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COVID-19 and Endogenous Public Avoidance: Insights from an Economic Model

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COVID-19 and Endogenous Public Avoidance: Insights from an Economic Model

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Abstract

In this paper, I study the transmission of COVID-19 in the dynamic SEIR (Susceptible, Exposed, Infectious, and Removed) model that allows individuals to optimally choose their public avoidance actions in response to the COVID-19 risk. I allow for heterogeneity in infection rates across age groups and structurally estimate the parameters to match the daily pattern of new cases and the ratio of patients by age group. Even in the absence of intervention, the elderly, who face a greater risk of death from COVID-19, are more likely than the young to take self-protective actions. In contrast to models with a fixed transmission rate, my model can capture the heterogeneity in the fraction of infected individuals among different age groups.

Keywords: COVID-19, infectious diseases, economic epidemiology

1 Introduction

As COVID-19 spreads around the world, a number of recent studies have attempted to provide estimates of COVID-19 cases. However, these studies cannot explain the mismatched pattern of fractions of the population and fractions of cases across age groups. As shown in Figure 1, the percentage of cases across age groups between 12 February – 16 March, 2020 are different from the age-group's share in the population. Only 5% of patients are ages 0–19 years old, yet this group comprises 25% of the population. The number of patients is more concentrated for ages 45 and above. Standard epidemiological models assume that the infection rate and the fatality rate are identical over all populations. In addition, these studies treat the transmission rates as exogenous and disregard changes in the self-protective behavior of individuals.

In this paper, I combine the dynamic SEIR (Susceptible, Exposed, Infectious, and Removed) model and a heterogenous-agent economic model to endogenize the public avoidance behavior

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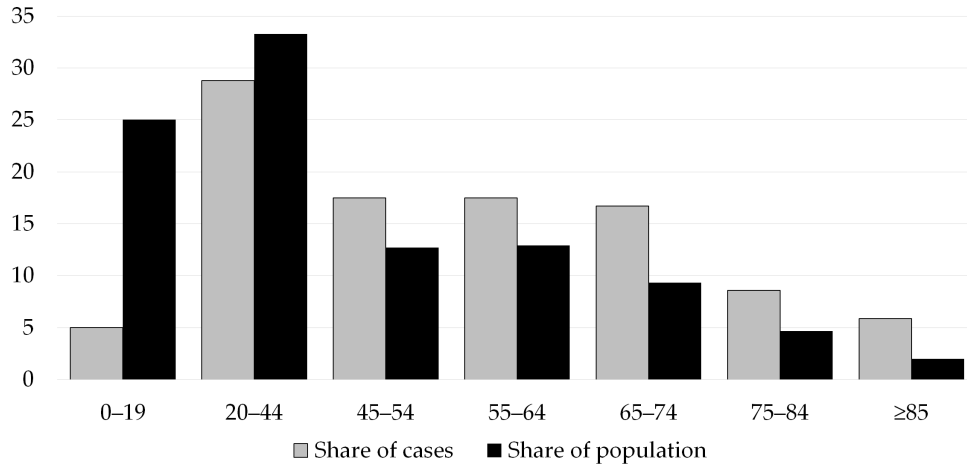


Figure 1: The share of cases and the share of the population, by age group.

of individuals and structurally estimate parameters to match the pattern of new cases in the U.S. and the share of patients in different age groups. The estimates suggest that the fatality rate is (weakly) increasing with individual age. Without including the endogeneity of the public avoidance level, standard epidemiological models overpredict the transmission rate in the early period of an epidemic.

The idea of endogenous self-protective action can be traced back to Kremer (1996), who studies how people respond to the HIV/AIDS disease. Studies that incorporate economic agents' endogenous behavior into an epidemic model to explore how the spread of an epidemic changes agents' behavior include Philipson and Posner (1993), Geoffard and Philipson (1997), Bauch and Earn (2004), Chen (2004), Reluga et al. (2006), Vardavas et al. (2007), Chen and Cottrell (2009), Chen et al. (2011), and Reluga (2010). This paper applies the ideas of these previous studies to study the spread of COVID-19 and structurally estimate a model to match the patterns of cases in the U.S.

The rest of the paper is organized as follows. Section 2 describes the model. Section 3 explains the estimation method and the simulations. Section 4 discusses insights from the model. Section 5 concludes.

2 The Model

This model is based on the infectious disease dynamic SEIR (Susceptible, Exposed, Infectious, and Removed) model used in Wang et al. (2020), Klein et al (2020), and Atkeson (2020). The contribution made by this paper is that I allow individuals to endogenously choose their public-avoidance levels and that I introduce heterogeneity across age groups.

2.1 Overview

Time is continuous. There is a mass N of the population, divided into seven groups based on age. The age groups are indexed by $j \in \{1, 2, \dots, 7\}$. The individuals in each group are classified into one of four types: susceptible (S), who are disease-free and are at risk of receiving the virus, exposed (E), who have received the virus but have not been infectious, infectious (I), who can transmit the virus, and removed (R), who have recovered or died. The differential equations are as follows:

$$\begin{aligned}\frac{dS_j}{dt} &= -\beta (1 - v_i) \frac{S_j I}{N}, \\ \frac{dE_j}{dt} &= \beta (1 - v_i) \frac{S_j I}{N} - \sigma_j E_j, \\ \frac{dI_j}{dt} &= \sigma_j E_j - (\gamma + \lambda_j) I_j, \\ \frac{dR_j}{dt} &= (\gamma + \lambda_j) I_j, \\ \beta &= R_0 \gamma, \\ I &= I_1 + I_2 + I_3 + I_4,\end{aligned}$$

where β is the natural (exogenous) transmission rate, v_i is the public avoidance action of individuals in group i , σ_j is the infection rate of group j , γ is the recovery rate, λ_j is the death rate of individuals of group j , and R_0 is the reproduction number.

In this paper, I allow individuals to choose their public avoidance level to minimize their instantaneous disutility. The optimization problem is given by

$$\min_{v_j} \quad c(v_j) + \beta (1 - v_i) \frac{I}{N} \lambda_j K,$$

where $c(v_j)$ is the disutility (cost) of public avoidance, and K is the disutility of death. The disutility of public avoidance $c(v_j)$ is twice-differentiable, strictly increasing, and convex. The disutility function captures the forgone income of work, the opportunity cost of forgone social activities, and the emotional cost of having to self-quarantine. The individuals face the trade-off between self-protective action and the risk of getting the virus. They can avoid exposing themselves in the public to reduce the risk of contracting the disease. The risk of an individual in group j getting the virus is given by $\beta (1 - v_i) \frac{S_j I}{N} / S_j$. This is conditional, as follows: If the person is infected, the chance of death is λ_j , and if the person dies, the disutility is K .

I assume that the disutility (cost) of public avoidance takes the form of $c(v_j) = v_j^\theta$. Therefore, the optimal public avoidance level is

$$v_j = \left[\left(\frac{\beta}{\theta} \right) \left(\frac{I}{N} \right) \lambda_j K \right]^{\frac{1}{\theta-1}}. \quad (1)$$

There are three factors that determine the optimal public avoidance level. The first factor is the time-invariant nature of the disease, which includes the transmission rate and the disutility parameter. The second factor is the time-varying fraction of infected individuals in the population. This factor suggests that individuals will avoid exposing themselves in public as the number of infected people in the general population increases. The last factor is the risk of death within an age group which is the source of the key mechanism in the model. The relationship between public avoidance levels v_j and v_k of groups j and k is given by

$$\frac{v_j}{v_k} = \left(\frac{\lambda_j}{\lambda_k} \right)^{\frac{1}{\theta-1}}.$$

This equation implies that individuals who face a greater risk of death will protect themselves more intensively. The effective transmission rate in this model is $\beta(1 - v_i)$, which is time-varying because of the second factor, the fraction of infected individuals in the population. As the virus spreads, susceptible individuals are more likely to come into contact with infected individuals. As a result, they become more cautious and employ more self-protective measures.

The source of time-variant effective transmission rates is different across studies. Wang et al. (2020) exogenously determine R_0 by phase; R_0 is equal to 3.1 from 1 December 2019 to 23 January 2020, 2.6 from 24 January 2020 to 2 February, 1.9 from 3 February to 15 February, and 0.9 after 16 February. Atkeson (2020) uses exogenous differential equations of R_t to represent social distancing. In contrast, the effective transmission rates in this model are time-varying and non-monotonic because individuals respond to the risk of infection.

3 Quantitative Results

3.1 Calibration and Estimation Strategy

The parameters are the natural (exogenous) transmission rate β , the infection rate σ_j , the recovery rate γ , the death rates λ_j , and the reproduction rate R_0 . In the baseline simulation, I assume that the infection rate σ_j is homogeneous across groups and is set at $1/5.2$, as the incubation period is 5.2 days (Li et al., 2020). The recovery rate γ is recovered from the average hospitalization period which is 7.62 to 17.76 days. I choose $\gamma = 1/17.76$ in the baseline simulations, which corresponds with the upper bound of the range. The last parameter, R_0 , is set to 3.1, which matches the early period in Imai et al. (2020).

The data on population is from the 2018 census.¹ The U.S. population is given as approximately 330 million people, divided into seven groups by age: 0-19, 20-44, 45-54, 55-64, 65-74, 75-84, and 85 and above. The shares of population in the age groups are 0.2505, 0.3329, 0.1273, 0.1293, 0.0934, 0.0468, and 0.0198. The data on the numbers of cases is from the CDC.² The death rates λ_j are set at 0.001, 0.0015, 0.0065, 0.02, 0.038, 0.074, and 0.1885, respectively. The duration of one period in

¹<https://www.census.gov/popclock/>

²<https://www.cdc.gov/mmwr/volumes/69/wr/mm6912e2.htm>

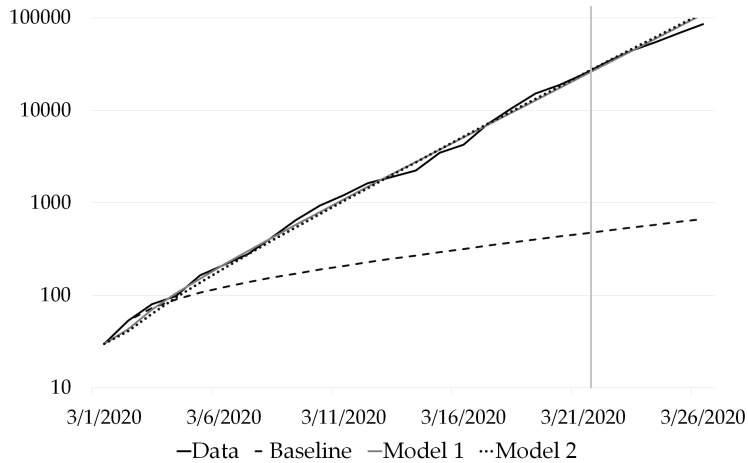


Figure 2: The number of new cases daily from the data, and the model predictions

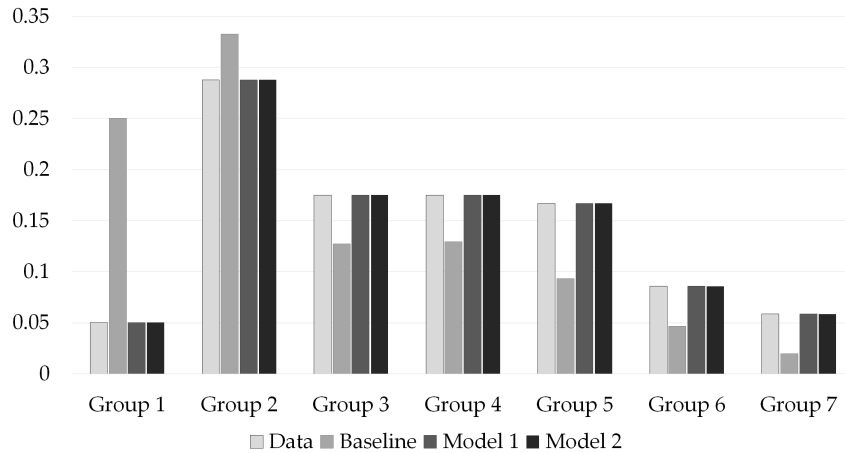


Figure 3: The shares of patients in each age group, from the data and model predictions.

the model is one day. The data starts from March 1, 2020. There are 30 cases at the beginning. Following Atkeson (2020), I assume the initial value of E is 132.

The CDC has data on new reported cases from March 1 to March 26. I hold the data from March 22-26 out for validation propose. To match the data on new cases between March 1 to March 21 and the data on the fraction of infected patients in each age group on March 16, I structurally estimate the model in two ways. In Model 1, I allow for heterogeneity in the infection rates σ_j across the age groups and estimate 9 parameters, $\{\beta, \gamma, \sigma_1, \dots, \sigma_7\}$. In Model 2, I introduce the endogenous public avoidance level discussed in Section 3. The number of parameters increases to 11. Details on the estimation are described in the Appendix. The baseline model is a simplified version of Atkeson (2020) without social distancing (declining R_0).

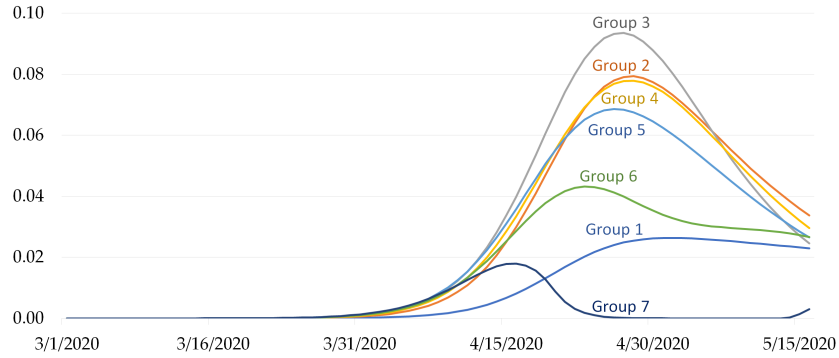


Figure 4: The share of infected patients in each group as predicted by Model 2.

3.2 Results

First, I compare the predictability of the models with the actual data in Figure 2. The Y-axis is in a logarithmic scale. The baseline model underpredicts the number of new reported cases. One possibility is that the calibrated parameters from the cases in China may not match the patterns in the U.S. Model 1 and Model 2, in which the parameters are structurally estimated to match the data from March 1 to March 21, fit the out-of-sample data well as they are able to predict the data from March 22 to March 26.

Model 1 and Model 2 are able to match the data on the shares of patients across age groups. Basic SEIR models generally fail to match this data because they assume the same parameters across all groups. As a result, the shares of patients in the basic SEIR models are equal to the share of the population in each age group.

I use Model 2 to predict the number of new cases and the public avoidance levels across the age groups, assuming that the individuals respond to the risk of getting the disease and that no policy interventions are implemented during the period.

According to Figure 4, Model 2 predicts that Group 7 would have the smallest share of infected patients, while Groups 2 and 3 would have the highest shares. The results could be counter-intuitive at first glance, as the populations in Group 2 and Group 3 are relatively healthier than the population in Group 7. The patterns are driven by the endogenous public avoidance levels. The population in Group 7 realize that they face a greater risk of dying, and therefore they use more self-protective actions.

As can be seen from Figure 5, the public avoidance level of Group 7 is the highest among all groups. It reaches 1 around mid-April and stays at 1 until the number of cases in the whole economy declines in mid-May. The model predicts that Group 7 would have a small number of new cases between mid-April to mid-May. In contrast to Group 7, Groups 1, 2, and 3 are predicted to choose small levels of public avoidance. The reason is that they believe they are unlikely to become infected or die.

One by-product of the estimation is that infection rate σ is likely age-dependent. The estimates

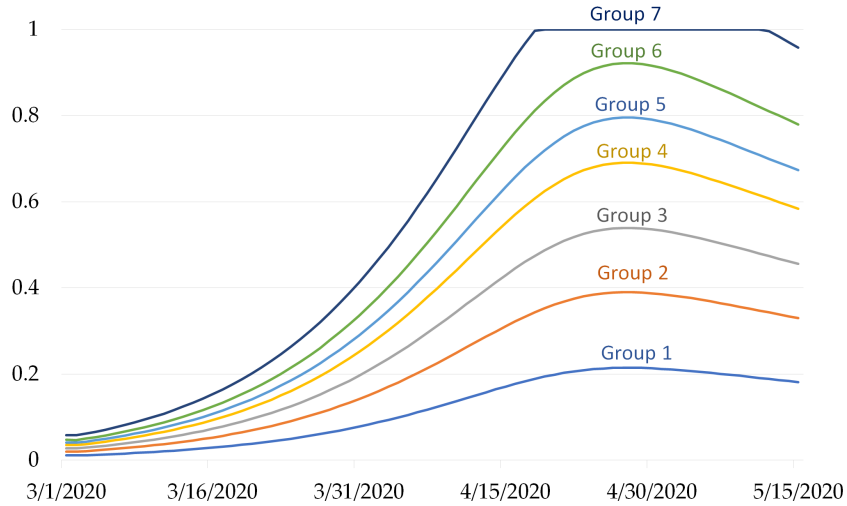


Figure 5: The public avoidance levels over time as predicted by Model 2.

suggest that the infection rate increases with age, as the estimate is 0.0133 for Group 1 and increases to 0.1917 for Group 6. Note that the estimates from the model are not necessarily equal to the actual infection rates.

4 Discussion

This study offers three main insights. First, if individuals do not consider their externality of possibly transmitting the virus to susceptible individuals, their public avoidance behavior is sub-optimal, in the sense that because they do not self-quarantine, and so they spread the virus to an innocent population. In Figure 4, Groups 1, 2, and 3 would carry the virus and risk spreading it to the other groups.

Second, the lockdown policy, which aims to reduce the number of transmissions, would affect the young more than the elderly. This corresponds to the fact that teens and young adults can be seen outside in public, while the elderly are reluctant to go outside in crowds, since the elderly are more likely to self-quarantine at all costs, even without a policy. We can see from Figure 5 that Groups 1, 2, and 3 would be constrained by a lockdown policy that imposes the minimum level of public avoidance.

Third, the government may announce a commitment to not hospitalize infected individuals. By so doing, the government would raise the cost of infection for each individual, and individuals would respond by becoming more self-protective. Other penalties such as taxes or penalties on being outside without an appropriate reason could incentivize individuals to raise their public avoidance level and lower the transmission rate.

5 Conclusion

This paper studies the transmission of COVID-19 in an epidemic model that allows for endogenous public avoidance levels and heterogeneous infection rates across all age groups. The model is structurally estimated to match the daily pattern of new cases in the U.S and the percentage of patients across all age groups. It predicts a variation in the share of infected population across those age groups and suggests that the infection rate σ is likely age-dependent.

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Appendix

The parameters in Model 1 that are structurally estimated are β , γ , σ_1 , σ_2 , σ_3 , σ_4 , σ_5 , σ_6 , and σ_7 . In Model 2, the public avoidance equation 1 is equivalent $v_j = [\mu (I/N) \lambda_j]^{\frac{1}{\theta-1}}$, where $\mu = \beta K / \theta$ is a constant. Thus, the estimation of Model 2 has 11 parameters: β , γ , σ_1 , σ_2 , σ_3 , σ_4 , σ_5 , σ_6 , σ_7 , θ , and μ . The estimations are implemented by command *fminsolve* in MATLAB software. The initial guesses follow from the parameters used in Atkeson (2020). The estimated values are described in Table 1.

Table 1: Estimation Results

Model 1			Model 2		
parameter	initial guess	estimate	parameter	initial guess	estimate
β	3.5	5.0847	β	3.5	4.7964
γ	1	0.6736	γ	1	0.4121
σ_1	0.1923	0.0154	σ_1	0.1923	0.0133
σ_2	0.1923	0.0788	σ_2	0.1923	0.0672
σ_3	0.1923	0.1437	σ_3	0.1923	0.1217
σ_4	0.1923	0.1406	σ_4	0.1923	0.1215
σ_5	0.1923	0.2118	σ_5	0.1923	0.1816
σ_6	0.1923	0.2201	σ_6	0.1923	0.1917
σ_7	0.1923	0.5741	σ_7	0.1923	0.4739
			θ	4	5.5338
			μ	100	148.8241