Article 3: New Social Norms under Uncertain Times: A dynamic study of Stay-At-Home and Vaccination Rates During the Covid-19 Pandemic

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Contents

1 Abstract

This paper examines how social norms are formed under conditions of uncertainty using the case studies of stay-at-home and vaccination rates during the Covid-19 pandemic. I test fear-based models of behavioral adaption to public health recommendations as well as patterns of complex social contagion using linear mixed effects models with random effects. I show that complex contagion is a valid framework for the social contagion of new norms during Covid-19 but also find a moderating effect of signal discordance, the contextual diversity of signals received by an ego.

Keywords: Social Networks, Social Norms, Health Behavior, Diffusion, Contagion

2 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 how individuals came to understand the threats of the disease (Bailey et al. 2020), but also due to habitus: the ingrained habits, skills and dispositions of individuals and groups (Bourdieu 1977). Habitus shapes how individuals perceive different social interactions and norms and shape how they adopt different policies, leading to different social outcomes and a divergence of attitudes (Madeira et al. 2018; Scott-Arthur, Brown, and Saukko 2021; Williams 1995).

There is little research on stay-at-home rates, especially in cases of pandemics or disasters. Though research on the causes of population mobility 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 stay-at-home rates. For instance, Gibbons, Yang, and Oren (2021) finds that social capital had spatially inconsistent effects on stay-at-home rates. Instead of focusing on cultural relationships with stay-at-home rates, this paper will instead 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). While some studies use social network analysis to study the discussions for an against vaccinations online (Milani, Weitkamp, and Webb 2020), vaccination rates are a great way to investigate the establishment of new social norms. First, vaccination uptake is measurable with stable information infrastructure and tracking and vaccination rates are varied across locations and time. Secondly, because vaccines have become politicized (Motta 2021; Motta et al. 2021), the social contagion effects can be studied.

This article researches the formation of social norms governing health behaviors in cases of extreme uncertainty using the above cases. 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, as well as other factors affecting associations like religious and political conservatism, and attention to television media sources, and online norms as measured by information-search behaviors. Before outlining my central hypotheses, I offer an overview of the current state of the social contagion literature. After that, I will outline how I compiled this unique longitudinal data set from Google, the CDC, Facebook and other sources and how I define and calculate signal and discordance, two key independent variables for this paper. To model stay-at-home and vaccination rates, I use linear mixed effects models with random effects as a longitudinal model of contagion. After interpreting the results of the models, I discuss the implications of these findings for the sociological understanding of social contagion and the formation of social norms.

2.1 Mechanisms of meso-level behavioral contagion

2.1.1 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 (Robert M. Bond et al. 2012b; 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.

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 (e.g. Flay, DiTecco, and Schlegel 1980). However, while this model can be valid in specific cases, more research has shown how the risks themselves do little to motivate behavioral change (Witte and Allen 2000; Wolburg 2006). Often, an appeal to fear is found to be a major driver of the adoption of information campaigns and some research has show that 'social network exposure to COVID-19 cases shapes individuals' beliefs and behaviors concerning the coronavirus.' (Bailey et al. 2020). Because of this, it is logical that higher local incidences of infection would inspire fear and increase adherence to public health measures according to this older model.

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

2.1.2 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.

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:

(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; 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, as seen in figure 1.

(3) *Hypothesis 3* the effect of signal direction on time spent in residence and vaccine uptake will be moderated by diversity in signals (discordance)

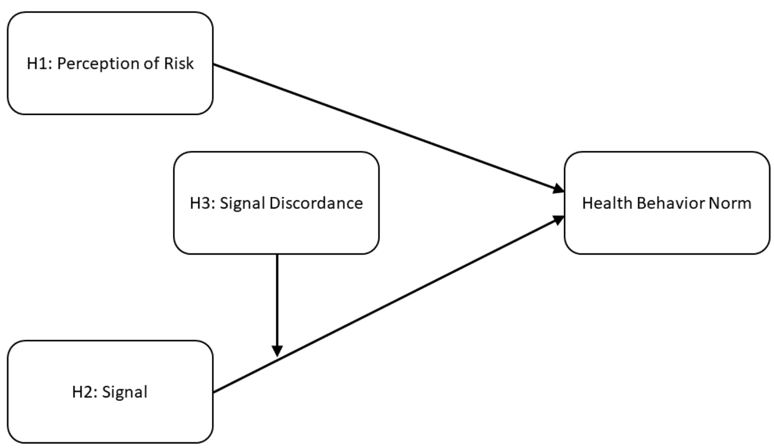


Figure 1: Elaboratory Theoretical Model of Health Behavior Norms

2.1.3 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 stay-at-home or vaccination behavior themselves were not contagious, but the cognitive association of precisely what social distancing or vaccination uptake *meant* were spreading between populations of individuals. Moreover, as Houghton (2021) outlines, diffusants - the things that are diffusing through a population, are not independent of each other (Mason, Conrey, and Smith 2007). When we take into account the interdependence between different beliefs that are diffusing, such as Covid-19 is a hoax, social distancing saves lives, the Covid-19 includes a microchip to control your thoughts, and lockdown is against the rights guaranteed in the US constitution, we can imagine how these various diffusants become associated together into structures of belief through schemas of perception (Houghton 2021). 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.

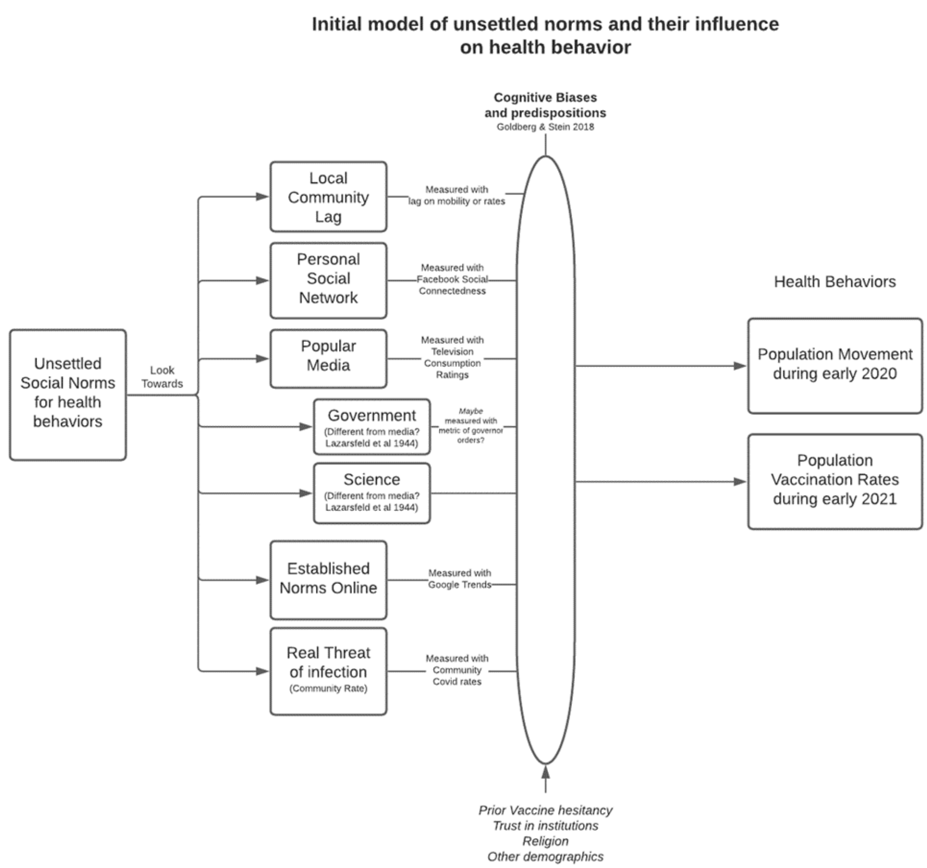


Figure 2: Preliminary model of norm formation

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; Gauchat 2012) are likely to lead to resistance to the government and scientific guidance.

3 Data and Methods

This article draws on two unique longitudinal datasets that I compiled for this analysis from sources like Facebook, Google, CDC, and more. Because the different datasets were on different scales (individual, zip-code, county, state, designated market area) and time points (cross-sectional, longitudinal), there was extensive data wrangling that had to be done to prepare these data for statistical analysis. The steps taken to prepare each of the different model features and where the data was sourced from is therefore covered in the following sections before diving into modeling specifications.

3.1 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

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	16.90	4.05
Median Income	28 951.00	142 299.00	59 773.61	15 264.50
Monthly Unemployment Rate	1.40	34.60	8.12	4.00
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	29.59	16.94
'Social Distancing' Trend	0.00	500.00	20.64	25.36
'Covid Conspiracy' Trend	0.00	825.00	42.51	80.44
Covid Case Rate	0.00	343.71	21.17	27.44
Week Number	0.00	43.00	23.14	11.77
Movement Signal	−2.06	26.44	8.31	4.22
Movement Discordance	0.15	11.05	2.22	0.80

Raw values presented in table. Values in models are normalized.
Notes: 1,375 counties, March 02 through December 28, 2020.

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. This means our sample is possibly 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. Google has not made it clear whether there are any weights in place to correct for these biases. 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 $n = 1375$ (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 every Monday in the sample for 44 measures from March 02, 2020 through December 28, 2020.

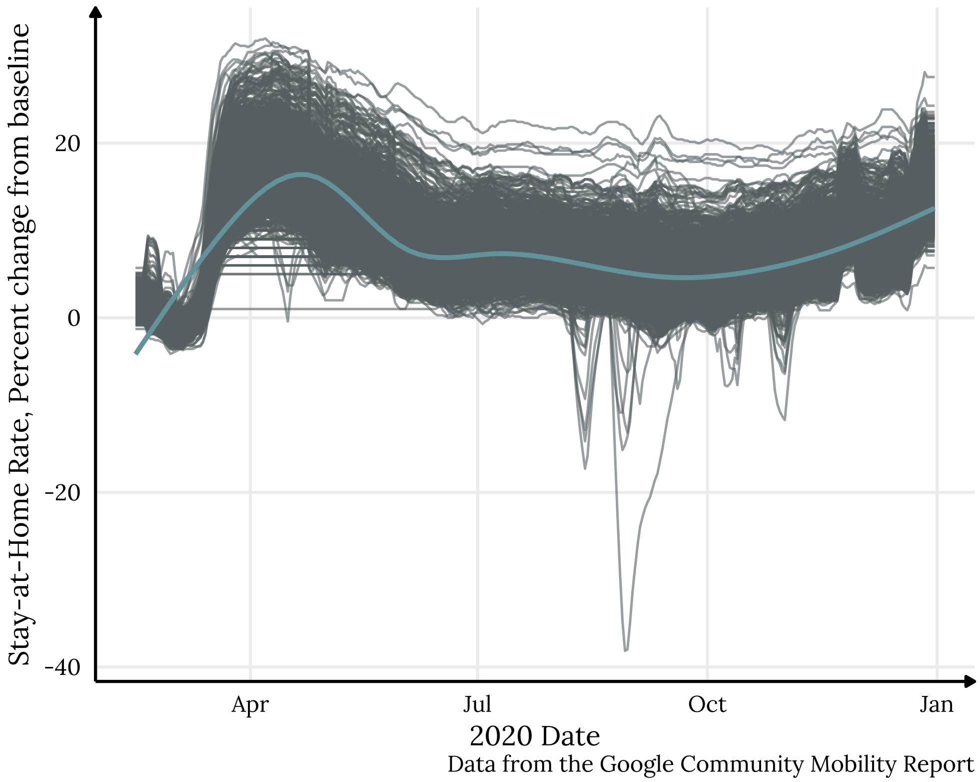


Figure 3: Stay at Home Rates over Time

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	4.50
Median Income	21 504.00	142 299.00	53 522.45	14 312.25
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	72.12	27.38
'Covid-19 vaccine' Trend	0.00	755.56	74.67	70.33
'Covid Conspiracy' Trend	0.00	2000.00	56.05	189.61
Covid Case Rate	0.00	998.58	22.79	27.23
Week Number	1.00	35.00	18.00	10.10
Vaccination Signal	0.00	62.84	19.62	14.84
Vaccination Discordance	0.00	22.40	5.26	3.62

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

Notes: 2,819 counties, January 04 through August 30, 2021.

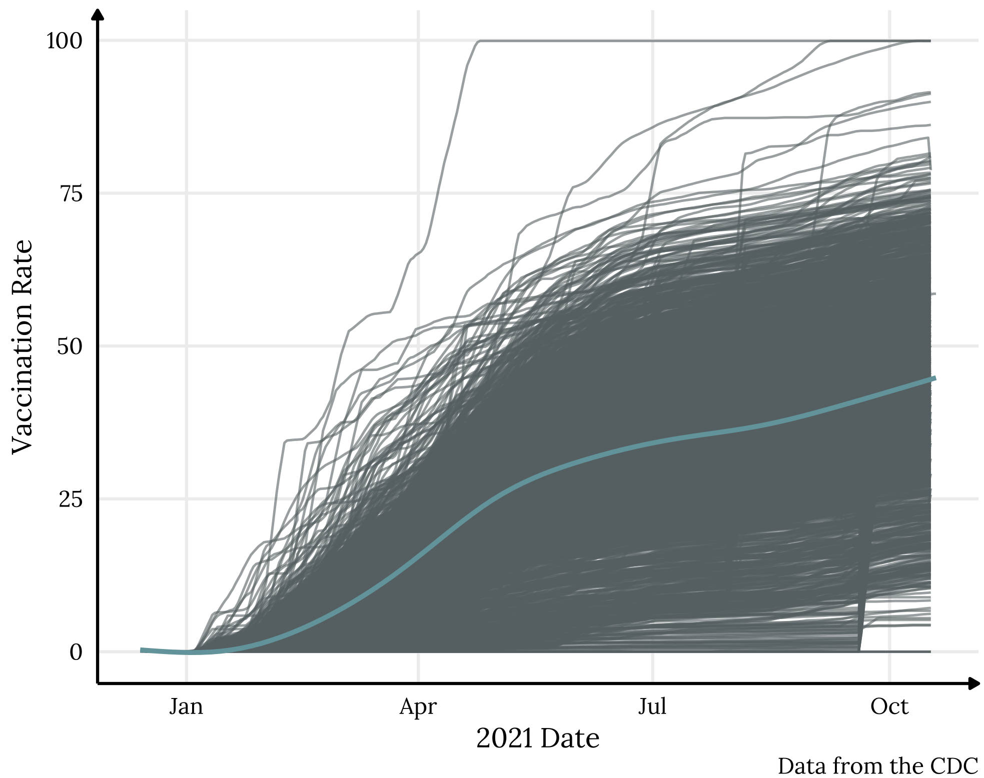


Figure 4: Vaccination Rates over Time

3.2 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 (Disease Control and Prevention 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 $n = 2819$ (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 intra-week noise. I sample every Monday between January 2021 through August 30 2021 for 35 total observations for each county.

3.3 Independent Variables

3.3.1 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).

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

3.3.2 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.

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

Figures 5 and **??** provide 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.

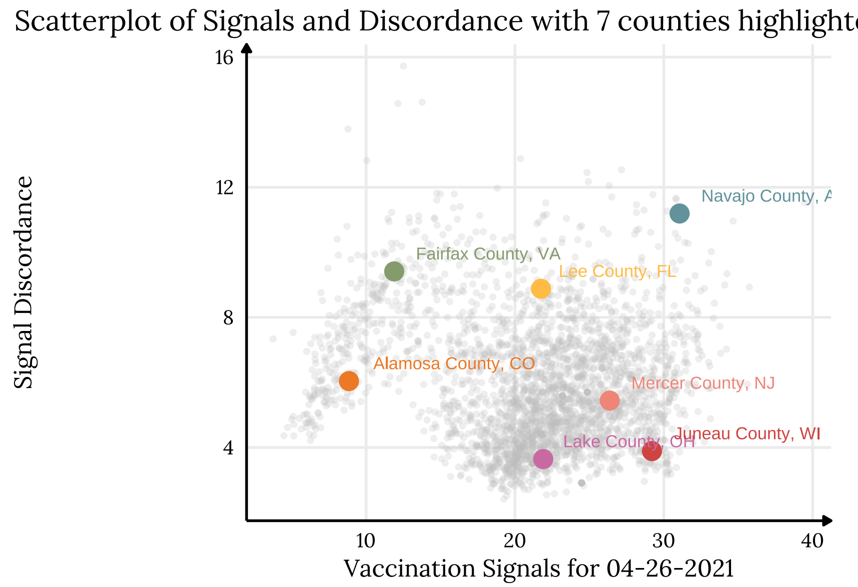
3.3.3 Case Rate

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 [Gu (n.d.); cdc20a] 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 intra-week noise. Case Rate is measured as number of cases per 100,000 population. Observations vary from 0 to 1,565 between the two datasets.

3.3.4 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

[1] Figures in this paper were all created using ggplot2 (Wickham 2011; Wickham, Chang, and Henry n.d.), patchwork (Pedersen n.d.), and ggridges (Wilke n.d.)



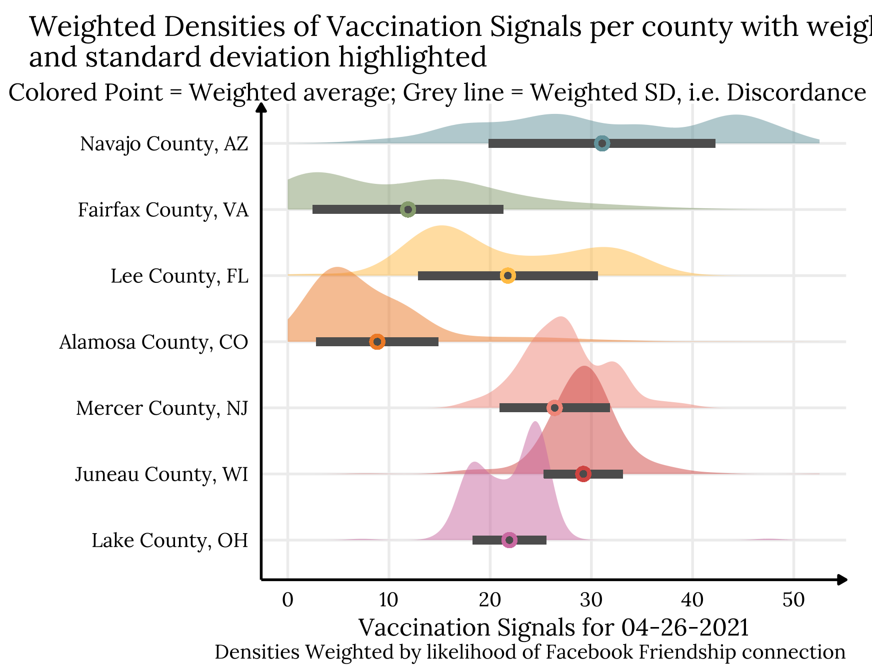
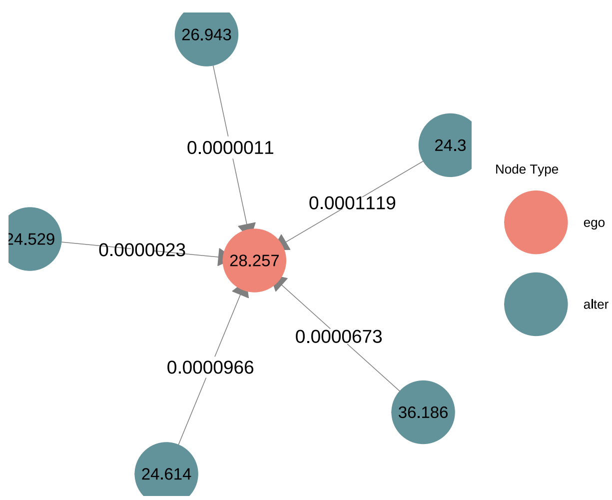


Figure 5: How Signal Mean and Signal Assortativity are Measured



$$w = \begin{bmatrix} 0.0000026 \\ 0.0000966 \\ 0.0000523 \\ 0.0001120 \end{bmatrix}, x = \begin{bmatrix} 17.4 \\ 42.8 \\ 24.6 \\ 24.3 \end{bmatrix} \longrightarrow \begin{matrix} \bar{x}, signal = 28.02 \\ s, discordance = 7.39 \end{matrix} \tag{3}$$

Figure 6: Visualization of how Network Signal and Discordance are Calculated

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.

3.3.5 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 (Sood 2016). 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).

3.3.6 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).

4 Analysis and Results

My analytic strategy proceeds in four steps. In Tables 1 (Stay-at-Home) and 2 (Vaccination Uptake), I present descriptive statistics for all study variables, including variable ranges, means, and standard deviations across the two cases. Then, in Tables 3 (Stay-at-Home) and 4 (Vaccination Uptake), I fit a series of three linear mixed effects regression models using the nlme package in R (Pinheiro et al. 2021; Pinheiro and Bates 2000) for our two cases, Stay-at-Home rates and Vaccination rates. 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. Models 1 through 3 address hypotheses 1 through 3 respectively. 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 first model will address Hypothesis 1. To test hypothesis 2, I estimate model 2 which builds on model 1 by first introducing vaccination signal. Because the signal varies by week, I estimate this model with an interaction between week and signal. And finally, because signal may have divergent effects across counties, I set a random effect for signal nested by county. A visual representation of this interaction can be seen in figures 7 and 9. Model 3 further elaborates the previous model by introducing both a fixed effect for signal discordance and an interaction term between signal and discordance. Figures 8 and 10 depict just how signal and discordance interact across these two cases.

4.1 Stay-at-Home Rate results

In Table 3 and Figures 7 - 8, I present the elaboratory county-level models that predict stay-at-home rates, or, time spent in residence. Model 1 addresses hypothesis 1, that relatively higher local rates of infection will lead to increased time spent in residence. This model's phi paramter is 0.933, which is a good indicator that adjacent time points for each county are related and the model is specified correctly (Finch, Bolin, and Kelley 2014). In this first model, many controls have an impact on the outcome. For instance, when controlling for everything else, the percent of GOP votes in 2016, the percentage of residents who identify racially as White, and higher rates of unemployment increased the stay-at-home rate increased the stay-at-home rate while Searches for norms online seems to have an effect on the outcome: searches for 'Fox News' are associated with decreased stay-at-home rates, while searching for both 'Social Distancing' and 'Covid Conspiracy' tend to increase time spent in residence. Interestingly, the perceived threat of the virus, measured through Covid-19 case rates, were not significantly related to stay-at-home rates in model 1. In other words, for every 1 standard deviation increase in Covid-19 case rates, stay-at-home rates actually decreased by 0.0003 ($p = 0.936$), a very small and insignificant effect. In this case, I fail to reject the null hypothesis that relatively higher local rates of infection will lead to increased time spent in residence.

Table 3 Model 2 investigates Hypothesis 2, that increased average time spent in residence (signal direction) from alters will have a positive effect on stay-at-home rates for the ego-county. This model builds on model 1 by adding in the variable for Movement Signal (see Network Signal for specifications). For every one standard deviation increase in the average time spent in residence of the county alters, an ego tends to also increase its' own stay-at-home rate by 0.473 ($p < 0.001$). I am therefore able to reject my null hypothesis

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

	Model 1	Model 2	Model 3
Percent White	0.088***	0.058**	0.060**
	(0.023)	(0.019)	(0.019)
Percent College Graduates	−0.016	0.010	0.020
	(0.028)	(0.023)	(0.024)
Percent over 65	−0.034+	−0.031*	−0.037*
	(0.018)	(0.015)	(0.015)
Median Income	−0.042	−0.032	0.015
	(0.030)	(0.024)	(0.025)
Monthly Unemployment Rate	0.087***	0.012***	0.065***
	(0.003)	(0.003)	(0.004)
Percent of GOP votes, 2016	0.077*	0.043	0.017
	(0.032)	(0.026)	(0.027)
Percent Evangelical Christian	−0.016	−0.008	−0.014
	(0.022)	(0.018)	(0.019)
’Fox News’ Trend	−0.030***	−0.028***	−0.026***
	(0.001)	(0.001)	(0.001)
’Social Distancing’ Trend	0.011***	0.004*	0.001
	(0.002)	(0.002)	(0.002)
’Covid Conspiracy’ Trend	0.024***	0.006***	0.010***
	(0.002)	(0.002)	(0.002)
Covid Case Rate	0.000	−0.009*	−0.007+
	(0.004)	(0.004)	(0.004)
Week Number	−0.002+	−0.002*	−0.004***
	(0.001)	(0.001)	(0.001)
Stay at Home Rate, county mean	0.898***	0.873***	0.846***
	(0.059)	(0.048)	(0.050)
Signal		0.473***	0.550***
		(0.005)	(0.008)
Signal x Week		−0.016***	−0.018***
		(0.000)	(0.000)
Signal Discordance			−0.101***
			(0.004)
Signal x Signal Discordance			−0.092***
			(0.002)
Log.Lik.	−23 007.044	−19 555.920	−18 655.837

N = 57,356, N of random Effects = 1375
Models 2-3 include a random effect for Movement Signal by FIPS
Model 1 includes a random intercept for FIPS,
* p < .05. ** p < .01. *** p < .001 (two-tailed test).

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

However, this coefficient is inadequate alone because the effect varies over time; the interaction between week and movement signal is negative, meaning that week partially moderates the effect of the signal. Figure 7 illustrates this interaction. In the early days of the Covid-19 pandemic, seeing a high rate of time spent in residence by alters led to a high rate of staying-at-home for county egos. However, as the pandemic progressed, these signals switched. In other words, towards the end of 2020, other factors may have come into play and if a county saw its’ alters social distancing and spending time in residence, ego counties spent less time at home. Theoretically, this may be because individuals saw their adjacent communities with strong

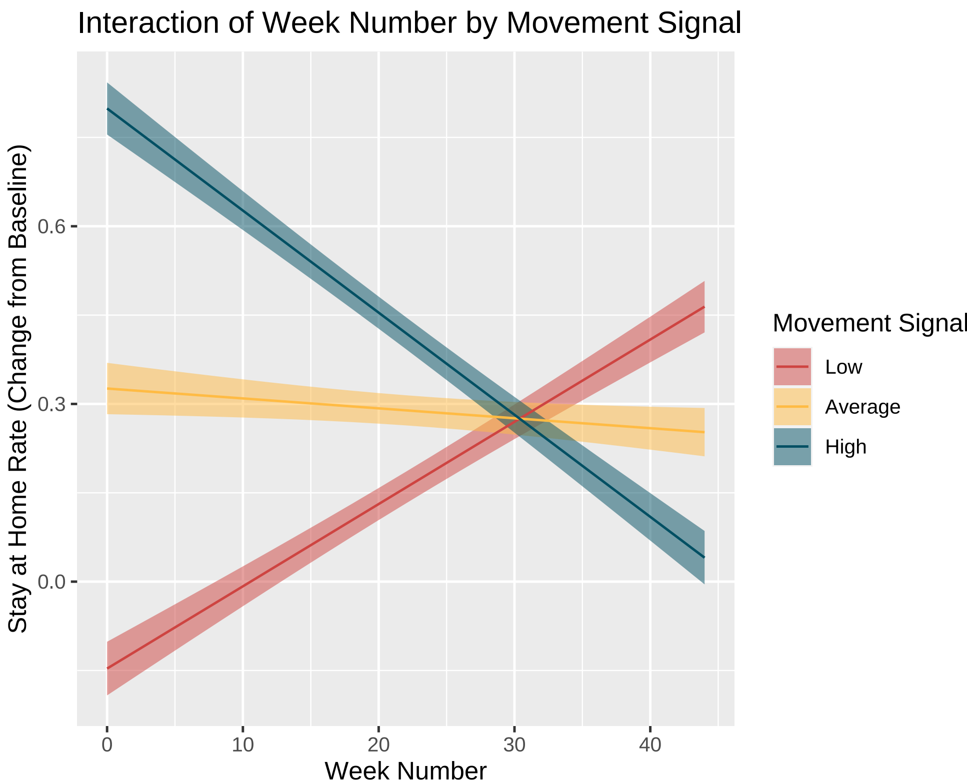


Figure 7: Predicted Values of Stay at Home Rate by Movement Signal

public health norms and felt safe and justified their own deviance. However, if an ego county received signals that others were failing to social distance, they were more likely to stay-at-home. In this case, the threat of the virus may have been more evident for individuals.

Model 3 then adds the concept of Signal Discordance to investigate Hypothesis 3, that the effect of signal direction on stay-at-home rates will be moderated by a diversity in signals (*discordance*). Many of the controls remain consistent throughout the models, with the exception of 'Social Distancing' Trend whose effect has been completed mediated by the inclusion of signal discordance. Importantly, signal discordance has a negative effect on stay-at-home rates, where every one standard deviation increase in discordance lowers rates by -0.101 ($p < 0.001$). The interaction between signal and signal discordance have a coefficient of a similar magnitude, with every one standard deviation increase in discordance and signal resulting in -0.092 lower rates of time spent in residence, indicating moderation. Figure 8 illustrates the moderating effect that signal discordance has on signal. Under high discordance, the social influence effect is almost completely moderated because there is no clear story or norm forming. However, under low discordance, the signal is condensed, allowing for social influence to have an effect. 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

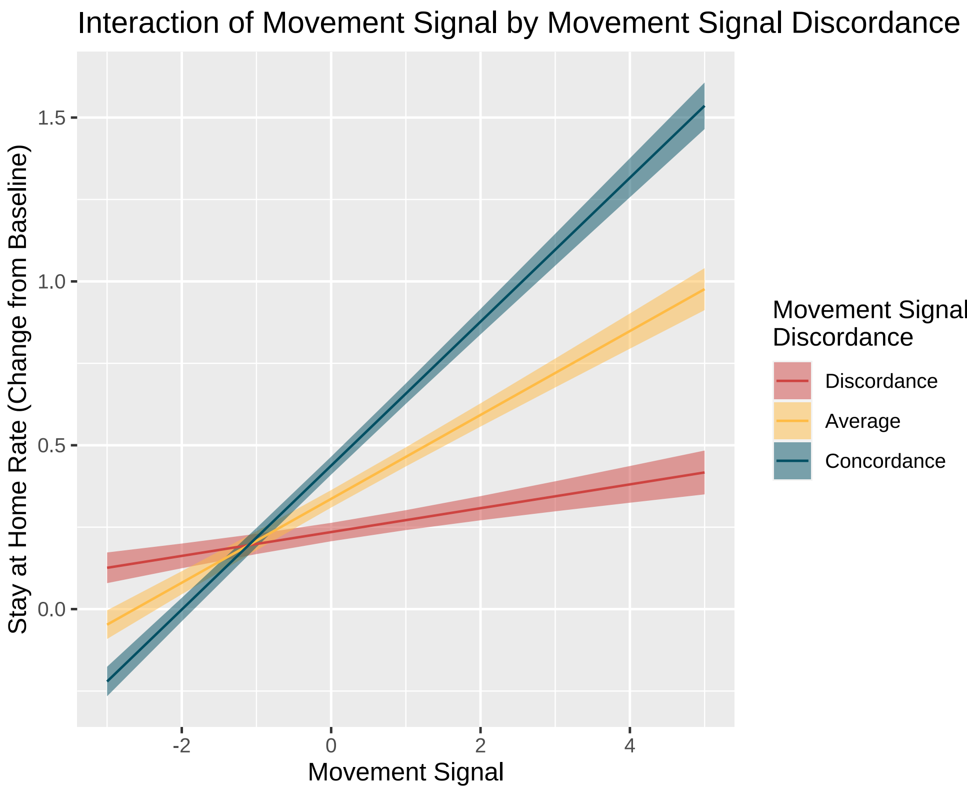


Figure 8: Predicted Values of Stay at Home Rate Moderated

in agreement, the theoretical effect of movement signaling on the ego are the strongest. With this, I am able to reject the null hypothesis of no relationship for hypothesis 4 and find that the effect of signal direction on time spent in residence and vaccine uptake will be moderated by diversity in signals.

4.2 Vaccination Rate results

In Table 4 and Figures 9 - 10, I present the elaboratory county-level models that predict vaccination uptake rates. The parameter phi in model 1 is .985, which is a good indicator that adjacent time points for each county are related and this is an appropriate modeling technique for the data (Finch et al. 2014). Table 4 Model 1 addresses hypothesis 1, that relatively higher local rates of infection will lead to increased vaccination uptake. In this first model, we see various controls impacting vaccination rates. For instance, when controlling for everything else, higher income areas lead to higher vaccination uptake. On the other hand, counties with higher unemployment, higher votes for Donald J. Trump in the 2020 election, are associated with lower vaccination rates. Interestingly, counties that search for Fox News are more likely to have higher vaccination rates while those searching for information about the vaccine on Google are likely to have lower rates of vaccination. The test of Hypothesis 1 also returns surprising results: every 1 standard deviation increase in

Table 4: Linear Mixed Effects Regression Results for Vaccination Rates

	Model 1	Model 2	Model 3
Percent White	0.023+	−0.029***	−0.027***
	(0.012)	(0.003)	(0.003)
Percent College Graduates	−0.004	0.009*	0.010*
	(0.013)	(0.004)	(0.004)
Percent over 65	−0.012	−0.002	0.000
	(0.008)	(0.002)	(0.002)
Median Income	0.002	−0.017***	−0.016***
	(0.011)	(0.003)	(0.003)
Monthly Unemployment Rate	−0.031***	−0.014***	−0.013***
	(0.001)	(0.001)	(0.001)
Percent of GOP votes, 2020	−0.070***	0.031***	0.028***
	(0.014)	(0.004)	(0.004)
Percent Evangelical Christian	0.000	0.000	−0.001
	(0.009)	(0.003)	(0.003)
'Fox News' Trend	0.002***	0.000	0.000*
	(0.000)	(0.000)	(0.000)
'Vaccine' Trend	−0.001***	0.000	0.000+
	(0.000)	(0.000)	(0.000)
'Covid Conspiracy' Trend	0.000*	0.001***	0.001***
	(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***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)
Vaccination Rate, county mean	0.800***	0.201***	0.170***
	(0.018)	(0.005)	(0.005)
Vaccination Signal		0.854***	0.865***
		(0.005)	(0.006)
Vaccination Signal x Week		−0.005***	−0.003***
		(0.000)	(0.000)
Vaccination Discordance			−0.072***
			(0.002)
Vaccination Signal x Discordance			−0.051***
			(0.002)
Log.Lik.	118 677.013	160 000.978	160 638.703

N = 99,890, N of random Effects = 2819
Models 2-3 include a random effect for Movement Signal by FIPS
Model 1 includes a random intercept for FIPS,
* p < .05. ** p < .01. *** p < .001 (two-tailed test).

county Covid-19 case rates is expected to yield a -0.008 decrease in vaccination rates. This may be due to time ordering or reverse causality, where individuals in counties who have higher rates of vaccination are less likely to take tests to Covid-19 infections because of the higher likelihood of asymptomaticity. However, it is important to note that the Case Rate variable actually becomes distorted with the addition of Vaccination Signal and Vaccination Discordance in models 2 and 3. Distortion occurs when the direction of a focal relationship reverses sign once a third (distorter) variable is controlled, in this case, those related to signal. Therefore, the results of hypothesis 1 are quite inconclusive.

Table 4 model 2 tests the hypothesis 2 that increase vaccine uptake by alters will have a positive effect on vaccine uptake for the ego-county. The results are incredibly clear: seeing alter counties receiving vaccines

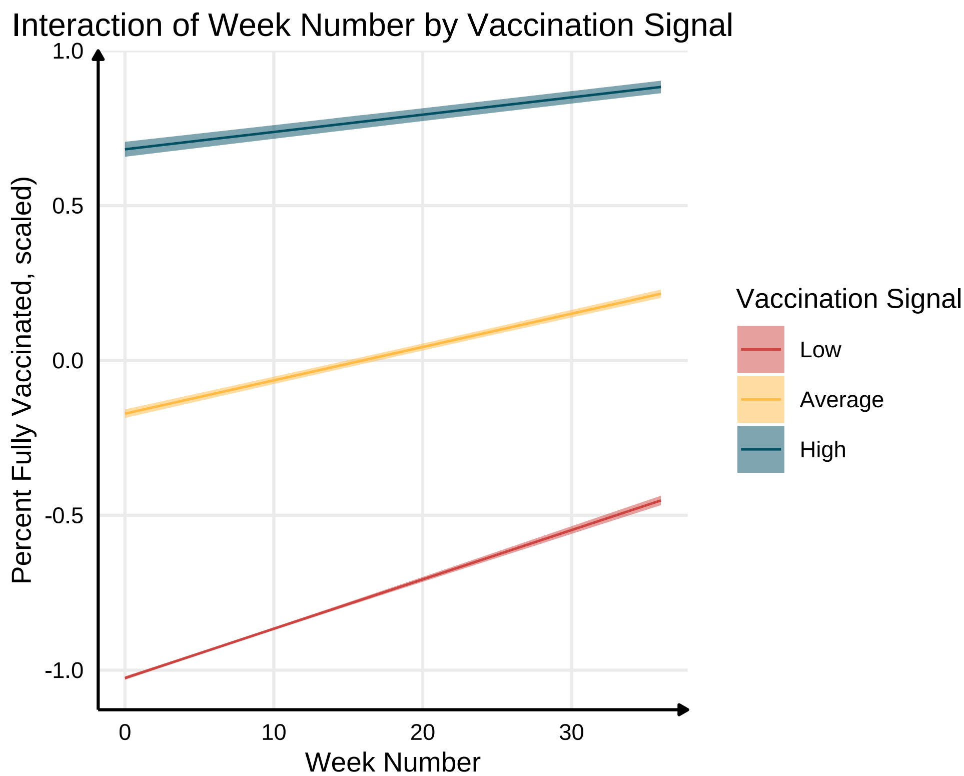


Figure 9: Predicted Values of Vaccination Rate

is associated with higher vaccination rates. Specifically, a 1 standard deviation increase in vaccine signal, the average rate of vaccination of a county's alters, is associated with a 0.854 percent increase of vaccination rates for the ego county. The strength of this result leads me to reject the null hypothesis for hypothesis 2 and find that increased average time spent in residence (signal direction) from alters will have a positive effect on time spent in residence for the ego-county. The interaction of vaccine signal can be seen in Figure 9. While the interaction is not as extreme as the results for Hypothesis 2 for Stay-at-Home rates, there is still a distinction between high and low vaccination signals over time. The slope for Higher Vaccination Signal is less pronounced than Low Vaccination Signal. This is likely an artifact where some counties vaccinated broadly early on, so their vaccination rate stays rather constant in later weeks. However, overall, the message is clear: ego-counties who 'see' high levels of vaccinations among their alters have higher vaccination rates; those who don't see that social norm forming are much less likely to vaccinate.

Table 4 Model 3 then models the moderation of signal direction for vaccine uptake by diversity in signals (*Discordance*). This is a second test of Hypothesis 3, that the effect of signal direction on vaccine uptake will be moderated by diversity in signals. The coefficients in model 3 are largely largely consistent with model 2 and there is very little change in the magnitude or significance of the coefficients. Vaccination

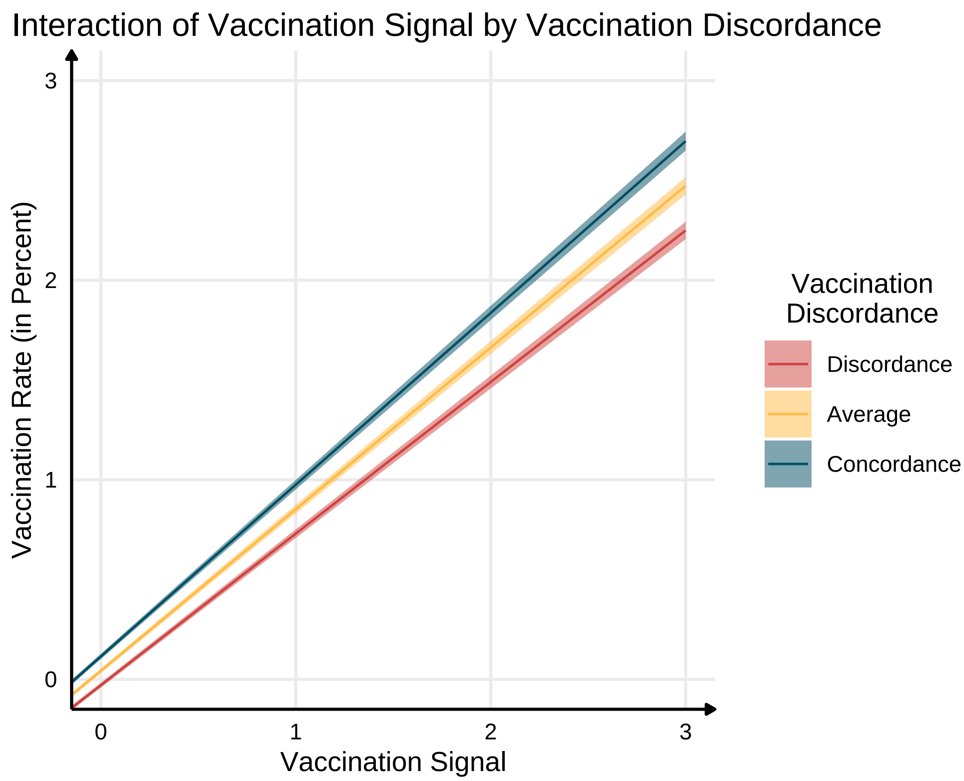


Figure 10: Predicted Values of Vaccination Rate

signal maintains to have a positive effect on the alter's vaccination rates, while vaccination discordance has a negative effect on stay-at-home rates, where every one standard deviation increase in discordance lowers rates by -0.072 ($p < 0.001$). The interaction between signal and signal discordance have a coefficient of a similar magnitude, with every one standard deviation increase in discordance *and* signal resulting in

lower rates of vaccination. Figure 10 illustrates this relationship, where there is slight moderation of the effect on vaccine signal on vaccination rates. If a county receives consistently high signals, they are more likely to have more residents vaccinated. If a county receives high but inconsistent signals, they are still decently likely to raise vaccination rates but to a lesser extent. While not as strong of moderation the the findings for Stay-at-Home Rates with hypothesis 3, I also reject the null hypothesis and find a moderation of the relationship between signal direction and vaccine uptake by diversity in signals (discordance).

5 Discussion and Conclusion

This paper examines how social norms are formed under conditions of uncertainty using the case studies of stay-at-home rates and vaccination rates during the Covid-19 pandemic. I test fear-based models of behavioral adaption to public health recommendations as well as patterns of complex social contagion. This article demonstrates that the establishment of social norms under patterns of uncertainty in my two cases do follow the theorized framework of complex contagion; however, I find a moderating effect of signal discordance to be an overlooked factor in theories of contagion.

This study is sensitive to aggregation error and sampling error derived from the multiple big-data sources (Facebook 2020; Google 2020). The aggregation errors are potentially linked to the assumption that the average stay-at-home behavior of a county is a good representation of the diversity in behaviors within that county. If stay-at-home rates are normally distributed, this is a correct assumption to make; however, little is known about each county's underlying distribution of behaviors that lead to the aggregate measures.

Regardless of limitations, this article is a unique and compelling contribution to the academic study of social contagion and social norms. First, this article demonstrates that it is possible to link, at least at a community level, information search by individuals, social relationships, and observed health behaviors without being limited to self-report measures of perceptions, attitudes, or intentions about behavior. 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.

This article also provides a new adaption of the theory of complex contagion using big data from the natural experiment of Covid-19. Because most studies of complex contagion utilize agent-based modeling or studies of social media (Aral and Nicolaides 2017; Robert M. Bond et al. 2012a; Latané, Nowak, and Liu 1994; Sprague and House 2017), combining measures of actual behavioral outcomes with data from social media websites provides a further test of ecological and external validity for the theory.

Researchers of contagion and social networks should be interested in this study. My theory of discordance, or a diversity of signals received, is not found in the literature on complex contagion; complex contagion focuses on the number of reinforcing actors, while other theories focus on how different diffusants interact with each other (Goldberg and Stein 2018; Houghton 2021; Mason et al. 2007). Discordance, on the other hand, looks specifically at the context of the reinforcing actors among the other signals. This study finds that indeed the context of the signals matters for diffusion.

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