**Covid-19 and the Economy: Policy**

We now consider the economic policy implications of covid-19. We will discuss the following paper:

Baqaee, D., Farhi, E., Mina, M., and J. Stock. 2020. "Reopening Scenarios. NBER Working Paper #27244.

This is a complicated model. It seeks to jointly consider the macroeconomic and public health impacts of covid-19. Much of the technical detaul is beyond the scope of the class, but we begin by going through the epidemiological model.

*The epidemiological model*:

There are five types of agents each day: S (susceptible), E (exposed), I (infected), Q (quarantined), and D (dead). All agents are divided into 5 age cohorts: 0-19, 20-44, 45-64, 65-74, and 75+.

There are a number of public health parameters: $\beta$ is the transmission rate, the probability of catching covid if exposed to a sick agents. $\delta_a$ is the death rate for agents in age group $a$. This is treated as exogenous. $\sigma$ is the latency rate, the share of exposed agents who begin showing symptoms each day. $\gamma$ is the recovery rate, the probability that a sick agent will recover on any day. $\chi$ is the quarantine rate, the chances that a sick agent will be placed into quarantine where, by assumption, they do not infect anyone else.

A key feature of the model is the contact matrix. This is the average number of contacts between people of any two age cohorts. It includes 25 elements to model all possible interactions:

$$C_{ab} = p_a^{home} C_{ab}^{home} + p_a^{other} C_{ab}^{other} + \sum_i p_{a,i}^{work} C_{ab,i}^{work} \tag{1}$$

$p_a^{home}$ is the probability that an agent in age cohort $a$ is at home at any point in time. $C_{ab}^{home}$ is the associated number of contacts that agent has with people in cohort $b$. The economy is divided into 66 different sectors where agents can work and $C_{ab,i}^{work}$ is the number of contacts between agents in cohorts $a$ and $b$ in sector $i$.

The authors use microeconomic data to calibrate the contact matrix. Policy interventions are modeled by prohibiting agents in some sectors (including schools for the 0-19 cohort) from working (in person) and thus moving them to home. Figure 1 on page 14 shows the impact of no lockdown, a full lockdown, and a partial one where only young workers work.

Equations 1-6 show the evolution of public health. Equation shows how the susceptible population for each age cohort, which is the population not yet infected by covid-19 evolves:

$$dS_a = -\beta S_a \sum_b C_{ab} \frac{I_b}{N_b} \tag{2}$$

Teh change in the susceptible population is simply those who become exposed. The authors assume that once exposed, agents are immune for the rest of the simulation period (the risk of re-infection remains unknown). Equation (2) is the risk of transmission, multiplied by the number of contacts with infected people.

The change in those who have been exposed is imply the newly exposed less those who were previously exposed, and are now showing symptoms:

$$dE_a = -dS_a - \sigma E_a \tag{3}$$

The change in the number of infected is the number of exposed who start showing symptoms, less those who recover, die, or are placed in quarantine:

$$dI_a = \sigma E_a - \gamma I_a - \delta I_a - \chi I_a \tag{4}$$

The change in the number quarantined is:

$$dI_a = \chi I_a - \gamma Q_a - \delta Q_a \tag{5}$$

The change in the number of recovered and dead agents is then:

$$dR_a = \gamma I_a + \gamma Q_a \tag{6}$$

$$dD_a = \delta I_a + \delta Q_a \tag{7}$$

Some of the public health parameters including $\gamma$, and $\sigma$ are then calibrated to deliver plausible values of $R_0$. This is the transmission rate where, absent any interventions, one newly exposed agents eventually infects $R_0$ other agents. The authors consider ranges of $R_0$ from 2.45 to 3.05. They also consider infection fatality rates, the fraction of infected agents who die, between 0.3% and 0.9%. Figure 3 on page 20 then plots the predicted vs. actual number of weekly U.S. deaths from mid-March to late May, when the paper was written. The fit is good which suggests that the model is useful for the analysis of the out of sample period that follows

*The Economic Model*

The economic part of the model is much smaller. Much of the analysis will focus on what the authors call the "GDP-to-Risk Ratio" ($\theta$). This is defined on page 12. Intuitively, suppose that one worker of age $a$ in sector $i$ goes back to working in person. This the change in GDP divided by the change in $R_0$. It thus depends both how how effective that worker may work from home (the more effective at home, the lower the GDP to risk ratio), the overall productivity of the sector, and the amount of interpersonal contact within the sector (as this increases, the lower the ratio).

Values of $\theta$ are shown for each sector in the Appendix on pages 39-40. These are normalized around zero. The largest values are in finance, management, and legal, sectors with fewer contacts. The worst are in education and transportation. The authors will consider re–opening plans that prioritize sectors with higher values of $\theta$.

*Baseline Results*

Before beginning, it is important to note that the authors' simulations have proven to be too optimistic. Their baseline simulations project less than 200,000 deaths by January 1, 2021. The U.S., however, passed that mark by early Fall. The following results may thus underestimate the differences in deaths among policies. Likewise, some of the authors economic simulations also seem to be too optimistic. It is possible, however, that the authors

The authors first compare the outcomes after some state's rapid re-opening plans versus the more cautious ones of other states. The slow reopening plan results in 140,000 deaths, a year end unemployment rate of 10%, and GDP about 5% below potential by year's end. The rapid reopening yields 165,000 deaths but with a full economic recovery by year's end.

These results yield a trade-off between 25,000 deaths and worse economic performance. We might view this sort of work as quantifying these tradeoffs scientifically, and then leaving it up to the public and policy makers to decide which outcome is desirable. One tool to evaluate these tradeoffs is the *statistical value of a life*. Suppose, for example that a policy maker may institute a public safety measure that with probability 0.01 will save a life. If they are willing to pay $100,000 for this measure, then the statistical value of a life is $10 million. Likewise, we can ask households how much they are willing to pay to reduce their risk of death by 1%. Both measures deliver results around $10 million.

*Alternate Re-opening Plans*

Figure 7 shows the results for a smart re-opening plan that opens sectors based on $\theta$. The effects here are small. For 140,000 deaths (the same as the slow reopening), this plan can deliver slightly higher unemployment with modestly higher GDP.

Figure 8 considers a re-opening where workers 65 or older do not return to work. This plan delivers much worse economic performance with unemployment about 5.4% higher. Deaths are reduced by less than expected, 2000 compared to the slow re-opening and 17,000 compared to the fast re-opening.

The contact matrix assumes that social distancing measures remain in effect through the re-opening. Figure 11 shows the impact of relaxing these restriction. Deaths by January 1 now range between 421,000 and 726,000 depending when governors' re-issue restrictions. The unemployment rate then rises once again.

Figure 12 shows the effects of re-opening schools. The left panel assumes that the governor chooses not to-reopen the economy at the same time. Deaths are 145,000 but the unemployment rate rises to about 13%. In this simulation, schools cost 5,000 deaths and 3% higher unemployment. If schools and the economy partly re-opens, there are 220,000 deaths and an unemployment around 5%. These are the trade-offs that policy makers must choose among.

Figure 13 is the "fuck it" scenario where the economy and schools re-open, and social distancing is relaxed. Deaths range between 569,000 and 856,000.

*Conclusions*

1. The goal of this paper is to scientifically quantify the tradeoffs facing policy makers trying to manage the pandemic. All of these tradeoffs are estimated with error, and it is also reasonable to question the model's assumptions that yield these trade offs. But this paper suggests (as we would expect) that the tradeoffs are real. It suggests skepticism towards those who have advocated that economic and public health interests are perfectly aligned.

2. Although written in May 2020, this paper is already old in some ways. A lot has been learned about cpvid-19 since May and this could affect the results. One example is that the

authors focus on an infection fatality rate of 0.6%. Their lower bound of 0.3% is, however, probably more accurate.