relational mobility on geographic mobility through cases was found to be not statistically significant (estimate = -.34, p = .92), indicating case growth is likely not mediating this effect. This finding points to the previous finding, relating high relational mobility to decreased geographic mobility after 100 COVID-19 cases, is not entirely explainable by the overall effect of rising cases and there is likely something unique about high RM cultures which enables individuals to decrease geographic mobility.

Next, a series of linear mixed-effects models were run using the LME4 (Bates et al., 2014) in R, similar to previous analyses, with the inclusion of country-level relational mobility, control variables selected from Salvador and colleagues (2020) and COVID-19 cases normalized per 100,000 population predicting geographic mobility. As before, analyses were limited to the first 30 days after a country reached 100 COVID-19 cases. A significant interaction was found between cases per 100,00 and relational mobility (estimate = -4.61, $p < .001$), such that individuals from nations high in relational mobility decreased geographic mobility to a greater degree than individuals from countries low in relational mobility, particularly when cases were high (Figure 4).

Figure 4

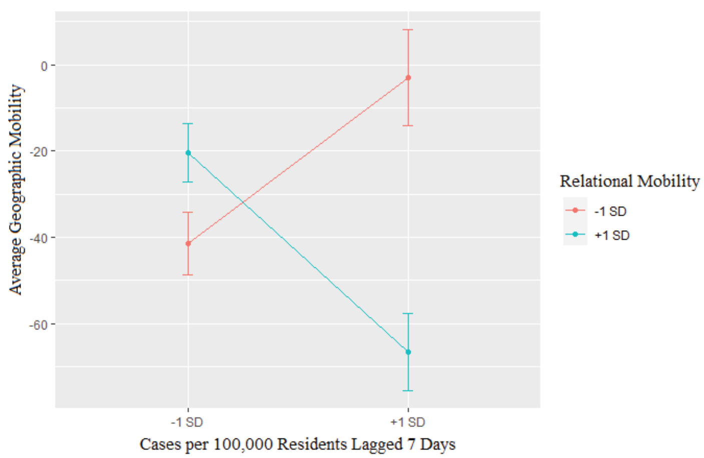
Influence of relational mobility on the effect of population-adjusted case-levels on average geographic mobility



To establish temporal precedence as to whether individuals were decreasing geographic mobility in response to increasing cases or vice versa, we ran another series of linear mixed-effects models utilizing a series of lagged variables. In our first analysis, we included relational mobility, a population-adjusted measure of COVID-19 cases lagged seven days prior, and all control variables described previously predicting current geographic mobility. Here, a significant interaction between lagged cases and relational mobility was found (estimate = -13.74, $p < .001$), suggesting that high case levels one week earlier predicted a greater subsequent decrease in geographic mobility in high relational mobility countries (Figure 5).

Figure 5

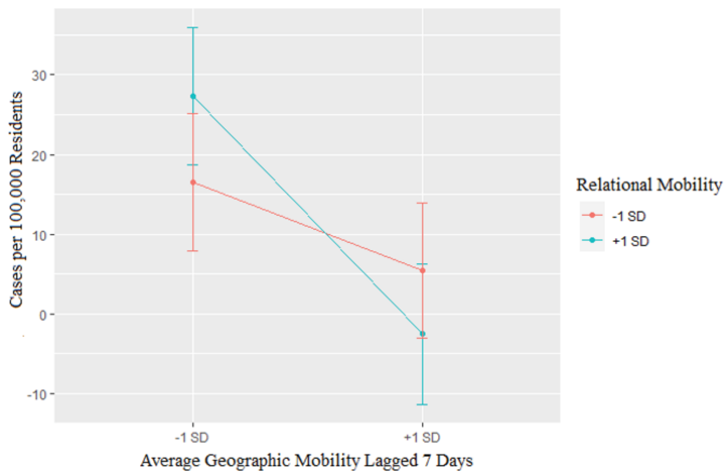
Influence of relational mobility on the effect of population-adjusted case-levels (lagged 7 days previous) on average geographic mobility



Another linear mixed effect model was also run including relational mobility, geographic mobility, and previously enumerated control variables predicting current case levels. In this analysis, no significant interaction between lagged changes in geographic mobility and relational mobility was found (estimate = -.43, $p = .142$). Paradoxically, it appears that lower geographic mobility seven days prior was associated with somewhat higher cases at present (Figure 6). This appears to support the idea that case levels are driving decreases in geographic mobility as moderated by relational mobility, and not the opposite. Based on this data it is more likely that relational mobility influences an individual's ability to decrease geographic mobility in response to increasing case levels, rather than relational mobility driving changes in geographic mobility which subsequently lead to decreasing case levels.

Figure 6

Influence of relational mobility on the effect of average geographic mobility (lagged 7 days previous) on population-adjusted cases



Chapter 3

Study 2: Pathogen Prevalence

Potential infection by dangerous pathogens has been a concern humanity has dealt with since antiquity (Dobson & Carper, 1996). Similar to many animal species, which have developed discrete mechanisms for detecting disease in (and subsequently avoiding) their compatriots (Behringer, Butler, & Shields, 2006; Kavaliers & Colwell, 1995), evolutionary theorists believe humans have evolved a "behavioral immune system" (BIS) tuned to avoid infection by pathogens (Schaller & Duncan, 2007). The BIS is tuned to allow individuals to avoid potentially costly infection by pathogens, particularly those harbored by out-group members which the individual may not have previous immunity for (Murray & Schaller, 2016). Unfortunately, as this system is refined by the experiences of ancient humans, the oversensitivity of this system sometimes results in errors in judgement in our modern world. BIS hyperactivity in areas high in pathogen threat has been correlated with increases in xenophobic attitudes (Faulkner et al., 2014) and prejudice (O'Shea et al., 2019).

In considering the COVID-19 pandemic, the influence of historical pathogen prevalence on the spread of and the response to the virus has been inconclusive. Some researchers argue that the BIS may not be tuned to respond to pandemic respiratory viruses such as COVID-19, as such viruses spread in ways that would be unfamiliar or unlikely to be encountered by our ancient ancestors (Ackerman, Tybur, & Blackwell, 2020). However, experiments have shown that at the individual level, high levels of BIS-related variables including pathogen disgust and germ aversion (Shook et al., 2020), or trait pathogen avoidance (Makhanova & Shepherd, 2020) have been associated with increased concern and endorsement of behaviors meant to avoid COVID-19 including social distancing. Likewise, at the country level, high historical pathogen prevalence has been associated with swifter action to implement NPIs and greater reduction in geographic mobility later in the pandemic period (Lu et al., 2021). It is not yet known if historical pathogen prevalence is associated with changes in country-level response to stay-at-home orders or differences in case growth and geographic mobility early in the pandemic period.

Study 2 – Methods

In this second investigation, we use a series of linear mixed-effects models to test the influence of pathogen prevalence on changes in geographic mobility in response to SAH orders and case growth in early outbreaks, similar to Study 1. As it is not yet known whether or not pathogen prevalence is associated with differences in case growth early in country-level outbreaks, we used a series of linear mixed-effects models similar to that of Salvador and colleagues (2020). All control variables referenced in Study 1 were included in secondary models in this study as well.

Pathogen Prevalence

As a measure of country-level pathogen prevalence, historical values previously obtained by Fincher and colleagues (2008) were utilized. To create this measure, researchers estimated the prevalence of nine pathogens (leishmanias, trypanosomes, malaria, schistosomes, filariae, leprosy, dengue, typhus, and tuberculosis) through old atlases of infectious disease and other epidemiological records. The prevalence estimates of these nine diseases were then coded on three or four-point scales and standardized into z-scores. The mean of these nine standardized z-scores would become the estimate of a region's historical pathogen prevalence. For this measure historical, rather than contemporary, pathogen prevalence values were used in order to capture potential adaptations to pathogen prevalence which may take place over the course of centuries.

Study 2 - Results

Effect of historical pathogen prevalence on the spread of COVID-19 cases

While relational mobility has been shown to influence the spread of COVID-19 in the early stages of country-level outbreaks (Salvador et al., 2020), research has not yet shown if historical pathogen prevalence influences early trends in COVID-19 cases. To test this, a series of linear mixed-effects models predicting both population-adjusted daily COVID-19 cases per 100,000 residents and log-transformed cases (to account for exponential growth early in the pandemic period) were utilized. Two models were run – an initial model only considering historical pathogen prevalence and days from the first 100 cases in a region, and a second model including demographic control variables previously mentioned. As higher historical pathogen prevalence has been associated with quicker imposition of NPIs including stay-at-home (SAH) orders (Lu et al., 2021), whether or not a SAH order was issued on a given day was included in our second model as well. As in Salvador and colleagues, our days variable was centered around the day in which a country reached 100 reported COVID-19 cases (“day zero” of the outbreak).

Table 3.

The impact of pathogen prevalence on COVID-19 cases per 100,00 residents following the first 100 cases in country-level outbreaks

	Model 1				Model 2			
Predictors	Estimate	*(SE)*	95 % CI	*p*	Estimate	*(SE)*	95 % CI	*p*
(Intercept)	-3.4	(3.51)	-10.27 – 3.47	0.332	-15.44	(10.05)	-35.13 – 4.25	0.124
Pathogen Prevalence (PP)	3.88	(5.43)	-6.77 – 14.53	0.475	22.76	(4.11)	14.70 – 30.81	<0.001
Day from 100 cases	1.44	(0.05)	1.34 – 1.54	<0.001	1.13	(0.08)	0.98 – 1.29	<0.001
PP × Day from 100 cases	-1.9	(0.07)	-2.03 – -1.76	<0.001	-1.22	(0.06)	-1.34 – -1.11	<0.001
Stay-at-Home (SAH) Issued					4.84	(0.69)	3.50 – 6.19	<0.001
Population Density					-3.27	(1.2)	-5.64 – -0.91	0.007
Population (Thousands)					-2.16	(1.13)	-4.38 – 0.07	0.057
Median Age					0.6	(0.26)	0.09 – 1.12	0.022
Net Migration					0.53	(0.31)	-0.07 – 1.13	0.085
GDP per capita					11.75	(2.13)	7.58 – 15.91	<0.001
% Urban Population					-0.2	(0.09)	-0.38 – -0.01	0.035
Random Effects								
σ2	468.07				260.99			
τ00 Country	1221.03				174.27			
τ00 Day from Stay-at-home order	1.82				10.85			
ICC	0.72				0.41			
N Countries	106				83			
N Day from Stay-at-home order	31				31			
Total N	3250				2537			
Marginal R2 / Conditional R2	0.237 / 0.789				0.462 / 0.685			

The results predicting cases per 100,000 residents can be found in Table 3. The results show a significant positive effect of day (estimate= -1.44, *p* <.001) and a significant day × pathogen prevalence interaction (estimate= -1.90, *p* <.001). This indicates that cases generally increased from the start of an outbreak, as one might expect. The interaction term here indicates that COVID-19 cases generally grew at a faster rate in countries low in historical pathogen prevalence (See Figure 7). These results remained significant in our second model, with the inclusion of demographic and SAH-related variables.

Figure 7

Influence of pathogen prevalence on growth of population-adjusted COVID-19 cases over time from outbreak start

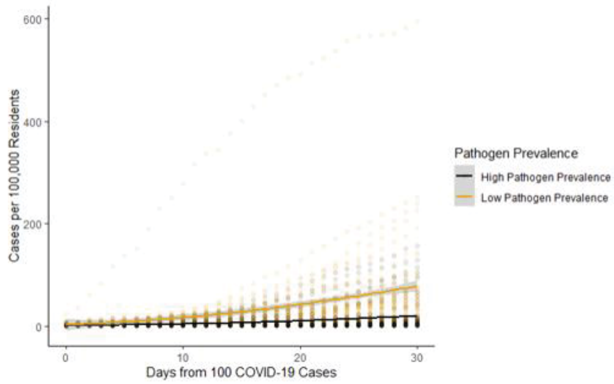


Table 4.

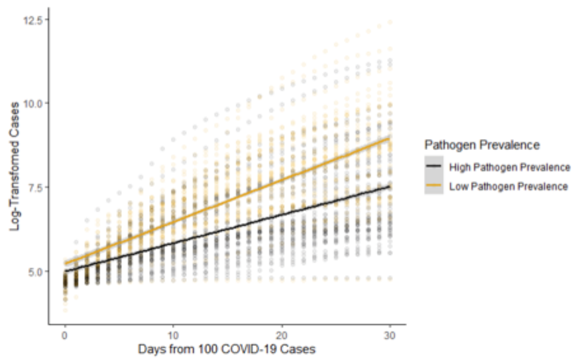
The impact of pathogen prevalence on log-transformed COVID-19 cases following the first 100 cases in country-level outbreaks

	Model 1				Model 2			
Predictors	Estimate	*(SE)*	95 % CI	*p*	Estimate	*(SE)*	95 % CI	*p*
(Intercept)	5.1	0.1	4.90 – 5.31	<0.001	3.96	(0.59)	2.80 – 5.12	<0.001
Historical Pathogen Prevalence (HPP)	-0.2	-0.13	-0.46 – 0.06	0.134	0.4	(0.24)	-0.07 – 0.87	0.096
Day from 100 cases	0.1	(0)	0.09 – 0.11	<0.001	0.1	(0)	0.09 – 0.10	<0.001
HPP × Day from 100 cases	-0.04	(0)	-0.04 – -0.03	<0.001	-0.03	(0)	-0.03 – -0.02	<0.001
Stay-at-Home (SAH) Issued					0.29	(0.02)	0.25 – 0.33	<0.001
Population Density					-0.23	(0.07)	-0.37 – -0.09	0.002
Population (Thousands)					0.21	(0.07)	0.08 – 0.34	0.002
Median Age					0.03	(0.02)	-0.00 – 0.06	0.058
Net Migration					0.03	(0.02)	-0.00 – 0.07	0.08
GDP per capita					0.35	(0.13)	0.10 – 0.60	0.005
% Urban Population					0	(0.01)	-0.01 – 0.01	0.948
Random Effects								
σ2	0.22				0.22			
τ00 Country	0.73				0.64			
τ00 Day from Stay-at-home order	0.03				0.02			
ICC	0.78				0.75			
N Countries	105				83			
N Day from Stay-at-home order	31				31			
Total N	3219				2537			
Marginal R2 / Conditional R2	0.532 / 0.896				0.618 / 0.904			

We found similar results when predicting natural log-transformed cases, complete results of which can be found in Table 4. A positive relationship was found between days from the first 100 cases in a given country and log-transformed cases (estimate= .10, p <.001), indicating that cases grew exponentially from the start of the outbreak period. Similar to the previous analysis, a significant interaction was found between days and pathogen prevalence (estimate= -.40, p <.001), indicating that cases in low pathogen prevalence environments grew exponentially quicker than did cases in higher pathogen prevalence nations (Figure 8).

Figure 8

Influence of pathogen prevalence on growth of log-transformed COVID-19 cases over time from outbreak start



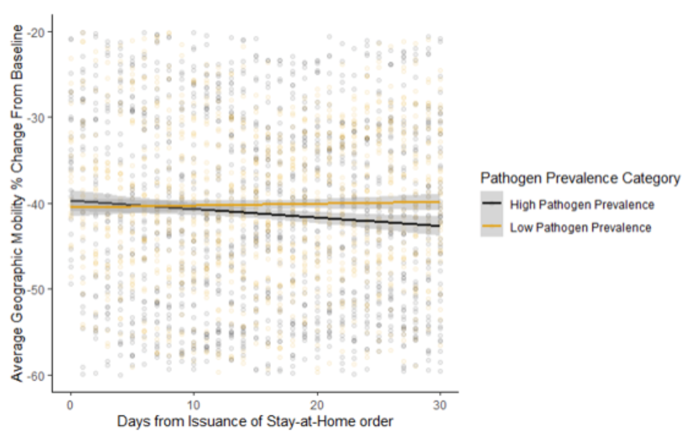
Changes in geographic mobility following the issuance of Stay-At-Home order

The results of a similar analysis utilizing historical pathogen prevalence values at the country level, instead of relational mobility, is available in Table 5. In this analysis, a significant negative effect of day (estimate= -.40, p < .001) and a positive Day × Pathogen Prevalence interaction (estimate = .11, p < .001) was found. This indicates that, as in our previous analysis, geographic mobility decreased over time after the issuance of a SAH order. The interaction term indicates that individuals from nations high in pathogen prevalence tended to reduce geographic mobility in response to SAH orders to a greater degree than individuals from low pathogen prevalence nations (Figure 9). These effects both remained when control variables were added in Model 2.

Table 5.
The impact of pathogen prevalence on geographic mobility following the issuance of Stay-at-Home orders in each country

	Model 1				Model 2			
Predictors	Estimate	*(SE)*	95 % CI	*p*	Estimate	*(SE)*	95 % CI	*p*
(Intercept)	-31.59	(1.68)	-34.89 – -28.29	<0.001	-18.89	(8.01)	-34.59 – -3.20	0.018
Pathogen Prevalence (PP)	-0.78	(2.03)	-4.75 – 3.20	0.702	-4.62	(3.26)	-11.01 – 1.77	0.157
Day from Stay-at-home order	-0.4	(0.06)	-0.53 – -0.27	<0.001	-0.43	(0.07)	-0.56 – -0.29	<0.001
PP × Day from Stay-at-home order	0.11	(0.03)	0.06 – 0.16	<0.001	0.14	(0.05)	0.05 – 0.23	0.003
Stay-at-Home (SAH) Order Mandatory					-12.21	(0.86)	-13.90 – -10.52	<0.001
RM × SAH Order Mandatory					5.45	(1.33)	2.84 – 8.06	<0.001
Day × SAH Order Mandatory					0.14	(0.04)	0.05 – 0.22	0.001
RM × Day × SAH Order Mandatory					-0.16	(0.06)	-0.28 – -0.04	0.011
Weekend					1.02	(0.35)	0.34 – 1.71	0.003
Population Density					1.07	(0.96)	-0.82 – 2.95	0.268
Population (Thousands)					2.99	(0.91)	1.21 – 4.78	0.001
Median Age					-0.04	(0.21)	-0.45 – 0.37	0.84
Net Migration					-0.01	(0.24)	-0.48 – 0.47	0.973
GDP per capita					0.52	(1.7)	-2.80 – 3.85	0.758
% Urban Population					-0.06	(0.07)	-0.21 – 0.08	0.407
Random Effects								
σ2	67.02				62.45			
τ00 Country	158.13				114.77			
τ00 Day from Stay-at-home order	9.74				8.31			
ICC	0.71				0.66			
N Countries	102				84			
N Day from Stay-at-home order	31				31			
Total N	3132				2574			
Marginal R2 / Conditional R2	0.055 / 0.730				0.251 / 0.748			

Figure 9
The impact of high vs. low relational mobility on geographic mobility following the issuance of Stay-at-Home orders



The results of this analysis support previous findings regarding the relationship between pathogen prevalence and geographic mobility reduction. Similar to Lu and colleagues (2021), who found that nations high in pathogen prevalence instituted SAH orders quicker than did low pathogen prevalence nations, individuals in high pathogen prevalence contexts appear to respond quicker to the imposition of SAH orders. It could be the case that increased activity of the BIS prompted individuals in high pathogen environments to respond more quickly when ordered to stay home. Next, we will test if this same relationship can be found when we consider responses to rising cases alone, rather than direct orders to stay home.

Changes in geographic mobility at the onset of the COVID-19 pandemic

Table 6.

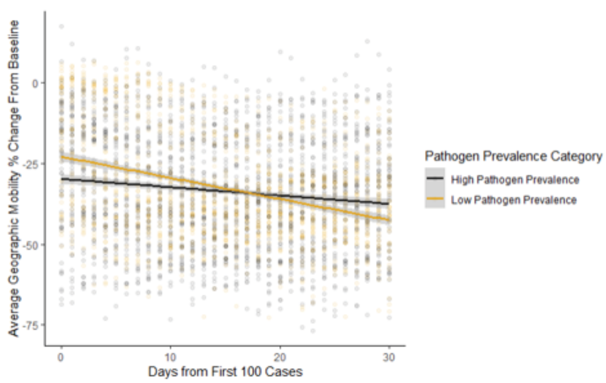
The impact of pathogen prevalence on geographic mobility following the first 100 cases of COVID-19 in each country

Predictors	Estimate	*(SE)*	95 % CI	*p*	Estimate	*(SE)*	95 % CI	*p*
(Intercept)	-26.91	(1.65)	-30.15 – -23.67	<0.001	-13.17	(9.42)	-31.64 – 5.29	0.162
Pathogen Prevalence (PP)	-5.63	(2.17)	-9.88 – -1.37	0.01	-3.18	(3.83)	-10.68 – 4.32	0.406
Days from 100 cases	-0.42	(0.05)	-0.52 – -0.31	<0.001	-0.24	(0.04)	-0.32 – -0.17	<0.001
PP × Days from 100 cases	0.43	(0.03)	0.38 – 0.48	<0.001	0.28	(0.03)	0.22 – 0.34	<0.001
Stay-at-Home order in effect					-9.28	(0.35)	-9.98 – -8.58	<0.001
Weekend					-0.14	(0.37)	-0.85 – 0.58	0.711
Population Density					1.22	(1.14)	-1.01 – 3.45	0.284
Population (Thousands)					-0.32	(1.07)	-2.42 – 1.78	0.766
Median Age					-0.31	(0.25)	-0.80 – 0.17	0.208
Net Migration					-0.01	(0.29)	-0.58 – 0.56	0.963
GDP per capita					4.28	(2.01)	0.34 – 8.22	0.033
% Urban Population					-0.02	(0.09)	-0.20 – 0.15	0.799
Random Effects								
σ2	76.3				68.63			
τ00 Country	206.02				161.33			
τ00 Days from 100 cases	6.09				2.42			
ICC	0.74				0.70			
N Countries	109				83			
N Days from 100 cases	31				31			
Total N	3343				2537			
Marginal R2 / Conditional R2	0.067 / 0.753				0.286 / 0.789			

Similar to the above, we created an initial model predicting decreases in geographic mobility from pathogen prevalence, day, and a pathogen prevalence × day interaction term, with intercepts for country and day acting as random effects. We then repeated the analysis with a second model including the previously described control variables. A significant effect of day (estimate= -.42, *p* <.001) and an interaction between day and pathogen prevalence (estimate= .43, *p* <.001) was found (see Table 6). This indicates that geographic mobility decreased during the 30 days of our initial outbreak period, with the interaction term indicating that nations lower in pathogen prevalence decreased geographic mobility in response to rising cases to a greater degree than did individuals in high pathogen prevalence countries (Figure 10). These effects remained when control variables were taken into account in Model 2.

Figure 10

The impact of high vs. low pathogen prevalence on geographic mobility after the first 100 cases of COVID-19



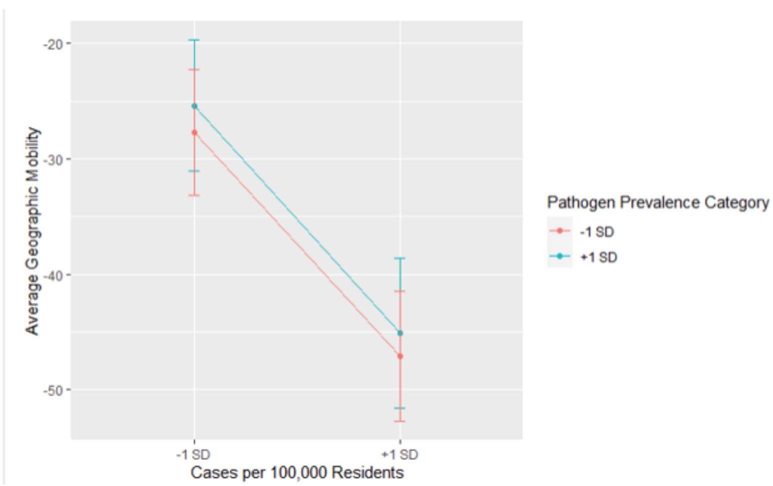
Similar to Study 1, where high RM was associated with both higher cases and in turn lower geographic mobility, low pathogen prevalence is associated with both higher cases and a larger decrease in geographic mobility. This fits with the idea that individuals are reducing geographic mobility in response to rising cases, but that low pathogen prevalence uniquely allows individuals to do so. This is in contrast, however, to the previous finding that individuals high in pathogen prevalence reduce geographic mobility more in response to SAH orders. Therefore, we will utilize a similar analysis to Study 1 to determine if case growth is driving the decrease in geographic mobility seen in this analysis.

Relationship between case growth and geographic mobility decrease

Similar to the above, a series of linear mixed-effects models were run with the inclusion of pathogen prevalence, control variables selected from Salvador and colleagues (2020) and COVID-19 cases normalized per 100,000 population predicting geographic mobility. As before, analyses were limited to the first 30 days after a country reached 100 COVID-19 cases. No significant interaction was found between cases and pathogen prevalence (estimate = 0.01, p = .866), indicating that individuals in high versus low pathogen prevalence contexts did not differ significantly in the degree to which they reduce geographic mobility in response to high COVID-19 case levels (Figure 11).

Figure 11

Influence of pathogen prevalence on the relationship between population-adjusted cases and geographic mobility



Together, these sets of analyses seem to indicate that relational mobility is a more reliable predictor of behavior change in response to the COVID-19 pandemic than is historical pathogen prevalence. While low pathogen prevalence seems to predict both faster case growth and decreased geographic mobility after 100 COVID-19 cases, based on the above analysis we cannot conclusively state that the latter effect is driven by response to case increases. This fits with the idea that the BIS is not innately fit to respond to modern threats such as COVID-19 (Ackerman, Tybur, & Blackwell, 2020), and the utility of purely BIS driven behavior change may be small in comparison to responses targeting sociality more generally. It is still possible that the BIS may interact with RM in some way to drive changes in mobility in response to COVID-19.

Chapter 4

Study 3 – Combined influence of Relational Mobility and Pathogen Prevalence

While we have previously explored the contributions of relational mobility and historical pathogen prevalence to the spread of, and response to, COVID-19 outbreaks, little is known about potential interplay between these social-ecological factors. Evolutionary theorists have historically viewed cultural change as occurring within and Environment of Evolutionary Adaptedness (EEA), by which cultural changes occur in response to difficulties faced by our early human ancestors from the Pleistocene era (Tooby & Cosmides, 1990). From this perspective historical pathogen prevalence should play a clear role in individual response to pandemic viruses through priming of the innate BIS. However, some theorists have argued that the BIS is ill-equipped to respond to modern respiratory viruses such as COVID-19 due to major differences between such viruses and those encountered by our ancient ancestors (Ackerman, Tybur, & Blackwell, 2020). However, development of culture can also be thought of as an iterative process, whereby the evolutionary environment shapes culture which then in turn shapes the evolutionary environment (see: Kusano & Kemmelmier, in press). From this perspective it is possible that regions high in historical pathogen prevalence have developed other important adaptations to respond to more “modern” pathogenic threats.

Importantly, many of the outlined deficiencies of the BIS in responding to COVID-19 concern personal contact, and the BIS adaptations to value of social contacts. Indeed, studies have shown BIS adaptation to the COVID-19 pandemic through increased preferences for social distancing from outgroups in high pathogen areas (Meleady, Hodson, & Earle, 2021) and an increase in BIS-related variables after the onset of the pandemic (Hromatko, Grus, & Kolderaj, 2021). In particular, germ avoidance behaviors associated with the BIS are less prominent around highly-valued interpersonal relationships (Tybur et al., 2020). This is problematic, as close others are equally likely to spread disease and individuals spend a great deal of time with close friends and family members. From this perspective, social-ecological factors which influence one’s ability to exert control over close personal relationships (such as relational mobility) would be particularly important in responding to pandemic viruses. We may further expect some synergy between relational mobility and aspects of the BIS controlling aversion to strangers in response to pathogen threat.

It is notable that research has provided some evli historical pathogen prevalence is negatively associated with present levels of relational mobility in a given region (Thomson et al., 2018). While the precise mechanisms underlying the relationship between pathogen prevalence and relational mobility has yet to be studied directly, pathogen prevalence has been shown to be a key antecedent in the development of cultural characteristics including individualism or collectivism (Fincher et al., 2008) and cultural tightness or looseness (Gelfand et al., 2011). It is therefore possible that these two constructs (pathogen prevalence and relational mobility) are similarly related in that the former acts as a historical antecedent which shapes the other in the present day. For this reason we should expect some relation between these constructs in the context of disease avoidance. However, this should be understood in the context that the contributions of these two constructs are not entirely the same (Ackerman, Tybur, & Blackwell, 2020), and the BIS and relational mobility address different aspects of an individual's response to a new, pandemic virus. Through this study we investigate the possibility that historical pathogen prevalence "sets the stage" in the development of pathogen avoidance behaviors which make the contributions of relational mobility either more or less important in avoiding pandemic respiratory viruses. If, for example, living in a nation with a high historical pathogen prevalence imparts a wider array of pathogen-avoidance behaviors mediated by a chronically hyperactive BIS, the ability to exert control over personal relationships imparted by high relational mobility becomes overall less important for avoiding disease.

Study 3 - Results

Combined effect of historical pathogen prevalence and relational mobility on spread of COVID-19 cases

While the effect of relational mobility on COVID-19 case growth early in country level outbreaks is previously known (Salvador et al., 2020), it is not well known how historical features of the social environment such as pathogen prevalence interface with this relationship. To test this, we utilized a series of linear mixed-effects models similar to our first analysis in Study 2, with the addition of a combined relational mobility x pathogen prevalence × days three-way interaction term. When predicting natural log-transformed cases, to account for exponential growth, there was a significant three-way interaction in both our initial unrestrained model (estimate= -.07, p <.001) and our second model with demographic and SAH related controls (estimate= -.07, p <.001). As shown in Figure 12, environments high in RM and low in historical pathogen prevalence appear to be most vulnerable to increased COVID-19 exponential case growth over time. When predicting population-adjusted cases per 100,000 residents, however, this three-way interaction term was non-significant (estimate= -.86, p = .09).

To mitigate potential loss of statistical power due to the smaller selection of countries with both RM and historical pathogen prevalence values available, the above analyses were repeated with interpolated RM values from Salvador and colleagues (20210). In these subsequent analyses, a significant three-way interaction was found in our initial unrestrained model predicting natural log-transformed cases (estimate= -.15, p=.003) and cases per 100,000 residents (estimate= -4.58, p = .005). These same relationships remained in subsequent models with control variables. As shown in Figure 12, countries high in RM but low in pathogen prevalence experience the fastest cast growth. High RM, low pathogen prevalence nations also experience the greatest rise in cases per 100,000 residents (Figure 12).

Figure 12

Combined effect of relational mobility and pathogen prevalence on log-transformed cases after 100 COVID-19 cases

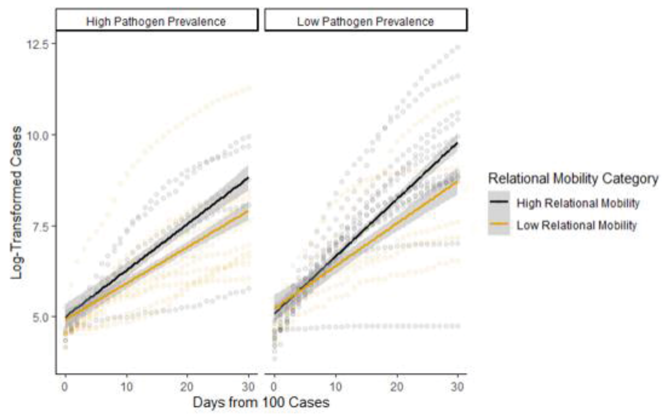
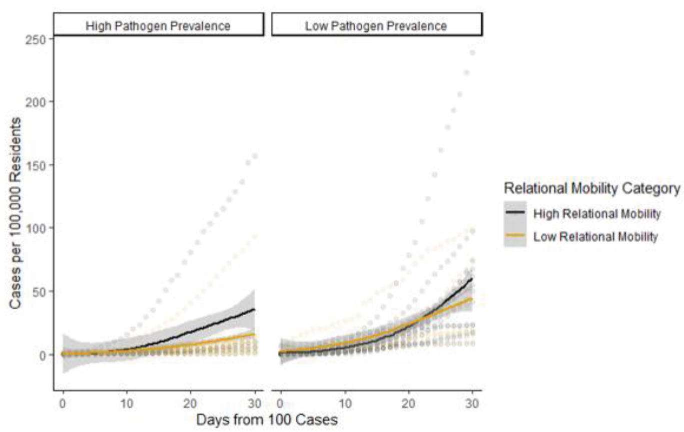


Figure 13

Combined effect of relational mobility and pathogen prevalence on population-adjusted cases after 100 COVID-19 cases



As expected, based on the findings of Studies 1 and 2, environments low in historical pathogen prevalence with citizens high in relational mobility appear to be especially vulnerable to COVID-19 case growth in early outbreaks. The difference in outcomes between high and low RM nations appears to be much more pronounced in areas with low historical pathogen prevalence (see Figure

13). This seems to suggest that, while the effect of RM on case growth is profound in general, RM is less important for predicting case growth in areas where pathogen levels have typically been relatively higher. As these models take into account the presence of SAH orders, it is unlikely this is simply the result of earlier SAH orders in high pathogen prevalence nations as seen by Lu and colleagues (2021). It is possible some combination of a lack of evolutionary experience with pathogen threat (and thus a collective BIS less sensitive to infection cues), combined with an increased ability to form relationships and socialize leads to a social environment uniquely at risk for the spread of novel respiratory viruses such as COVID-19.

Changes in geographic mobility following issuance of Stay-At-Home order

Next, to check for potential combined effect of environmental pathogen levels and relational mobility in predicting geographic mobility reduction in response to SAH orders, we utilized a series of linear mixed-effects models similar to our previous analyses in Study 1 and Study 2, with the addition of a pathogen prevalence × RM × days 3-way interaction term. There was not a significant three-way interaction found in either our initial model (estimate= -.38, p= .13) or our 2nd model including control variables (estimate= -.80, p= .10).

Due to the relatively smaller number of countries included in this combined RM and pathogen prevalence analysis (n= 32), we replicated these analyses utilizing a larger set of interpolated relational mobility values from Salvador and colleagues (2020) increasing the number of countries we were able to analyze (n= 62). In this second set of analysis our initial model showed a significant relationship between pathogen prevalence, RM, and days from the start of SAH orders (estimate= 4.08, p <.001). However, this same result was not present in our second model when we accounted for the influence of demographic controls (estimate= -.43, p = .78). It is notable that RM (estimate = -2.68, p = .04), but not pathogen prevalence (estimate= 0.01, p = .87), interacted with days to predict changes in geographic mobility (see Figure 14).

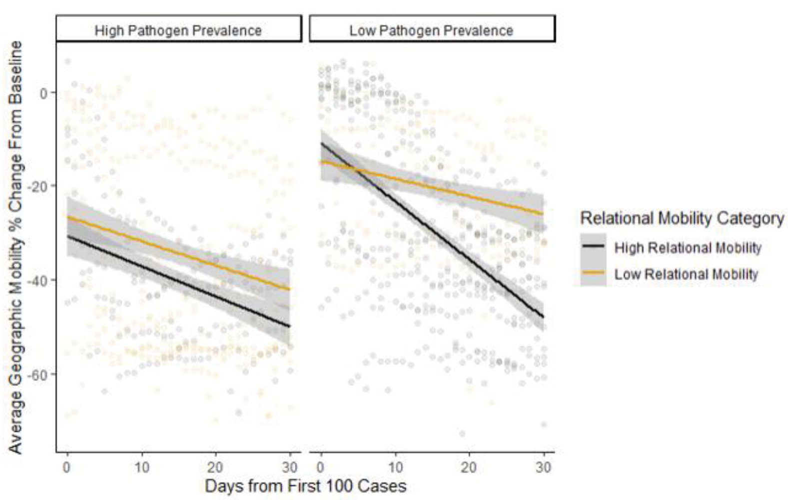
Taken together, these results indicate that does not appear to be an interactive effect whereby historical environmental pathogen levels interact with relational mobility to predict population-level ability or desire to decrease geographic mobility in response to governmental orders. One possible reason for this is that SAH orders (which often came after a period of awareness of increasing cases) may have been a relatively weaker call to action than the rising cases themselves, as indicated by our analyses. That is, by the time SAH orders were issued, individuals had already changed their behavior and the start of SAH orders themselves is a poorer starting point for measuring behavior change. This fits within the framework of the results of Study 1, where response to rising cases appears to be a stronger driver of changes in geographic mobility than do SAH orders.

Changes in geographic mobility at the onset of the COVID-19 pandemic

Next, we ran a series of mixed-effects models to determine if there would be a combined effect of historical pathogen levels and relational mobility on the effect of rising cases on decreases in geographic mobility over time. To test this, a series of mixed effect models were utilized similar to our previous analyses in studies 1 and 2, with the addition of a pathogen prevalence × relational mobility × days interaction variable. In these analyses, a significant three-way interaction was found in our initial unrestricted model (estimate= 1.96, p <.001) and in our second model including demographic control variables (estimate= 1.80, p <.001). As shown in Figure 14, differences in geographic mobility decrease between high and low RM nations were most prevalent when those same nations were low in historical pathogen prevalence. In low pathogen environments, high relational mobility countries reduce their geographic mobility in response to rising cases to a much greater degree.

Figure 14

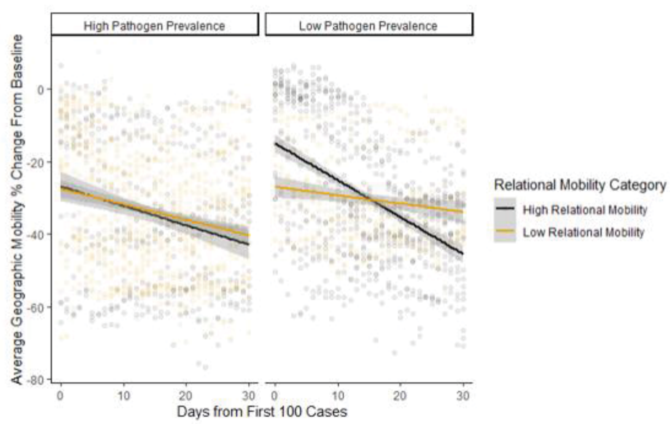
Combined effect of relational mobility and pathogen prevalence on geographic mobility after 100 COVID-19 cases



These same sets of analyses were repeated using the interpolated RM values from Salvador & colleagues (2020) to see if this same pattern would hold for a larger sample of countries. As before, a significant three-way interaction between pathogen prevalence, relational mobility, and days was found for both our initial unrestrained model (estimate= 6.05, p <.001) and our second model with control variables (estimate= 4.94, p <.001). As shown in Figure 15, the interaction effect can be illustrated similarly to our previous analysis using the non-interpolated RM values. In this case, the difference in mobility reduction between high and low RM in low pathogen environments appears unremarkable, while in high pathogen environments high-RM nations reduce geographic mobility to a greater degree than their low-RM counterparts.

Figure 15

Combined effect of relational mobility and pathogen prevalence on geographic mobility after 100 COVID-19 cases



Chapter 5

Discussion

We utilized a series of linear mixed-effects models to examine how country-level relational mobility values or pathogen prevalence values influenced geographic mobility (as measured by Google mobility data) after the imposition of SAH orders and while cases increased during the onset of the pandemic. Our analyses showed that individuals from countries high in relational mobility tended to decrease their geographic mobility to a greater degree in response to the initial rise in cases and following the issuance of SAH orders in their country. Individuals from nations high in pathogen prevalence were more responsive to the imposition of stay-at-home orders, however individuals from low pathogen prevalence nations appeared to reduce mobility more so in the initial outbreak period. While we showed through a series of lagged analyses that high RM is likely to allow individuals to decrease geographic mobility above and beyond what would be expected in response to case increases alone, the same cannot be said for pathogen prevalence. Importantly, the end result of these three studies shows that an individual's evolutionary environment and prevailing cultural norms surrounding relationship formation interact such that low pathogen prevalence and high relational mobility allow individuals to respond most strongly to pathogen threat.

The finding that individuals in low relational mobility nations are less likely to decrease their geographic mobility in response to rising cases at the onset of the pandemic or to stay at home orders is consistent with the idea that social constraints in low relational mobility contexts may make it difficult to forgo social obligations needed to reduce geographic mobility. In low relational mobility contexts, individual behavior is more likely to reflect strategies to avoid harming one's reputation in close relationships (e.g., Yamagishi, Hashimoto, & Schug, 2009; Yamagishi, Hashimoto, Li, & Schug, 2011) and acting to avoid the possibility of social exclusion (e.g., Schug, Yuki, & Maddux, 2010). In this way, high relational mobility may act to reduce the extent to which individuals are bounded by pre-existing social obligations and are therefore able to more readily reduce geographic mobility in response to the perceived threat of rising cases at the start of the pandemic.

Relational mobility appears to be a better predictor of geographic mobility in the early stages of the COVID-19 pandemic than environmental factors such as pathogen prevalence. Paradoxically, it appears as though low pathogen prevalence leads to a greater decrease in geographic mobility in the early stages of the pandemic than does high pathogen prevalence. There are many potential explanations for why this may be the case that unfortunately cannot be addressed with this dataset. For example, it is possible that individuals in high pathogen environments may have other evolved responses to infectious diseases that mitigate the need for geographic mobility reduction. It is also possible that a moderate level of "social distancing" is endemic to cultures where pathogen threat is prominent, which would not be detectable in a data set such as Google Mobility, which relies on percent changes from baseline.

Limitations

Results of this manuscript should be interpreted with caution as there are several limitations that limit the generalizability of our findings. Our analyses are primarily correlational in nature and, as a result, causal relationships cannot be determined. For instance, we cannot be sure the extent to which unmeasured third variables which may also influence geographic mobility outside of stay-at-home orders or COVID-19 case increases, such as differences in media coverage, may have influenced our results. Future research may seek to elucidate the relationship between the sentiment of media coverage across nations and later decreases in geographic mobility.

Our geographic mobility data set itself presents several limitations as well. It is important to note that data is presented only as a percent change from a pre-pandemic baseline period rather than raw mobility scores. It is therefore not possible to control for differences in baseline mobility between countries or know the influence of events that occurred during the baseline period which may nonetheless impact geographic mobility. While this data set represents a large population of cell phone users, it only includes individuals which opted to share cell phone geolocation information with Google and may not be completely representative of a given country.

It is also possible that there exist other cross-cultural differences which may contribute to the relationship between case increases, SAH orders, and geographic mobility. For example, some research has shown that general trust, a construct highly correlated with relational mobility (Thomson, Yuki, & Ito, 2015), contributes to the spread of COVID-19 (Elgar, Stefaniak, & Wohl, 2020). Future research may seek to directly test our proposed mechanism by which high relational mobility translates to an increased ability to reduce geographic mobility. That is, if a higher internal locus of control associated with high relational mobility (e.g., San Martin, Schug, & Maddux, 2019) mediates the relationship between high relational mobility and decreased geographic mobility. One may also consider the role of cultural differences in general trust (Yamagishi, 2011; Thomson et al., 2018, Yuki et al., 2007) in mediating this same relationship.

Through this series of three studies, we have advanced knowledge in the area of social-ecological determinants of geographic mobility reduction in response to pandemic respiratory viruses such as COVID-19. High relational mobility appears to allow individuals to respond to increasing case levels by decreasing their geographic mobility, possibly due to an increased ability to exert control over social obligations. This relationship is not likely to be driven by aggregate differences in the timing of SAH orders or case levels in high relational mobility countries. Likewise, nations low in pathogen prevalence have been shown to experience faster case growth early in the COVID-19 pandemic, and subsequently a greater decrease in geographic mobility than nations high in historical pathogen prevalence. The effect of these two constructs have been shown to interact, such that it appears nations high in relational mobility and low in historical pathogen prevalence are particularly willing and able to reduce geographic mobility in response to the increasing spread of infectious diseases. The precise reason for this is speculative based on these data, but future research may seek to elucidate other factors which may underlie this relationship.

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