I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16307

Social Connections and COVID-19 Vaccination

Arnab K. Basu
Nancy H. Chau
Oleg Firsin

JULY 2023

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16307

Social Connections and COVID-19 Vaccination

Arnab K. Basu
Cornell University and IZA

Nancy H. Chau
Cornell University and IZA

Oleg Firsin
University of Maryland

JULY 2023

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Social Connections and COVID-19 Vaccination

This paper unpacks the effects of social networks on monthly county-level COVID19 vaccinations in the US. To parse out short-term community-level externalities where people help each other overcome immediate access barriers, from learning spillovers regarding vaccine efficacy that naturally take time, we distinguish between the contemporaneous and dynamic network effects of vaccination exposure. Leveraging an extensive list of controls and network proxies including Facebook county-to-county links, we find evidence showing positive, stage-of-pandemic dependent contemporaneous friendship network effects. We also consistently find null dynamic network effect, suggesting that social exposure to vaccination has had limited effect on alleviating COVID vaccine hesitancy.

JEL Classification: I12, D83, H12

Keywords: friendship network, COVID-19, vaccine uptake

Corresponding author:
Nancy H. Chau
Charles H. Dyson School of Applied Economics and Management
Cornell University
Ithaca, NY 14853
USA
E-mail: hyc3@cornell.edu

1 Introduction

Social networks can facilitate information exchange, shape opinions and ultimately affect decision-making. In the context of the many unprecedented public health challenges brought on by the COVID19 pandemic, social network ties have featured prominently as predictors of the direction of spread of the pandemic (Kuchler et al., 2021), as mediators of social distancing practices (Holtz et al., 2020; Bailey et al., 2020), and as channels through which misinformation can spread (Roozenbeek et al., 2020). This paper adds vaccine uptake to the list of possible social network correlates, and investigate potential contemporaneous and dynamic spillover effects of vaccination decisions within social networks. We investigate a host of possible spillover channels (such as education, ethnicity, occupation, industry-of-employment, and geographic linkages), and evaluate the role of friendship links in the context of these alternative channels.

Vaccine uptake can be a function of information and access, and the case of COVID19 underscores the importance of both. From viral sampling to approval, the COVID19 vaccines broke the speed record, outdoing the mumps vaccines record to date of 4 years in the 1960s by a wide margin (Ball, 2020).[1] Arguably, this rapid development renders efficient information dissemination to aid learning about the potential benefits and side effects of the vaccine all the more essential. In addition, the roll-out of the newly approved COVID19 vaccines took place via novel channels. In the United States, adjusting to advance online reservations, pop-up vaccination sites with varying vaccine availability presented additional structural and access-related challenges (Center for Disease Control and Prevention (2022), Lin et al. (2022)).

Social networks can shape both the information and access dimensions of vaccine uptake (Ananyev et al., 2021). Studies have shown that getting information from experienced peers is a strong predictor of government program participation (Dahl et al., 2014). In the specific context of COVID19, Bailey et al. (2020) shows that perception regarding COVID19 severity travels through social networks, as individuals with stronger friendship exposure to COVID19 are more likely to exhibit restricted movement and spending during the pandemic. As vaccination is a key means of preventing hospitalization from contracting

[1] The emergency use authorization dates were Dec 11, 2020 for the Pfizer vaccine, Dec 18, 2020 for Moderna and Feb 27,2021 for the Johnson and Johnson vaccine.

COVID19, an important public policy question that still remains is whether exposure to vaccinated friends in one's network can change minds about the benefit-costs tradeoffs of vaccination.

In addition to communicating information and experiences, social networks can also help individuals overcome vaccine access barriers. In the earlier phases of vaccine roll-outs when demand often outstripped local vaccine supply and finding vaccine appointments required internet savvy, friends can coordinate with and/or help friends make vaccine appointments, relay information about vaccine eligibility and appointment availability, particularly where disparities in internet access are binding vaccine access constraints (Michaels et al., 2021). Alternatively and at the network level, members of the same friendship network may have access to similar resources that offer on-the-spot insights about appointment availability. This form of common access is automated in social media via algorithmic and personalized friend / groups suggestions based on mutual ties, recommendations, and group similarities, for example. Thus, vaccine uptakes can be simultaneously synchronized across network members when friends confront and solve access barriers as a group, or make use of similar resources to overcome access problems.[2] Indeed, many "vaccine hunter" or "vaccine angel" Facebook groups emerged early in 2021 with members numbering over tens of thousands.[3]

Thus, to unpack the role of social connections in COVID19 vaccine uptake, we incorporate both dynamic and synchronized network effects on vaccine uptake in a linear-in-means model augmented with county-specific, leave-one-out social interactions (Bramoullé et al., 2009; Lin, 2010; Goldsmith-Pinkham and Imbens, 2013). We leverage weekly vaccination data in the United States from December 2020 at the county level from the Center of Disease Control. Our definition of vaccine uptake is the percentage of fully vaccinated adults in a county. Since the two-dose COVID19 vaccines take at least 21 days to course-complete, we aggregate weekly vaccination data to construct our dependent variable, which we take to be month-to-month change in vaccine uptake at the county level.

[2]For example, in a study about flu vaccine uptake in a college setting, Rao et al. (2017) finds evidence that friends make coordinated flu vaccination decisions as a group.

[3]See for example Maryland Vaccine Hunters group (`https://www.facebook.com/groups/462938984877900`), which included more than 77,000 members. There are many other Facebook groups dedicated to assist group members to find COVID19 vaccine, for example in Massachusetts, Texas, Virginia, and New York, with similarly high member counts.

In defining county-level networks, we cast a wide net and allow for ethnic, occupational, industry-of-employment, political preference and geography based networks, to complement similarly constructed county-level Facebook friendship networks measured prior to the pandemic as in Bailey et al. (2020), and Holtz et al. (2020).[4] Naturally, friendship links may be derived from a host of reasons why individuals came in contact. We incorporate these alternatives linkages to distinguish between networks of people who keep in touch with each other through social media – Facebook in our case - and groups of individuals that exhibit similar characteristics.

To address possible correlated shocks due to unobservables, we estimate the effect of change in network exposure to vaccination uptake, both current and lagged, on change in vaccination uptake during that month, an approach also adopted in Bailey et al. (2020) in their study of friendship exposure to COVID19 impact on mobility patterns. We find that the spatial patterns of the change in vaccination uptake is highly variable over the course of our study period, where early vaccination waves in the Northeast and the West coast were replaced by later waves in Southwest and Southeast.[5] We use this change-on-change approach to defend against concerns that our findings are driven by unobservable characteristics across counties.

We find a strong synchronized friendship network exposure effect on COVID19 vaccination – a one standard deviation larger increase in vaccination exposure mediated by friendship links gives rise to about half a standard deviation faster growth in an average county's vaccination rate during the first several months of 2021. We also find that the size of this effect diminishes over time, to about half the size in the last 4 months of the year. Interestingly, we find that vaccination exposure mediated by a host of other county-pair proximity weights, including geographic, political, ethnic, educational, occupational, and industrial, do not seem to be associated with vaccination, once friendship exposure is accounted for.[6]

[4]Facebook is the most popular social media in the United States (Pew Research Center, 2021). With over 230 million users, the Facebook dataset provides, to our knowledge, the most comprehensive coverage of friendship networks at the national level in the US.

[5]We discuss these changes in vaccination rates in greater detail in Section 3.

[6]We also included variables commonly included in the vaccine uptake literature such as gender, level of education, general vaccine acceptance (e.g. flu vaccine), political orientation, median income, ethnicity shares, and population density. Our results on these factors are consistent with existing studies.

By sharp contrast, we find that there is a notable lack of dynamic social network effects, in that lagged (greater than one month) vaccination exposure mediated by friendship and other similarity measures do not seem to affect vaccination dynamics in a county. These null dynamic findings suggest that vaccine hesitance may be resistent to change even after lagged exposure to lived experiences that can reveal evidence of efficacy and / or side-effects. These findings are consistent with studies that suggest that individuals are slow to change vaccine preferences, even when incentivized via financial incentives (Jacobson et al., 2022).

Taken together, the lessons we draw from this analysis is that there is a high degree of heterogeneity in any given local population in terms of the ease of vaccine access as well as the preference regarding vaccine uptake. In so doing, we point to areas where public policy can work towards complementing the role of social networks in improving vaccine accessibility, as well as the challenges ahead regarding vaccine hesitancy that seems to persist even with due demonstration of effectiveness and potential side effects.

2 Literature

This paper contributes to the literature on vaccine hesitancy by highlighting the access and preference dimensions of vaccine uptake. The results to date are nuanced. For example, Sato and Takasaki (2019) uses cash incentives and finds that randomly assigned exposure to vaccination against tetanus among women in Nigeria can improve vaccine uptake. Godlonton and Thornton (2012) similarly uses cash incentives to induce exogenous variations in exposure to neighbors who have taken an HIV test in Malawi. By contrast, other studies have shown that individuals who are COVID19 vaccine-hesitant to begin with tend not to respond to health information or financial incentives to vaccinate (Jacobson et al., 2022). Our paper cautions against viewing these results from separate studies as contradictory findings. Rather, our findings point to possibly separate pockets of sub-populations. For some, social networks may demonstrate and facilitate access, and for others, information alone will not alter deep-rooted beliefs.

We also investigate the potential role of a host of distinctive peer effect channels (such as ethnicity, occupation, industry-of-employment and geographic linkages) on vaccine uptake. Indeed, studies have shown that different types of peer networks can impact health seeking behavior (e.g. friends, peers in the workplace). For example, Rao et al. (2017) finds that exposure to friends who live in residential halls with flu vaccine clinics increases the perceived health value of flu vaccination. Dahl et al. (2014) studies workplace peer effects on paternity leave and finds information transmission about employer response to be a key contributing factor. Multiple studies have looked at alternative group membership criteria that are correlated with friendship networks. These include individuals who are more likely to comply with public health guidance (Roozenbeek et al., 2020), those who are less likely to receive information from traditional media sources (Murphy et al., 2021), and those who may attempt to fact-check information (Loomba et al., 2021).[7]

Finally, this paper complements a fast-growing literature on the influence of social media on health-seeking behaviors. Social media play a particularly important role in an unanticipated crisis, wherein quick access to credible sources of information can save lives. Due to low entry cost, and user-generated content, social media differ from traditional media in that non-mainstream messages are rife (Zhuravskaya et al., 2020), and COVID19 misinformation can easily spread through social media channels (Roozenbeek et al., 2020). The mechanisms driving social media influence are thus varied, depending particularly on the perceived trustworthiness of information (Ajzenman et al., 2020; Banerjee et al., 2020; Fetzer et al., 2020; Breza et al., 2021; Besley and Dray, 2022). The findings of this paper add to this list, and show that vaccination uptake when exposed to friends with experience in overcoming new channels of vaccine access is quick and positive. We also show that this facilitation effect is not replicated by non-social media related network exposures to vaccine access.

3 Data and Empirical Specification

We are primarily interested in examining the role that a person's social network plays in vaccine uptake – more specifically, whether family/friends/acquaintances getting vaccinated affects one's probability of being fully vaccinated. The latter, of course, depends on

[7]Other related studies include Kremer and Miguel (2007) on deworming pills uptake, Cohen and Dupas (2010) on the purchase of insecticide-treated bed nets, Cohen et al. (2015) on rapid malaria diagnostic tests uptake, for example.

both willingness and ability to get vaccinated, and it is plausible for one's social network to affect one or both of these factors. In the absence of individual-level data, we will focus on county-level aggregates. Since similar patterns of vaccination among people in different counties may reflect similar characteristics of counties and of people living in these counties, we control for county characteristics and vaccination patterns in similar counties.

3.1 Data

COVID19 vaccination. Our outcome of interest is the percentage of adults fully vaccinated against COVID19,[8] which was defined in 2021 as 2 doses of Moderna or Pfizer vaccines or 1 dose of Johnson & Johnson vaccine. Center for Disease Control and Prevention (2022) provides this data at the county level, based on local reporting.[9] We label full vaccination of county $i = 1, ..., J$ as FV_i and monthly change in FV_i as ΔFV_i. For ease of notation, we will often drop the index i, unless needed for clarity.

Social-connection index. To operationalize social connections, we follow and then expand on the approach of Bailey et al. (2020).[10] Specifically, the first step is to utilize their Social Connection Index (SCI), constructed based on Facebook (FB) connections data, where

$$SCI_{ij} = \frac{\text{FB Connections}_{ij}}{\text{FB Users}_i \times \text{FB Users}_j}.$$

SCI effectively measures the ratio of FB connections between two counties to all the possible connections. The next step reflects the idea that, for a given SCI_{ij} intensity, more populous counties have a greater impact on their social networks. Hence, we calculate the population-weighted social connection index, or PCI_{ij}, which is the fraction of all FB friends of a resident of county i who reside in county j.[11] Specifically,

$$PCI_{ij} = \frac{SCI_{ij} \times Pop_j}{\sum_{j \in J} SCI_{ij} \times Pop_j}.$$

[8] We focus on full vaccination, since it was the medical target level of vaccination in 2021, but the results (available upon request) are similar if we look at 1 dose.

[9] Some localities did not provide data for at least part of 2021. Notably, Texas data is only available starting in week 43, and West Virginia even later, so these two states are mostly omitted from analysis. Other than those in Texas and West Virginia, the vast majority of counties had the required information for all weeks of 2021. Colorado and Viriginia county-level data was obtained by email from respective state authorities.

[10] We follow the version of approach with publicly available data, applying at the county level, as opposed to the zip code tabulated area, since our outcome of interest is at the county level.

[11] Bailey et al. (2020) refer to this measure as FracConnect.

To capture the vaccination rate of county i's social network, we use the PCI-weighted sum of all the vaccination rates of other counties:

$$PCIFV_{it} = \sum_{j \neq i} PCI_{ij} \times FV_{jt}. \tag{1}$$

$PCIFV_{it}$ measures the full vaccination exposure of residents in county i at time t mediated by FB friendship network intensity PCI_{ij}. In what follows, it may help to think of PCI as the $J \times J$ network intensity matrix where a typical element is PCI_{ij}, with zero diagonal values.

Other proximity/similarity measures. We include a battery of similarity measures to control for potential confounders of social network effects. In a nutshell, friends may share similarities that lead to similar health-seeking behavior such as vaccination, and the connection between individuals per se may have little to do with behavior. We define a population-weighted similarity measure as

$$PSM_{ij} = \frac{SM_{ij} \times Pop_j}{\sum_{j \in J} SM_{ij} \times Pop_j},$$

where SM indicates a similarity measure.[12] Like PCI, PSM denotes the $J \times J$ similarity intensity matrix where a typical element is PSM_{ij}, with zero diagonal values.

One obvious measure of similarity is simply geographic proximity, which we define as living in a bordering county ($SM_{ij} = 1$ if county j borders county i). This accounts for the tendency of both COVID19 exposure and vaccine availability to cluster geographically, and also captures the idea that people living close by are more likely to have similar views, including regarding vaccination. Since geographic proximity is an important factor in affecting the strength of social network ties (Bailey et al., 2018), it is a crucial factor to control for in order to distinguish between the effect of social network ties from common factors resulting from geographic proximity.

Another relevant measure is political similarity due to reported tendencies for Republicans to treat the health threat posed by the virus as less severe than Democrats (Barrios and Hochberg (2021), Bolsen and Palm (2022), Stroebe et al. (2021), Timoneda and Vallejo Vera (2021)), and vast differences in vaccination rates between Democratic

[12]The population measure is the ACS 5-year 2016-2020 estimate.

and Republican voters.[13] Political similarity is also shown by Bailey et al. (2018) to be an important predictor of social connections.

We also include educational, ethnic, occupational and industry-of-employment similarity. The first two characteristics may reflect socialization patterns and affect both friendship probability and attitude toward vaccination. The latter two may reflect professional networks as well employment-related infection risk and vaccination requirements. These measures are constructed based on the Euclidean distance of the respective categories' shares (see Appendix A for the specifics of how these measures are constructed).[14]

To capture vaccination rates in similar counties we weight their vaccination rates by the respective similarity measures:

$$PSMFV_{it} = \sum_{j \neq i} PSM_{ij} \times FV_{jt}, \tag{2}$$

where PSM stands for a given similarity/proximity index, such as the border/contiguity dummy or political similarity. Symmetrically to how we assess full vaccination exposure mediated by FB friendship network, $PSMFV_{it}$ measures the full vaccination exposure of residents in county i at time t mediated by similarity intensity PSM_{ij}.

County characteristics. In the empirical specification, we will control for county characteristics that may affect vaccination rates and trends. We include demographic characteristics (median age, % male, % black, % hispanic, % asian), median household income, % with college education or above, total county population size and area–all based on 2016-2020 5-year American Community Survey.[15] We also include percentage of votes for the Democratic candidate in 2020 presidential elections (MIT Election Data and Science Lab, 2022), % urban (2010 Census), and % vaccinated against flu in 2018 to assess general vaccine acceptance.

[13] See, for example, https://www.kff.org/policy-watch/the-red-blue-divide-in-COVID19-vaccination-rates-continues-an-update/.

[14] For example, for political similarity, we use as categories the shares respectively of Democratic voters, Republican voters, and voters voting for other party candidates in 2020 presidential elections. For education, the categories are less than high school education, high school completion, and college education or above. For ethnic similarity, the categories are White, Black, Hispanic, Asian, and other. The full list of occupation and industry categories are included in Appendix A.

[15] Retrieved from NHGIS (Manson et al., 2021)

3.2 Descriptive Statistics

To start exploring the empirical association between county i's own vaccination rate and that of counties connected to it through social networks, it is informative to observe spatial representation of the two measures. To this end, we present three sets of paired maps (Figure 1), showing monthly change in vaccination in county i and the change in full vaccination exposure mediated by friendship network intensity for April, July and October. We make four observations: 1) there is a positive association between changes in county-level full vaccination (FV) and full vaccination exposure mediated by friendship network ($PCIFV$);[16] 2) full vaccination exposure mediated by friendship links is geographically clustered, reflecting the fact that social networks are geographically clustered; 3) vaccination increased faster in April than in July or October; 4) in April, the West Coast, the Northeast and the Great Lakes regions saw fastest growth in vaccination, but other regions saw higher rates of growth in October. The first observation provides raw data evidence of a potential link between vaccination and vaccination exposure. The next three suggest that the salience of such a link vary over time for a given location, and across geographical regions in different periods of time.

Next, we calculate and note that the correlation coefficient between full vaccination exposure mediated by friendship links and full vaccination exposure mediated by bordering county links is very high, at almost 0.9, whereas it is low-moderate for other measures, including education, ethnicity, occupation, and industry-of-employment similarity.[17] This highlights the need to control for bordering county vaccination trends to prevent misattribution of the effect of geography to that of social networks.

In addition to uneven vaccination trends across regions over time, the overall vaccination rate in the country changed significantly over the course of 2021. Figure 2 shows that new monthly vaccinations grew rapidly in the beginning of the year, achieving peak in late April-early May, then dropped in July and started increasing again, reaching a new but much lower peak in September. Meanwhile cases dropped from January to June, before rapidly increasing in what constituted the Delta wave, reaching peak in August-September

[16] This is shown more directly in Figure A1, which presents a binned scatter plot of FV and $PCIFV$.

[17] Details on the exact figures for the correlation coefficients between the full vaccination exposure change mediated by friendship links and full vaccination exposure change mediated by other similarity measures are in Table A3.

(likely inducing the second wave of vaccinations). The wide swings in COVID19 exposure strength and vaccinations over time, highlight the need to conduct analysis at various points in time, rather than just one.

3.3 Empirical Specification

Although we saw in the previous section that there is a positive association between county i's vaccination change and that of the county's social network, this relationship need not be causal and may simply be driven by similarity of county i and its network, in terms of geographic location, political orientation, demographic characteristics, and so on. For example, counties located in the same state were subject to the same policy changes, such as lowering of the vaccination eligibility age. More liberal areas on the coasts and in big cities featured more politically similar views of the virus and also had greater vaccination rates early on (Figure 1). Geographic proximity is naturally a factor leading to clustering of infections transmissible through physical contact. These and other factors are not only associated with similar vaccination patterns but also with the strength of the social networks. Hence, we control for state fixed effects, full vaccination exposure based on geographic, political and other similarity measures ($PSMFV$), and county characteristics.

To account for both contemporaneous and lagged effects, we include lagged change in $PCIFV$, other lagged confounders, and lagged FV within the same county. Furthermore, we adopt a change-on-change approach in order to speak to concerns about unobservable differences that are correlated with friendship links prior to the pandemic driving the results. Hence, we formulate the following empirical specification which examines the impact of the change in full vaccination exposure on the change in vaccination rate at the county level:

$$\begin{aligned}\Delta FV_{it} = \beta_{0t} + \beta_{1t}\Delta FV_{it-1} + \beta_{2t}\Delta PCIFV_{it} + \beta_{3t}\Delta PCIFV_{it-1} + \boldsymbol{\beta_{4t}}\Delta PSMFV_{it} + \\ \boldsymbol{\beta_{5t}}\Delta PSMFV_{it-1} + \boldsymbol{\beta_{6t}}\text{Controls}_i + S_i + \epsilon_{it}.\end{aligned} \tag{3}$$

where ΔFV_{it} is the monthly change in vaccination rate in county i in calendar month t and $\Delta PCIFV_{it}$ is the change in PCI-weighted vaccination rate of other counties. We take into account the possibility that friends exhibit similar behavior because they share similar characteristics by including as controls $\Delta PSMFV_{it}$ – a vector of changes in proximity-weighted full vaccination rates of other counties. Furthermore, to distinguish between contemporaneous and dynamic effects of these peer influences and correlates, the lagged terms $\Delta PCIFV_{it-1}$ and $\Delta PSMFV_{it-1}$ represent corresponding changes in the previous month. We also control for ΔFV_{it-1}, since it may be correlated with both ΔFV_{it} and $\Delta PCIFV_{it-1}$, and omitting it might introduce bias. We have also explored longer and shorter lags, available upon request, which did not lead to qualitatively different results. Finally, $Controls_i$ are time-invariant county characteristics, S_i are state fixed effects and ϵ_{it} is the error term, potentially clustered at the state level.

We separately estimate the relationships in equation (3) for each month in 2021 starting in February. The relationships may differ by month because of the different stages of vaccine roll-out, varying eligibility of different demographic groups throughout the year, and different levels of COVID19 severity, corresponding to different "waves". For notational simplicity we will drop the t subscript in β_{kt}, but it will still be month-specific. The first coefficient we are interested in is β_2, which represents the extent to which an increase in full vaccination exposure mediated by friendship links is associated with an increase in vaccination in county i, controlling for county i characteristics and vaccination changes in counties similar to county i by other proximity measures. Effectively, a 1 percentage point greater increase in the full vaccination exposure mediated by friendship links, is associated with a β_2 greater increase in county i. ***A positive β_2 would suggest that social networks may foster stronger contemporaneous willingness and/or ability to obtain the COVID19 vaccine***.

The second coefficient we are interested in is β_3, which shows the effect of the lagged full vaccination exposure mediated by friendship links on the current change in vaccination in county i, controlling for the lagged change in county i's vaccination, and other lagged confounders. ***A positive β_3 would suggest that social networks may have a dynamic effect on vaccination behavior – previously vaccinated individuals may positively influence their friends' willingness/ability to get vaccinated.***

As a robustness check, in the appendix, to explore whether county i's vaccination can be affected not just by vaccination in socially connected counties, but also by COVID exposure level of other counties connected in different ways, we modify the previous specification accordingly. We control both for lagged cases in county i, as well as proximity-weighted cases in other counties.

Although the timing of vaccination matters, and achieving a higher vaccination rate earlier provided more months of protection, the eventual "steady-state" level of vaccination achieved matters as well. Therefore, we examine whether monthly relationship between ΔFV and $\Delta PCIFV$ translated into a relationship between cumulative vaccination rates. Towards this end, we formulate the following specification that examines determinants of cumulative vaccination rate in week 45 of 2021, when all adults had been eligible for vaccination for quite some time, Delta wave had mostly died down, and Omicron was yet to hit with full force:

$$FV_{i,t=45} = \alpha_0 + \alpha_1 PCIFV_{i,t=45} + \alpha_2 PSMFV_{i,t=45} + \alpha_3 \text{Controls}_i + S_i + \epsilon_{i,t=45}. \tag{4}$$

3.4 Identification Concerns and Limitations

Equation (3) belongs to a class of linear-in-means models augmented with leave-one-out social interactions that are specific to the individual unit in question, which is county in our case (Bramoullé et al., 2009; Lin, 2010; Goldsmith-Pinkham and Imbens, 2013). Studies have addressed the identification of the determinants of individual behavior depending on whether group behavior / norms (endogenous effect), group background characteristics (contextual effect), or commonly experienced environmental characteristics (correlated effect) drive individual-level behaviors (Manski, 1993). Bramoullé et al. (2009) shows that augmenting linear-in-means model with individual-specific social interactions (or reference groups) can enable the researcher to achieve separate identification of endogenous and contextual effects in a way free of the well-known reflection problem. In our context, social interaction heterogeneity is accomplished via the county-specific network intensity matrix, for example leveraging the Facebook friendship network, which has been shown to guide the direction of spread of the COVID19 pandemic (Bailey et al., 2020), the social distancing practices among connected individuals (Holtz et al., 2020; Liu, 2021), and the spread of misinformation (Roozenbeek et al., 2020). We then control for other correlated effects using a battery of heterogeneous county-level characteristics as controls.

Even when the network effect terms are identified, however, since $\Delta PCIFV$ is not randomly assigned, concerns regarding estimation bias remain even after the addition of relevant controls. Primarily, we may have failed to include factors that affect new vaccinations in county i and that are correlated with $\Delta PCIFV_{it}$ or $\Delta PCIFV_{it-1}$. It is informative to think of what these factors might be. Below, we discuss potential factors related to what determines the probability of Facebook friendship.

First, people are more likely to be friends with those they have met, which is highly dependent on physical proximity, as shown by Bailey et al. (2018) and is implied by Table A3. Whereas we do control for vaccination changes in bordering counties as well as state fixed effects (and have alternatively included distance and distance squared as the weights, with essentially the same results), it is possible these measures do not fully capture the physical proximity characteristics that affect both friendship probability and vaccination determinants. Thus, our approach is to adopt the physical proximity measure jointly with a list of other similarity indicators to control for confounders that are correlated with friendship and COVID19 vaccine uptake.

One of the major determinants of COVID19 vaccination (as can be seen in Table 1) has been political affiliation. Since people are more likely to be Facebook friends with those of similar political leanings (Bailey et al. (2020)), and groups of counties of similar political affiliation may have experienced waves of vaccination distinct from other counties, omitting political similarity of counties might lead to bias in our estimators of interest. Since we do include political-similarity-weighted vaccination of other counties, the concern is that perhaps the index does not capture the importance of political similarity fully. Nevertheless, the problem of omitted political similarity is at the very least mitigated.

We note that educational, ethnic, work-related (occupation and industry) characteristic may affect both friendship probability and vaccination decisions. It is also possible that we have failed to include some non-obvious determinants of friendship, which are also related to changes in vaccination. By adopting the full list of similarity measures discussed above in our estimation, our approach in this paper is to minimize estimation biases by controlling for the factors that have been singled out in the literature on vaccination uptake (e.g. political and friendship proximities), and new ones introduced here for the first time (e.g. industry- and occupational similarities).

4 Results

4.1 Main Results

The results of the empirical specification in equation 3 are presented in Figure 3. All the variables have been standardized by subtracting the mean and dividing by standard deviation. The change in the dependent variable as a result of a 1 standard deviation increase in the independent variable has been mapped to 0.2 standard deviation wide groups; the resulting blocks/rectangles have been colored in accordance with the legend, with empty rectangles for statistically insignificant coefficients. Thus, the coefficient values represented by colored rectangles are comparable across variables and months. Each vertical set of rectangles represents a regression for a given month. Each horizontal set of rectangles represents the value of the coefficient on a given variable for the different months.

We first observe that changes in county i vaccination rate are consistently positively associated with PCI-weighted and – to a lesser extent – border-weighted changes in other counties, unlike other measures of similarity.[18] In the first half of 2021 (before July), a one standard deviation greater full vaccination exposure mediated by friendship links is associated with a 0.4 to 0.6 s.d. greater change in county i's vaccination; after no statistically significant effect in July, it becomes 0.2 to 0.4 from August to October and not statistically different from 0 thereafter. The break in the association between FV and PCIFV in July may be due to loss of vaccination momentum after the initial vaccination movement waned, before the Delta wave, which peaked in late August-early September, created a renewed push. In terms of county characteristics, it appears that different county characteristics predict faster or slower vaccination rates at different points throughout the year, with no characteristic important in all months.

Looking at the lagged changes, only the lag in county i's own vaccination rate change has a consistently significant effect on month t vaccination changes – counties that increased vaccination rates in a given month were more likely to increase vaccination the next, although that effect wore off towards the end of the year, likely after a high level of vaccination had been achieved and a fast pace of growth could not be sustained, or after

[18]This point is reinforced in Figure A2, a binned scatterplot between the $PCIFV$ and residualized FV, with residual obtained after regressing on all the variables in the heatplot except change in social network-mediated vaccination exposure change.

achieving broader base familiarity about how to get vaccinated.

The lack of an effect of lagged $PCIFV$ paired with the consistently strong effect of same-period change in $PCIFV$ points to a contemporaneous but not lagged effect of the social network. Whether friends/relatives come together to jointly overcome barriers to vaccination access or decide to get vaccinated, they appear to do that around the same time, with past behavior of social connections not affecting people's present decisions.

4.2 Additional Results

Bailey et al. (2020) show that greater COVID19 exposure in Facebook friends' counties may affect behavior–in particular, it increases social distancing behavior, such as staying at home. We want to examine whether friends' exposure also leads to greater vaccination, both as a test for an additional mechanism of the social network effect and as a robustness check for the previous results. We focus on PCI- and border-based measures of proximity, since other mediators of vaccination exposure did not seem to be important in predicting county i's vaccination change and we want to guard against attributing to social networks what is explained by geographic proximity. The results are presented in Figure A3. First we note that greater lagged change in a county's own cases per capita does seem to predict greater vaccination uptake the following month, which stands to reason. On the other hand, lagged friends' COVID19 exposure seems to have no effect on county i's vaccination (since no month features a statistically significant effect, the variable is dropped from the figure). Importantly, the effect of the contemporaneous friends vaccination change remains strong.

4.3 Cumulative Vaccination

Although the pace of early vaccination is important, it is also of interest to look at cumulative vaccination rate towards the end of 2021, and test whether there is a relationship between cumulative FV and $PCIFV$. To measure that, we look at a point in time, November 31, 2021, after vaccine roll-out had been completed (meaning, vaccines were available to virtually all interested adults throughout the country) and the Delta wave ran its course, but before the Omicron wave and the transition to booster shots. The results of this analysis are presented in Table 1. A higher cumulative vaccination in friends' counties is indeed associated with higher cumulative vaccination in county i. This is also true for bordering counties. Overall, using Shapley decomposition, we find that 40% of the variation in county vaccination rate is explained by variation in other counties, 31% by state fixed effects, and 30% by county characteristics. Thus, the association between monthly vaccination dynamics in socially connected and similar counties observed earlier translates into a very strong relationship between cumulative rates, explaining more variation in county i's vaccination than either state fixed effects or county characteristics.

5 Conclusion

In this study, we find a strong synchronized friendship network exposure effect on vaccination– a one standard deviation larger increase in social proximity weighted vaccination of other counties leads to an about half a standard deviation faster growth in an average county's vaccination rate during the first several months of 2021 (and a smaller effect after that), controlling for county lagged vaccination change, county characteristics, state fixed effects, vaccination of other counties weighted by a variety proximity indexes (geographic, political, ethnic, educational, occupational, and industry-of-employment), and severity of COVID19 exposure. On the other hand, we document a general lack of dynamic social network effects, in that lagged vaccination trends in other counties and lagged exposure do not seem to affect vaccination dynamics in a county.

The findings point to simultaneous decision making and/or joint efforts to overcome access barriers among socially connected individuals. While it is difficult to further investigate the former, there is plenty of suggestive evidence for the latter. A larger number of "vaccine hunter" Facebook groups emerged early in 2021.[19] This paper provides further evidence of the existence of this beneficial effect of social networks. The lack of dynamic effects suggests that social network is not a panacea. Our findings on the lack of dynamic effects are consistent with studies showing that attitudes towards the COVID19 vaccine are often immune to financial incentives (Jacobson et al., 2022) and subject to a high degree of politicization (Barrios and Hochberg (2021), Fridman et al. (2021), Bolsen and Palm (2022), Stroebe et al. (2021), Timoneda and Vallejo Vera (2021)).

[19] https://www.vaccinehunter.org/ contains links to dozens of such groups with tens of thousands of members.

Figure 1: Vaccination Change in 2021

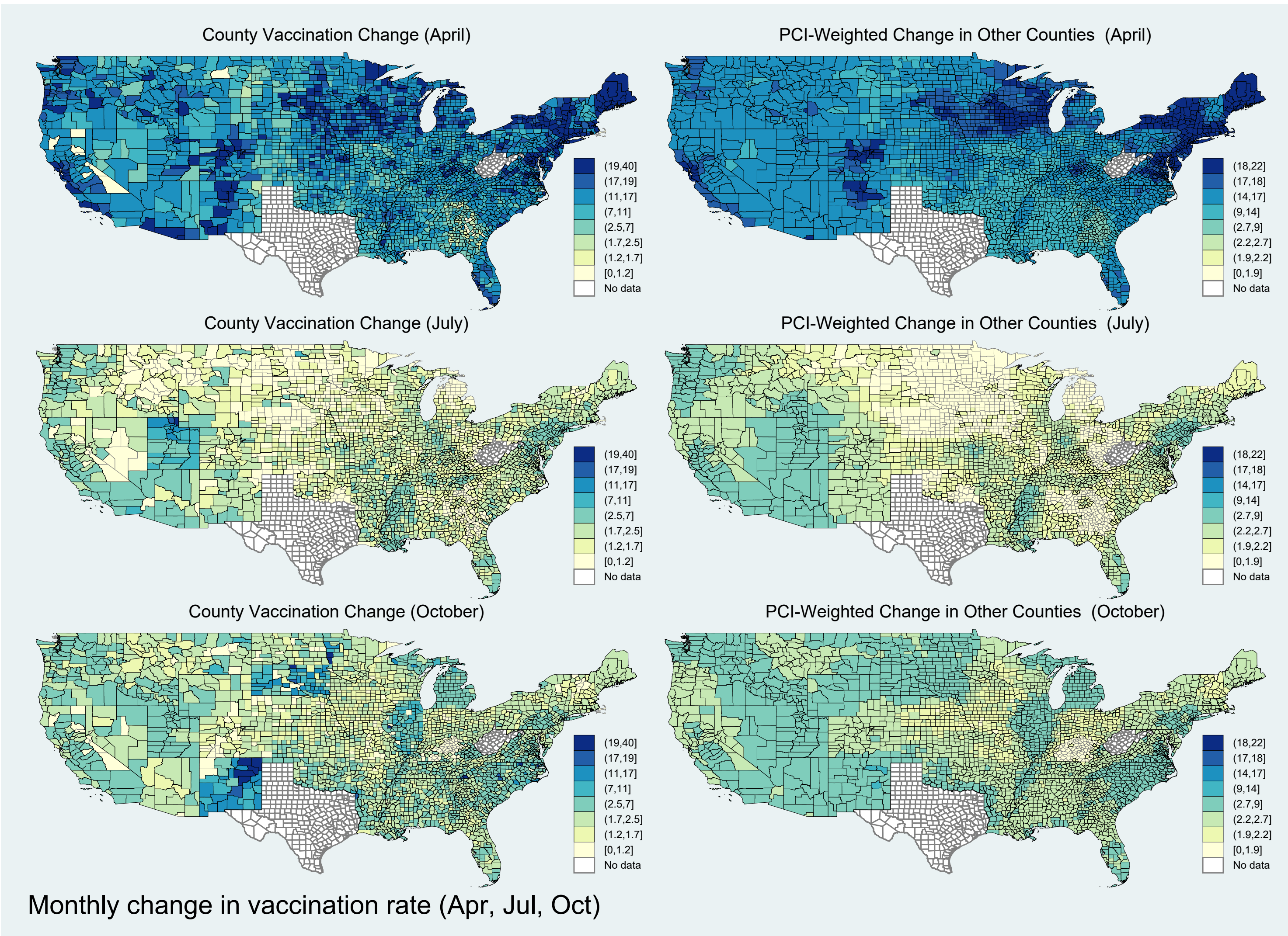


Figure 2: Monthly New Cases and Vaccination in 2021

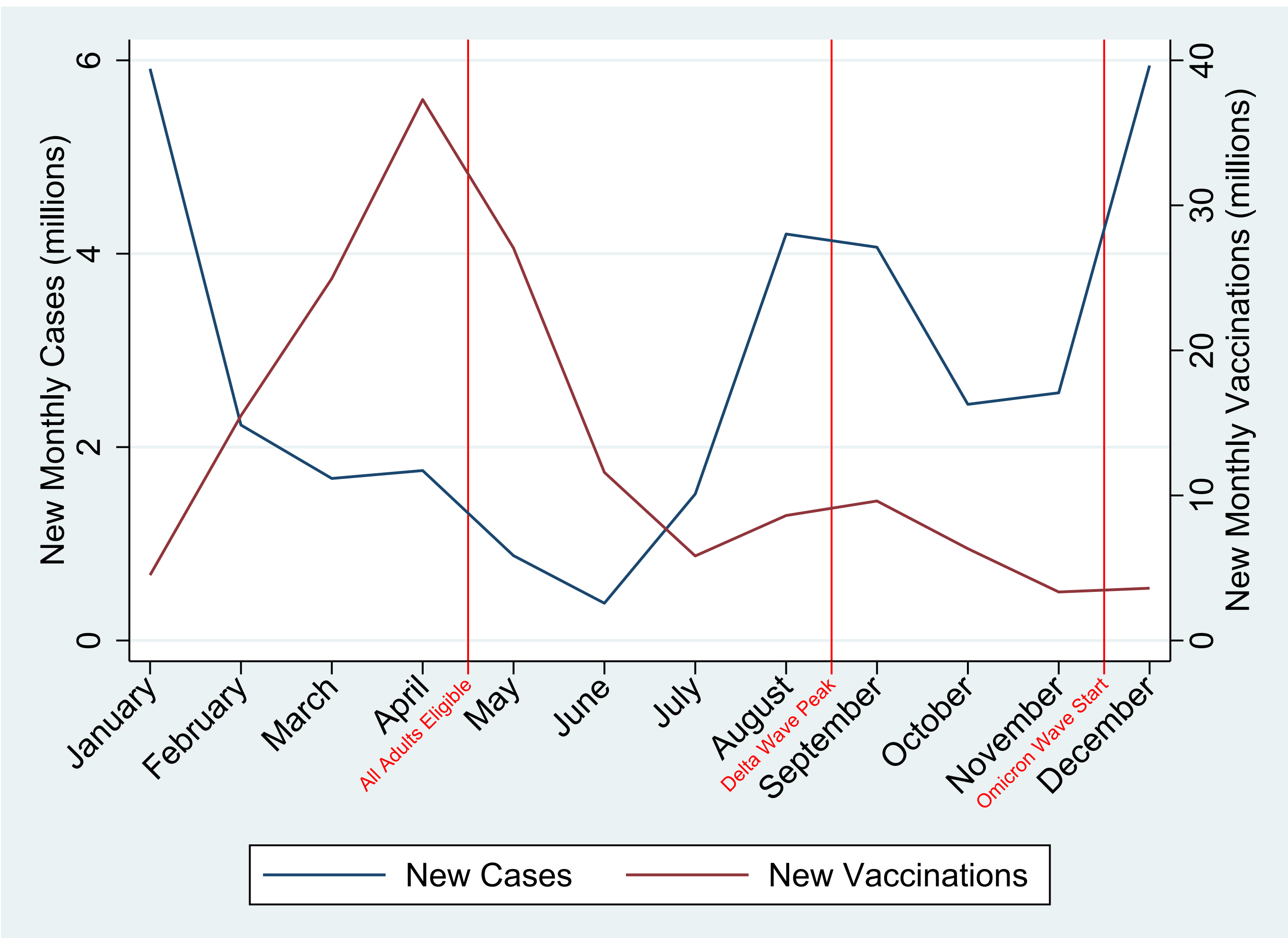
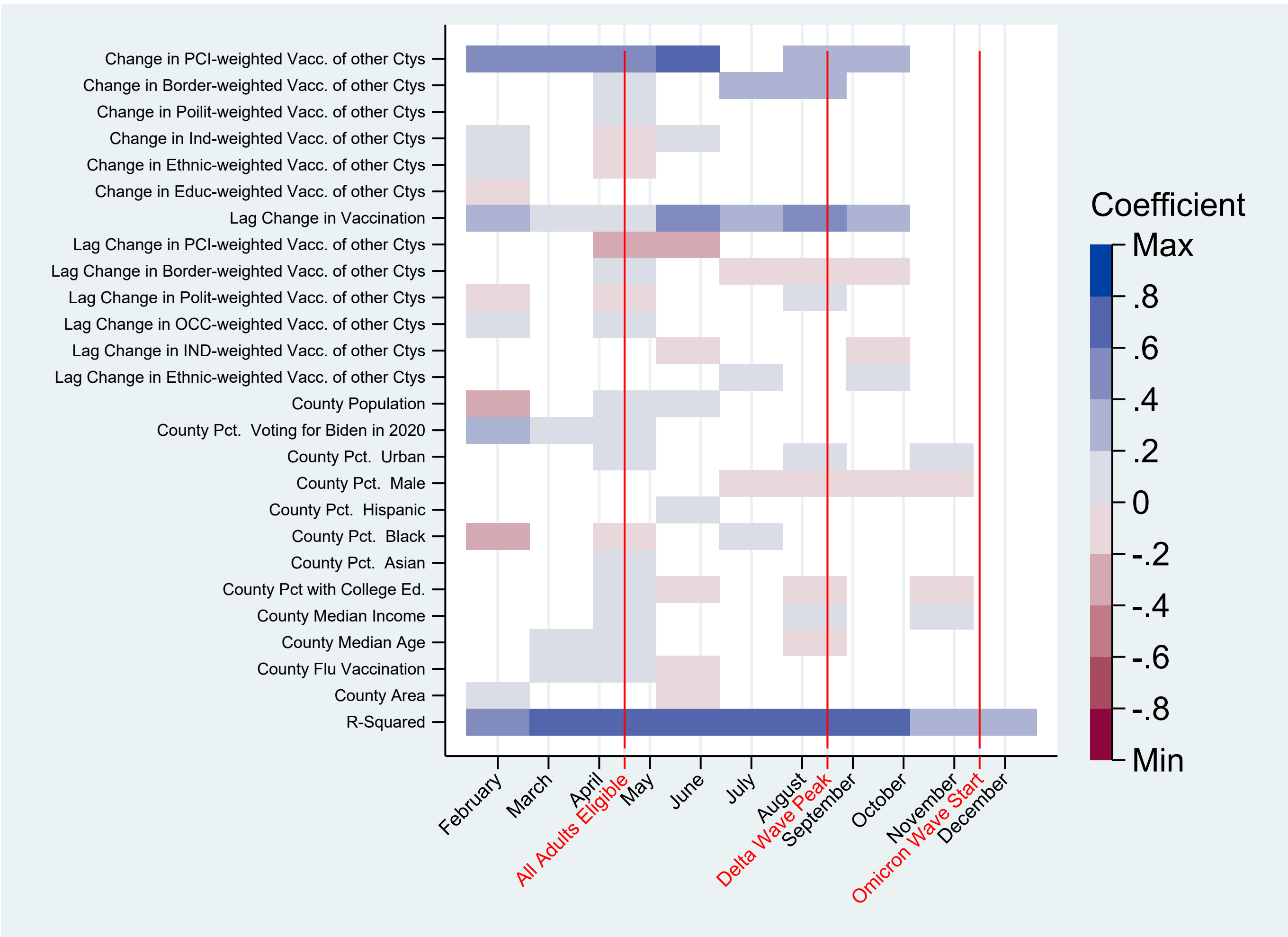


Figure 3: Coefficient Values by Month (Depvar = change in vaccination rate)



Notes: 1. This figure shows a heatmap of the estimated effects of the displayed list of variables on the county-level monthly change in COVID19 vaccination from February 2021 to December 2021. 2. All variables have been standardized by subtracting the mean and dividing by s.d.. 3. White squares=p-value> 0.05. 4. The R-square of each individual regression shown are shown in the first row. 4. Other variables included the regressions but not shown are state fixed effects.

Table 1: Correlates of County Vaccination Rate as of November 30 (2021)

	(1)	(2)	(3)	(4) GROUP SHAPLEY
PCI-weighted Vacc. of other Ctys	1.274***	1.285***	0.780***	39.8%
	(0.122)	(0.128)	(0.150)	
Educ-weighted Vacc. of other Ctys	0.168**	–0.0175	0.00147	
	(0.0603)	(0.0444)	(0.0390)	
Ethnic-weighted Vacc. of other Ctys	0.0494	0.0395	–0.0684	
	(0.0932)	(0.150)	(0.158)	
Polit-weighted Vacc. of other Ctys	0.219***	–0.0712	0.00203	
	(0.0453)	(0.0377)	(0.0344)	
Weighted Vacc. of bordering Ctys	0.0285	0.0313	0.00316	
	(0.0426)	(0.0389)	(0.0416)	
OCC-weighted Vacc. of other Ctys	–0.0748	0.203	0.489	
	(0.247)	(0.244)	(0.282)	
IND-weighted Vacc. of other Ctys	0.00334	–0.306	–0.211	
	(0.256)	(0.292)	(0.241)	
Pct. Male		–0.342*	–0.229	29.7%
		(0.157)	(0.154)	
Pct. Black		–0.0157	–0.185***	
		(0.0484)	(0.0460)	
Pct. Hispanic		–0.00162	0.141	
		(0.0404)	(0.0749)	
Pct. Asian		–0.0957	0.252	
		(0.140)	(0.269)	
Median Age		–0.00219	0.179	
		(0.0967)	(0.0936)	
Pct. College Educated		0.155**	–0.0340	
		(0.0573)	(0.0908)	
Median Income		–3.271	4.345*	
		(2.549)	(1.919)	
Dem. Vote Share in 2020 Pres. E.		0.179*	0.396***	
		(0.0707)	(0.0623)	
Population		–0.125	–0.563	
		(0.417)	(0.662)	
Pct. Urban		0.0170	0.0356**	
		(0.0107)	(0.0132)	
Flu Vaccination		0.0609	0.0264	
		(0.0367)	(0.0356)	
Area		–0.332	1.182	
		(0.483)	(0.610)	
Constant	–44.69***	5.863	–31.84	
	(10.83)	(20.63)	(17.70)	
State Fixed Effects	NO	NO	YES	30.5%
Observations	2791	2791	2791	
R-squared	0.617	0.637	0.695	

Standard Errors in Parentheses. Clustered at the state level. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

References

Ajzenman, N., Cavalcanti, T., and Da Mata, D. (2020). More than Words: Leaders' Speech and Risky Behavior During a Pandemic. Cambridge Working Papers in Economics 2034, Faculty of Economics, University of Cambridge.

Ananyev, M., Poyker, M., and Tian, Y. (2021). The safest time to fly: pandemic response in the era of fox news. *Journal of Population Economics*, 34(3):775–802.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., and Wong, A. (2018). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives*, 32(3):259–80.

Bailey, M., Johnston, D. M., Koenen, M., Kuchler, T., Russel, D., and Stroebel, J. (2020). Social Networks Shape Beliefs and Behavior: Evidence from Social Distancing During the COVID-19 Pandemic. NBER Working Papers 28234, National Bureau of Economic Research, Inc.

Ball, P. (2020). The lightning-fast quest for covid vaccines - and what it means for other diseases. *Nature*, 589(7840):16–18.

Banerjee, A., Alsan, M., Breza, E., Chandrasekhar, A. G., Chowdhury, A., Duflo, E., Goldsmith-Pinkham, P., and Olken, B. A. (2020). Messages on covid-19 prevention in india increased symptoms reporting and adherence to preventive behaviors among 25 million recipients with similar effects on non-recipient members of their communities. Working Paper 27496, National Bureau of Economic Research.

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

Besley, T. and Dray, S. (2022). Pandemic responsiveness: Evidence from social distancing and lockdown policy during covid-19. *PloS one*, 17(5):e0267611.

Blume, L. E., Brock, W. A., Durlauf, S. N., and Jayaraman, R. (2013). Linear social interactions models. Working Paper 19212, National Bureau of Economic Research.

Bolsen, T. and Palm, R. (2022). Politicization and covid-19 vaccine resistance in the us. *Progress in molecular biology and translational science*, 188(1):81.

Bramoullé, Y., Djebbari, H., and Fortin, B. (2009). Identification of peer effects through social networks. *Journal of Econometrics*, 150(1):41–55.

Breza, E., Stanford, F. C., Alsan, M., Alsan, B., Banerjee, A., Chandrasekhar, A. G., Eichmeyer, S., Glushko, T., Goldsmith-Pinkham, P., Holland, K., and et al. (2021). Effects of a large-scale social media advertising campaign on holiday travel and covid-19 infections: a cluster randomized controlled trial. *Nature Medicine*, (9):1622–1628.

Center for Disease Control and Prevention (2022). COVID-19 Vaccinations in the United States, County.

Cohen, J. and Dupas, P. (2010). Free Distribution or Cost-Sharing? Evidence from a Randomized Malaria Prevention Experiment*. *The Quarterly Journal of Economics*, 125(1):1–45.

Cohen, J., Dupas, P., and Schaner, S. (2015). Price subsidies, diagnostic tests, and targeting of malaria treatment: Evidence from a randomized controlled trial. *American Economic Review*, 105(2):609–45.

Dahl, G. B., Løken, K. V., and Mogstad, M. (2014). Peer effects in program participation. *American Economic Review*, 104(7):2049–74.

Fetzer, T. R., Witte, M., Hensel, L., Jachimowicz, J., Haushofer, J., Ivchenko, A., Caria, S., Reutskaja, E., Roth, C. P., Fiorin, S., Gómez, M., Kraft-Todd, G., Götz, F. M., and Yoeli, E. (2020). Global behaviors and perceptions at the onset of the covid-19 pandemic. NBER Working Papers 27082, National Bureau of Economic Research, Inc.

Fridman, A., Gershon, R., and Gneezy, A. (2021). Covid-19 and vaccine hesitancy: A longitudinal study. *PloS one*, 16(4):e0250123.

Godlonton, S. and Thornton, R. (2012). Peer effects in learning HIV results. *Journal of Development Economics*, 97(1):118–129.

Goldsmith-Pinkham, P. and Imbens, G. W. (2013). Social networks and the identification of peer effects. *Journal of Business & Economic Statistics*, 31(3):253–264.

Holtz, D., Zhao, M., Benzell, S. G., Cao, C. Y., Rahimian, M. A., Yang, J., Allen, J., Collis, A., Moehring, A., Sowrirajan, T., Ghosh, D., Zhang, Y., Dhillon, P. S., Nicolaides, C., Eckles, D., and Aral, S. (2020). Interdependence and the cost of uncoordinated responses to covid-19. *Proceedings of the National Academy of Sciences*, 117(33):19837–19843.

Jacobson, M., Chang, T. Y., Shah, M., Pramanik, R., and Shah, S. B. (2022). Can financial incentives and other nudges increase covid-19 vaccinations among the vaccine hesitant? a randomized trial. *Vaccine*, 40(43):6235–6242.

Kremer, M. and Miguel, E. (2007). The Illusion of Sustainability*. *The Quarterly Journal of Economics*, 122(3):1007–1065.

Kuchler, T., Russel, D., and Stroebel, J. (2021). The geographic spread of covid-19 correlates with the structure of social networks as measured by facebook. *Journal of Urban Economics: Insight*, page 103314.

Lin, Q., Paykin, S., Halpern, D., Martinez-Cardoso, A., and Kolak, M. (2022). Assessment of Structural Barriers and Racial Group Disparities of COVID-19 Mortality With Spatial Analysis. *JAMA Network Open*, 5(3):e220984–e220984.

Lin, X. (2010). Identifying peer effects in student academic achievement by spatial autoregressive models with group unobservables. *Journal of Labor Economics*, 28(4):825–860.

Liu, P. L. (2021). Covid-19 information on social media and preventive behaviors: Managing the pandemic through personal responsibility. *Social Science & Medicine*, 277:113928.

Loomba, S., de Figueiredo, A., Piatek, S. J., de Graaf, K., and Larson, H. (2021). Measuring the impact of covid-19 vaccine misinformation on vaccination intent in the uk and usa. *Nature Human Behavior*, 5(3):6235–6242.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, 60(3):531–542.

Manson, S., Schroeder, J., Van Riper, D., Kugler, T., and Ruggles, S. (2021). Ipums national historical geographic information system: Version 16.0.

Michaels, I. H., Pirani, S. J., and Carrascal, A. (2021). Disparities in internet access and covid-19 vaccination in new york city. *Preventing Chronic Diseases*, 18(E83).

MIT Election Data and Science Lab (2022). County Presidential Election Returns 2000-2020.

Murphy, J., Vallières, F., Bentall, R. P., Shevlin, M., McBride, O., Hartman, T. K., McKay, R., Bennett, K., Mason, L., Gibson-Miller, J., Levita, L., Martinez, A. P., Stocks, T. V. A., Karatzias, T., and Hyland, P. (2021). Psychological characteristics associated with covid-19 vaccine hesitancy and resistance in ireland and the united kingdom. *Nature Communications*, 12.

Pew Research Center (2021). Social media use in 2021. Technical report, Pew Research Center.

Rao, N., Mobius, M., and Rosenblat, T. (2017). Social networks and vaccination decisions. Technical report, FRB of Boston.

Roozenbeek, J., Schneider, C. R., Dryhurst, S., Kerr, J., Freeman, A. L. J., Recchia, G., van der Bles, A. M., and van der Linden, S. (2020). Susceptibility to misinformation about covid-19 around the world. *Royal Society Open Science*, 7(10):201199.

Sato, R. and Takasaki, Y. (2019). Peer effects on vaccination behavior: Experimental evidence from rural nigeria. *Economic Development and Cultural Change*, 68(1):93–129.

Stroebe, W., vanDellen, M. R., Abakoumkin, G., Lemay Jr, E. P., Schiavone, W. M., Agostini, M., Bélanger, J. J., Gützkow, B., Kreienkamp, J., Reitsema, A. M., et al. (2021). Politicization of covid-19 health-protective behaviors in the united states: Longitudinal and cross-national evidence. *PloS one*, 16(10):e0256740.

Timoneda, J. C. and Vallejo Vera, S. (2021). Will i die of coronavirus? google trends data reveal that politics determine virus fears. *PLOS ONE*, 16(10):1–9.

Zhuravskaya, E., Petrova, M., and Enikolopov, R. (2020). Political effects of the internet and social media. *Annual Review of Economics*, 12(1):415–438.

6 Appendix A

The similarity measure for two counties based on a given characteristic is calculated as the inverse Eucledian distance of category shares: $SM_{ij} = \sqrt{\sum_{k \in K} (\alpha_{ik} - \alpha_{jk})^2}$, where k is a given category, K is the set of all categories, α_{jk} is the share of population of county j in group k, and α_{ik} is the same for county i. For political similarity, $\alpha_{jdemocrat}$ represents the share of Democratic voters in county j, $\alpha_{jrepublican}$ represents the share of Republican voters, and α_{jother} represents the share of those voting for other party candidates in 2020 presidential elections. For education, the set of groups includes those without completed high school education, those with completed high school education but without completed college education, and those with BA or above. For ethnic similarity, the included categories are White, Black, Hispanic, Asian, and other. Occupational and industrial groups are listed below.

Occupations: Management, business, science, and arts occupations; Management, business, and financial occupations Management, business, science, and arts occupations; Computer, engineering, and science occupations Management, business, science, and arts occupations; Education, legal, community service, arts, and media occupations Management, business, science, and arts occupations; Healthcare practitioners and technical occupations Service occupations; Healthcare support occupations Service occupations; Protective service occupations Service occupations; Food preparation and serving related occupations Service occupations; Building and grounds cleaning and maintenance occupations Service occupations; Personal care and service occupations Sales and office occupations; Sales and related occupations Sales and office occupations; Office and administrative support occupations Natural resources, construction, and maintenance occupations; Farming, fishing, and forestry occupations Natural resources, construction, and maintenance occupations; Construction and extraction occupations Natural resources, construction, and maintenance occupations; Installation, maintenance, and repair occupations Production, transportation, and material moving occupations; Production occupations Production, transportation, and material moving occupations; Transportation occupations Production, transportation, and material moving occupations; Material moving occupations

Industries: Agriculture, forestry, fishing and hunting, and mining; Construction;

Manufacturing; Wholesale trade; Retail trade; Transportation and warehousing, and utilities; Information; Finance and insurance, and real estate, and rental and leasing; Professional, scientific, and management, and administrative, and waste management services; Educational services, and health care and social assistance; Arts, entertainment, and recreation, and accommodation and food services; Other services, except public administration; Public administration;

Table A1: Summary Statistics for Week 45

	mean	sd	min	max
Cumulative Vaccination of County i	56.11	14.42	0.00	99.90
PCI-weighted Vacc. of other Ctys	61.32	7.18	33.51	77.50
Educ-weighted Vacc. of other Ctys	59.51	7.02	25.63	87.41
Ethnic-weighted Vacc. of other Ctys	61.89	4.11	47.31	75.40
Polit-weighted Vacc. of other Ctys	57.59	9.74	20.90	86.64
Weighted Vacc. of bordering Ctys	58.75	11.84	7.55	90.70
OCC-weighted Vacc. of other Ctys	65.67	2.39	61.20	74.37
IND-weighted Vacc. of other Ctys	65.63	2.04	61.46	73.75
Pct. Male	49.99	2.31	41.99	69.54
Pct. Black	9.35	15.02	0.00	87.79
Pct. Hispanic	7.45	10.07	0.00	84.66
Pct. Asian	1.34	2.48	0.00	37.43
Median Age	41.75	5.36	22.20	68.00
Pct. College Educated	22.90	9.78	3.40	79.14
Median Income	3.98	0.25	3.10	4.99
Dem. Vote Share in 2020 Pres. E.	34.09	15.80	4.98	89.26
Population	10.32	1.47	6.04	16.12
Pct. Urban	41.30	31.40	0.00	100.00
Flu Vaccination	43.71	9.83	4.00	67.00
Area	6.51	0.87	0.69	9.91
Observations	2791			

Table A2: Summary Statistics for Monthly Changes

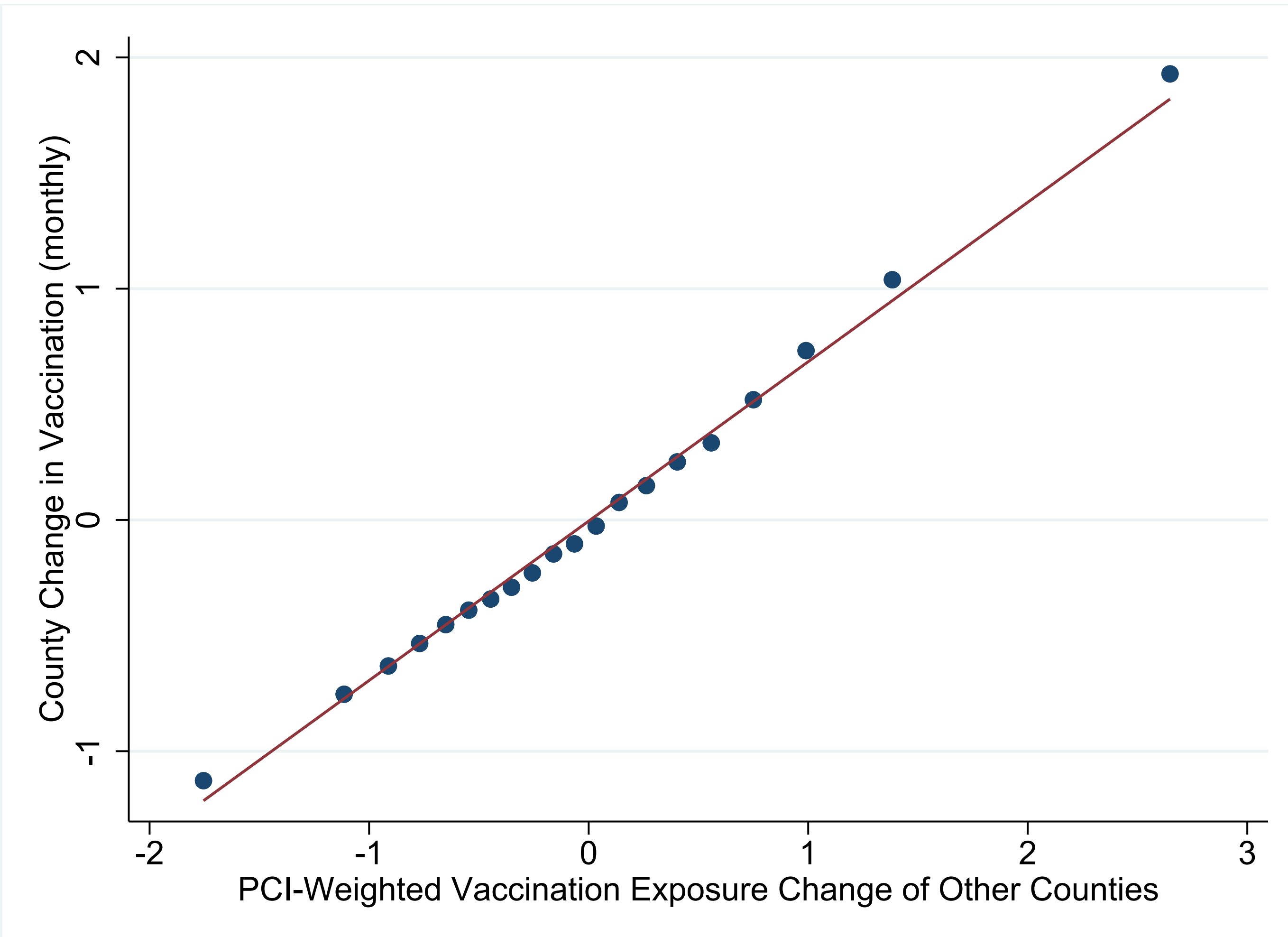
	mean	sd	min	max
Change in County i Vaccination	4.82	4.88	0.00	52.10
Change in PCI-weighted Vacc. of other Ctys	5.24	4.47	0.42	26.78
Change in PCI-weighted Vacc. of other Ctys	5.24	4.47	0.42	26.78
Change in Educ-weighted Vacc. of other Ctys	5.10	4.22	0.08	37.12
Change in Ethnic-weighted Vacc. of other Ctys	5.30	4.48	0.25	36.26
Change in Polit-weighted Vacc. of other Ctys	4.93	4.15	0.00	25.28
Change in Weighted Vacc. of bordering Ctys	5.01	4.71	0.00	46.55
Change in OCC-weighted Vacc. of other Ctys	5.62	4.59	1.46	19.35
Change in IND-weighted Vacc. of other Ctys	5.62	4.61	1.40	18.98
PCI-weighted New Cases in other Ctys (per 1000 p.)	8.89	6.30	0.51	40.42
Weighted New Cases of Bordering Ctys (per 1000 p.)	8.91	7.45	0.00	57.35
New Cases in County i (per 1000 p.)	8.95	8.35	0.00	142.42
Observations	33588			

Table A3: Correlation Coefficient

	(1) Change in PCI-weighted Vacc. of other Ctys
Change in Educ-weighted Vacc. of other Ctys	0.22***
Change in Ethnic-weighted Vacc. of other Ctys	0.31***
Change in Polit-weighted Vacc. of other Ctys	0.23***
Change in Weighted Vacc. of bordering Ctys	0.89***
Change in OCC-weighted Vacc. of other Ctys	0.26***
Change in IND-weighted Vacc. of other Ctys	0.28***
Observations	30789

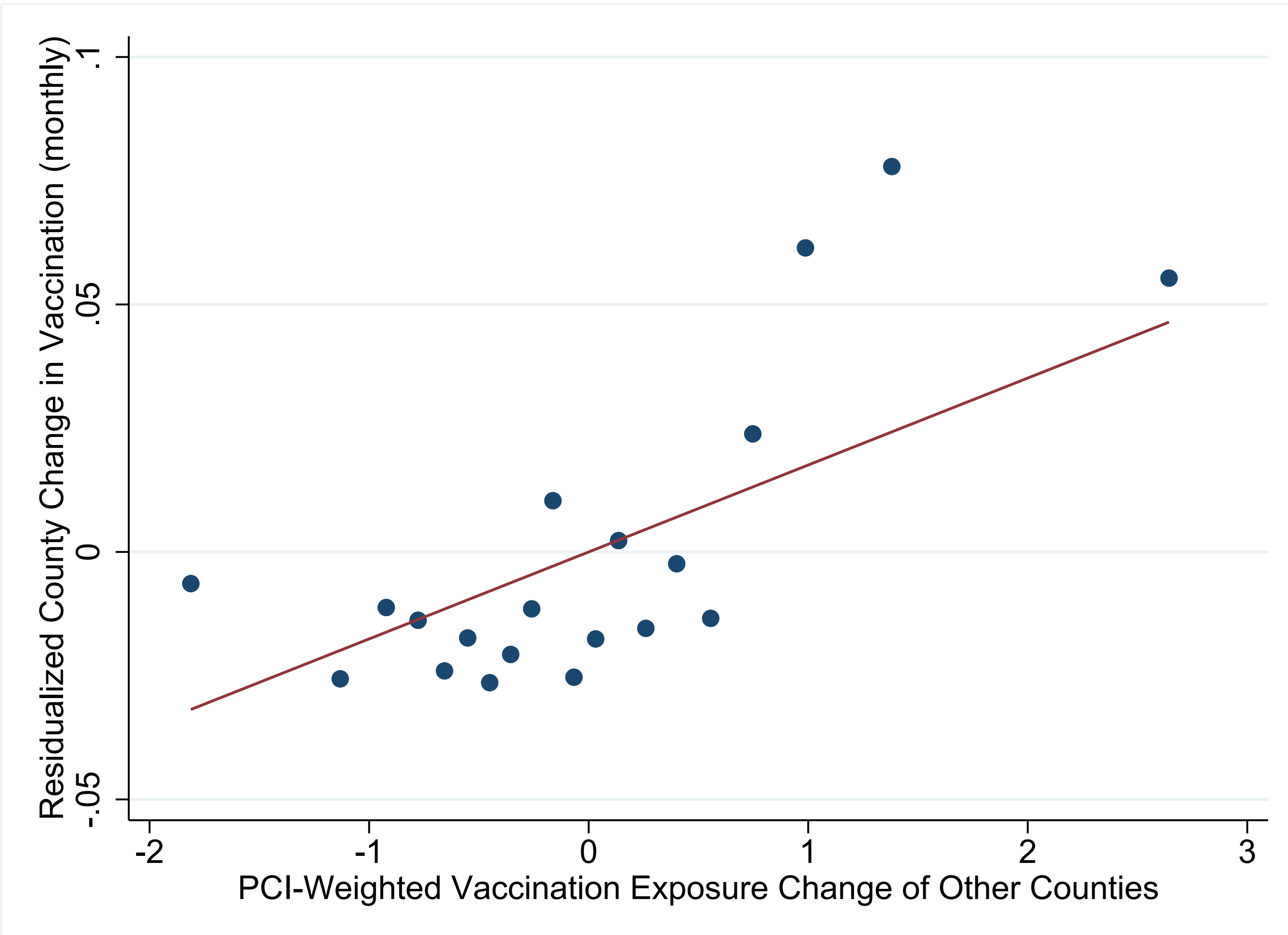
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A1: Correlation Between County's FV Change and Social Network-Mediated Vaccination Exposure Change of Other Counties (Monthly)



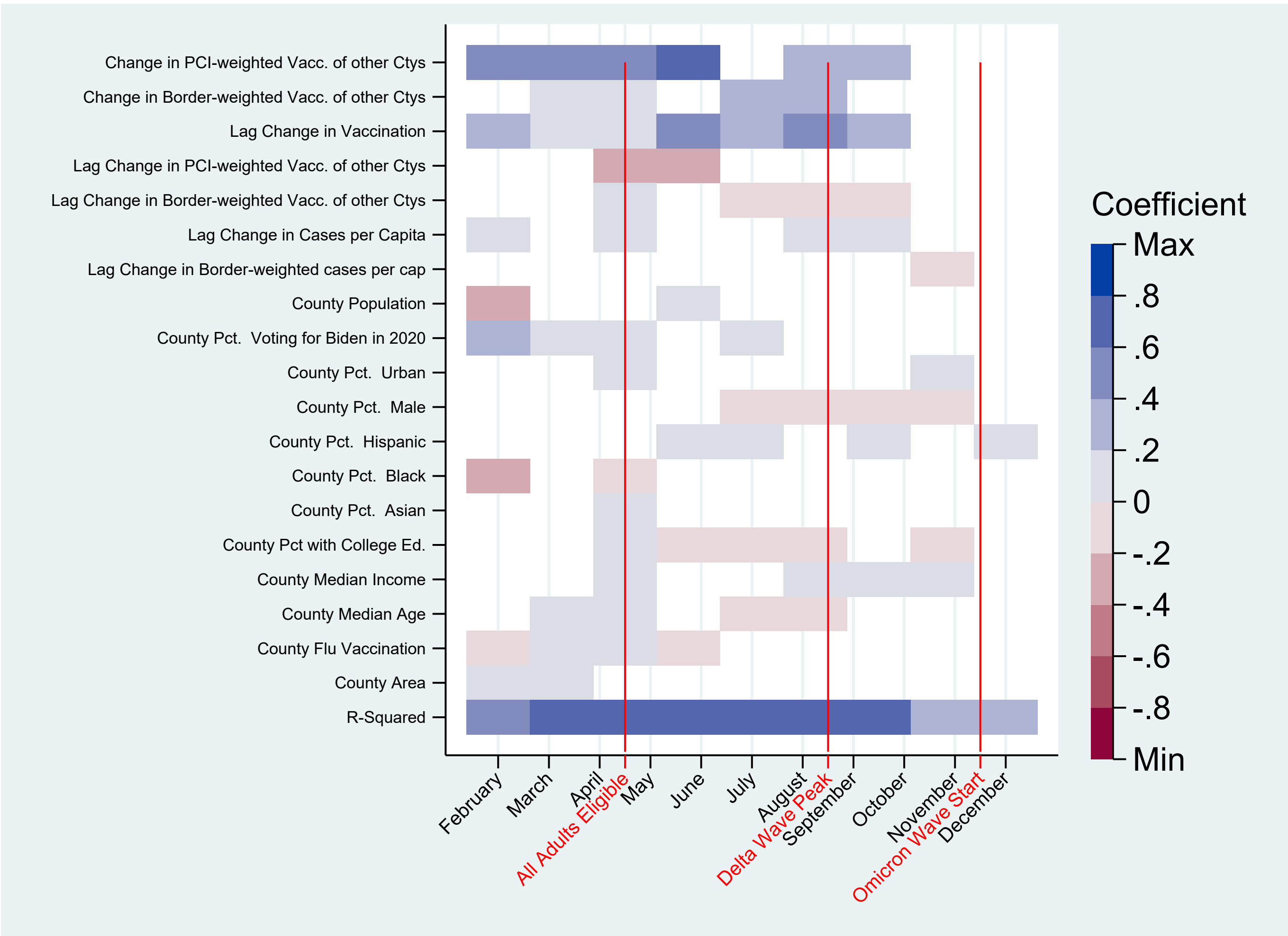
Notes: 1. Counties have been grouped using Stata's binscatter package. 2. Variables have been standardized by subtracting the mean and dividing by s.d.

Figure A2: Correlation Between Residualized County's FV Change and Social Network-Mediated Vaccination Exposure Change of Other Counties (Monthly)



Notes: 1. Counties have been grouped using Stata's binscatter package. 2. Variables have been standardized by subtracting the mean and dividing by s.d. 3. The residualized county change in vaccination was obtained by first regressing on all the explanatory variables used in the specification in Figure A3 except social network-mediated vaccination exposure change of other counties.

Figure A3: Coefficient Values by Month (Depvar = change in vaccination rate)



Notes: 1. This figure shows a heatmap of the estimated effects of the displayed list of variables on the county-level monthly change in COVID19 vaccination from February 2021 to December 2021. 2. All variables have been standardized by subtracting the mean and dividing by s.d.. 3. White squares=p-value> 0.05. 4. The R-square of each individual regression shown are shown in the first row. 4. Other variables included the regressions but not shown are state fixed effects. 5. Lag Change in PCI-weighted new cases in other counties dropped due to lack of statistically significant coefficients for any months.