Article 3: The Formation of Behavioral Norms: The Case of Population Mobility and Vaccination Rates During the Covid-19 Pandemic

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Contents

1   Abstract

This article researches the formation of social norms governing health behaviors in cases of extreme uncertainty using the cases of both a) population mobility during early 2020 and b) vaccination rates during early 2021, both as responses to public health recommendations to mitigate the Covid-19 pandemic. Using theories of complex contagion, associative diffusion and the integrated theoretical framework of norms, I test how these health behaviors are outcomes of contagion and discordance of signals, and other factors affecting associations like religious and political conservatism, and attention to television media sources, and online norms as measured by information-search behaviors. The data for this article derives from a unique longitudinal data set that I compiled from Google, the CDC, Facebook and other sources. To model mobility and vaccination rates, I linear mixed effects models with random effects as a longitudinal model of contagion.

2   TODO

to cite: - (**wimmerDomainsDiffusionHow2021?**) - vaccine misinformation (**mottaRepublicansNotDemocrats2021?**; **mottaIdentifyingPrevalenceCorrelates2021?**) - Association Between What People Learned About COVID-19 Using Web Searches and Their Behavior Toward Public Health Guidelines: Empirical Infodemiology Study (**akpanAssociationWhatPeople2021?**) - Politicization of Science in the Public Sphere: A Study of Public Trust in the United States, 1974 to 2010 (**gauchatPoliticizationSciencePublic2012?**)

3   Background

After spreading around the world in a matter of months, the coronavirus (COVID-19) became a leading cause of death in the United States. Although the Centers for Disease Control and Prevention(CDC) (2020) proposed several potential mitigation strategies, the method of mitigation that received the most national attention is the call to stay-at-home and social distance for non-essential workers. CDC officials and frontline health care professionals advise that the best way to prevent exposure to the virus is to stay at home and avoid close contact with people.

A second strategy pushed by the CDC, once available, was to receive vaccination to prevent the effects of the Covid-19 virus if infected. Vaccinations like Pfizer-BioNTech (Comirnaty, tozinameran, BNT162b2), and Janssen/Johnson & Johnson, Moderna (mRNA-1273) started receiving approved for emergency use authorization by the United States Food and Drug Administration (FDA) in December 2020.

Although these public health interventions were pushed by policy makers throughout 2020 and 2021, policy makers often struggle to promote public adoption of policies that rely on the publics' willingness to

adjust their current 'risky' behaviors to less-risk behaviors based on scientific facts. The lack of adaption to newly recommended behaviors is partially due to the variation in the levels of understanding of the threats of the disease (Bailey et al. 2020), but it is also due to the current norms that are already in place. TODO: discuss norms, how it's hard to diverge from current norms, habitus

There is little research on shelter-in-place or stay-at-home rates, especially during pandemics or disasters. Though research on the causes of population mobility (how much a community leaves their homes) did expand after the onset of the Covid-19 pandemic (Bargain and Aminjonov 2020; Bourassa 2020; Bourassa et al. 2020; Grossman et al. 2020; Hagger et al. 2020; Hill, Gonzalez, and Burdette 2020; Hill, Gonzalez, and Davis 2021; Hill, Gonzalez, and Upenieks 2021; Huynh 2020), most research focused on unchanging cultural determinants of the reduction in mobility. Instead, this paper will focus on the dynamic nature of population mobility across population networks.

There is more research on vaccine uptake (Schmid et al. 2017) because of increased hesitancy and anti-vaccination movements over previous decades (Baumgaertner, Carlisle, and Justwan 2018; Hornsey et al. 2020; Johnson et al. 2020; Whitehead and Perry 2020), even using methods such as social network analysis (Milani, Weitkamp, and Webb 2020). However, using both population mobility and vaccine uptake provide an opportunity to conduct related but unique analyses of the establishment of social health norms. I will first cover the research on social networks and contagion before covering proposed mechanisms of the spread of mobility behavior and their respective hypotheses.

3.1 Mechanisms of meso-level behavioral contagion

3.1.1 The Social Contagion Model

Individuals engage with each other and their distributive ties to create community contexts where norms, beliefs, and values circulate. These clusters of interaction are called social networks, and if "each person continues to interact primarily with others nearby in space, the forces of conformity will be strongest locally, leading to the emergence of clusters of people sharing similar behavior" (Kitts and Shi 2018). This community interaction ultimately leads to converged communities of belief structures with variations in divergence from the norm (Cullum and Harton 2007; Latané and Bourgeois 1996; Okada 2017).

"Culture" diffuses through communities and social networks. Information and opinions spread (Bond et al. 2012; Fowler and Christakis 2010; Klar and Shmargad 2017), behaviors are adopted (Aral and Nicolaides 2017; Centola 2010, 2011; Christakis and Fowler 2008; Rosenquist et al. 2010) , and there are patterns of health contagion (Cacioppo, Fowler, and Christakis 2009; Christakis and Fowler 2007). However, "different things spread in different ways and to different extents" (Christakis and Fowler 2013, p 563) and when

modeling diffusion and contagion, we must be very specific about our scope conditions as they are relevant to our theory and not to cross theories to infer connections where they may not exist (Kitts and Quintane 2020).

Most of the diffusion literature does not focus on establishment of new norms but the adoption of culture and specific deviant behaviors (see Centola and Baronchelli (2015) for an exception). DellaPosta and colleagues (-DellaPosta, Shi, and Macy (2015)) outline how the spread of culture and behavior is tied to network autocorrelation, or "the tendency for people to resemble their network neighbors." They show that the distance between to agents in sociocultural space can determine the likelihood of the adoption of a new behavior. Like Axelrod (1997) this outlines how the of local convergence of close network actors becomes amplified and can lead to global polarization between groups.

- Write a sentence about (Bailey et al. 2020) 'We show that social network exposure to COVID-19 cases shapes individuals' beliefs and behaviors concerning the coronavirus.'

Outdated models found in early public health research claim that information about the risks of behaviors will lead to changes in behaviors to mitigate those said risks (TODO CITE). However, while this model can be valid in specific cases, more research has shown how the risks themselves do little to motivate behavioral change (TODO CITE).

(1) *Hypothesis 1* Relatively higher local rates of infection will lead to increased time spent in residence and increase vaccination uptake

   cite Gibbons, Yang, and Oren (2021)

(2) *Hypothesis 2* Being connected Facebook friends living outside of the county will not lead to an increase in time spent in residence and decrease in vaccine uptake.

3.1.2 Complex Contagion and Discordance:

Centola and Macy (2007) theorize that simple contagions are not enough to spread behavioral change. Simple contagions are those in which only one point of contact is needed to receive contagion, like with infectious disease or to learn simple bits of information. Centola and Macy (2007)'s large contribution was the theorizing of complex contagions, those that require "independent affirmation or reinforcement from multiple sources" (p 703) and is not based on the number of exposures but the number of sources of exposure. In the case of behavioral contagion, this means that the behavior must be reinforced through witnessing multiple alters perform this behavior before contagion can take effect.

TODO Cite (**houghtonSocialContagionInteracting2021?**) in here somewhere

In the case of stay-at-home rates or vaccination rates, this theoretically means that a person exposed to many sources of the same signal (high, medium, low rates) will be more likely to adopt the behavior based on the reinforcement from the multiple sources of exposure. As norms are inherently social, I theorize that we can see complex contagion happening in real time with the following hypothesis:

(3) *Hypothesis 3* increased average time spent in residence (signal direction) from alters will have a positive effect on time spent in residence for the ego-county; increase vaccine uptake by alters will have a positive effect on vaccine uptake for the ego-county

To make the contagion more complex, different sources of exposure (county-alters) adhere to CDC recommendations to stay-at-home at differing rates. Whereas one county-alter may be greatly increasing its time in residence, another may have made little change. When the majority of alters is in concordance with each other, the signal to the ego is reinforced and more impactful on the ego. When these signals are mixed with high variance from different sources, agreement is low and makes the behavioral change less likely. For this paper, I theorize that a new concept of 'Discordance' must be considered as impacting complex contagion. Discordance is the variance of signals received by an alter; high discordance prevents reinforcement while low discordance enables complex contagion. Instead of adopting a 'majority' rules attitude, this means that the more Discordance perceived by an ego, the less likely the alters will have any effect on the ego. I theorize that the behavior of a county-alter will be positively correlated with the behavior of another county-ego if the county-ego receives highly discordant signals.

(4) *Hypothesis 4* the effect of signal direction on time spent in residence and vaccine uptake will be moderated by diversity in signals (discordance)
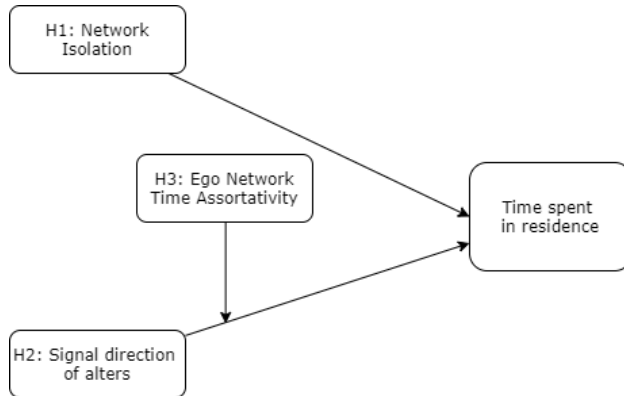

Figure 1: Proposed Elaboratory Theoretical Model

3.1.3   Associative Diffusion

While much of the social contagion literature, like the theories above, focuses on structural boundaries and homophily as causes of how diffusion occurs, Goldberg and Stein (-Goldberg and Stein (2018)) propose a disrupting alternative mechanism. They argue that what actually diffuses during social contagion are the perceptions about which beliefs or behaviors are compatible with one another, what they call "associative diffusion." This argument that culture does not spread like a virus but instead is dependent on how belief structures are connected to each other is important to test because norms around health behaviors became politicized issues during the Covid-19 pandemic. This means that the population mobility behavior itself was not contagious, but the cognitive association of social distancing or vaccination uptake meant were spreading between populations of individuals. While this cognitive theory of cultural variation is difficult to test, the theory it supplies provides a solid framework for how behavioral norms formed during the pandemic.

The figure above illustrates how I interpret associative diffusion will impact population movement and vaccination rates in times of unsettled norms. An individual enters this framework when they realize they don't have a normative set of responses in their cultural toolkit to respond to an unfamiliar situation they are presented with. Individuals look to norms to regulate behavior, avoid deviance, and to maintain order (Horne and Mollborn 2020; Shepherd 2017); when they don't have a normative behavior to follow (or rebel against), individuals look to the other sources in their "community" to mimic behavior, such as high-status individuals, institutions, and members of their social network. I theorize that individuals look towards their physical community, to their social network, popular media (which may include government and science recommendations), established norms that they may find online through search, and to the real threat of infection (what would happen if I do nothing about this norm). Following both the Integrated Theoretical Framework of Norms (Horne and Mollborn 2020) and associative diffusion (DellaPosta et al. 2015; Goldberg and Stein 2018), I theorize that the viewing and interpretation of what is viewed by the ego of their "community" is filtered through their cognitive biases and behavioral predispositions to determine their formation of new behavioral norms.

There is some evidence I can draw upon to support the associative diffusion fraemwork. For instance, there is a central conflict between religious and scientific ideologies which I theorize leads more religious counties to reject the stay-at-home order and vaccines (Evans and Evans 2008) because the associative diffusion places public health recommendations against realigious ideologies. Furthermore, as COVID-19 has become a politically polarizing issue, conservative ideology and a general mistrust of "big government" (Frank 2007) are likely to lead to resistance to the government and scientific guidance.
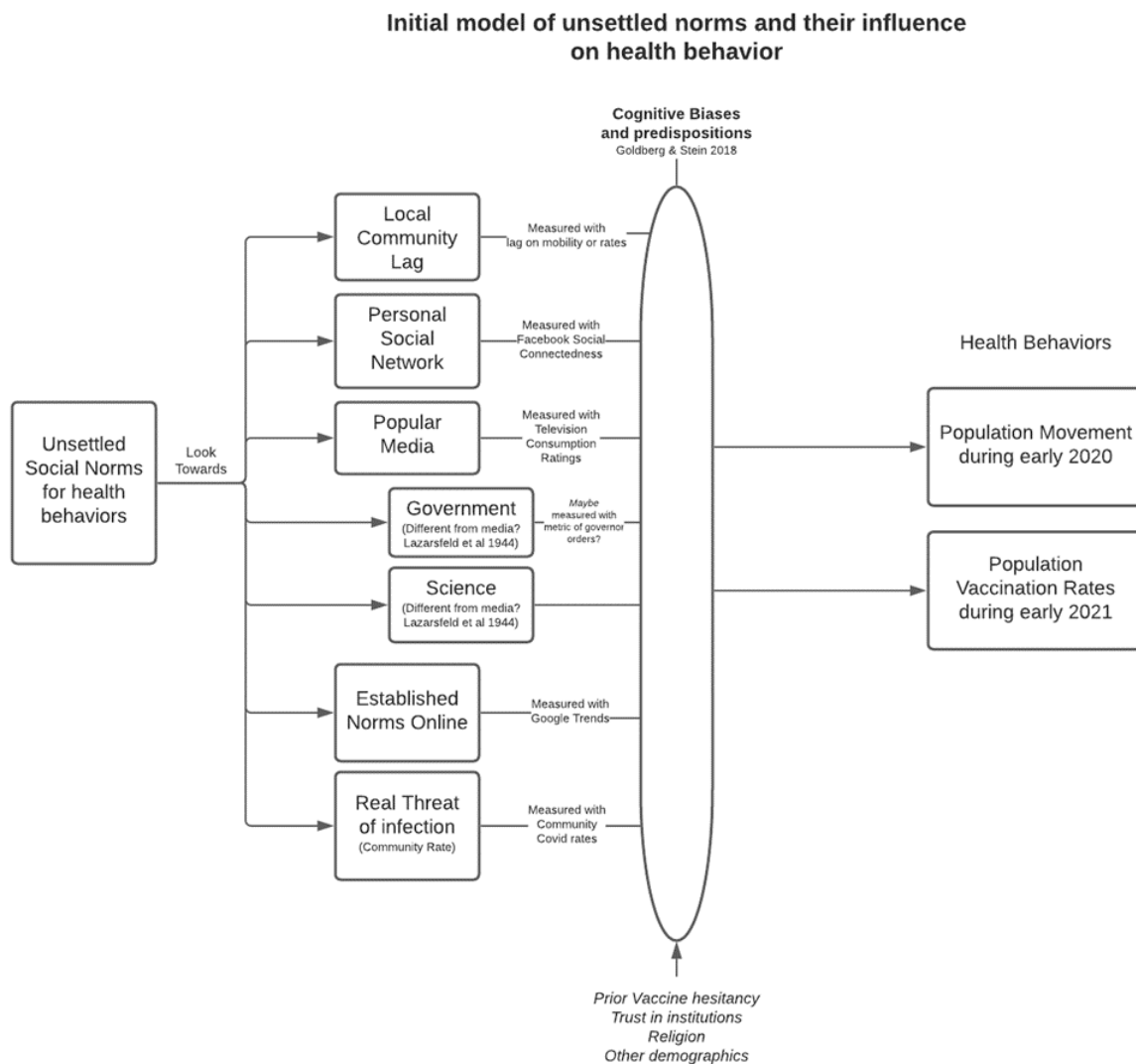
Figure 2: Preliminary model of norm formation

4   Objectives and Significance of the Study

This paper is an important contribution to a few different fields. It contributes to the literature on social influence and contagion, as social connectedness of counties will impact regional population mobility. Moreover, using a aggregated community-level analysis presents a unique test of the contagion literature. Finally, looking at the diffusion of high-risk health behaviors will be an important contribution to public health and social epedimiology.

Unlike many observations of social networks that mediate between questions of influence and self-selection (Lewis, Gonzalez, and Kaufman 2012), this project is unique because self-selection is a precondition to the natural experiment of the virus. I will control for various demographic differences in county, allowing for an isolation of behavioral change during the study period.

5   Data and Methods

This article draws on two unique longitudinal datasets that I compiled for this analysis from sources like Facebook, Google, CDC, etc.

5.1   Stay at Home Rates

My first dependent variable aims to operationalize behavioral norms as stay-at-home rates with data from Google (Google 2020). While the Google COVID-19 Community Mobility Reports include multiple measures of mobility based on location and activity information, the change in time spent in Residences most closely aligns to an operationalization of an obedience to CDC and governor orders, a new and emerging norm in 2020. The change in time spent in Residences variable represents percent change of time spent from Google Location History within geographic areas that Google has designated as a residential area. These data are aggregated to the county-level based on anonymized sets of data from users who have turned on the Location History setting, which is off by default. Google calculates the relative change in mobility in comparison to the median value of movement in the area for the same the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. As Google did not provide data on certain US counties if they did not have sufficient statistically significant levels of data, my final county sample is $n = 1367$ (compared to the total population of 3,107 US counties). Particular areas that are excluded in this analysis include all counties in Alaska and DC, and over half of the counties in North Dakota, South Dakota, and a few other counties. Full list of excluded counties available upon request. These data are longitudinal measures calculated by creating a moving average of stay-at-home rates for each county (rolling window width = 7 days) and then sampling

Table 1: Descriptive Statistics for Stay-at-Home Models (county-level)

	min	max	mean	sd
Percent White	0.14	0.98	0.81	0.15
Percent College Graduates	0.08	0.75	0.26	0.10
Percent over 65	6.60	56.70	16.89	4.05
Median Income	28 951.00	142 299.00	59 818.94	15 239.78
Monthly Unemployment Rate	1.40	34.60	8.13	4.01
Percent of GOP votes, 2016	0.08	0.90	0.57	0.15
Percent Evangelical Christian	0.00	0.67	0.20	0.14
'Fox News' Trend	0.00	204.08	29.55	16.90
'Social Distancing' Trend	0.00	500.00	20.65	25.40
'Covid Conspiracy' Trend	0.00	825.00	42.68	80.60
Covid Case Rate	0.00	343.71	21.15	27.43
Week Number	0.00	43.00	23.14	11.77
Movement Signal	−2.06	26.44	8.32	4.22
Movement Discordance	0.15	11.05	2.22	0.80

Raw values presented in table. Values in models are normalized.
Notes: 1,367 counties, March 02 through December 28, 2020.

every Monday in the sample for 44 measures from March 02, 2020 through December 28, 2020.

5.2 COVID vaccination uptake

The second dependent variable aims to operationalize vaccination uptake through vaccination rate information in the United States from January 2021 through August 30 2021 (CDC 2021). Data represents all vaccine partners including jurisdictional partner clinics, retail pharmacies, long-term care facilities, dialysis centers, Federal Emergency Management Agency and Health Resources and Services Administration partner sites, and federal entity facilities. Vaccination data is available for all US counties with the exception of parts of California and Massachusetts, Hawaii, Texas. In Texas and Hawaii, no county level information is available, and California does not report the county of residence for vaccinations when the county of residence has a population less than 20,000 people. Finally, Massachusetts does not provide vaccination data for Barnstable, Dukes, and Nantucket counties because of their small populations. Therefore, my final county sample for vaccination rates is $n = 2800$ (compared to the total population of 3,107 US counties). A list of included FIPS are available upon request. Vaccination rates are scaled with a rolling mean with a rolling window width of seven days to smooth out inter-week noise. I sample every Monday between January 2021 through August 30 2021 for 35 total observations for each county.
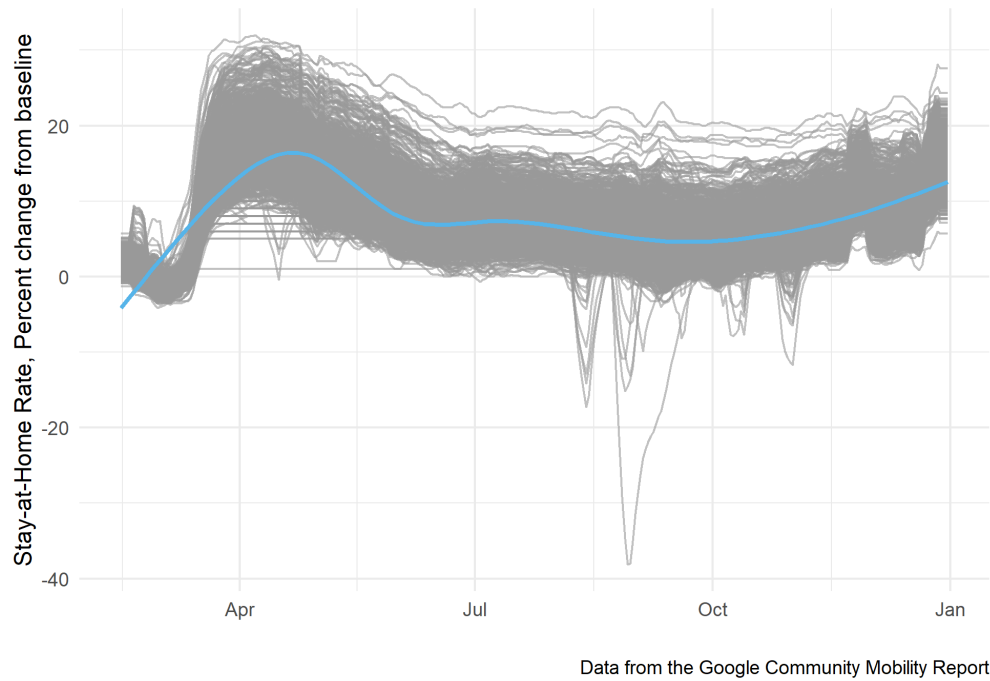
Data from the Google Community Mobility Report

Figure 3: Stay-at-Home over Time

Table 2: Descriptive Statistics for Vaccination Models (county-level)

	min	max	mean	sd
Percent White	0.08	1.00	0.83	0.17
Percent College Graduates	0.03	0.78	0.22	0.10
Percent over 65	3.20	56.70	18.86	4.51
Median Income	21 504.00	142 299.00	53 596.33	14 284.66
Monthly Unemployment Rate	0.90	22.00	4.96	1.95
Percent of GOP votes, 2020	0.09	0.94	0.64	0.16
Percent Evangelical Christian	0.00	1.31	0.22	0.16
'Fox News' Trend	5.00	405.88	72.00	27.33
'Covid-19 vaccine' Trend	0.00	755.56	74.62	70.45
'Covid Conspiracy' Trend	0.00	2000.00	56.32	189.98
Covid Case Rate	0.00	998.58	22.77	27.23
Week Number	44.00	78.00	61.00	10.10
Vaccination Signal	0.00	62.84	19.63	14.86
Vaccination Discordance	0.00	22.40	5.25	3.61

Raw values presented in table. Values in Models are normalized.

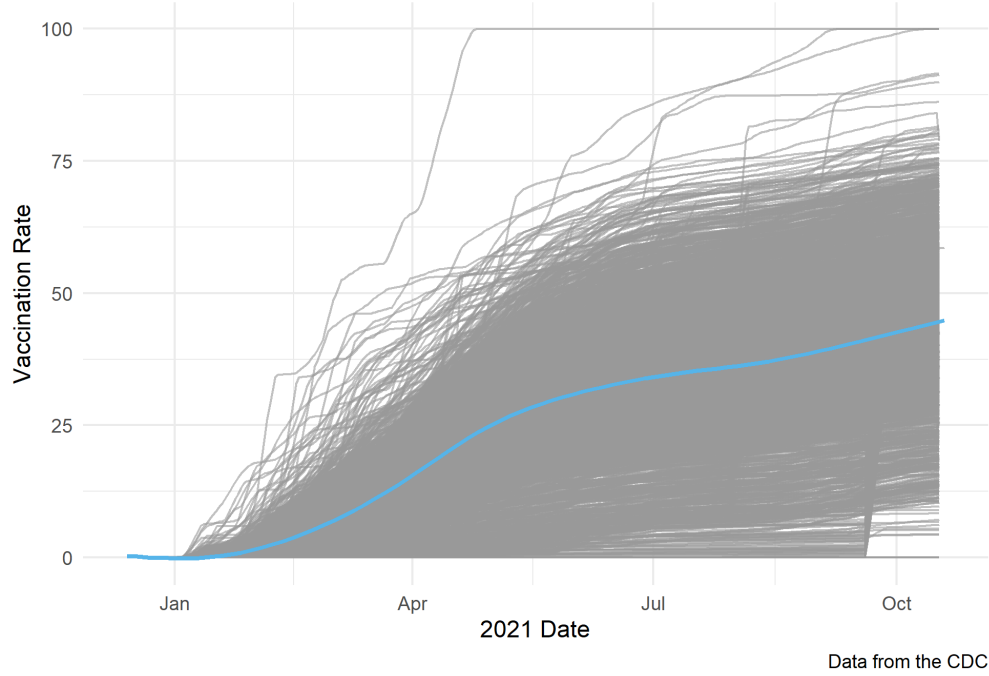Notes: 2,800 counties, January 04 through August 30, 2021.

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Figure 4: Vaccination Rates over Time

5.3 Independent Variables

5.3.1 Network signal

Secondly, I utilize the likelihood of a friendship connection between counties to create a county-level social network weighted by the probability of a tie. Using this network and the two independent variables above, I examine how the vaccination and stay-at-home rates of peer counties is contagious to the ego-county. To do this, I first take the weighted average of each ego's network signals using the equation (1) where x denotes the vaccination and stay-at-home rates of each alter county and w represents the likelihood of a friendship connection between the ego county and each of their alters, lagged by one week. This 'signal' of norms gives us insight into the coevolving contagion patterns of the new social norm being established. The likelihood of friendship connection comes from the "Social Connectedness Index" (Bailey, Rachel Cao, et al. 2018; Facebook 2020) which indexes the social links between geographies by the likelihood of Facebook friends. It is an aggregated measure of Facebook friendship connections between counties. It corresponds to "the (relative) probability that two arbitrary Facebook users across two geographies are friends with each other." The data is available at various geographic aggregation levels, such as U.S. zip codes or entire countries. However, data is only available at one time point because Facebook has found that although there are individual changes in friendship connections over time, the aggregate statistical probabilities of friendship remain stable. This measure is based on user-provided information and real-time location-service

data gathered by Facebook. Facebook data has been shown to be highly representative of the U.S. population and Facebook friendship links largely represent real-world friendships (Bailey, Ruiqing Cao, et al. 2018; Jones et al. 2013). The data has been tested to show how initial COVID-19 hotspots are related to subsequent virus spread to non-hotspots, even after controlling for population density and geographic distance (Kuchler, Russel, and Stroebel 2020).

$$signal = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{1}$$

5.3.2 Signal Discordance

The third independent variable, *Signal Discordance*, builds on the network signal but looks specifically at the extent to which a given ego-network receives diverse contagion signals. Based on the hypothesis that when the majority of alters is in concordance with each other, the signal to the ego is reinforced and more impactful on the ego, a high discordance coefficient is indicative of diverse signals which may prevent any clear interpretation of a norm developing, whereas a low discordance coefficient would indicate reinforced signaling. I use the formula to calculate weighted standard deviations, (see equation (2)) to provide a metric of a diversity of signals. In this formula, x denotes the vaccination and stay-at-home rates of each alter county and w represents the likelihood of a friendship connection between the ego county and each of their alters, lagged by one week. Furthermore, $\bar{x}^*$ represents the weighted mean.

$$discordance = \sqrt{\frac{\sum_{i=1}^{n} w_i (x_i - \bar{x}^*)^2}{\sum_{i=1}^{n} w_i}} \tag{2}$$

Figure 5 provides a visualization of both network signal and signal discordance for April 26, 2021 for 7 selected counties.[1] While a county like Lake County, Ohio has low discordance meaning the signal of vaccination rate is reinforced, Navajo County, Arizona receives very diverse signals from their county-alters, negating any contagion effects.

5.3.3 Case Rate

To estimate the concept of 'real threat of infection' in figure 2, the models use county-level Covid-19 case rates with data from The New York Times (2021). It is widely acknowledged that there are biases in this data due to inconsistencies and availability in testing as well as different community propensity to test (TODO CITE). However, it is the best measure we have of actual case rates. County data are scaled with a rolling mean with a rolling window width of seven days to smooth out inter-week noise. Case Rate is measured as

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[1]Figures in this paper were all created using ggplot2 and patchwork Wickham (2011)

Scatterplot of Signals and Discordance with 7 counties highlighted
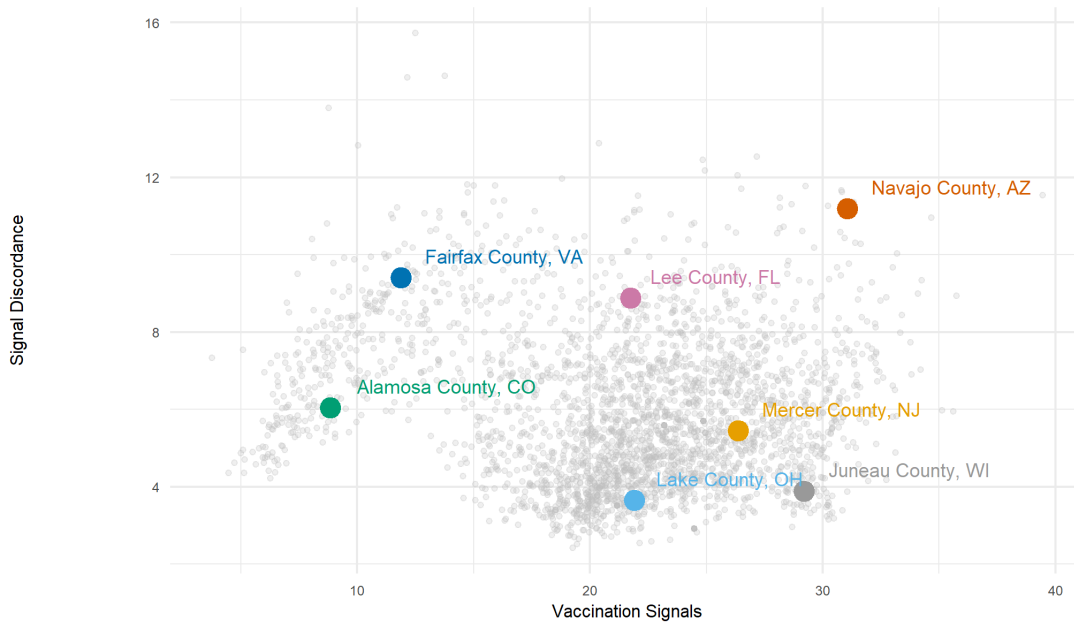
Weighted Densities of Vaccination Signals per county with weighted average
and standard deviation highlighted

Colored Point = Weighted average; Grey line = Weighted SD, i.e. Discordance

Densities Weighted by likelihood of Facebook Friendship connection
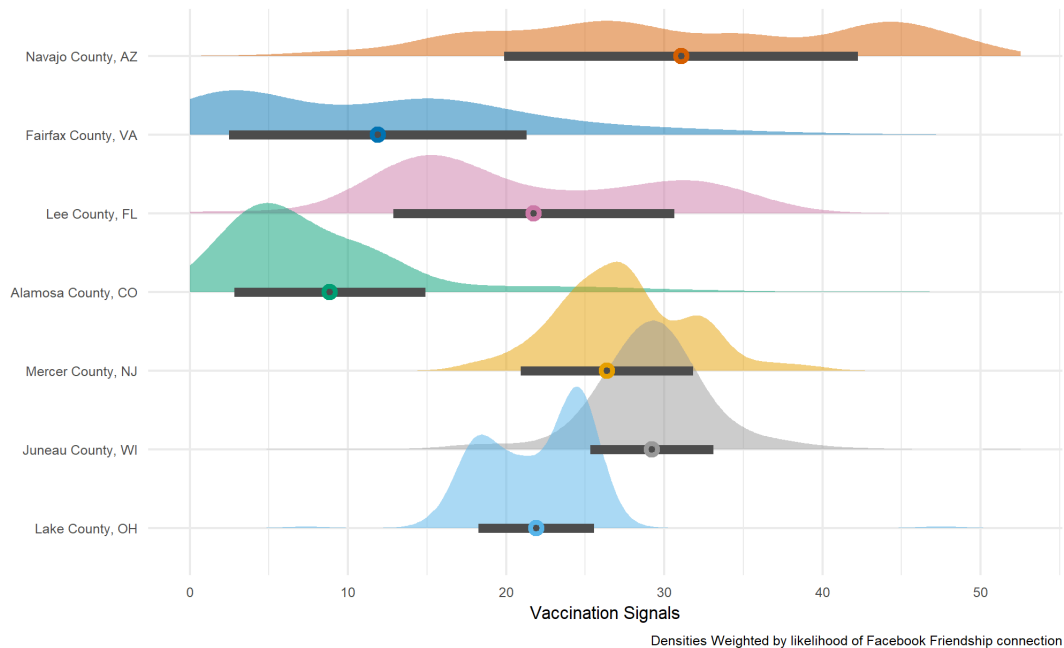
Figure 5: How Signal Mean and Signal Assortativity are Measured

number of cases per 100,000 population. Observations vary from 0 to 1,565 between the two datasets.

5.3.4 Pillars of Convervatism

Research has shown that stay-at-home rates and other pandemic health behaviors are related to various 'pillars of conservatism' (Gonzalez et al. 2021; Hill et al. 2020; Hill et al. 2021, 2021). Namely, research shows that politically conservative indicators, such as Republican political leadership, conservative Protestantism and consumption of right-wing media are related to higher rates of movement and lower rates of mask usage. Based on these findings, this article controls for these factors in the following ways: to measure Republican political leadership, I include percentage of votes for Donald Trump in the previous presidential election; for the 2020 study, I use the 2016 results and for the 2021 study, I use the 2020 results to infer proper time ordering. Second, to measure conservative Protestantism with the county's percentage of evangelical Christians. These county-level data were collected through the 2010 U.S. Religion Census: Religious Congregations and Membership Study (Grammich et al. 2018). Finally, right-wing media consumption is assessed using Google Search Trends to capture "Fox News" searches over the study period across individual designated media markets areas (DMAs), a nonoverlapping aggregation of U.S. counties to 210 media markets based on similar population clusters. Each DMA value represents the popularity of the search term on a scale of 0 to 100, with 100 being the maximum search popularity out of all DMAs and all searches. However, these rates are rescaled using a process described in Online Norms below. I use this measure to indicate active interest in and attention toward Fox News. Google Search Trends have been validated for use in a range of research contexts and for use with survey data, voting data, and ecological data (Bail, Brown, and Wimmer 2019; Reyes, Majluf, and Ibáñez 2018; Scheitle 2011; Stephens-Davidowitz 2014; Swearingen and Ripberger 2014).

5.3.5 Online Norms

To operationalize the search for online norms, I again use Google search trends over the study period across individual designated media markets areas (DMAs), a nonoverlapping aggregation of U.S. counties to 210 media markets based on similar population clusters. To investigate the rate of *searching* for norms online in both cases, I use the following search topics: 'Social Distancing' (2020, stay-at-home case only), 'Covid-19 Vaccine' (2021 Vaccination Uptake case only) and Covid Conspiracy (2020-2021, both cases). Search topics are a more robust measurement than a single search term: topics are aggregations of the rates of multiple, highly correlated search terms together into a cohesive topic. For example, while 'Beyoncé,' 'Beyonce' and 'beyonce knowles' are all separate search terms, 'Beyoncé Knowles' encompasses all of these into a single search topic. While the data is originally on a original scale of 0 to 100, with 100 being the maximum

search popularity out of all DMAs, Google Search Trend are now only available cross-sectionally (a single time period across a geography) or time-series (a single geo-location across time). To remedy this and build a longitudinal dataset of each search topic, I follow the method proposed in Park, Kwak, and An (n.d.), p. 5. This method involves building a dataset of unscaled cross-sectional values, selecting a DMA to use to establish the rescaling ratio (I use 'Los Angeles CA'), and then finding the time-series values for the one DMA. To find the rescaling ratio for each week in the time-series, you divide the time-series value for each week by the cross-sectional value for each week, resulting in a rescaling vector to be used for all weeks in the dataset across geographies. To rescale each longitudinal value, multiply the respective week's rescaling ratio by the cross-sectional value. Rescaled longitudinal data was compared against time-series data for multiple test counties and was equivalent.

5.3.6 Demographics

These models also control for (1) percent of the population that is above 65 years old (those most at risk of hospitalization), (2) percent of the population that identifies as white, (3) percent of the population that holds a college degree, (4) median income, and (5) monthly county unemployment rate. Measures 1 through 4 are obtained from the 2018 American Community Survey: 5-Year Estimates (US Census Bureau 2018); unemployment rates are gathered from the U.S. Bureau of Labor Statistics (Labor Statistics 2021).

5.4 Modeling Prodecures

Descriptive statistics for the stay-at-home rate model can be found in Table 1. Descriptive statistics for the vaccination uptake model can be found in Table 2.

For each case study, I employ a series of four linear mixed effects regression models using the nlme package in R (Pinheiro et al. 2021; Pinheiro and Bates 2000) to address hypotheses 1 through 4. Linear mixed effects models are a form of hierarchical linear models that contain both random and fixed effects. These models treat the dependent variables as continuous. The following strategies I will outline are identical for both case studies. Each model utilizes normalized independent variables, i.e. variables that have been centered and scaled to have a mean of 0 and standard deviation 1. The first model is a baseline linear mixed effects model that employs all basic controls to predict the dependent variable, allowing both time-varying and county-level variables to predict the outcome. All variables have fixed effects, meaning that the county-level exogenous effects are controlled for when estimating the coefficient. In addition, models are specified with a random intercept per county. The lme models are set with a autoregressive correlation structure (correlation = corAR1()) to control for temporally autocorrelated error structures; models are also optimized using Nelder–Mead,

quasi-Newton and conjugate-gradient algorithms for box-constrained optimization and simulated annealing (control = lmeControl(opt = "optim")). This model will address Hypothesis 1. To test hypothesis 2, I estimate model 2 which builds on model 1 by first introducing the movement of vaccination signal. Because the signal varies by week, I estimate this model with an interaction between week and signal. Moreoever, because signal may have different effects across different counties, I set a random effect for both signal. A visual representation of this interaction can be seen in figures 6 and 8. Model 3 then builds on model 2, introducing a fixed effect for the interaction between signal and discordance. Model 4 tests hypothesis 4. Figures 7 and 9 depict how signal and discordance interact.

6 Results

6.1 Stay at Home results

1. Hypothesis 1 Relatively higher local rates of infection will lead to increased time spent in residence

The parameter phi is .95, which is a good indicator that adjacent time points for each person are related.(Finch, Bolin, and Kelley 2014)
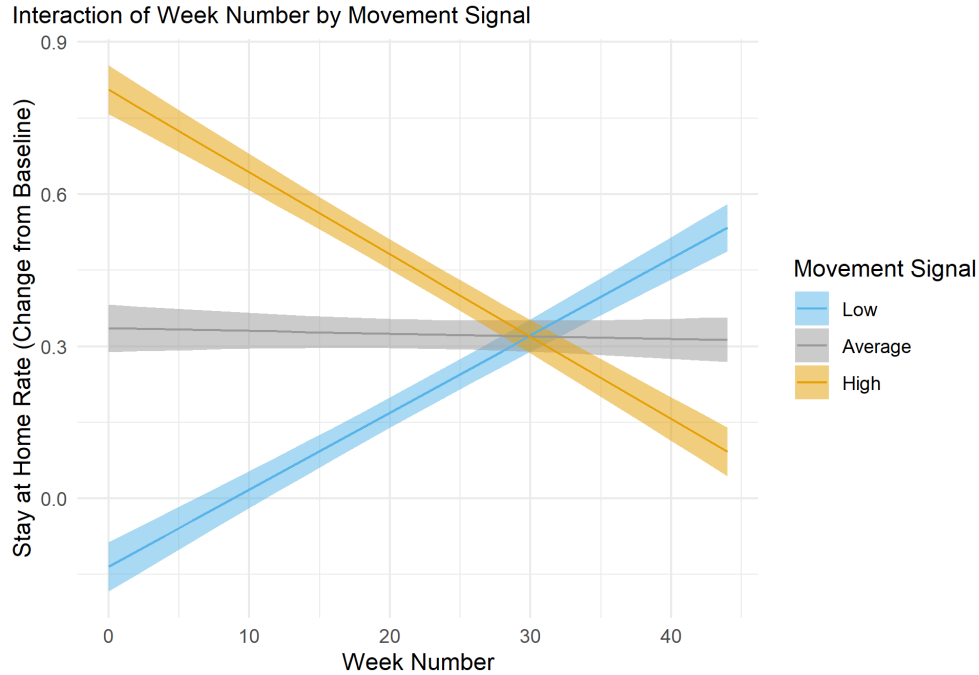
3

Figure 6: Predicted Values of Stay at Home Rate by Movement Signal

Table 3: Linear Mixed Effects Regression Results for Stay-At-Home Rates

	Model 1	Model 2	Model 3
Percent White	0.058*	0.029	0.030
	(0.025)	(0.021)	(0.022)
Percent College Graduates	0.056+	0.080**	0.084**
	(0.030)	(0.025)	(0.026)
Percent over 65	−0.092***	−0.089***	−0.091***
	(0.019)	(0.016)	(0.017)
Median Income	0.195***	0.201***	0.238***
	(0.027)	(0.023)	(0.024)
Monthly Unemployment Rate	0.088***	0.014***	0.062***
	(0.004)	(0.003)	(0.004)
Percent of GOP votes, 2016	−0.099**	−0.129***	−0.146***
	(0.032)	(0.027)	(0.028)
Percent Evangelical Christian	−0.017	−0.011	−0.011
	(0.024)	(0.020)	(0.021)
'Fox News' Trend	−0.031***	−0.028***	−0.027***
	(0.001)	(0.001)	(0.001)
'Social Distancing' Trend	0.011***	0.003*	0.002
	(0.002)	(0.002)	(0.002)
Covid Case Rate	−0.001	−0.012**	−0.008*
	(0.004)	(0.004)	(0.004)
Week Number	−0.001	−0.001	−0.003**
	(0.001)	(0.001)	(0.001)
Movement Signal		0.470***	0.532***
		(0.006)	(0.006)
Movement Signal x Week		−0.016***	−0.018***
		(0.000)	(0.000)
Movement Discordance			−0.079***
			(0.004)
Movement Signal x Discordance			−0.076***
			(0.002)
Num.Obs.	57 030	57 030	57 030
R2 Marg.	0.114	0.248	0.246
R2 Cond.	0.114	0.248	0.246

Model 1 includes a random intercept for FIPS,

Models 2-3 include a random effect for Movement Signal by FIPS

2. Hypothesis 2 increased average time spent in residence (signal direction) from alters will have a positive effect on time spent in residence for the ego-county

So if you SEE your friends moving around more, you start staying at home more. ~ Righteous superiority. If you see people staying at home, you assume it's safer and then start moving around more.

See Figure 7.

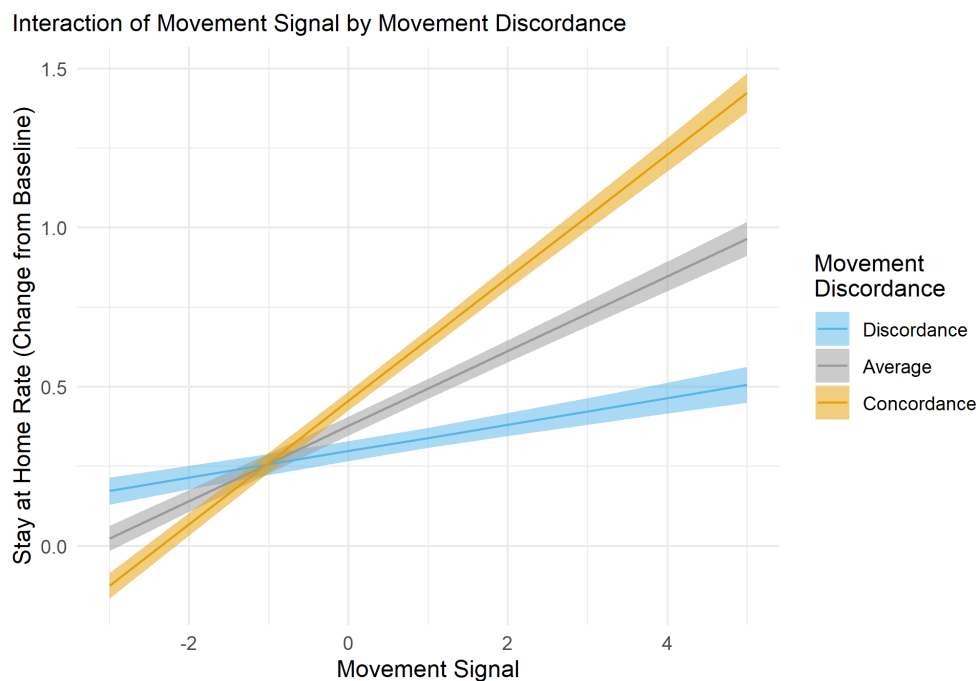Interaction of Movement Signal by Movement Discordance

Figure 7: Predicted Values of Stay at Home Rate Moderated

3. Hypothesis 3 the effect of signal direction on time spent in residence will be moderated by diversity in signals (Discordance)

high Discordance = completely moderates the social influence effect low Discordance , condensed signal = allows for social influence to have an effect

High signal Discordance moderates the effects of the signal. Explicitly, if a county is receiving a wide array of low and high signals, their stay at home rates won't be affected. When a signal is concentrated or in agreement, the theoretical effect of movement signaling on the ego are the strongest.

See Figure **??**.

6.2 vaccines results

1. Hypothesis 1 Relatively higher local rates of infection will lead to increased vaccination uptake

Table 4: Linear Mixed Effects Regression Results for Vaccination Rates

	Model 1	Model 2	Model 3
Percent White	0.141***	−0.004	−0.002
	(0.015)	(0.004)	(0.004)
Percent College Graduates	−0.002	−0.003	0.000
	(0.017)	(0.004)	(0.004)
Percent over 65	0.043***	0.006*	0.007*
	(0.011)	(0.003)	(0.003)
Median Income	0.046**	−0.009*	−0.011**
	(0.015)	(0.004)	(0.004)
Monthly Unemployment Rate	−0.031***	−0.013***	−0.013***
	(0.001)	(0.001)	(0.001)
Percent of GOP votes, 2020	−0.265***	−0.003	−0.003
	(0.017)	(0.004)	(0.004)
Percent Evangelical Christian	−0.031**	−0.007**	−0.009**
	(0.011)	(0.003)	(0.003)
'Fox News' Trend	0.002***	0.000	0.000
	(0.000)	(0.000)	(0.000)
Covid Case Rate	−0.008***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Week Number	0.067***	0.010***	0.012***
	(0.000)	(0.000)	(0.000)
Vaccination Signal		1.067***	1.170***
		(0.008)	(0.009)
Vaccination Signal x Week		−0.005***	−0.006***
		(0.000)	(0.000)
Vaccination Discordance			−0.059***
			(0.002)
Num.Obs.	99 225	99 225	99 225
R2 Marg.	0.657	0.787	0.793
R2 Cond.	0.657	0.981	0.982

Model 1 includes a random intercept for FIPS,

Models 2-3 include a random effect for Movement Signal by FIPS

The parameter phi is .99, which is a good indicator that adjacent time points for each person are related.
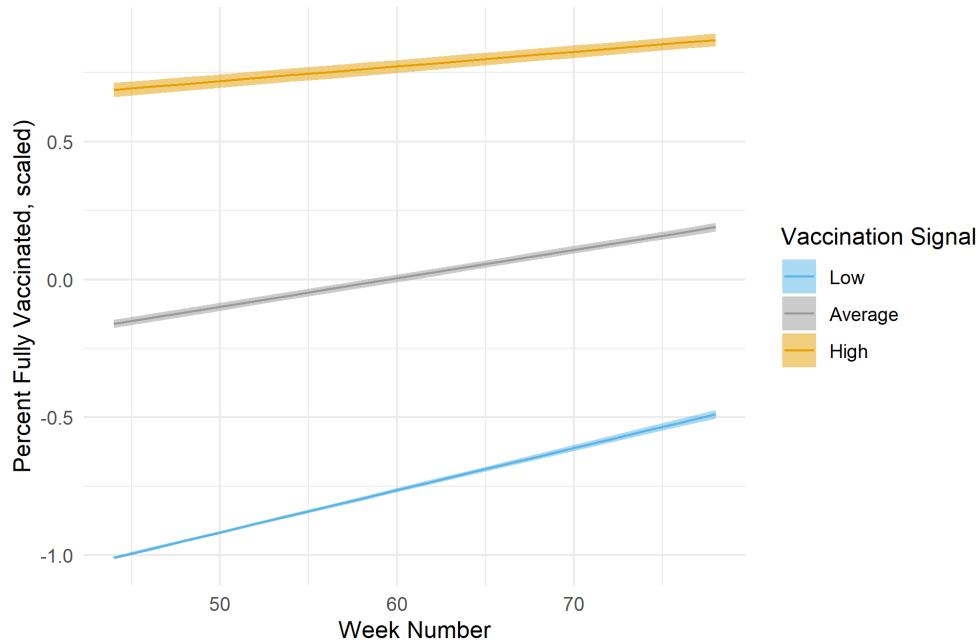
References: (Finch et al. 2014)

4

Figure 8: Predicted Values of Vaccination Rate

2. Hypothesis 2 increase vaccine uptake by alters will have a positive effect on vaccine uptake for the ego-county

see a lot vaccinated, get vaccinated. see few vaccinated, don't vaccinate. See Figure 9.

3. Hypothesis 3 the effect of signal direction vaccine uptake will be moderated by diversity in signals (Discordance)

see consistent high signals, most likely to get vaccinated, see inconsistent signals but still high, less likely but still decently likely to raise vaccination rates. See Figure **??**.

7   Conclusion

There are a few clear limitations to this study. This is sensitive to aggregation error and sampling error from who the mobility and social connectedness data is coming from. The aggregation errors are potentially linked to the assumption that the average mobility behavior of a county is a good representation of the diversity in

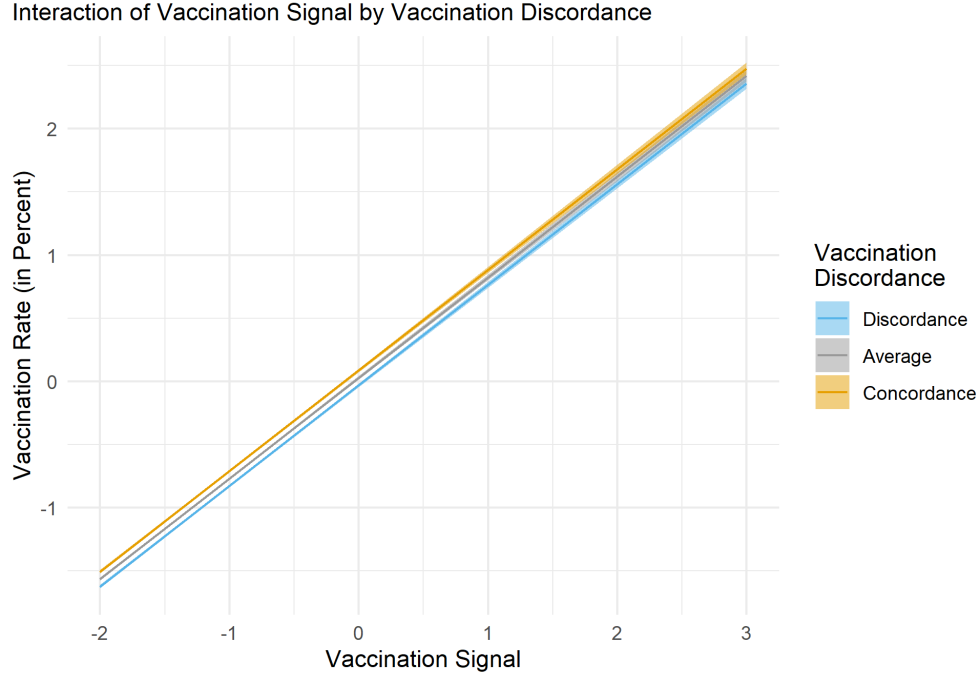Interaction of Vaccination Signal by Vaccination Discordance

Figure 9: Predicted Values of Vaccination Rate

movement behaviors within that county. However, aggregating the network data provides a unique network perspective that hasn't, to my knowledge, been explored. Sociological research has long debated about the agency of individuals and the social and institutional structure in which individuals are immersed. In this study, I aggregate beyond the individual case to explore overall patterns of movement which summarizes individual agency of movement together.

Another limitation of this study is possible sampling error. This project draws on two big-data sources (Facebook 2020; Google 2020). While Facebook and Google do extract data from a large portion of the population, I must be mindful of the sampling issues involved in both data sets. The Facebook data is potentially biased by both a skew of who allows location permissions but also who has a Facebook account and has added their friends. While I have not found any research comparing the demographics of Facebook users to actual population (JK CHECK OUT (Bailey, Ruiqing Cao, et al. 2018; Jones et al. 2013)), it is easy to theorize how it may over or underrepresent different subsets of the population in different areas (Salganik 2017:2.3.6). The friendship indicator should also be read critically, because some individuals add everyone they know as a friend, others add only close personal friends, and another subset of the population adds many people who they do not know offline (Courtois, All, and Vanwynsberghe 2012). To my knowledge, there has been little research testing whether these friendships represent offline connections (Dunbar 2016; Golder, Wilkinson, and Huberman 2007). In my case, however, the question of an online connection versus and offline

connection is unimportant because the movement contagion could spread through online communication, offline communication, or simply shared news stories and informal knowledge networks (Kitts and Quintane 2020).

The Google data must also be read critically because it is based on the geo-behavioral data collected through Google Maps from users who have turned on the Location History setting, which is off by default. This means our sample is skewed to people in the United States a) with a mobile phone, b) with a Google account, and c) with knowledge of how to synchronize their location history. These requirements likely mean that there mobility data is skewed to a younger, more affluent audience. Google has not made it clear whether their demographic biases in their location history data are weighted in some way to rebalance the data set so that it is representative (Salganik 2017:2.3.6; Wang et al. 2015). It is therefore possible that the sampling bias may confound my results if the age distribution through a population is associated with mobility during COVID-19. Furthermore, Google has defined time spent in residential areas without much context or explanation for how they classify a residential area. In counties with a lot of vertical mobility (i.e. skyscrapers) where a residential area may overlap with a shopping mall, there is a much larger margin of error.

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