Social Connection and COVID-19 Vaccine Hesitancy in the US

Yongyin Liang, Keyu Chen, Xiaotong Cui, Yinzhong Shuai

The Chinese University of Hong Kong, Shenzhen
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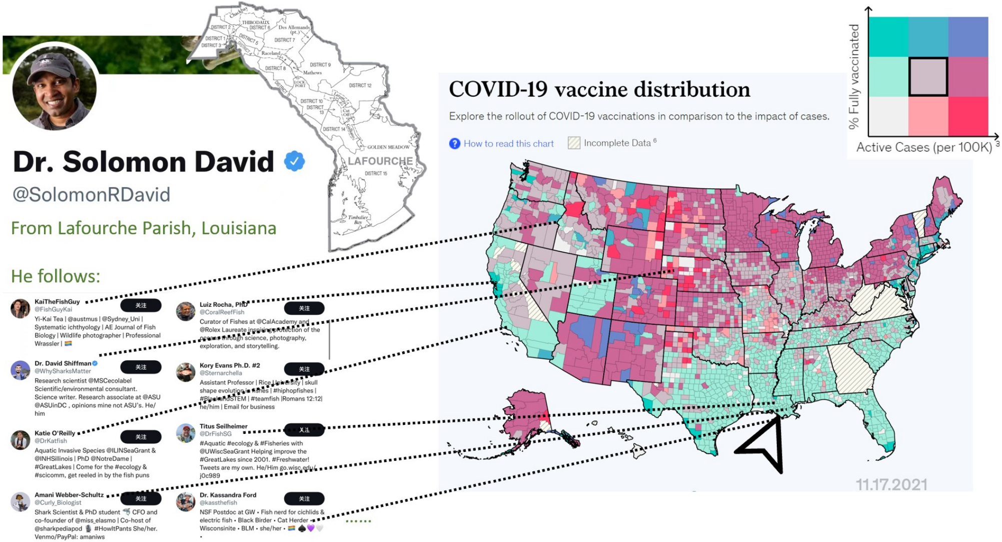
Research Question

Fixing the location (county) and time (weeks from the vaccine's introduction), are **individuals connecting with a friend population with a higher vaccination rate** less hesitant to get vaccinated?



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@SolomonRDavid
From Lafourche Parish, Louisiana
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@FishGuyKai
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Luiz Rocha, PhD
@CoralReefFish
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LAFOURCHE
COVID-19 vaccine distribution
Explore the rollout of COVID-19 vaccinations in comparison to the impact of cases.
How to read this chart
Incomplete Data
% Fully vaccinated
Active Cases (per 100K)
11.17.2021

Choice Modelling in Social Network

- Based Theory: Optimal Decision Theory
- Dynamic Discrete Choice Modelling: Agents maximize their present value of utility to make optimal decision in every stage (Rust, 1987).
- Discrete Choice with Social Interaction: Social network effects in terms of the presence of social norms: mobility decisions (Abou-Zeid et al., 2013), consumer goods and services (Bapna & Umyarov, 2015).

Behavior Diffusion in Social Network

- Based Theory: The diffusion of innovation
- Network Intervention: People can be affected by their social network to adopt new practices (Valente, 2012).
- Contagion behaviors of sports (Aral & Nicolaides, 2017), mobility (Bailey et al., 2018; Charoenwong et al., 2020), HPV vaccines (Humlum et al., 2022).

Data

1. **Twitter Users**
   - Sample: All the Twitter users in the US that self-reported COVID vaccination
   - Sample size: 123,999
   - Time span: 33 weeks (2020/11/17 - 2021/7/2)
   - Location: 50 states + DC
   - Predicted Characteristics: gender, races, ages, (income, political partisanship)
2. **Twitter Connection** figures
   - Definition of friends: the accounts a user is following
   - Exclude bots; identify news outlet, big names by political tendency;
   - Identify friends' county.
     For those who only report states ⇒ assign it to the most populated county in the state
3. **US County Pandemic Data**
   - State vaccination supply per capita, population, weekly infection cases, voting partisanship

Measurement

1. **Vaccination decision**
   Static binary vaccination measure (Humlum et al., 2022)
   vax_i is the week when Twitter user i reported her first dose of COVID-19 vaccine

$$\mathrm{Vax}_{ijt} = \begin{cases} 0 & 0 \leq t_j < \mathrm{vax}_i \\ 1 & t_j \geq \mathrm{vax}_i \end{cases}$$

2. **Friend Exposure**
   We use the vaccination rate of a friend's county to proxy her vaccination status **last week**.

$$\mathrm{FriendVax}_{it-1} = \sum_{k=1}^{51} \mathrm{FracFriends}_{ik} \times \mathrm{VaxSupply}_k^{t-1}$$

Baseline Results: Three Settings

1. Logit + Cumulative Vaccine Supply

$$\text{logit}(\text{Vax}_{ijt}) = \alpha + \beta \text{FriendVax}_{it-1} + X_i + \lambda_j + \theta_t + \epsilon_{ijt}$$

2. Logit + 1st Difference Vaccine Supply

$$\text{logit}(\text{Vax}_{ijt}) = \alpha + \beta \Delta \text{FriendVax}_{it-1} + \theta \text{FriendVax}_{it-2} + X_i + \lambda_j + \theta_t + \epsilon_{ijt}$$

3. Conditional Logit + 1st Difference Vaccine Supply

$$\text{logit}(\text{Vax}_{ijt} | \text{Vax}_{ijt-1} = 0) = \alpha + \beta \Delta \text{FriendVax}_{it-1} + \theta \text{FriendVax}_{it-2} + X_i + \lambda_j + \theta_t + \epsilon_{ijt}$$

Baseline Results: Logit + Cumulative Vaccine Supply

Table: Baseline Results

	(1)	(2)	(3)	(4)
FriendVax Lag1	5.028***	-1.477***	1.088***	-13.821***
	(0.006)	(0.065)	(0.079)	(0.807)
FriendVax Lag2				16.320***
				(0.876)
State FE		Yes	Yes	Yes
Week FE		Yes	Yes	Yes
Controls			Yes	Yes
N	2,584,820	2,430,316	1,624,784	1,392,672

Baseline Results: Logit + 1st Difference Vaccine Supply

Because the vaccination rate is a cumulative measure, it is natural to assume that **the effect of an increase (first difference) in the vaccination rate** may decay in time (lags). Therefore, we further include the first differences in vaccination rate to differentiate the effects.

$$\text{logit}(\text{Vax}_{ijt}) = \alpha + \beta\Delta\text{FriendVax}_{it-1} + \theta\text{FriendVax}_{it-2} + X_i + \lambda_j + \theta_t + \epsilon_{ijt}$$

in which $\Delta\text{FriendVax}_{it-k} = \text{FriendVax}_{it-k} - \text{FriendVax}_{it-k-1}$ is the increase in the weighted vaccination rate at time $t-k$.

Baseline Results: Conditional Logit + 1st Difference Vaccine Supply

Because the vaccination decision is one-shot, it is meaningless to consider one's vaccination status after they get vaccinated. Mathematically, that is $P(\text{Vax}_{ijt} = 1|\text{Vax}_{ijt-1} = 1) = 1$. Instead, it is more sensible to consider **the vaccination decisions of previously unvaccinated individuals**, or the conditional probability $P(\text{Vax}_{ijt}|\text{Vax}_{ijt-1} = 0)$. Therefore, we revise the model to consider the conditional logit.

$$\text{logit}(\text{Vax}_{ijt}|\text{Vax}_{ijt-1} = 0) = \alpha + \beta\Delta\text{FriendVax}_{it-1} + \theta\text{FriendVax}_{it-2} + X_i + \lambda_j + \theta_t + \epsilon_{ijt}$$

Baseline Results: Cond. Logit + 1st Diff. Vax. Supply (Contd.

Table: Conditional Logit 1st Difference Vaccine Supply

	Dependent variable:		
	(1)	(2)	(3)
FriendVax Diff1	2.623***	−8.228***	−2.535*
	(0.012)	(1.182)	(1.363)
FriendVax Lag2	3.653***	1.255***	2.023***
	(0.010)	(0.163)	(0.195)
Constant	−4.191***	−6.904***	−7.972***
	(0.007)	(0.166)	(0.247)
State FE	No	Yes	Yes
week FE	No	Yes	Yes
Control	No	No	Yes
Observations	1,602,677	1,507,473	1,033,791
Note:			*p<0.1; **p<0.05; ***p<0.01

Results Interpretation

Odds of vaccination when friends' vaccination = x: $\frac{\pi(x)}{1-\pi(x)} = \exp(\alpha + \beta x) = e^{\alpha}\left(e^{\beta}\right)^{x}$

$\frac{\text{odds}_{x+1}}{\text{odds}_{x}} = e^{\beta}$ As friends' vaccination grows from 0 to 1, the odds increase by $e^{1.088} - 1 = 1.968$

$\frac{\text{odds}_{x+1\%}}{\text{odds}_{x}} = e^{\beta\%}$ As friends' vaccination grows 1%, the odds increase by $e^{1.088\%} - 1 = 0.011$

Robustness: Vax Rate instead of Vax Supply

Table: Robustness: Vaccination Rate as FriendVax Measure

	(1)	(2)	(3)	(4)
FriendVax Lag1	5.0373***	-1.8079***	1.0885***	-13.8208***
	(0.0064)	(0.0736)	(0.0786)	(0.8066)
FriendVax Lag2				16.3200***
				(0.8757)
Intercept	-4.1582***	-16.7442	-18.8134	-18.5544
	(0.0055)	(23.6537)	(26.8376)	(0.0934)
State FE		Yes	Yes	Yes
Week FE		Yes	Yes	Yes
Controls			Yes	Yes
N	2,239,103	2,114,587	1,624,783	1,392,671

Robustness: Alternative Connection using SCI

Table: Robustness: Alternative Connection using SCI

	Dependent variable: Vax			
	(1)	(2)	(3)	(4)
log(SCI)-Vaxrate Lag1	0.031^{***}	0.011^{***}	0.009^{***}	-0.385^{***}
	(0.00004)	(0.001)	(0.001)	(0.013)
log(SCI)-Vaxrate Lag2				0.419^{***}
				(0.014)
State FE	No	No	No	No
week FE	No	Yes	Yes	Yes
Control	No	No	Yes	Yes
Observations	3,211,628	3,211,628	1,726,032	1,479,456
Note:		*p<0.1; **p<0.05; ***p<0.01		

Robustness: Alternative Sample with Inner Network

Table: Robustness: Inner Friends' Effects within Network

	(1)	(2)	(3)	(4)	(5)
FriendVax Lag1	52.437***	18.224***	11.171***	7.531***	7.479***
	(0.102)	(0.179)	(0.226)	(0.456)	(0.474)
FriendVax Lag2				4.703***	4.755***
				(0.514)	(0.631)
FriendVax Lag3					0.829
					(0.721)
FriendVax Lag4					−0.994
					(0.704)
State FE		Yes	Yes	Yes	Yes
Week FE		Yes	Yes	Yes	Yes
Control			Yes	Yes	Yes
Observations	2,784,192	2,618,784	1,754,560	1,699,730	1,590,070

Robustness: Alternative Functional Forms and Trimmed Sample

Table: Robustness: Functional Forms and Trimmed Sample

	Dependent variable: Vax			
	baseline	log function	sqrt function	friendnum=(10,1702)
	(1)	(2)	(3)	(4)
FriendVax Lag1	1.088***			1.779***
	(0.079)			(0.092)
log(friendvax_lag1 + 1)		1.838***		
		(0.146)		
sqrt(friendvax_lag1 + 1)			2.851***	
			(0.215)	
State FE	Yes	Yes	Yes	Yes
week FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Observations	1,624,784	1,624,784	1,624,784	1,265,012
Note:	umn4r*p<0.1; **p<0.05; ***p<0.01			

Robustness:Treatment Placebo Test

- We reproduces the core analysis with an alternative treatment variable by reshuffling the friend matching.
- We establish our placebo treatment group (*temporarily* 1 iteration due to complexity and storage) by "mismatching" 150 following and follower relationship for each user to validate that the spurious treatment has no significant impact on vaccination willingness.

Robustness: Treatment Placebo Test

Table: Regression Results

	Dependent variable: Vax	
	(1)	(2)
FriendVax Lag1	0.0001	−0.004
	(0.0001)	(0.004)
FriendVax Lag2		0.004
		(0.005)
State FE	Yes	Yes
week FE	Yes	Yes
Control	Yes	Yes
Observations	1,394,456	1,195,248
Note:	*p<0.1; **p<0.05; ***p<0.01	

Robustness: Bootstrapping Placebo Test

- We also conduct a bootstrapping placebo test to measure the accuracy of the main result. Due to storage and complexity issue, we only iterate the process for ten time by adding state, week FE and all controls.

Robustness: State Shock IV

Use DID as an IV. IV instrument: $\text{AfterWeek23}_t \times \text{LateFriendFrac}_i$

- Earliest states that open public vaccination (Early States): Alaska, Mississippi, West Virginia, Utah, Georgia, Arizona from 2021-3-9 to 2021-3-24.
- Latest states that open public vaccination (Late States): District of Columbia, Hawaii, Massachusetts, New Jersey, Oregon, Rhode Island, Vermont, Virginia on 2021-4-18 or 2021-4-19 (week 23 defined in our data)

Robustness: State Shock IV

IV Equation:

- First Stage:

$$\text{logit}(\text{FriendVax}_{ijt}) = \beta_0 + \beta_1 \text{AfterWeek23}_t + \beta_2 \text{AfterWeek23}_t \times \text{LateFriendFrac}_i + X_i + \lambda_j + \theta_t + \epsilon$$

- Reduced Form:

$$\text{logit}(\text{Vax}_{ijt}) = \beta_0 + \beta_1 \text{AfterWeek23}_t + \beta_2 \text{AfterWeek23}_t \times \text{LateFriendFrac}_i + X_i + \lambda_j + \theta_t + \epsilon_{ijt}$$

Robustness: State Shock IV

Table: IV Result

	Dependent variable: Vax			
	Estimate	Std. Error	z value	Pr
FriendVax	1.0704125	0.0019728	542.592	$2e^{-16}$***
(Intercept)	-0.2477774	0.0054946	-45.095	$2e^{-16}$***
State FE	Yes			
week FE	Yes			
Control	Yes			
Observations	1,371,944			
Note:				*p<0.1; **p<0.05; ***p<0.01

Mechanism: Heterogeneity in Individual characteristics

	Dependent variable:				
	(1)	(2)	(3)	(4)	(5)
FriendVax	1.088***	0.924***	0.634***	1.130***	0.179
	(0.079)	(0.079)	(0.079)	(0.079)	(0.143)
FriendVax*Female		0.296***			
		(0.008)			
FriendVax*18-39			0.259***		
			(0.012)		
FriendVax*40+			0.778***		
			(0.014)		
FriendVax*Asian				−0.108***	
				(0.011)	
FriendVax*Mid Asian				−0.072***	
				(0.020)	
FriendVax*Indian				−0.287***	
				(0.029)	
FriendVax*Hisp				−0.032**	
				(0.013)	
FriendVax*Black				−0.125***	
				(0.012)	
FriendVax*MD					0.060***
					(0.015)
FriendVax*AZ					−1.038***
					(0.081)
FriendVax*JS					−0.381***
					(0.022)
friendvax_lag1:factor(type)99					−0.701***
					(0.028)
Observations	1,624,784	1,624,784	1,624,784	1,624,784	561,064
Note:					*p<0.1; **p<0.05; ***p<0.01

Female > Male
40+ > 18 to 39 > under 18
White > Asian > Black
Moderna > Pfizer

Mechanism: Celebrity Effect

Method 1.0:

- Use 30K as threshold, separate individual i's followings into two groups: normal friends and celebrities.
- Conduct base-line regression separately using those two groups. (Percentage of friends in each state and FriendVax are influenced).
- Celebrity:Normal = 2:5

Mechanism: Celebrity Effect

Table: Regression Results

	Dependent variable:			
	(1)	(2)	(3)	(4)
FriendVax Lag1	0.015^{***}	-0.0002^{*}	-0.001^{***}	-0.122^{**}
	(0.001)	(0.0001)	(0.0005)	(0.052)
FriendVax Lag2				0.124^{**}
				(0.053)
State FE	No	Yes	Yes	Yes
Yes				
week FE	No	Yes	Yes	Yes
Yes				
Control	No	No	Yes	Yes
Yes				
Observations	2,582,412	2,428,076	1,623,916	1,391,928

Mechanism: Celebrity Effect

Table: Regression Results

	Dependent variable:			
	(1)	(2)	(3)	(4)
FriendVax Lag1	0.399***	−0.108***	−0.053***	−6.775***
	(0.001)	(0.002)	(0.002)	(2.162)
FriendVax Lag2				6.719***
				(2.161)
State FE	No	Yes	Yes	Yes
Yes				
week FE	No	Yes	Yes	Yes
Yes				
Control	No	No	Yes	Yes
Yes				
Observations	2,581,656	2,427,236	1,623,412	1,391,496

Mechanism: Mutual Friend

Table: Robustness: Mutual Friends Effect

	Dependent variable:			
	(1)	(2)	(3)	(4)
FriendVax Lag1	2.380***	0.541***	0.531***	−1.904***
	(0.004)	(0.007)	(0.008)	(0.230)
FriendVax Lag2				2.575***
				(0.243)
State FE	No	Yes	Yes	Yes
week FE	No	Yes	Yes	Yes
Control	No	No	Yes	Yes
Observations	2,144,996	2,023,756	1,371,944	1,175,952
Note:		*p<0.1; **p<0.05; ***p<0.01		