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Attitudes Toward Vaccination and Its Impact on Economy

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ABSTRACT

Rapid rollouts of the vaccine are imperative for economic recovery; however, vaccine hesitancy could draw out not only the pandemic but also social distancing and lockdown requirements. The main purpose of this paper is to empirically investigate whether the vaccination rate affects government budget constraints as well as whether vaccine hesitancy matters in controlling the dynamics of the Covid-19 epidemic in Uzbekistan. We integrated a Susceptible-Exposed-Infectious-Removed (SEIR) epidemic model with a macroeconomic model to explore the impact of the vaccination. Our results show that vaccine hesitancy substantially influences excess COVID-19-related deaths, such that governments that are able to sustain quick vaccine rollout rates would have a 20-times lower excess death rate. A slow-paced vaccine rollout has compounded effects over time, producing much heavier consequences for the population than a rapid rollout rate. In Uzbekistan, a counterfactual exercise that intensified vaccine hesitancy between April and November 2021 likely increased the death toll by approximately thousand deaths. Therefore, the policy gains of accelerating the vaccination rate are significant, given that it would minimize both cumulative mortality and the risk of new virus variants while achieving herd immunity. Concurrently, efforts to mitigate hesitancy are crucial, particularly if the percentage of the population that is against the vaccination is greater than the percentage needed for herd immunity. To this end, our empirical study helps shed light on the challenging dynamics between health and the economy during the pandemic as well as the mechanisms through which these effects take place.

JEL Classification: I15, I18, D58, E17

Keywords: Vaccination; Vaccine Hesitancy; Pandemic; Nonlinear Epidemic Model; Dynamical Systems

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INTRODUCTION

Vaccine hesitancy refers to when individuals elect not to be vaccinated, which has been a long-standing issue in public health. During the COVID-19 pandemic, vaccine hesitancy can potentially draw out the crisis as well as extend social distancing and lockdown measures. Unfortunately, many remain wary of the COVID-19 vaccine for various reasons, including misinformation on its side effects (particularly long-term ones), its production timeline, and widespread socio-political conspiracy theories. In fact, such skepticism is rising among the public, with one report indicating that about 36.5 percent of citizens are hesitant to accept the vaccine[1] (Republican Center for the Study of Public Opinion, 2021). This is alarming as proper coverage of the vaccine relies mainly on the general population's perception and trust in the vaccine. Hesitation towards the vaccine is related to health and financial concerns, whereby those with a higher level of COVID-19 health concerns (i.e., those aged between 45 and 54) are more willing to accept the vaccine, whereas those with greater personal financial burdens (i.e., those aged between 18 and 35) are more reluctant to accept it. Academics and policy-makers are paying special interest to vaccine hesitancy, since it is potentially important for epidemic dynamics which may have a significant impact on the national economy.

There are several views on how vaccination contributes directly and indirectly to the economy. For example, Philipson and Posner (1993), Geoffard and Philipson (1996), Kremer (1996), Gersovitz and Hammer (2004), and Greenwood et al. (2019) incorporated future-oriented rational economic actors into epidemiological models to examine the efficacy of different prevention, treatment, and social welfare interventions (e.g., taxes, subsidies) on epidemic dynamics. Drawing on previous findings, it is clear that the rate of vaccination administration should parallel that of infection. However, though the availability of vaccines has increased substantially, vaccinated individuals remain low in number, possibly due to factors like vaccine hesitancy. This paper argues that the poor growth of the vaccine rate can be attributed to the high hesitancy rate stemming from individuals' negative attitude that they can take costly social distancing actions to manage their own infection risk if they remain unvaccinated. Slow pace of vaccination could delay the epidemic situation, creating long lasting problems of the public health system, such as strengthening of social distancing and isolation requirements which in turn could cause ominous socioeconomic consequences. Specifically, a household's unwillingness to vaccinate directly affects infection transmission dynamics, which eventually determines the government's cost. Thus, the goal of this research is to empirically investigate the impact of vaccine hesitancy on infection dynamics and subsequently, on government cost. Moreover, we attempt to explain, at least in part, how individuals' attitude to vaccination changes with the increase of financial stimulus packages and vaccine safety awareness campaigns for those concerned about finances and health, respectively.

Like many other countries, Uzbekistan was not immune to the aftermath of the COVID-19 outbreak. The first positive case of COVID-19 in Uzbekistan was confirmed on 15 March 2020, and by the end of the year, the number of officially registered cases had reached 77,060, including 614 deaths. On 1 April 2021, the country's Health Ministry announced a mass vaccination campaign against COVID-19, by which time COVID-19 cases and deaths had amounted to 83,050 and 630, respectively. Increasing confirmed cases is quite alarming as it leads to higher government expenditures associated with vaccine purchases and treatment expenditures. Besides, disrupted international supply chains, trade, investment, and tourism flows can lead to increased government budget deficit and thus expanding government expenditures during the pandemic might have substantial socioeconomic impact. Therefore, the aim of this study is to model the economic impacts of COVID-19 in Uzbekistan by integrating the Susceptible-Exposed-Infectious-Removed (SEIR) epidemic model into the macroeconomic dynamic budget constraint model to estimate the effects of vaccine hesitancy on pandemic dynamics as well as on the rate of vaccination. Given the dire socioeconomic consequences, this study focuses on exploring the optimal rate of vaccination and hesitancy for soft economic costs. The novelty of this study is that we extend research on how vaccinations affect infectious disease dynamics (Chen and Toxvaerd, 2014; Toxvaerd and Rowthorn, 2020; Radzikowski and Dizioli, 2021) by including vaccination interventions and hesitancy in the canonical SEIR model. Our findings validate that trust and peers are critical factors influencing vaccine acceptance, even when demographic traits and perceived COVID-19 risk are controlled. As such, our study has important implications on the sensitivity of government costs to vaccination hesitancy.

[1] https://www.ijtimoiyfikr.uz/ru/issledovaniya/obschestvo/otnoshenie-grazhdan-k-vaktsinatsii-ot-covid-19.htm

The following sections of this paper are divided into four. Section 2 develops the study's conceptual model; Section 3 discusses its parameterization; Section 4 outlines the model simulations; and Section 5 highlights the study's conclusions and recommendations for policymakers.

LITERATURE REVIEW

The paper is part of the growing literature on vaccine hesitancy, vaccine rates, and government costs. To date, most nations have endured three outbreaks or waves of the epidemic. The non-existence of a vaccine throughout the first year of the pandemic meant that the only viable actions were to alleviate pressure on the health system via social distancing, self-isolation, and partial and full movement control orders. Once COVID-19 vaccines were made available, various compartmental models started to emerge in research aiming to examine the vaccination's impacts on the virus infection rate. These linkages have captured the attention of researchers and policymakers because of their potential effect on infection dynamics and thus, economic cost. One strand of literature adopts the view that vaccine hesitancy might decrease the vaccine rate, evidenced by the works of Philipson and Posner (1993), Kremer (1996), and Greenwood et al. (2019).

The pioneer scholars who first integrated future-oriented, rational economic actors into epidemiological models were Gersovitz and Hammer (2004). They explored the distinct impacts of prevention and treatment measures on epidemic dynamics, which enabled them to identify existing externalities as well as the efficacy of various social welfare interventions (e.g., taxes and subsidies). Similar models were constructed by Philipson (2000), Gersovitz (2011) and, more recently, Gans (2021) and Muus et al. (2021). Likewise, Toxvaerd and Rowthorn (2020) and Rachel (2020) developed micro-models of endogenous social distancing to compare decentralized outcomes against socially optimal outcomes. In relation to vaccination, Toxvaerd and Rowthorn (2020) investigated the optimal ratio of prevention to treatment, whereas Goodkin-Gold et al. (2020) examined the effects of vaccine pricing on epidemiological outcomes. Makris and Toxvaerd (2020) also looked at how behavior, especially cautious behavior, responds to the imminent arrival of the vaccine.

Gaipov et al. (2021) examined the epidemiologic characteristics of patients with positive and negative PCR-test results to examine the mortality rate between hospitalized and recovered patients. The authors found that incidence and mortality rates of repository diseases were 4 and 11 times higher in 2020 than in 2019, where patients with positive PCR test results had 2 times higher mortality rate. Neumann-Böhme et al. (2020) and Bughin et al. (2021) proposed that individuals' preference for vaccination is dictated by their perceptions of the vaccine's advantages and risks. Hesitancy also appears to be related to people's social media usage and lack of trust in conventional or authoritative media sources (Murphy et al., 2021).

Though there have been numerous empirical studies related to COVID-19[2], there is a lack of literature examining vaccine hesitancy, which is the focus of this paper. Based on the prior literature, this study evaluates the impacts of vaccine hesitancy on COVID-19 case and death numbers by expanding the existing SEIR model. To do so, we introduce vaccine hesitancy into the model by accounting for hesitant individuals who are unwilling to be vaccinated. Specifically, we split the population into nine mutual categories, which are explained in the following section.

METHODOLOGY

In this section, we model epidemic-related government costs, including income tax revenue, epidemic hospitalization costs, and vaccination costs. This helps us understand the impacts of vaccination hesitation, vaccination rates, and the education rate of hesitant individuals on government costs. With this, we should be able to simulate daily hospitalizations due to the disease, daily vaccinated individuals, and daily individuals with vaccine hesitancy. It should be noted that epidemic dynamics is a complex system and is best described with non-linear mathematical models, as we have used in this paper.

[2] For instance, Issanov et al. (2020), Chin et al. (2022) and Lee et al. (2022).

Deterministic Epidemic Model

Assuming that an epidemic is spreading through an economy, we put forth an extended version of the traditional SEIR model (Kermack and McKendrick, 1927). To model the epidemic, we make the following assumptions:

1. The population is well-mixed.
2. Only susceptible and unhesitant individuals are vaccinated.
3. Vaccination and recovery from the disease do not provide lifetime immunity. There is a small probability that recovered and/or vaccinated individuals may be exposed to infection a second time.
4. The disease has an incubation period.
5. Hesitant individuals may change their minds from being unwilling to being willing to get the vaccination as a result of education or personal experience.
6. We assume that about 10 percent of COVID-19 patients go to the hospital.

With these assumptions in mind and taking into account hesitant individuals' unwillingness to get vaccinated, we split the population into nine categories: 1) Vaccinated (V); 2) Susceptible and willing to get vaccinated (S_w); 3) Susceptible and unwilling to get vaccinated (S_u); 4) Exposed and willing to get vaccinated (E_w); 5) Exposed and unwilling to get vaccinated (E_u); 6) Infectious and willing to get vaccinated (I_w); 7) Infectious and unwilling to get vaccinated (I_u); 8) Recovered and willing to get vaccinated (R_w); and 9) Recovered and unwilling to get vaccinated (R_u). The flow diagram of the model is shown in Figure 1.

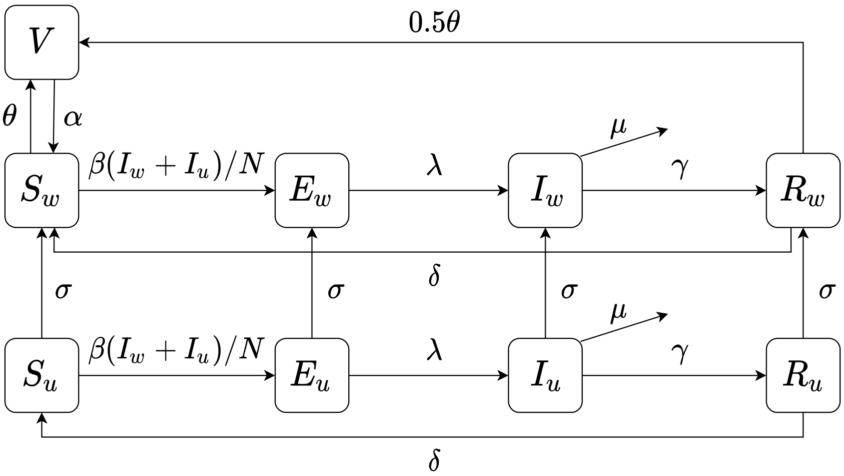


Figure 1 Schematic representation of the epidemic model

Here, all the parameters are positive. It also follows from the flow diagram that the system of differential equations governing the epidemic dynamic system satisfies:

$$
\begin{aligned}
\frac{dS_w}{dt} &= -\frac{\beta S_w(I_w + I_u)}{N} - \theta S_w + \alpha V + \delta R_w + \sigma S_u \\
\frac{dS_u}{dt} &= -\frac{\beta S_u(I_w + I_u)}{N} - \sigma S_u + \delta R_u \\
\frac{dE_w}{dt} &= \frac{\beta S_w(I_w + I_u)}{N} - \lambda E_w + \sigma E_u \\
\frac{dE_u}{dt} &= \frac{\beta S_u(I_w + I_u)}{N} - \lambda E_u - \sigma E_u \\
\frac{d\mathrm{I_w}}{dt} &= \lambda E_w + \sigma I_u - (\gamma + \mu)I_w \\
\frac{d\mathrm{I_u}}{dt} &= \lambda E_u - (\gamma + \mu + \sigma)I_u \\
\frac{dR_w}{dt} &= \gamma I_w - (\delta + 0.5\theta)R_w + \sigma R_u \\
\frac{dR_u}{dt} &= \gamma I_u - (\delta + \sigma)R_u \\
\frac{dV}{dt} &= \theta S_w + 0.5\theta R_w - \alpha V
\end{aligned}
\tag{1}
$$

The interpretation of each parameter is given in Table 1.

Table 1 Parameter descriptions

Parameter	Description
N	Total size of initial population
β	Transmission rate
θ	Vaccination rate
α	Rate of losing immunity due to vaccination
δ	Rate of losing immunity after recovery
σ	Rate of transfer from unwilling group to willing group
λ	Incubation rate
γ	Recovery rate
μ	Rate of death due to disease

The model is a generalization of the classical SEIR deterministic model and is adopted from Oduro et al. (2021). One main distinction from their work is that we assume that both recovery and vaccines provide immunity against the disease only for a limited period.

We now use the next generation matrix technique to calculate the basic reproduction number R_0. To this end, for any S_w^* we have the following Disease Free Equilibrium (DFE):

$$(S_w^*, S_u^*, E_w^*, E_u^*, I_w^*, I_u^*, R_w^*, R_u^*, V^*) = \left(\frac{\alpha N}{\alpha+\theta}, 0, 0, 0, 0, 0, 0, 0, \frac{\theta N}{\alpha+\theta}\right) \tag{2}$$

Using the same notation as in the next generation method, we have:

$$F = \begin{bmatrix} 0 & 0 & \frac{\beta S_w^*}{N} & \frac{\beta S_w^*}{N} \\ 0 & 0 & \frac{\beta S_u^*}{N} & \frac{\beta S_u^*}{N} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \; and \; V = \begin{bmatrix} \lambda & -\sigma & 0 & 0 \\ 0 & \lambda+\sigma & 0 & 0 \\ -\lambda & 0 & \gamma+\mu & -\sigma \\ 0 & -\lambda & 0 & \gamma+\mu+\sigma \end{bmatrix} \tag{3}$$

Thus, the basic reproduction number R_0 can be obtained as the spectral radius of the next generation matrix FV^{-1}, that is:

Theorem. *The basic reproduction number R_0 satisfies*

$$R_0 = \frac{\beta\alpha}{(\gamma+\mu)(\alpha+\theta)} \tag{4}$$

In particular, when $R_0 < 1$ the DFE is locally asymptotically stable and when $R_0 > 1$ the DFE is unstable and the epidemic occurs.

In the next section, we model the government budget constraint.

Government Budget Constraint

The system of differential equations given in the previous subsection is autonomous; thus, the equations are independent of time. To highlight that our compartments are functions of time, we next use $N(t), S_w(t), I_w(t), I_u(t)$ to mean the total population, the population of the susceptible willing to get vaccinated, the population of the infectious willing to get vaccinated, and the population of the infectious unwilling to get vaccinated, respectively, at day t. The government operates a social security program, which provides treatment cost coverage as well as free vaccination for each infected $I_w(t)$ and $I_u(t)$ individual. Individuals are taxed on their consumption and labor income $\tau w N(t)$. Subsequently, the government budget constraint can be modeled by the formula:

$$G = \sum_{t=1}^{\infty} e^{-rt}\left[\tau w N(t) - 0.1\, h\left(I_w(t) + I_u(t)\right) - v\,\theta\,(S_w(t) + 0.5\, R_w)\right] \tag{5}$$

Here, r stands for the discount rate, τ is the tax rate, w is the average daily wage, h represents daily hospital costs per patient due to disease, and v is the cost of vaccination per person. The value 0.1 is based on our assumption that about 10 percent of COVID-19 patients go to the hospital.

Calibration

We parameterized the baseline model with data from the Uzbekistan Statistics Committee, the World Health Organization (WHO), and the United Nations Uzbekistan, with respect to recent scholarly works as well. We computed the transition dynamics starting on 1 April 2021, which corresponds to mass vaccination. The government had set a goal to vaccinate 70 percent of the population by the end November 2021, that is within 240 days. For this reason, we use 240 time period to simulate the disease dynamics and to calculate the corresponding government cost. In total, over 21.4 million people over 18 years old were subject to vaccination. Currently, three COVID-19 vaccines have been recognized, recommended, and used in Uzbekistan (Appendix). The first is the Sputnik-V (Russian) for people aged above 16, of which two doses must be completed within three weeks. The second is Moderna (USA), recommended for those aged above 18. It must also be double-dosed a month or 28 days apart via an injection into the upper arm muscle. The third is the Chinese COVID-19 vaccine named Sinovac, also for adults above 18 years old. Similar to the previous two, this vaccine also must be completed in two doses within a three-week gap. These vaccines may curb the rate of COVID-19 infection if most of the population take the initiative to get vaccinated. Parametrization of the initial economy is summarized in Table 2. The initial value of the total population is 34,558,900, corresponding to susceptible willing (S_w) and unwilling (S_u) values of 10,367,670 and 24,191,230 respectively. The initial value $Ew = 283$ and $Eu = 661$ corresponds to the initial 17,990 individuals who carry the virus but are not yet contagious, where I_0 represents 1,285 ($I_w = 385$ and $I_u =$ 899) infected individuals and D_0 represents 630 cumulative deaths. The total number of recovered individuals was 81,135 on April 1, 2021. The parameter value λ refers to the rate at which people get infected following exposure to the disease. It is also considered a fixed parameter of the disease, being set to the inverse of the incubation period of 5 days. Likewise, γ is the parameter rate (per day) at which infected people either recover or die, which is also a fixed parameter of the disease that reflects an estimated duration of illness of 14 days. Lastly, $\mu = 0.0002$ is the death rate, while $\alpha = 0.0056$ is the fraction of vaccinated individuals that become infected.

Table 2 Calibration parameter values (exogenous variables)

Parameter	Unit	Value	Description
N	People	34558900[3]	Population
θ	Percentage	0.7[4]	Available Vaccine
v	USD per person	4.67*3=14.01[5]	Vaccine Fee on Average
β	Percentage	0.28	Transmission Rate
γ	Percentage	1/14	Recovery Rate
μ	Percentage	0.0002[6]	Death Rate
λ	Ratio	1/5[7]	Incubation Period
α	Percentage	0.0056 (4-5 month 2 years[8])	Rate of losing immunity due to vaccination
σ	Ratio	0.001	Rate of transfer from unwilling group to willing group
δ	Percentage	0.01 (1-2 years[9])	Rate of losing immunity after recovery
h	USD	320/9	Treatment cost per regular COVID patient (for whole recovery period)
w	USD	1.6	Average Daily Wage
r	Percentage	0.14/365[10]	Discount Rate
τ	Percentage	0.15[11]	Tax rate

[3] Stat.uz
[4] Gezeta.uz
[5] Gazeta.uz
[6] coronavirus.uz
[7] 11gdp.by
[8] 1prime.ru
[9] bbc.com
[10] cbu.uz
[11] mf.uz

Sensitivity analysis

For the sensitivity analysis, following Li (2018), we report the normalized elasticity of G to any parameter, say r, given by:

$$\epsilon_G^r = \frac{\partial G}{\partial r}\left|\frac{r}{G}\right| \tag{6}$$

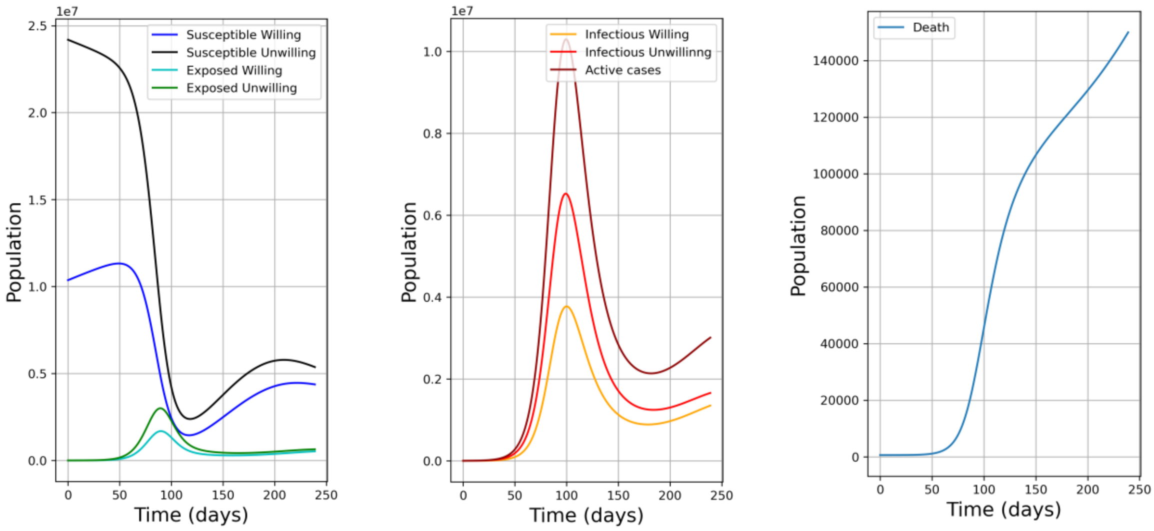
This number can be numerically approximated using $\frac{\partial G}{\partial r} \approx \frac{\Delta G}{\Delta r}$ with a small Δr, which we take to be $10^{-5}r$. After simplification we have:

$$\epsilon_G^r \approx \frac{G(r + r\,10^{-5}) - G(r)}{10^{-5}|G(r)|} \tag{7}$$

As mentioned before, we assess the sensitivity results for the parameters, τ, θ, and the ratio of hesitant populations.

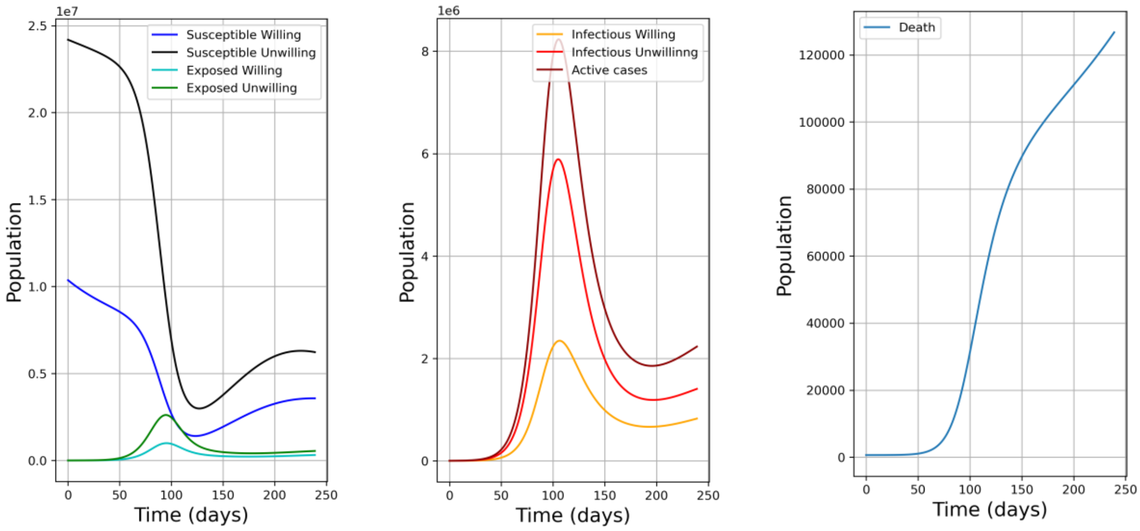
RESULTS AND DISCUSSION

Our results begin with an examination of the epidemiological SEIR model in the absence of vaccination (Figure 1) and when vaccination exists (Figure 2). These time series were simulated using *scipy.integrate.odeint* function of python programming language. Day zero starts at April 1 and the parameter values are taken as described above. In the early stage starting April 1, almost the whole population was susceptible. The spread of the disease required time to build momentum, as evidenced by the curve for susceptible individuals that neared 25 percent throughout the first 110 days. During this period, initial infected and recovered people numbered 1,285 and 81,135, respectively. Interestingly, the growing number of infected individuals was in tandem with a sharp drop in the number of susceptible individuals. Meanwhile, there was a rapid increase in the number of recovered individuals as well, given that with more infections, there were also more recoveries. As the epidemic moved towards its peak, we see that the active cases exceed 28% of all citizens in the absence of the vaccination. On the other hand, this number is less than 24% with vaccination. (see Table 3a and Figure 2 and Figure 3). Herd immunity is achieved when 75 percent (reproduction number 3.91) individuals are infected and recovered. The macroeconomic components become more stable when herd immunity is achieved or the epidemic comes to an end.



Susceptible and exposed cases | Active cases | Cumulative deaths

Figure 2 Model simulations without vaccination, $\boldsymbol{R_0 = 3.91}$



Susceptible and exposed cases | Active cases | Cumulative deaths

Figure 3 Model simulations with vaccination, $R_0 = 1.73$

Figure 4 and Table 3 show the optimal ratio of government cost to hesitancy (S_w), vaccination rate (θ), and education rate (σ). In general, changes in parameters create expected changes in the government budget, vaccine rate, infection rate, death toll, and reproduction number. In Scenario 1 of Table 3a, Government expenses decrease as the vaccine rate increases. The rates of vaccination and death (for $\theta = 0.00$ and 0.0017) are 0 and 3,242,705, and 149,948 and 143,220. Therefore, vaccination might save an extra 6,728 individuals.

Table 3a Optimal Government Cost to Infection Dynamics when $\theta = 0.0017$

Parameters Value	Government Cost, USD	Total vaccinated	Total reported infected willing	Total reported infected unwilling	Death	Reproduction Number
Scenario 1						
$\theta = 0.00$	$63 292 283	0	2,151,078	3,497,463	149,948	3.91
$\theta = 0.0017$	$61 398 271	3,242,705	1,941951	3,441976	143,220	2.92
Scenario 2						
$S_w = 0.4N$	$59 545 062	4,039660	2,375,699	2,937,281	141,388	2.92
$S_w = 0.5N$	$60 162 727	4,839,594	2,805,014	2,436,774	139,550	2.92
$S_w = 0.6N$	$60 780 345	5,642,586	3,229,810	1,940,537	137,705	2.92
$S_w = 0.7N$	$61 397 938	6,448,721	3,649,994	1,448,652	135,853	2.92
Scenario 3						
$\sigma = 0.1$	$59 743 090	8,516,421	4,925869	1644	131,465	2.92
$\sigma = 0.01$	$61 397 938	6,149,128	3,938,491	1,239,910	138,120	2.92
$\sigma = 0.001$	$61 398 271	3,242,705	1,941951	3,441976	265,875	2.92

Scenario 2 of Table 3b, named willingness to vaccinate, compares the population of those susceptible and willing to get vaccinated (S_w). For $S_w = 0.3N$ and $S_w = 0.7N$, the government budget expenses, vaccine rate, and death toll are $61,398,271 and $61,397,938, 6,919,955 and 13,805,564, and 135,309 and 119,059, respectively. The results indicate that there is a slight reduction in the government budget if S_w increases from 0.3 to 0.7; concurrently, the vaccine rate increases substantially while the death rate reduces significantly. Moreover, we have verified whether government costs, the number of infected people, and the death toll will change when the daily vaccination rate (θ) is increased from 0.004 (Table 3) to 0.007 (Table 3). If population hesitancy for the vaccination decreases, government costs may increase from $58 899 012 to $43 288 417, whereas the number of deaths may decline significantly from 135,853 to 100,398 (Table 3). In other words, 35,455 lives might be saved with a 0.007 daily vaccination rate. With this daily vaccination speed ($\theta = 0.004$), if one out 10 people change their mind instead of one out of 1000, both government expenditures and the death rate from COVID-19 will fall from $58 988 145 to $51,521,238 and from 135,309 to 108,895, correspondingly.

Table 3b Optimal Government Cost to Infection Dynamics when $\theta = 0.004$

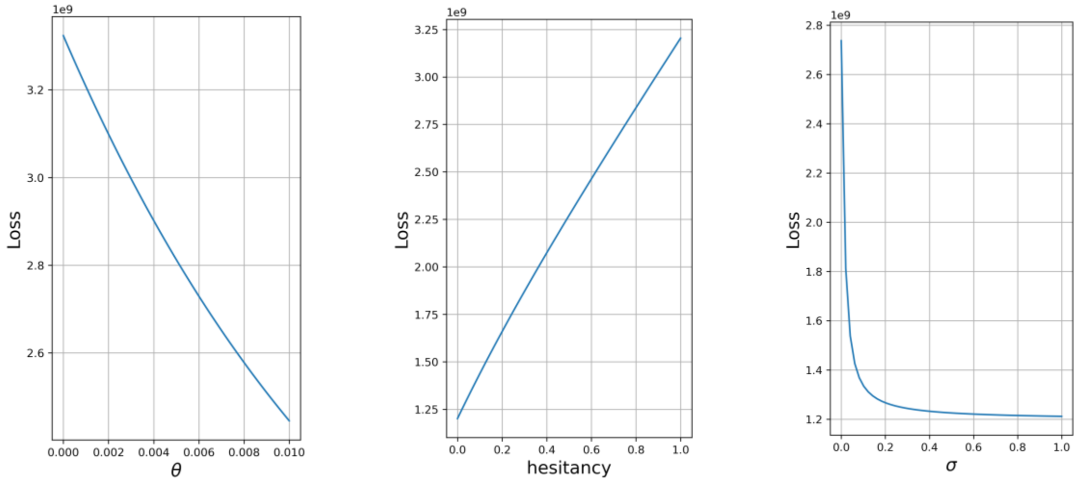
Parameters Value	Government Cost, USD	Total vaccinated	Total reported infected willing	Total reported infected unwilling	Death	Reproduction Number
Scenario 1						
$\theta = 0.004$	$58 988 145	6,919,955	1,700,286	3,373,571	135,309	2.22
Scenario 2						
$S_w = 0.4N$	$54 599 913	8,619,617	2,057,635	2,861,759	131,307	2.22
$S_w = 0.5N$	$56 033 061	10,333,100	2,404,602	2,359,164	127,269	2.22
$S_w = 0.6N$	$57 466 095	12,011,367	2,740,658	1,866,168	123,189	2.22
$S_w = 0.7N$	$58 899 012	13,805,564	3,065,175	1,383,198	119,059	2.22
Scenario 3						
$\sigma = 0.1$	$51 521 238	18,388,155	4,055,874	1,424	108,895	2.22
$\sigma = 0.01$	$52 927 410	13,309,684	3,433,028	1,183,425	123,881	2.22
$\sigma = 0.001$	$58 988 145	6,919,955	1,700,286	3,373,571	135,309	2.22

In Scenario 3 of Table 3c, the rate of transfer from the unwilling group to the willing group (σ) changes. The results show that changing individuals' minds has a significant effect on the vaccine rate and the death toll. For example, government expenditures, the vaccine rate, and the death rate (for $\sigma = 0.1$ and $\sigma = 0.001$) are $9,729,888 and $43,366,281, 28,960,635 and 10,743,423, and 126,722 and 82,338, respectively. This implies that if the σ rate is lower, the government budget is higher, the vaccine rate is much lower, and the death toll is higher. More optimistic scenarios are given in Table 3c, where the government accelerates the daily vaccination rate up to $\theta = 0.007$. According to the results of Table 3c, an increase in individuals' confidence from $S_w = 0.3$N to $S_w = 0.7$N leads to a substantial decrease in the death toll by 100,398. In addition, a change in transfer rate from the unwilling to willing group (σ), namely from 0.001 to 0.1, helps decrease government costs from $43,366,281to $9,729,888 and saves more than 44,000 lives.

Table 3c Optimal Government Cost to Infection Dynamics when $\theta = 0.007$

Parameters Value	Government Cost, USD	Total vaccinated	Total reported infected willing	Total reported infected unwilling	Death	Reproduction Number
Scenario 1						
$\theta = 0.007$	$43 366 281	10,743,423	1,443,978	3,294,969	126,722	1.73
Scenario 2						
$S_w = 0.4N$	$23 703 859	13,372,776	1,720,652	2,773,752	120,348	1.73
$S_w = 0.5N$	$30 232 978	16,035,646	1,979,551	2,267,039	113,862	1.73
$S_w = 0.6N$	$36 761 222	18,736,801	2,218,705	1,775,717	107,228	1.73
$S_w = 0.7N$	$43 288 417	21,482,833	2,435,353	1,300,985	100,398	1.73
Scenario 3						
$\sigma = 0.1$	$ 9 729 888	28,960,635	3,054,502	1,203	82,338	1.73
$\sigma = 0.01$	$ 16 090 333	20,994,654	2,881,086	1,110,374	107,828	1.73
$\sigma = 0.001$	$43 366 281	10,743,423	1,443,978	3,294,969	126,722	1.73

To sum up, the results confirm the positive relationship between the daily vaccination rate and government loss; when the vaccine rate is increased, the initial government cost reduces as the fewer people are infected and more people are vaccinated over time (Figure 4 and Table 4). A negative relationship has also been witnessed between vaccine hesitancy and government cost (Figure 4). More vaccine-related hesitancy among the population puts pressure on the government budget. Lastly, the more people change their mindset from the unwillingness to be vaccinated to the willingness to be vaccinated, the lower the government loss on vaccination (Figure 4).



Government Cost vs θ Government Cost vs Hesitancy Government Cost vs σ

Figure 4 Government cost against the parameters of interest

According to the results, in the absence of the vaccination and the other prevention measures such as wearing masks, social distancing, hygiene measures, temporary lockdowns and so on, reproduction number of the epidemic would be 3.91 (it means that, on average, every 10 people with Covid-19 will infect 39 other people), in turn, it would cause 70 % of the population to be infected in 110 days. Starting vaccination from April allowed reproduction number to decrease from 3.91 to 1.73.

Table 4 Sensitivity of parameters to the Government cost

Sensitivity to vaccination	Sensitivity to hesitancy	Sensitivity to transfer rate from unwilling to willing
ϵ_G^{θ}	$\epsilon_G^{hesitancy}$	ϵ_G^{σ}
-0.2	0.71	-0.03

From Table 4 we see that while vaccination rate and transfer rate are negatively correlated with the government cost, and this relation is positive for hesitancy percentage. The is also justified in Figure 3. The sensitivity $\epsilon_G^{\theta} = -0.2$ and $\epsilon_G^{\sigma} = -0.03$ mean that 1% increase in the vaccination rate θ or transfer rate σ will decrease the government cost by 20% or 3%, respectively. Likewise, the 1% increase in hesitancy will increase the government cost by 71%. In particular, we see that the government cost is highly sensitive to the hesitancy.

CONCLUSION AND POLICY RECOMMENDATION

Our study offers an alternative model to the existing SEIR epidemiology model by integrating it with the macroeconomic dynamic budget constraint model which incorporates different rates of vaccination and hesitancy. Our model's predictions on the sensitivity of government cost to hesitancy indicate that if governments can maintain a rapid vaccine rollout rate that curtails the negative impacts of vaccine hesitancy, the number of excess deaths could be up to 20 times lower. This is mainly attributed to the efficacy of the vaccination. A fast-paced vaccine rollout has compounded effects over time, producing much greater impacts on the population than a slow rollout rate, especially if the population becomes less hesitant towards the vaccine and rapidly gets vaccinated. Similar findings have been reported by Toxvaerd et al. (2020) and Gan (2021). In Uzbekistan, a counterfactual exercise that intensified vaccine hesitancy between April and November 2021 likely increased the death toll by approximately thousands of deaths. According to the government's data, a total of 33,672,515 vaccine doses have been administered in Uzbekistan between this period and approximately 51% of population are vaccinated[12]. The daily COVID-19 confirmed cases have dropped from the peak of 1,304 cases on 22 January 2022 to 96 cases on 1 March 2022. The daily Covid-19 confirmed cases remains as double digit and the death cases remains zero since 1 March 2022[13]. Therefore, the

[12] Refer to https://covidvax.live/location/uzb

[13] Refer to https://coronavirus.jhu.edu/region/uzbekistan

policy gains of accelerating the vaccination rate are significant, given that it would minimize cumulative mortality while achieving herd immunity. Additionally, a vaccinated population would minimize the risk of the virus evolving into new and more dangerous variants. Our findings in this study thus emphasize a clear implication for policy, which is that vaccine hesitancy substantially affects epidemic dynamics if it hampers the vaccination rate. Consequently, the health ministry and related authorities should prioritize accelerating the vaccine rollout rate until each willing and eligible citizen has been fully vaccinated. Concurrently, efforts to mitigate hesitancy are crucial, particularly if the percentage of the population that is against the vaccination is greater than the percentage needed for herd immunity. Indeed, addressing the issue of vaccine hesitancy has various benefits that extend beyond its reduction of COVID-19-related mortality. Ultimately, lower vaccine hesitancy and fast administration of the vaccine facilitates societies' achievement of herd immunity as well as the safe reopening of the economy, which is crucial for economic recovery and growth.

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APPENDIX

Table A1 Available Vaccines in Uzbekistan

	Quantity	Price (USD)	Price per Dose
ZF-UZ-VAC-2001	8500000	$39100000	4,60$
«Sputnik V»	370000	$3681500	9,95$
AstraZeneca	710000	$1980000	2,79$
Total	9580000	$44761500	4,67

Source: https://www.gazeta.uz/ru/2021/07/29/vaccination/