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Revealing decision-making strategies of Americans in taking COVID-19 vaccination

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Efficient coverage for newly developed vaccines requires knowing which groups of individuals will accept the vaccine immediately and which will take longer to accept or never accept. Of those who may eventually accept the vaccine, there are two main types: success-based learners, basing their decisions on others' satisfaction, and myopic rationalists, attending to their own immediate perceived benefit. We used COVID-19 vaccination data to fit a mechanistic model capturing the distinct effects of the two types on the vaccination progress. We estimated that 47% of Americans behaved as myopic rationalists with a high variation across the jurisdictions, from 31% in Mississippi to 76% in Vermont. The proportion was correlated with the vaccination coverage, proportion of votes in favor of Democrats in 2020 presidential election, and education score.

1 Introduction

Vaccination is a primary measure to reduce morbidity and mortality of new infectious diseases (*1*), especially in areas that admit high coverage (*2*). High vaccination coverage requires high vaccine acceptance–a collective outcome of individual-level decision-making processes (*3*). Particularly, when facing a new vaccine, people need to decide between the promised immunity followed by potential side-effects associated with accepting the vaccine versus the mortality risk and governmental restrictions of refusing the vaccine. Individuals, however, vary in their decision-making strategies (*4–6*), and different strategy compositions can result in different collective outcomes (*7*), including different vaccination rates and coverage (*8, 9*). Effective promotion of vaccination benefits from identifying the different types of decision-makers and deploying tailored communication methods.

In various contexts, people are known to be mainly one of the following two decision-making types (*6, 7, 10, 11*): *(i)* those who learn from others' success, particularly, those who take the action of others with a higher payoff, known as *success-based learners* (*12*), or *imitators* (*13*), and *(ii)* those who base their decisions on their own perceptions of the environment, often aiming to maximize their instant perceived payoff (*5, 6*), named *myopic rationalists*, or *best-responders* (*14*). Exclusive populations of myopic rationalists who perceive the social context similarly are likely to reach satisfactory decisions (*15*) whereas exclusive populations of success-based learners may undergo perpetual changes of decisions (*12, 16, 17*). Mixed populations of the two may exhibit a wide range of behaviors depending on the proportions (*8, 18, 19*). Understanding the collective outcome of mixed populations, hence, requires knowing the proportions of success-based learners and myopic rationalists.

The two types of decision makers also differ in the type of information they attend to (*12*). Myopic rationalists seek information that shapes their payoffs, whereas success-based learners focus on the satisfaction achieved by others. Hence, in addition to providing insights to the vaccination dynamics, knowing the proportions of the two types inform health management and media.

The proportion, however, is unknown and needs to be estimated from data – a yet unaccomplished challenging task. The challenge is mainly because the proportions of decision-makers are unobserved. A natural approach to tackle this problem is to build a mechanistic model with the proportion of decision-makers as a parameter and estimate it by fitting the equations to existing data on measured quantities such as vaccine uptake. However, for this approach to be successful, it must be first shown that such a parameter is identifiable. Several other challenges exist. There may be insufficient detail in data from previous seasonal or relatively old diseases, where decisions were made typically once a year (*20, 21*) or lifetime (*22*). Baseline trust regarding a vaccines' effectiveness and safety may change as an initially distrustful public gradually becomes accustomed to it (*23*). The resulting hesitancy followed by the desire for immunity results in frequent decision revisions, e.g., on a bi-weekly basis (*23*). Finally, not all the population may be concerned about the vaccine as can be seen in some previously recorded vaccination programs (*24*).

The recorded data on COVID-19 in the US provides a unique opportunity to tackle each of these challenges. Although the proportion is unobservable, the two decision-making groups have different vaccination paces and differently shape the vaccination progress curve, which is observable. Indeed, we prove that the proportion of myopic rationalists is an identifiable parameter. Hence, by fitting the collective decision-making dynamics of the two types to vaccination data, we can estimate the proportion and use bootstrapping methods to obtain confidence intervals. Owing to the importance of timely vaccination and thanks to the advancement of technology, the vaccination data are available on a daily basis (*25*). The changes in baseline attitude toward the vaccine's side effects were captured through longitudinal surveys (*26*). Moreover, almost every resident had to decide on vaccination (*27*).

Our objective was to estimate the proportions of myopic rationalists and success-based learners in each of the 50 states of the US and the District of Columbia (D.C.) separately, in deciding whether to take first dose of COVID-19 vaccination. We excluded later doses as they are influenced by the experience in the first dose (*28*). We developed a mechanistic model to capture the behavior of the two types of interacting individuals augmented by a third group *vaccine refusers*, those *a priori* known to refuse the vaccine based on surveys (*29*). A fixed parameter (α) was used as the proportion of myopic rationalists in the population in each jurisdiction. The perceived excess payoff of vaccination is shaped by the epidemiological conditions represented by weekly cases and deaths, the risk of vaccine side effects, and the social and governmental pressure on unvaccinated individuals.

2 Materials and Methods

In this section, we describe the data collection procedure and the model developed to capture the vaccination progress among myopic rationalists and success-based learners. Additionally, we describe the utilized parameter estimation and inference approaches.

2.1 Data Collection

To calculate the cumulative number of available COVID-19 vaccine doses for administering the first shot, we used the temporal data on the number of delivered doses to each jurisdiction's provider locations. The data were available on the website of Centers for Disease Control and Prevention (CDC) (*30*) and captured the last part of the vaccine distribution process (*31*). To estimate the number of allocated doses for the first shot, the number of individuals completing the primary series of a two-dose vaccine, as well as the numbers of those receiving the first and the second booster doses were subtracted from the data. In majority of the US jurisdictions, the decision whether to vaccinate children under the age of 12 was left up to their guardians (*32*). Hence, we narrowed the population to those of 12 years and older. As the emergency authorization of vaccinating children of age 5 through 11 was issued on late October, 2021, we set October 31, 2021 as the last day of the dataset (*33*).

December 14, 2020 was selected as the starting date. Daily data on the total number of individuals who received their first dose, the number of individuals who completed the primary course of vaccination, and the number of individuals who received their first and second booster doses were collected from (*34*). State-level data on daily new COVID-19 cases and deaths were obtained from (*35*). We converted the temporal scale from daily to weekly.

The estimated percentage of strongly hesitant adults, available on "state_hesitancy_estimates" sheet of the Excel file "Predicted Vaccine Hesitancy by State, PUMA, and County" (*29*), was expressed as proportion and then used as the state-wide estimated proportion of COVID-19 vaccine refusers. To estimate the trend of the reduction in the perceived risk of vaccine side-effects, we used the data collected by the US Census Bureau (*26*). To determine the start date at which containment, closure or health policies differentiated based on individuals' vaccination status, we used the US sub-national data available in (*25*). The data on the state-level population by age was obtained from (*36*).

We additionally explored a number of variables that could possibly relate to the proportions of success-based learners and rationalists. We collected data on votes in favor of each political party from (*37*), income per capita and the proportion of people below the poverty line from (*38*), and the state-level education score from (*39*). The data on education score were originally in the interval of $[0, 100]$ and we scaled them to $[0, 1]$. Data on the number of potential vaccination facilities per 10K residents and the proportion of population with driving distance greater than 10 miles to the closest potential vaccination facility were obtained from (*40*). The methodology was elaborated in (*41*). The data on age, sex distribution, education level distribution, number of intensive care unit beds, ventilator capacity, percent insured residents, meat plants, religious congregation ratio, and immigrant student ratio were obtained from (*42*).

2.2 Model Formulation

We modeled the vaccination progress as the collective outcome of the vaccination behaviour of two decision-making types: myopic rationalists and success-based learners. In this regard, for each jurisdiction, a large, fixed population of N interacting individuals aged 12 and above is considered. An unknown fixed portion α are myopic rationalists, a known fixed portion (see Section 2.1) are COVID-19 vaccine refusers, and the remainder are success-based learners.

It is assumed that non vaccine refusers, i.e., myopic rationalists and success-based learners decide based on the perceived excess payoff for receiving a dose of a COVID-19 vaccine, denoted by $\Delta\pi(t)$. Myopic rationalists go for vaccination if their perceived payoff for vaccination is larger than that of remaining unvaccinated, that is, $\Delta\pi > 0$, while success-based learners base their decisions on their interactions with others in the population: Upon an interaction, an unvaccinated success-based learner compares their own payoff with those of others, who may be vacccinated or unvaccinated. Unvaccinated others conceive the same payoff as the unvaccinated success-based learner, resulting in no learning. If vaccinated others have a higher payoff, the success-based learners consider receiving vaccination with a probability proportional to the perceived excess payoff for vaccination $\Delta\pi$. We hence consider a two-state differential equation, where one state models the evolution of vaccination progress among myopic rationalists and the other one captures that of success-based learners.

The myopic rationalists follow the *best-response dynamics* (*43*), that is, unvaccinated myopic rationalists compare the payoff for vaccination with that of remaining unvaccinated and become vaccine seekers if the excess payoff is positive, i.e.,

$$\overbrace{M_s(t)}^{\substack{\text{number of}\\ \text{vaccine-seeker myopic}\\ \text{rationalists}}} = \overbrace{(\alpha_1 N_n - M_v(t))}^{\substack{\text{number of}\\ \text{unvaccinated}\\ \text{myopic rationalists}}} \overbrace{H(\Delta\pi(t))}^{\substack{\text{sign indicator of}\\ \text{excess payoff}}}, \tag{1}$$

where $M_s(t)$ denotes the number of vaccine-seeker myopic rationalists at time t, α_1 denotes the proportion of myopic rationalists in the total number of myopic rationalists and success-based learners, N_n, $M_v(t)$ denotes the number of vaccinated myopic rationalists until time t, and $H(\cdot)$ equals one for a positive argument and zero otherwise.

At it mentioned earlier, the success-based learners learn via interaction with others. When an unvaccinated success-based learner meets vaccinated individuals, if those vaccinated individuals have a higher payoff, the success-based learner becomes a vaccine-seeker with a probability proportional to the excess payoff. The number of vaccine-seeker success-based learners at time t is then

$$\overbrace{L_s(t)}^{\substack{\text{number of}\\\text{vaccine-seeker}\\\text{success-based}\\\text{learners}}} = \overbrace{((1-\alpha_1)N_n - L_v(t))}^{\substack{\text{number of}\\\text{unvaccinated}\\\text{success-based learners}}} \overbrace{\frac{L_v(t)+M_v(t)}{N}}^{\substack{\text{proportion of}\\\text{vaccinated}\\\text{individuals}}} \overbrace{\sigma[\Delta\pi(t)]_+}^{\substack{\text{dimensionless}\\\text{excess}\\\text{payoff}}}, \quad (2)$$

where $L_s(t)$ is the number of vaccine-seeker success-based learners at time t, $L_v(t)$ is the number of vaccinated success-based learners until time t, σ is the constant of proportionality (*44*), and $[x]_+$ equals x if $x > 0$ and equals zero otherwise. We focused on the first dose, indicating that vaccinated individuals never changed their strategies.

Providing there are sufficient vaccine doses, each vaccine seeker can get vaccinated. In the presence of vaccine limitations, however, not all vaccine seekers can be inoculated at once. In this case, it is assumed that the available doses are assigned randomly to the vaccine seekers of each group of decision-making types. The per capita available vaccine doses for vaccine seekers can be formulated as $v(t)/(L_s(t) + M_s(t))$ where $v(t)$ denotes the number of available doses at time t for the first shot and $L_s(t) + M_s(t)$ represents the total demand for vaccination at time t. Having $v(t)/(L_s(t) + M_s(t)) > 1$ simply means that given the available doses, each vaccine seeker has the opportunity to receive the vaccine. The rate of change of vaccinated myopic rationalists can be written as

$$\overbrace{\dot{M}_v(t)}^{\substack{\text{rate of change of}\\\text{vaccinated myopic}\\\text{rationalists}}} = \overbrace{\kappa}^{\substack{\text{max rate of}\\\text{vaccination}}} \overbrace{M_s(t)\min\{1, \frac{v(t)}{L_s(t)+M_s(t)}\}}^{\substack{\text{number of vaccine-seeker}\\\text{myopic rationalists}\\\text{who can get a vaccine}}}, \quad (3)$$

where κ represents the maximum vaccination rate. Similarly, for the rate of change of vaccinated success-based learners, we have

$$\overbrace{\dot{L}_v(t)}^{\substack{\text{rate of change of}\\\text{vaccinated success}\\\text{based learners}}} = \overbrace{\kappa}^{\substack{\text{max rate of}\\\text{vaccination}}} \overbrace{L_s(t)\min\{1, \frac{v(t)}{L_s(t)+M_s(t)}\}}^{\substack{\text{number of vaccine-seeker}\\\text{success-based learners}\\\text{who can get a vaccine}}}. \quad (4)$$

The difference between the rate of change of vaccinated success-based learners and that of myopic rationalists stems from their respective number of vaccine seekers. Once the excess payoff for vaccination is positive, all unvaccinated myopic rationalists become a vaccine seeker, irrespective of the vaccination coverage. However, the number of vaccine-seeker success-based learners is affected by the value of the excess payoff and the vaccination coverage–(2). For example, at day zero, when no one is vaccinated, no success-based learner is vaccine seeker, whereas all myopic rationalists are vaccine seekers if the excess payoff is positive. Consequently, the vaccination progress at the beginning of the vaccine roll-out is mainly shaped by the myopic rationalists.

It is assumed that both types of decision-makers conceive the same excess payoff for receiving a dose of COVID-19 vaccine which is defined by

$$\Delta\pi(t) = \overbrace{c_{\bar{v}} - \underbrace{c_{v0}(t - t_0 + 1)^{\lambda}}_{C_v(t)}}^{C_s(t)} + C_d\frac{D(t)}{\mathtt{N}} + C_i\frac{I(t)}{\mathtt{N}}, \tag{5}$$

where $\mathtt{N}$ is the total population including children, $I(t)$ is the weekly number of confirmed COVID-19 cases, and $D(t)$ is the weekly number of confirmed deaths from COVID-19 as a function of time. The conceived excess payoff for vaccination comprises of three terms: First, the quantity $C_s(t)$ is the perceived benefit of vaccination in the absence of confirmed cases or deaths and is equal to the perceived risk of remaining unvaccinated in a disease-free situation, $c_{\bar{v}}$ minus the perceived risk of vaccine associated side-effects, $C_v(t)$, i.e., $C_s(t) = c_{\bar{v}} - C_v(t)$. Second, the perceived vaccine-induced risk reduction of dying from COVID-19, C_d, that is the perceived normalized value of an actual life times the perceived effectiveness of the first dose, multiplied by $D(t)/\mathtt{N}$, which is the perceived chance of death from COVID-19. Third, the perceived vaccine-induced risk reduction of COVID-19 infection is defined similarly as $C_i I(t)/\mathtt{N}$. According to Household Pulse survey, a longitudinal survey conducted by Census Bureau, the perceived risk of vaccine associated side-effects declines over time (*23*). Our fitting result indicates that this decreasing trend can be best described by a power law function of the form $(t - t_0 + 1)^{\lambda}$, $\lambda < 0$ (see SI). Hence, $C_v(t)$ is replaced with $c_{v_0}(t - t_0 + 1)^{\lambda}$ where c_{v_0} is a free parameter (see SI). The perceived risk of remaining unvaccinated in the absence of confirmed deaths or cases is modeled by a free parameter, $c_{\bar{v}}$.

2.3 Parameter Estimation

The parameters $\{\alpha_1, c_{v_0}, c_{\bar{v}}, C_i, \sigma, \kappa\}$ were estimated by fitting the derived equations to time series data. For each jurisdiction, the valid interval for C_i was capped at $\min_t D(t)/I(t)$ for a nonzero $D(t)$ to limit the impact of morbidity on the excess payoff by that of mortality. The valid intervals for c_{v_0} and $c_{\bar{v}}$ were capped at 1. The valid interval for κ was set to $[0, 10]$. The constant of proportionality σ was bounded at 1.

A time-varying $c_{\bar{v}}$ was also considered to capture the possible impacts of differentiating policies based on the vaccination status on the perceived excess payoff for vaccination. In this regard, $c_{\bar{v}}$ is allowed to be varying over the time following a piece-wise-linear function–Fig S1. A time-varying $c_{\bar{v}}$ was captured by three additional parameters, i.e., s_f, η, and s_u. More specifically, as of the announcement date of the differentiating policies, a linear increment in the perceived cost of remaining unvaccinated is introduced with a start value, $c_{\bar{v}_0}$, inclination, s_u, and the peak value, $\eta c_{\bar{v}_0}$, as free parameters. The increment was then followed by a linear reduction whose inclination was a free parameter denoted by s_f.

The initial conditions, $L_v(0)$, $M_v(0)$ were set to zero. For each US state and D.C., the power law exponent λ was estimated using the available data on the Americans' concern about vaccine side-effects (see SI). We fit the model to the reported number of weekly vaccinated individuals, i.e., $n_v[k] = N_v[k] - N_v[k-1]$ with $n_v[0] = N_v[0]$. The error function was chosen to be the residual sum of squares, i.e., $\Sigma_k ||n_v[k] - \hat{n}_v[k]||^2$, where $\hat{n}_v[k]$ denotes the estimated number of those who received their first dose of COVID-19 vaccine at time k. The error was minimized using the dual annealing optimization algorithm (*45*) and its Python implementation (*46*). The control parameters *initial_temp* and *maxiter* were set to 50000 and 1000, respectively. The algorithm was executed with five distinct seeds–2023, 2024, 2025, 2026, 2027–for each jurisdiction. For each jurisdiction, the set of parameters corresponding to the least sum of squared residuals was selected from the five obtained sets.

We obtained the 95% confidence intervals of the estimated parameters using both parametric and non-parametric bootstrapping approaches. Following (*47*) 500 bootstrapped datasets were synthesized. For implementing the parametric bootstrap, for each time k, we assumed a Poisson error structure whose mean was the estimated number of newly vaccinated individuals at k. For each bootstrapped dataset, the number of newly vaccinated individuals at time k was drawn from the constructed Poisson distribution for week k (*48*). To synthesize the datasets based on the non-parametric approach, due to serial correlation between residual data points, an auto-regressive model was constructed and out of the resultant uncorrelated residuals, 500 time-series were drawn with replacements (*49*); see SI for more details. The 95% confidence interval was then calculated using the percentile approach (*50*).

After inferring the parameters of the excess payoff function with a time-varying $c_{\bar{v}}$, it turned out that the a time-varying $c_{\bar{v}}$ imposes high variability in the estimated parameters (Tables S17-S24). We, hence, modeled $c_{\bar{v}}$ as a constant free parameter. In addition, it turned out that although σ was identifiable (Subsection 3.1), its point estimate was not reliable (Table S16). Hence, it was set to one. Fixing the constant of proportionality to one, did not, however, impact the estimated value of our parameter of interest, i.e., α_1. More specifically, the percentage of variations in the estimated α_1 was less than 10% for all jurisdictions. Therefore, the fitting results of the model, where σ was set to one and $c_{\bar{v}_0}$ was treated as a time-invariant parameter, were reported in Subsection Fitting Results.

2.4 Correlation with Explanatory Variables

The linear correlations between a variety of variables–including socio-economic factors, vaccination coverage, and voting behaviour–and the estimated proportion of people who behaved like myopic rationalists in taking the first dose of COVID-19 vaccine α were investigated. There was insufficient data available for the D.C. across most potential explanatory variables. Additionally, the distribution of the proportion of myopic rationalists did not follow a normal distribution, as indicated by the Shapiro test. The distribution, however, became normal by excluding the D.C. and the state of Vermont. Consequently, these two jurisdictions were excluded from the linear regression analysis.

As for the linear correlation analysis, we used Pearson-r coefficient and the simple linear regression was performed using the Python implementation of Ordinary Least Squares (*51*). To check whether the assumptions of simple linear regressions were satisfied, we utilized Shapiro-Wilk test, which is a test of normality (*52*), and also Breusch-Pagan test to test the presence of heteroscedasticity in a regression model (*53*).

3 Main Results

In this section, we provide the identifiability analysis of the developed model and report the fitting results.

3.1 Identifiability Analysis

In this section, we investigate the identifiability of the parameters $\alpha_1, \kappa, c_{v_0}, \sigma, C_i$, and $c_{\bar{v}}$, that is whether theoretically it is possible to uniquely determine these parameters by observing the accumulated number of vaccinated individuals over time. There are a variety of definitions of parameter/model identifiability (*54*). We consider the following definition.

Definition 1 *Consider the following dynamical system*

$$\Sigma^{\boldsymbol{\theta}} = \begin{cases} \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}), \quad \mathbf{x}_0 = \mathbf{x}(0), \\ \mathbf{y}(t, \boldsymbol{\theta}) = \mathbf{h}(\mathbf{x}(t), \boldsymbol{\theta}), \\ t \in \mathbb{R}_{\geq 0}, \\ \mathbf{x} \in \mathcal{X} \subseteq \mathbb{R}^{x}, \mathbf{u} \in \mathcal{U} \subseteq \mathbb{R}^{u}, \mathbf{y} \in \mathcal{Y} \subseteq \mathbb{R}^{y}, \boldsymbol{\theta} \in \boldsymbol{\Theta} \subseteq \mathbb{R}^{\theta}. \end{cases} \tag{6}$$

Parameter θ_i of (6) *is said to be uniquely identifiable if for almost every $\boldsymbol{\theta}' \in \boldsymbol{\Theta}$, every input $\mathbf{u}$ in $\mathcal{U}$, and the given initial condition $\mathbf{x}_0$, the following holds:*

$$\forall t \geq 0 \quad y(t, \boldsymbol{\theta}) = y(t, \boldsymbol{\theta}') \implies \theta_i = \theta_i'.$$

For the sake of readability, the multiplication of the excess payoff $\Delta\pi(t)$ and the constant of proportionality σ is represented as $\sum_{i=0}^{i=3} c_i u_i(t)$. The coefficients c_is are as follows: $c_0 = \sigma c_{v_0}$, $c_1 = \sigma c_{\bar{v}}$, $c_2 = \sigma C_i$, and $c_3 = C_d \sigma$. The actual effectiveness of the first dose in death prevention was estimated to be 85% (*55*). Its perceived effectiveness is set equal to 100%, and the perceived normalized value of life is chosen to be 1 (the highest possible value), resulting in $C_d = 1$ and in turn $c_3 = \sigma$. The inputs u_is, $i = 0, \ldots, 3$, are $u_0(t) = -(t - t_0 + 1)^\lambda$, $u_1(t) = 1$, $u_2(t) = I(t)/\mathtt{N}$, and $u_3(t) = D(t)/\mathtt{N}$, where $\mathtt{N}$ is the total population and assumed to be fixed and known.

In the following, the cumulative number of vaccinated success-based learners $L_v(t)$ and the cumulative number of vaccinated myopic rationalists $M_v(t)$ are denoted by $x_1(t)$ and $x_2(t)$, respectively. The success-based learner and myopic rationalist dynamics are then rewritten as

$$\begin{aligned}
M_s(t) &= (\alpha_1 N_n - x_2(t))H(\Delta\pi(t)), \\
L_s(t) &= ((1-\alpha_1)N_n - x_1(t))\frac{x_1(t) + x_2(t)}{N}\sigma[\Delta\pi(t)]_+, \\
\dot{x}_1(t) &= \kappa L_s(t)\min\{1, \frac{u_4(t) - x_1(t) - x_2(t)}{L_s(t) + M_s(t)}\}, \\
\dot{x}_2(t) &= \kappa M_s(t)\min\{1, \frac{u_4(t) - x_1(t) - x_2(t)}{L_s(t) + M_s(t)}\}, \\
y(t) &= x_1(t) + x_2(t),
\end{aligned} \tag{7}$$

where the accumulated number of COVID-19 vaccine doses distributed for the first shot up to time t is denoted by $u_4(t)$. The accumulated number of vaccinated people $x_1(t) + x_2(t)$ is the measured output denoted by $y(t)$.

A negative perceived excess payoff $\Delta\pi(t)$ means that no one will get vaccinated and in turn $\dot{y}(t)$ will be equal to zero. However, during the course of COVID-19 vaccination, the number of weekly vaccinated individuals was always greater than zero (*34*). Hence, we make the following assumption.

Assumption 1 *There exists some $T > 0$ such that for all $t \in [0, T)$, the excess payoff $\Delta\pi(t)$ is positive. The time interval T is sufficiently large for the identification purpose.*

Inputs u_0 and u_1 are differentiable. In the following assumption, we further assume that the number of confirmed cases, deaths, and the accumulated number of distributed COVID-19 vaccine doses are differentiable.

Assumption 2 *The inputs u_i, $i = 2, \ldots, 4$, are differentiable.*

During the first months of COVID-19 vaccine roll-out, there was vaccine supply limitation, and then the shortage was relaxed. This observation motivates the following assumption.

Assumption 3 *There exists some $t_1 \in (0, T)$ such that*

$$\begin{cases} u_4(t) - x_1(t) - x_2(t) < L_s(t) + M_s(t) & \text{if } t < t_1, \\ u_4(t) - x_1(t) - x_2(t) > L_s(t) + M_s(t) & \text{otherwise.} \end{cases} \tag{8}$$

In words, the vaccination demand was higher than the available vaccine doses for $t < t_1$, and for $t > t_1$ the limitation was eased.

In view of eq. (7), $\sigma y(t)\Delta\pi(t)/N$ is indeed the proportion of vaccine-seeker success-based learners, and therefore, it does not exceed one.

Assumption 4 *For all $t \in [0, T)$, where T was defined in Assumption 1, $\sigma y(t)\frac{\Delta\pi(t)}{N} < 1 - \epsilon$ for an arbitrary positive constant ϵ.*

In this paper, the population of individuals aged 12 and above, the total population, and the population of non vaccine refusers are obtained from the available sources (*29,36*). This justifies the next assumption.

Assumption 5 *The population of individuals of age 12 and above N, the total population* $\mathtt{N}$*, and the population of non vaccine refusers N_n are known and fixed.*

In our model $\mathcal{U}$ is the set of inputs satisfying Assumptions 1-4, and $\boldsymbol{\Theta}$ is defined as $\{\boldsymbol{\theta} \in \mathbb{R}^6 | \theta_1, \theta_3, \theta_4 \geq 0$ and $0 \leq \theta_2 \leq 1\}$, where $\theta_1 = \kappa$, $\theta_2 = \alpha_1$, $\theta_3 = \sigma$, $\theta_4 = C_i$, $\theta_5 = c_{\bar{v}}$, $\theta_6 = c_{v0}$.

Proposition 1 *Consider the dynamical system* (7) *with the single output $y(t)$ and five inputs, $u_i, i = 0, \ldots, 4$. Provided that Assumptions 1-5 hold, the parameters κ, α_1, σ, $C_i, c_{\bar{v}}$, and c_{v_0} are uniquely identifiable.*

Proof. Assume that we are given two systems S and S' described by (7) with parameter sets $(\kappa, \alpha_1, \sigma, C_i, c_{\bar{v}}, c_{v_0})$ and $(\kappa', \alpha_1', \sigma', C_i', c_{\bar{v}}', c_{v_0}')$, respectively. Moreover, assume that these systems have the same initial conditions, outputs, and inputs. To show the identifiability of the parameters, we need to conclude that

$$(\kappa, \alpha_1, \sigma, C_i, c_{\bar{v}}, c_{v_0}) = (\kappa', \alpha_1', \sigma', C_i', c_{\bar{v}}', c_{v_0}'). \tag{9}$$

For the time interval $t \in (t_1, T)$, where there is no dose limitation, we construct a generalized input-output equation (for more information on the notion of generalized input-output equations, please refer to (*56*)). In this regard, a differential polynomial based on (7) should be calculated which does not contain x_1, x_2, or their derivatives. In view of (7) and Assumptions 1 and 4,

$$\begin{aligned} x_1(t) &= y(t) - x_2(t), \\ \dot{y}(t) &= \kappa((1-\alpha_1)N_n - y(t) + x_2(t))\frac{y(t)}{N}\sigma\Delta\pi(t) + \kappa(\alpha_1 N_n - x_2(t)). \end{aligned}$$

Considering Assumptions 2 and 3, we will have

$$
\begin{aligned}
&(1-\frac{y(t)\sigma\Delta\pi(t)}{N})\frac{\ddot{y}(t)}{\kappa} = \big(\kappa(1-\frac{y(t)\sigma\Delta\pi(t)}{N}) + y(t)\frac{\sigma\dot{\Delta\pi}(t)}{N} + \dot{y}(t)\frac{\sigma\Delta\pi(t)}{N}\big)\times \\
&\quad \big(-\frac{\dot{y}(t)}{\kappa} - \frac{y^2(t)\sigma\Delta\pi(t)}{N} + \alpha_1 N_n + (1-\alpha_1)N_n\frac{y(t)}{N}\sigma\Delta\pi(t)\big) \\
&\quad - \kappa\alpha_1 N_n(1-\frac{y(t)\sigma\Delta\pi(t)}{N})^2 + (1-\alpha_1)N_n\frac{\dot{y}(t)}{N}\sigma\Delta\pi(t)(1-\frac{y(t)\sigma\Delta\pi(t)}{N}) + \\
&\quad (1-\alpha_1)N_n\frac{y(t)}{N}\sigma\Delta\dot{\pi}(t)(1-\frac{y(t)\sigma\Delta\pi(t)}{N}) - 2y(t)\dot{y}(t)\frac{\sigma\Delta\pi(t)}{N}(1-\frac{y(t)\sigma\Delta\pi(t)}{N}) \\
&\quad - \frac{y^2(t)}{N}\sigma\dot{\Delta\pi}(t)(1-\frac{y(t)\sigma\Delta\pi(t)}{N}),
\end{aligned} \tag{10}
$$

which results in

$$
\begin{aligned}
&\frac{\ddot{y}(t)y(t)}{N\kappa}\sum_{i=0}^{i=3}c_i u_i(t) - \frac{1}{\kappa}\ddot{y}(t) - \dot{y}(t) - \frac{y(t)\dot{y}(t)}{N}\sum_{i=0}^{i=3}c_i u_i(t) + \\
&\frac{\dot{y}(t)y^2(t)}{N^2}(\sum_{i=0}^{i=3}c_i u_i(t))^2 - \frac{\dot{y}^2(t)}{\kappa N}\sum_{i=0}^{i=3}c_i u_i(t) - \frac{\kappa}{N}y^2(t)\sum_{i=0}^{i=3}c_i u_i(t) + \frac{\kappa}{N^2}y^3(t)(\sum_{i=0}^{i=3}c_i u_i(t))^2 + \\
&\frac{\kappa}{N}N_n y(t)\sum_{i=0}^{i=3}c_i u_i(t) - \frac{\kappa}{N^2}N_n y^2(t)(\sum_{i=0}^{i=3}c_i u_i(t))^2 + \\
&\frac{N_n\dot{y}(t)}{N}(\sum_{i=0}^{i=3}c_i u_i(t)) + \big(-\frac{y^2(t)}{N} - \frac{y(t)\dot{y}(t)}{\kappa N} + \frac{y(t)N_n}{N}\big)\sum_{i=0}^{i=3}c_i\dot{u}_i(t) = 0.
\end{aligned} \tag{11}
$$

According to (*56*), for single-output systems, the coefficients of a generalized input-output equation are identifiable. The following coefficients of the monomials can hence be uniquely identified for system S [1] :

$$
\frac{N}{c_3}, \quad \frac{N\kappa}{c_3}, \quad \frac{c_0}{c_3}, \quad \frac{c_1}{c_3}, \quad \frac{c_2}{c_3}. \tag{12}
$$

Similarly, the following coefficients can be uniquely identified for system S'

$$
\frac{N}{c'_3}, \quad \frac{N\kappa'}{c'_3}, \quad \frac{c'_0}{c'_3}, \quad \frac{c'_1}{c'_3}, \quad \frac{c'_2}{c'_3}. \tag{13}
$$

In view of equations (12) and (13) and the fact that population of people aged 12 and above N is assumed to be fixed and a *a priori* known parameter, it is readily concluded that $c_3 = c'_3$. By equating $\frac{N\kappa'}{c'_3} = \frac{N\kappa}{c_3}$, it is concluded that $\kappa' = \kappa'$. In a similar manner, we will have $c_0 = c'_0, c_1 = c'_1$, and $c_2 = c'_2$.

[1]Here we assume the following ranking system $y < \dot{y} < \ddot{y}$ and $\{u_0, u_1, u_2, u_4\} < u_3$.

To show $\alpha_1 = \alpha_1'$, let us define $\beta(t) = x_2(t) - \alpha_1 N_n$. In view of the identifiability of c_0, c_1, c_2, c_3, and κ, by equating $\dot{y}(t) = \dot{y}'(t)$, we obtain the following equation

$$\beta(t) = \beta'(t), \quad \forall t \in (t_1, T). \tag{14}$$

We prove $\alpha_1 = \alpha_1'$ by contradiction. Without loss of generality, let us assume that $\alpha_1 > \alpha_1'$. Consider the time interval $[0, t_1)$, where the demand exceeds the supply. Based on Definition 1, the initial condition is specified, i.e., $x_2(0) = x_2'(0)$, and consequently $\beta(0) < \beta'(0)$. Let us assume that at time t' we have $\beta(t') = \beta'(t')$, i.e., $x_2(t') - x_2'(t') = N_n(\alpha_1 - \alpha_1')$. In what follows we show that $t' \nless t_1$.

Let us assume that $t' < t_1$. Now, consider the following differential equation

$$\dot{\beta}(t) - \dot{\beta}'(t) = -f(t)(\beta(t) - \beta'(t)), \tag{15}$$

where

$$f = \frac{k(u_4 - y)(N_n - y)\frac{y\sigma\Delta\pi}{N}}{\frac{y\sigma\Delta\pi}{N}(N_n - y)(\beta + \beta')(\frac{y\sigma\Delta\pi}{N} - 1) + \beta\beta'(1 + \frac{y^2\sigma^2\Delta\pi^2}{N^2}) - 2\beta\beta'\frac{y\sigma\Delta\pi}{N} + (N_n - y)^2 y^2 \frac{\sigma^2\Delta\pi^2}{N^2}}. \tag{16}$$

For the time interval $t \in [0, t_1)$, we have

$$\begin{aligned} u_4(t) - y(t) &< -\beta(t) + \beta\frac{y(t)\sigma\Delta\pi(t)}{N} + (Nu_4 - y(t))\frac{y(t)\sigma\Delta\pi(t)}{N} \\ &< \alpha_1 N_n + 0 + N_n \\ &\leq 2N_n. \end{aligned} \tag{17}$$

In addition, for all t, $(N_n - y(t)) < N_n$ and $\frac{y(t)\sigma\Delta\pi(t)}{N} < 1$. On the other hand, for $t < t_1$ the first inequality of (8) holds, i.e, $u4(t) - y(t) < 2N_n$. Therefore, for $t < t_1$ the nominator of $f(t)$ is upper bounded by $2kN_n^2$.

The absolute values of $\beta(t)$ and $\beta'(t)$ are decreasing over time, suggesting that for all $t \in [0, t_1)$ the denominator of $f(t)$ satisfies

$$\underbrace{\frac{y\sigma\Delta\pi}{N}(N_n - y)(\beta + \beta')(\frac{y\sigma\Delta\pi}{N} - 1)}_{>0} + \underbrace{\beta\beta'(1 + \frac{y^2\sigma\Delta\pi^2}{N^2}) - 2\beta\beta'\frac{y\sigma\Delta\pi}{N}}_{\underbrace{\beta\beta'(1 - \frac{y\sigma\Delta\pi}{N})^2}_{>\beta(t_1)\beta'(t_1)(1 - \frac{y(t_1)\sigma\Delta\pi^{\max}}{N})^2}} + \underbrace{(N_n - y)^2 y^2 \frac{\sigma\Delta\pi^2}{N^2}}_{>0} \tag{18}$$

where $\Delta\pi^{\max} = \max_{t \leq t_1} \Delta\pi(t)$. Note that for $t < t_1$, the demand was higher than supply (Assumption 3), resulting in $\beta(t_1) = x_2(t_1) - \alpha_1 N_n < 0$. In overall, for all $t \in (0, t_1)$, we have

$$f(t) \leq \frac{2kN_n^2}{\beta(t_1)\beta'(t_1)(1 - \frac{y(t_1)\sigma\Delta\pi^{\max}}{N})^2}. \tag{19}$$

In view of the fact that for $t \in (0, t')$, we have $\beta(t) - \beta'(t) < 0$, the following holds:

$$\dot{\beta}(t) - \dot{\beta}'(t) \leq -\frac{2kN_n^2}{\beta(t_1)\beta'(t_1)(1 - \frac{y(t_1)\sigma\Delta\pi^{\max}}{N})^2}(\beta(t) - \beta'(t)). \tag{20}$$

Now consider the following differential equation

$$\dot{z}(t) = -\frac{2kN_n^2}{\beta(t_1)\beta'(t_1)(1 - \frac{y(t_1)\sigma\Delta\pi^{\max}}{N})^2} z(t), \quad z(0) = \beta(0) - \beta'(0), \quad t \in [0, \infty). \tag{21}$$

According to Grownwall's Inequality, we know that for $t \in [0, t_1)$, $\beta(t) - \beta'(t) < z(t)$. The solution of this system is $z(t) \leq z(0) \exp(-\frac{2kN_n^2}{\beta(t_1)\beta'(t_1)(1 - \frac{y(t')\sigma\Delta\pi^{\max}}{N})^2} t)$ which suggests that for all finite time $z(t) < 0$. Therefore $\beta(t) - \beta'(t) < 0$, for all $t < t_1$. This contradicts our assumption that $t' < t_1$. On the other hand, in view of eq. (14), $\beta(t) = \beta'(t)$, for all $t \in (t_1, T]$. The only possible case where both $\beta(t) - \beta'(t) < 0$, for all $t < t_1$, and eq. (14) are satisfied is that $\beta(t)$ jumps at $t = t_1$. This, however, cannot happen. More specifically, a jump in $\beta(t)$ is attributed to a jump in $x_2(t)$. Considering eq. (7), the first order time derivative of $x_2(t)$, i.e., $\dot{x}_2(t)$ may experience a jump. However, through integration, this possible jump vanishes, and as a result $x_2(t)$ cannot jump. Therefore, the assumption of $\alpha_1' < \alpha_1$ is contradicted. As a result, the parameters $\kappa, \alpha_1, \sigma, C_i, c_{\bar{v}}$, and c_{v_0} are uniquely identifiable. This completes the proof.

Although it is still possible that the vaccination coverage of two populations with different α_1s reaches the target level at the same time (Figs S28-S29), the identifiability of α_1, under the mentioned assumptions, implies that different proportions of decision-makers result in different vaccination progresses over time.

3.2 Fitting Results

Our fitting results suggested that 47% ($\alpha = 0.47$) of Americans aged 12 years and above behaved as myopic rationalists in receiving the first dose of COVID-19 vaccine, i.e., about 131 millions out of 279 million Americans, an equal proportion acted as success-based learners, and the remaining 6% were COVID-19 vaccine refusers. The estimated percentage of rationalists across the US varied from 31% in Mississippi to 76% in Vermont (Fig. 1). In fifteen states, myopic rationalists composed more than 50% of residents.

To ensure that the estimations were as robust as possible, we reported the confidence intervals (CIs) obtained from non-parametric bootstrapping as they resulted in larger CIs than parametric bootstrapping (Table S1). The length of 95% CI for the proportion of myopic rationalists was 0.13 or less for all jurisdictions (Table S1). For 20 states, the upper limit of the CI was lower than the estimated proportion across the US, i.e., 0.47, as well as the estimated proportions of 25 other states, implying a significant difference in the proportions.

As of November 2021, all eligible American myopic rationalists were vaccinated. Success-based learners had lower vaccine coverage. While in all jurisdictions more than half of the

Table 1: Linear correlation between explanatory variables and the estimated proportion of myopic rationalists.

Predictor variable	**Pearson-r**	**R-squared**
Vaccination coverage	0.87	0.76
Proportion of votes in favor of Democrats	0.82	0.68
Education score	0.74	0.54
Proportion of people living further than 10 miles from vaccination facilities	-0.37	0.14
Density of vaccination facilities	-0.24	0.06

imitators received at least one dose of a COVID-19 vaccine, in no jurisdiction were they all vaccinated.

The weekly number of vaccinated individuals, particularly rationalists, was greatly influenced by the vaccine doses available during the first months of vaccine roll-out which was due to vaccine supply limitations (Fig. 2A, B, E, F). The success-based learners participation in vaccination was negligible in the beginning compared to that of myopic rationalists (Fig. 2C, G). The changes in the perceived benefit of vaccination in some states were negligible compared to other states (Fig. 2D, H, Figs. S3-S27).

The proportion of myopic rationalists was correlated with the vaccination coverage, proportion of votes in favor of Democrats in the 2020 presidential election, and education score (Table 1–see Table S2 for the other explanatory variables with lower correlations). The proportion of myopic rationalists was not highly correlated with the accessibility to the vaccination facilities (Table 1–last two rows).

We evaluated the impact of each model component on the fitting results. The averaged residual sum of the squares (RSS) over all jurisdictions increased if any of the components were altered. More specifically, by assuming a fully myopically rational population ($\alpha = 1$), the RSS increased by 616%, whereas a population of success-based learners ($\alpha = 0$), resulted in an increase of 626%. To investigate the effect of the possible delay in delivering the vaccine doses compared to what was reported in the data, we introduced a 3-day delay based on California vaccine distribution plan (*57*). The estimated composition of myopic rationalists and success-based learners at the state level was fairly insensitive to the introduced delay. More specifically, the variations in the estimated proportion of myopic rationalists were less than 10% (see Table S3).

4 Discussion

We considered vaccination coverage as a collective outcome resulting from decisions of individuals that are known to be mainly either myopic rationalists or success-based learners. Although crucial to the vaccination dynamics, the proportion of the two types of decision makers has to date been unknown and not measured directly. We tackled this problem by developing a mechanistic model capturing the evolution of vaccinated population with fixed ratios of the two types of decision-makers in the context of vaccine uptake. We additionally considered a third type of vaccine refusers who never intended to be vaccinated. By fitting the model to data on the number of first-dose COVID-19 vaccinated individuals in the US, we found that, excluding the 6% vaccine refusers, about half of the Americans behaved as myopic rationalists, and half as success-based learners. The results may inform health management and guide tailored communication towards promoting vaccination uptake.

The main challenge in this work was how to estimate this unobserved proportion of myopic rationalists. We took the natural approach of building a mechanistic model with the proportion of decision-makers as a hidden parameter and then estimated it by fitting the equations to existing data on observed quantities such as vaccine uptake. However, there are two potential drawbacks with this approach. First, there could be parameter identifiability issues, resulting in a low estimation confidence. We tackled this issue by proving that the proportion of myopic rationalists is an identifiable parameter that can be uniquely estimated.

The fact that the proportion is identifiable implies that it can be estimated using a sufficiently rich dataset, which appeared to be the case for our study due to the sufficiently narrow confidence intervals. As the fitting errors did not follow a normal distribution and were temporally correlated, the confidence intervals could not be obtained based on the common assumption of independence and normally distribution. We addressed this issue by using non-parametric bootstrapping methods and applying an auto-regression to reduce the temporal correlation. Estimating the parameters using Bayesian methods could be another plausible approach which is left for future investigation.

The second drawback is that even with a unique solution, there may be other possible models for the observed human behaviour. Alternative explanations of the vaccine uptake trends could be a population consisting of *(i)* multiple groups of success-based learners with different learning rates, *(ii)* multiple groups of myopic rationalists with different uptake rates, *(iii)* multiple groups of both success-based learners learning at different rates and myopic rationalists with different uptake rates who are interacting, and *(iv)* multiple groups of success-based learners with different learning rates, myopic rationalists with different uptake rates, and intermediate learners who are both myopic rationalists and success-based learners to some degree (*58*). The first two hypotheses ignore the evidence from other studies of the existence of variations in people's reliance on social learning (*59,60*). Indeed, the dichotomy of decision-making populations has been acknowledged in previous vaccination studies (*8, 61*) as well as other contexts, such as marketing and psychology (*4, 7, 10–12, 62, 63*). The last two hypotheses, however, are likely to be more realistic. Despite this, we have considered the simplest model that includes both myopic rationalists and success-based learners and the more complex models are left for future work.

The proportion of the two types of decision-makers has not been estimated in previous vaccination studies; only homogeneous models have been fitted to data (*64, 65*). Some marketing studies estimated the relative proportion of the two types in adopting several products using the

Bass model (*7, 66, 67*). Our work complements these studies in that *(i)* rather than estimating the proportion among the final adopters, we estimated the proportion in the whole population, including unvaccinated individuals, *(ii)* we considered the influence of time-varying variables including epidemiological indices, and the perceived risk associated with vaccine side effects, *(iii)* we incorporated supply limitation in the model, and *(iv)* we showed that the proportions of these decision-makers are identifiable.

We found that myopic rationalists greatly determined the evolution of the number of weekly vaccinated individuals (vaccination speed) during the first months of the vaccine roll-out – a crucial factor in the success of vaccination programs (*68–70*). In later months, the vaccination speed was mainly determined by success-based learners. Considering the excess payoff formulation, the only factor capable of inducing a negative excess payoff is the perceived risk associated with side effects. This factor, however, according to a longitudinal survey, declines over time (*23*). This suggests that once vaccination has a higher payoff than remaining unvaccinated, which was the case during the first months, all myopic rationalists tended to take the vaccine–the only limiting factor being vaccine availability. Although success-based learners also tended to take the vaccine once the excess payoff is positive, they based their decisions on others' success, determined by the magnitude of the excess payoff and the number of vaccinated individuals. Hence, they tend to delay vaccination during the first months of the vaccine roll-out but exhibit a higher vaccination speed when many are vaccinated and available to imitate.

Myopic rationalists also greatly determined the vaccination coverage – another key factor in the success of vaccination programs (*71*). Our findings suggest that as of November 2021, all American rationalists have received their first dose of vaccine and consequently, excluding the vaccine refusers, those who remained unvaccinated were success-based learners.

The results suggest the proportion of success-based learners as a factor behind the collective vaccination behavior and contributing to the success of mass vaccination programs. The beginning of vaccination programs may mainly address access issues to expedite vaccination among myopic rationalists. Later on, vaccine-promoting interventions should be tailored to success-based learners to increase their perceived benefit of vaccination. The initiation of this second phase depends on the composition of the decision-makers, i.e., the more success-based learners in the population, the sooner the second phase should be initiated.

We observed high variations in the estimated proportion of myopic rationalists across the US jurisdiction, ranging from 0.31 to 0.76. The result is in line with studies highlighting the variation of different indices throughout the states (*72, 73*). The delivered doses in the first months shaped the number of vaccinated rationalists. However, the variation may not be attributed to vaccine supply disparity, because the doses were distributed proportionally to the state populations (*74*).

There are candidate factors to explain the inter-state differences in the ratio of myopic rationalists and success-based learners. The proportion of myopic rationalists was positively correlated with the vaccination coverage (Pearson-r = 0.87). The proportion of myopic rationalists was also positively correlated with the proportion of votes in favor of Democrats in 2020 presidential election (Pearson-r = 0.82). These findings are then consistent with the known relation between vaccination coverage and 2020 presidential election outcome (*75*). The ratio of myopic rationalists was also positively associated with education score. In view of the correlation between the ratio of myopic rationalists and vaccination coverage, this is indirectly corroborated by studies suggesting American adults with less education being less likely to receive the vaccine (*23, 76*).

Our model shows how interactions between myopic rationalist and success-based learner groups have determined the course of the vaccination for COVID-19 in the United States. Admittedly, true population could have additional heterogeneities, where different age, gender, or socio-economic status groups have different perception of the payoff (*77–79*). The extension of the model to capture this heterogeneity is subject to future work. Another limitation of this work comes from assuming a well-mixed population rather than the more realistic structured population as supported by Twitter echo-chambers (*80*). This assumption may not greatly affect myopic rationalists as important information about the excess payoff is often obtained from and shared by all reputable and publicly accessible news agencies. In the same way, online influencers – usually perceived as the most successful – make the interactions of success-based learners more well-mixed than structured (*81*). Overall, while acknowledging the aforementioned limitations, the results of this study provide strong evidence that the COVID-19 vaccine uptake dynamics were determined by interactions between myopic rationalists and success-based learners and about half of the Americans relied on the success of others in taking COVID-19 vaccine.

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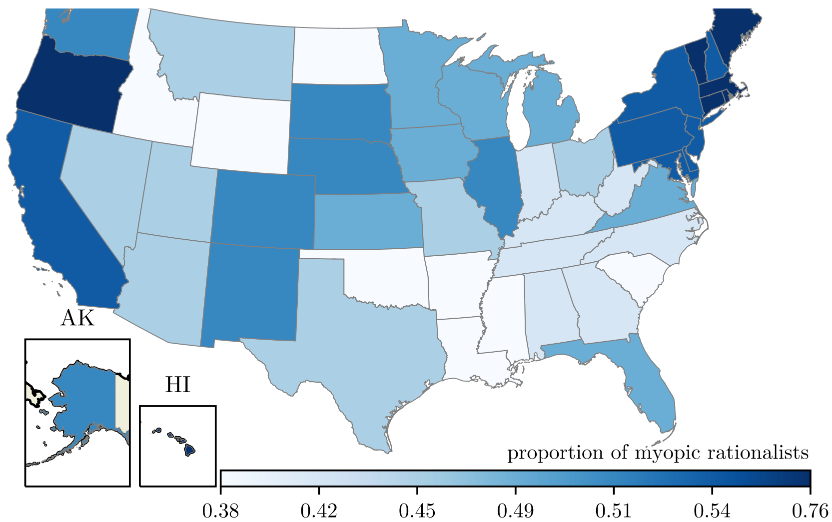

Figure 1: **Estimated proportion of myopic rationalists in taking the first dose of COVID-19 vaccination across the 50 states and the D.C. in the US**. Darker colors show a higher proportion of myopic rationalists. For each jurisdiction, the proportion of myopic rationalists aged 12 years and above was estimated by fitting the developed mechanistic model to the data on weekly newly vaccinated individuals starting from Dec 2020 to Nov 2021. The vaccine supply limitations during the first months of vaccine roll-out were captured by using the data on delivered doses to each jurisdiction over time. The national wide estimated proportion of myopic rationalists was 0.47. There was a high degree of variation across the 51 jurisdictions, i.e., 0.31 for Mississippi to 0.76 for Vermont. About 52% of the residents of the states located in the Northeast region behaved as myopic rationalists in taking COVID-19 vaccination, while in southern states, this proportion was about 43%. The estimated proportion of myopic rationalists in West and Midwest regions was respectively 0.49 and 0.46.

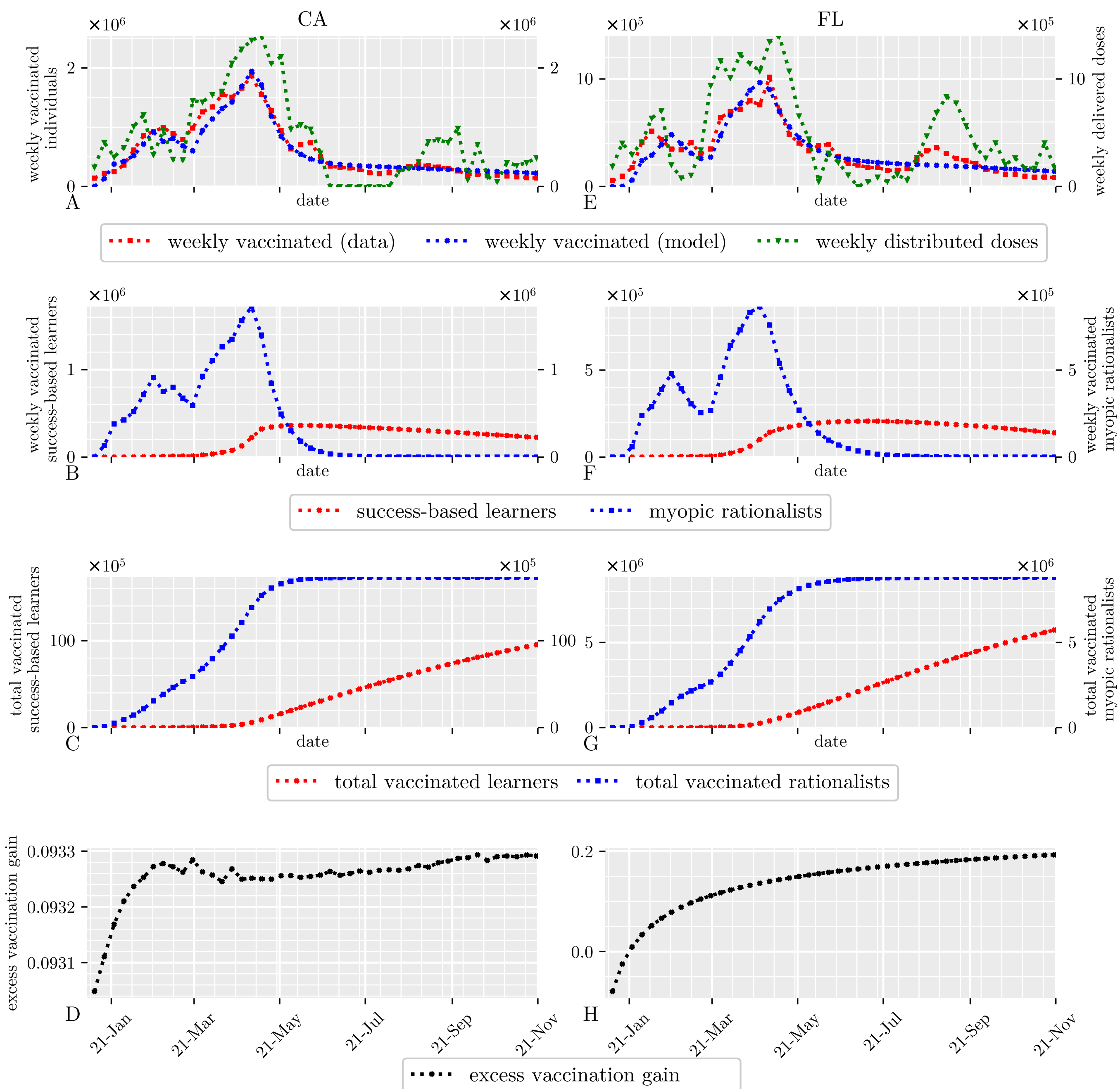
CA
FL
weekly vaccinated individuals
weekly delivered doses
date
A
E
weekly vaccinated (data)
weekly vaccinated (model)
weekly distributed doses
weekly vaccinated success-based learners
weekly vaccinated myopic rationalists
B
F
success-based learners
myopic rationalists
total vaccinated success-based learners
total vaccinated myopic rationalists
C
G
total vaccinated learners
total vaccinated rationalists
excess vaccination gain
D
H
21-Jan
21-Mar
21-May
21-Jul
21-Sep
21-Nov
excess vaccination gain

Figure 2: **Number of weekly vaccinated individuals, myopic rationalists, success-based learners, and the excess payoff over time for states of California and Florida, Dec 2020-Nov 2021**). Left panels depict the results and data for California and the right ones are for Florida. Panels A and E depict the weekly number of vaccinated residents in red, its estimation in blue, and weekly number of delivered doses in green. Panels B and F depict the estimated weekly number of vaccinated myopic rationalists and success-based learners in blue and red, respectively. Panels C and G depict the estimated total number of vaccinated myopic rationalists and success-based learners over time in blue and red, respectively. The panels in the last row depict the evolution of the benefit of vaccination (excess payoff). The number of weekly vaccinated individuals is shaped by the vaccine doses available particularly during the first months of vaccine roll-out (Panels A and E). Almost all myopic rationalists receive the vaccine by July, 2021 (the blue curves in Panels C and G). The vaccination progress is many due to myopic rationalists in the first months. As vaccination progresses, success-based learners are persuaded to receive a vaccine (Panels B and F), and then shape the vaccination progress curve (Panel C and G). Over the studied time interval, the perceived benefit of vaccination among Californians changes slightly compared to that of Floridians (Panels D and H).

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