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Inequality of fear and self-quarantine: Is there a trade-off between GDP and public health? ☆

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ABSTRACT

We construct a quantitative model of an economy hit by a pandemic. People choose occupations and make work-from-home decisions to maximize income and minimize their fear of infection. Occupations differ by wage, infection risk, and the productivity loss when working from home. The model is calibrated to South Korea (SK) and the United Kingdom (UK) to compare SK's intensive testing and quarantine policy against UK's lockdown. We find that SK's policies would have worked equally well in the UK, dramatically reducing both deaths and GDP losses. The key contrast between UK's lockdown and SK's policies was not in the intensity of testing, but weak restrictions on the activity of many (UK) versus strict restrictions on a targeted few (SK). Lockdowns themselves may not present a clear trade-off between GDP and public health either. A premature lifting of the lockdown raises GDP temporarily, but infections rise over time and people voluntarily choose to work from home for fear of infection, generating a W-shaped recession. Finally, we find that low-skill workers and self-employed always lose the most from both the pandemic itself and containment policies.

To contain the COVID-19 pandemic, most governments turned to quarantine and lockdown policies. Some are selective and targeted, based on testing and tracing, while others are more indiscriminate. The urgency of the situation and the lack of real-time data have not allowed a thorough analysis of the economic and epidemiological impact of such policies. Which policies are more effective in arresting the pandemic? How big are the economic costs of the quarantine policies? How are the impacts of the pandemic and the governments' countermeasures distributed across people of different socioeconomic standings?

To answer these timely, important questions, we develop a quantitative economic-epidemiological model, in which the progression of the epidemic affects people's economic decisions and vice versa. The model has several novel features that make it unique in the fast-growing literature of pandemic economics. First, to evaluate how the impact of the epidemic and the policies are distributed, the model incorporates rich heterogeneity: People differ by skill and age, and there are multiple sectors and occupations. Second, people choose their occupations and whether to commute to work or stay home, to maximize income and minimize their fear of infection. Working from home entails lower earnings but reduces the risk of infection. Occupations are different in terms of wages, infection risks, and the productivity loss when working from home. Third, true health states are unobservable, and people must be tested to find out their infection status.[1] Finally, governments have access to three policy tools: testing, tracking (targeted quarantine), and lockdowns.

Our model provides a framework for *quantitative* analysis and can be used for evaluating and predicting the aggregate and distributive effects of real-world policies. We calibrate the pre-COVID model to South Korea and the United Kingdom (henceforth SK and UK, respectively) in 2019, and then vary only policy parameters to replicate the progression of COVID-19 in each country. SK

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[1] The testing technology is not perfect either and false positives are possible.

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responded early with aggressive testing and tracking, largely containing the epidemic. The UK had belatedly imposed a blanket lockdown, with arguably limited success.[2]

There are four key results. First, if the UK had adopted SK policies, GDP losses would have been minuscule (0.5 percent rather than 11 percent), with fewer than 600 cumulative deaths (rather than over 65,000) through October 2020, similar to SK figures. Thus, it was policies, not economic or demographic differences, that determined the progression of COVID, at least in the case of SK and UK. In addition, an earlier implementation of the lockdown in the UK would have made only a small difference to the course of the pandemic. This means that aggressive testing and tracking policies can deliver better economic *and* public health outcomes.[3]

Second, while wide-spread testing, tracing and strict quarantine enforcement were all essential for SK's successful containment of the virus, quarantine enforcement was the single most important factor that determined the path of the virus. This calls into question the UK government's—and others'—proposed exit strategy from lockdowns: Much more effective than a testing and tracing system is a targeted quarantine enforcement scheme. Thus the contrast between UK's and SK's policies was weak restrictions on many versus strict restrictions on a targeted few.[4]

Third, lockdowns may not represent as clear a trade-off between GDP and public health as commonly thought. In the short run, a lockdown prevents people from working normally, so it curbs new infections at the expense of GDP. A premature lifting of the lockdown may increase GDP but also raise infections. In a matter of months, infections can rise to a level at which people voluntarily work from home for fear of infection, leading to a W-shaped recession. For the UK, an extended lockdown would have led to 18,000 fewer deaths out of about 65,000 cumulative deaths by October, with GDP losses between March and October 2020 rising only from 11 to 13 percent of 2019 levels.[5]

Finally, the pandemic and the policies countering it do not affect people equally. Low-skill jobs tend to be more contact-intensive, implying (i) the low-skilled face higher infection risks and suffer more from the fear of infection, and (ii) their earnings loss is larger when they work from home. Consequently, low-skill workers and self-employed are disproportionately affected by the pandemic and government quarantines (be it through testing, tracking and/or lockdown). In particular, the high-skill are barely affected under SK's testing and tracking policy.

Contribution to the literature Most economics papers that extend the SIR epidemiology model of Kermack et al. (1927) consider lockdowns as the means to contain the epidemic (Alvarez et al., 2020; Garriga et al., 2020; Piguillem and Shi, 2020). In contrast, Eichenbaum et al. (2020), Farboodi et al. (2020) and Chudik et al. (2020) emphasize people's voluntary reduction in social activities.

To our knowledge, we are the first to model testing and tracking (targeted quarantine enforcement) policies in addition to voluntary self-quarantines and lockdowns. Moreover, we differentiate between symptomatic testing and asymptomatic testing. We are also the first to explicitly calibrate a structural model to fit both country-level data on GDP and employment in conjunction with empirical infection/death counts, as well as inequality in both economic and epidemiological outcomes.[6] In addition, we match confirmed infections (tested positive) in the model to the confirmed cases in the data, rather than follow the literature and assume that the cases in the data correspond to the true number of infections in the model.

1. Model

Time is discrete, and one model period is one day. At $t = 0$, there is an influx of infected people into the economy, but nobody is aware of it until the government starts testing at some later date $\tau > 0$. We allow for asymptomatic carriers and also for similar symptoms not caused by the novel coronavirus. People start the day with a health status and in the job they chose last night, and in the morning, decide whether to commute or work from home. Then they work and consume, and prices are determined to clear markets. Over the course of the day, the virus spreads, and some of the infected people recover. Their health status (sick or not sick) also gets updated. In the evening, if $t \geqslant \tau$, people may get tested. Given the test results and their updated health status, they decide whether to stay in their job or switch to a new job. The whole cycle repeats itself the next day. The daily timeline is depicted in Appendix Fig. 7 .

1.1. Individual states

Immutable states People are either young or old, and given our focus on short-term dynamics, we ignore aging. People die with or without COVID-19. The old are retired and do not work. We also assume that the old are all in self-quarantine during the epidemic. The young are either high-skilled or low-skilled, indexed by $x \in \{l, h\}$, which is a permanent characteristic.

True epidemiological states The true epidemiological side of the model is the SIR model with four states: susceptible (S), infected (I), recovered (R) and dead (D). We assume that those recovered become immune, although there have been rare cases of re-infection. An important distinction we make is that the true epidemiological states, with the exception of death, are not observable to the people or the government in the model.

Observed epidemiological states People are either healthy (asymptomatic, a) or sick (symptomatic, s), both with and without SARS-CoV-2 ("the virus" hereafter). It is well known that some infected people exhibit no symptoms. In addition, someone without the virus can be sick with symptoms similar to COVID-19 (for example, because of the flu). Testing partially reveals the virus, so people fall into three categories: untested or tested negative (superscript 0), tested positive (superscript c), and confirmed recovered (superscript r). We allow for false negatives, but not for false positives. As a result, we have seven observed epidemiological states: two symptom categories by three test categories, plus death: $\{a^0, s^0, a^c, s^c, a^r, s^r, d = D\}$.

1.2. The economic model

We construct our economic model with two features in mind. First, one's economic outcomes (as well as epidemiological out-

[2] SK is chosen as one of the few countries that successfully contained the pandemic without ever imposing a lockdown, while UK is chosen as a representative country that imposed a nationwide lockdown. While different in many aspects, the two countries are comparable in population, economic size and economic inequality.

[3] The obvious question is then why UK did not implement these superior policies. Testing, and tracking even more so, cannot be rolled out overnight and require a high level of preparedness. While UK built up its testing capacity quite quickly, tracking requires legislation that different societies may choose not to adopt for privacy concerns, for example. SK had relevant legislations and containment plans in place for thorough contact tracing and tracking after the MERS epidemic in 2015.

[4] For example, the compliance rates for the self-quarantine instructions from the UK's NHS testing and tracing scheme were less than 20 percent. In contrast, non-compliance led to hefty fines in SK.

[5] The model simulation of the actual UK policy predicts even more deaths and GDP losses due to the fear factor after November. The extended lockdown not only saves many more lives, but also costs *less* in terms of GDP. We do not report this as our main result, because on November 5, 2020, England imposed a second lockdown, which we do not consider in our exercise.

[6] Piguillem and Shi (2020) is one of the first attempts at calibrating models to actual data (Italy).

comes) depend on others' economic decisions, both directly (e.g., complementarity among coworkers) and indirectly through equilibrium effects (e.g., demand effects). Second, the pandemic and the governments' policies have differential impact across socioeconomic groups (e.g., by education and industry/occupation), which has been well documented in the literature—see Aum et al. (2020a) and the references therein.

Preferences and technology For utility out of consumption, we assume $u(c) = \log(1 + c)$, with one unit of "free consumption" to allow for zero earnings. We will also introduce additively-separable disutility terms from sickness and/or infection.

There are three sectors of production. Two of them produce intermediate inputs and are labeled "high-skill" and "low-skill" in reference to the skill levels of the people who work in them. The other is the final good sector, which combines high- and low-skill output using a Cobb-Douglas production function $Y = Y_l^{\theta} Y_h^{1-\theta}$, where $0 < \theta < 1$ is the low-skill share. We assume a representative final good firm, and normalize the final good price $P = 1$.

Within each sector indexed by $x \in \{h, l\}$, there are two modes of production. First, a healthy self-employed person who commutes to work produces $z_{x,1}$ units of the skill-x good without hiring any additional labor, where the subscript 1 denotes self-employment. Second, a healthy manager with skill x who commutes to work hires workers of the same skill and operates a span-of-control technology:

$$y_{x,2} = z_{x,2}^{\alpha_x} l_{x,3}^{1-\alpha_x}, \tag{1}$$

where $z_{x,2}$ is the productivity as a manager (subscript 2), $l_{x,3}$ the efficiency units of workers (subscript 3) hired, and $1 - \alpha_x$ the labor share.[7] Skill-x output produced by either mode is perfectly substitutable. The price of the high- and the low-skill goods are denoted by p_h and p_l, respectively, and all producers are price-takers.

Work-from-home decision The old make no decisions. The young choose an occupation at the end of each period. There are three occupations for each of the two skills: self-employment (non-employer), manager, and worker, indexed by $j = 1, 2, 3$. Having entered the current period with a given occupation, the self-employed and managers decide whether to work from home (quarantine) or work normally (commute, not in quarantine). Managers additionally decide whether their workers should work from home. Workers cannot decide: They are told by their managers to either commute or work from home.

Working from home makes people less productive, as measured by a discount factor $\psi_{x,j} \in [0, 1)$, which varies across the 2-by-3 skill-occupation groups. Sickness (symptomatic, $e \in \{s^0, s^c, s^r\}$) also makes people less productive, discounting their productivity by $\phi_{x,j} \in (0, 1)$, whether or not they have the virus. In addition, commuting while symptomatic causes disutility κ.[8] Note that κ is equal across all skill-occupation groups.

The self-employed and managers ($j \in \{1, 2\}$) with skill x and observable epidemiological state e choose to work normally (n) or from home (q):

$$V_{x,j}(e; \mathbf{p}) = \max_{\iota \in \{n,q\}} \left\{ V_{x,j}^n(e; \mathbf{p}) + \epsilon_n, V_{x,j}^q(e; \mathbf{p}) + \epsilon_q \right\}, \tag{2}$$

where $\epsilon_\iota, \iota \in \{n, q\}$ are i.i.d. extreme value preference shocks. The work location choice is made *after* the realization of the preference shocks. The aggregate state $\mathbf{p}$ is the vector of market-clearing prices and wages from yesterday: We assume adaptive expectations for tractability.[9] The values of commuting or working from home are

$$V_{x,j}^n(e; \mathbf{p}) = u\left[\bar{\phi}_{x,j}(e) \cdot r_{x,j} z_{x,j}\right] - \kappa(e) - \chi_{x,j}(I^*, e) \tag{3a}$$
$$V_{x,j}^q(e; \mathbf{p}) = u\left[\psi_{x,j} \bar{\phi}_{x,j}(e) \cdot r_{x,j} z_{x,j}\right] - \chi_q(I^*, e). \tag{3b}$$

The self-employed with skill x produce $z_{x,1}$ units of output without using any input, and the return to their skill is the output price, $r_{x,j} = p_x$. For managers, the return is $r_{x,j} = \pi_x$, where

$$\pi_x = \alpha_x p_x \cdot \left[\frac{(1-\alpha_x) p_x}{w_x}\right]^{\frac{1-\alpha_x}{\alpha_x}},$$

is the maximized profit per efficiency unit of managerial skill, and w_x the wage per efficiency unit of skill-x labor. The sickness discount $\bar{\phi}_{x,j}(e) = \phi_{x,j}$ if $e \in \{s^0, s^c, s^r\}$ and 1 otherwise.

The term $u[\cdot]$ is utility from hand-to-mouth consumption, and $\chi(I^*, e)$ the disutility from fear of infection.[10] Note that fear depends not on I, the total mass of infected, but on I^*, the mass of infected individuals who are not isolated. For example, some infected may self-quarantine, or others may be locked down, as we describe below. However, the confirmed recovered ($e \in \{a^r, s^r\}$) know that they are immune and no longer have fear.[11]

In addition, managers decide whether their workers will work normally or from home, like a "paternalistic planner" maximizing a modified version of the workers' objective function. A manager's problem for a worker with skill x and observed health status $e = e_{x,3}$ is:

$$\max_{\iota \in \{n,q\}} \left\{ u\left[\bar{\phi}_{x,3}(e) \cdot w_x z_{x,3}\right] + \epsilon_n, u\left[\psi_{x,3} \bar{\phi}_{x,3}(e) \cdot w_x z_{x,3}\right] + \epsilon_q \right\}, \tag{4}$$

where the first term for each choice is the worker's utility from consuming his labor income—wage w_x times labor efficiency units $z_{x,3}$, discounted by $\bar{\phi}_{x,3} = \phi_{x,3}$ if sick and/or $\psi_{x,3}$ if working from home. The manager draws i.i.d. extreme value preference shocks ϵ_ι for each worker. Compare this paternalistic objective function with the actual values of a worker in (3), with $r_{x,3} = w_x$: Managers ignore the workers' disutility from commuting while sick κ, and fear χ. Because of this, to avoid infection risks at work, workers will switch occupations.

The extreme value assumptions on the preference shocks for work location imply that the fraction of self-employed, managers and workers working from home, $\Pr_{x,j}^q(e, \mathbf{p})$, is easily computed from the values in Eqs. (3) and (4) as conditional choice probabilities. Keep in mind that for workers, the values in (4) are used, not (3), since they do not get to choose.

Quarantines or lockdowns are modeled as the government forcing people to work from home. Let $\rho_{x,j}(e)$ denote the fraction of people of skill-occupation x-j with epidemiological state e prevented from commuting. Then the actual fraction of people who stay home is

$$\overline{\Pr}_{x,j}^q(e, \mathbf{p}) = \max\left\{\rho_{x,j}(e), \Pr_{x,j}^q(e, \mathbf{p})\right\}. \tag{5}$$

[7] The distinction of managers, workers and the self-employed is useful for considering real-world policies aimed at mitigating the economic impact of the pandemic, which often treated workers and the self-employed differently, for example in the form of employment subsidies, paid furloughs, and expanded unemployment benefits.

[8] This is distinct from a general disutility from being sick, which we ignore as it does not alter choices.

[9] We conjecture that this assumption does not matter quantitatively, because information gets updated daily in this model.

[10] Our specification can capture a direct disutility from high infections, but also the expected loss in future earnings from becoming infected tomorrow (i.e., lower continuation value) as well as altruistic concerns of infecting others.

[11] People do not know whether they are infected/recovered without testing, and the government does not know who is infected either. However, they still know the total number of infected by quarantine status, as long as they know the deterministic epidemiological laws of motion in Section 1.3 and the history of confirmed cases. Thus I^* is an admissible argument for individual preferences.

Occupational choice At the end of each period, after production takes place and everyone's true and observable epidemiological states are updated, the young choose occupations for tomorrow. However, only a fraction $\nu < 1$ of those who want to switch occupations can do so. This friction prevents unrealistically high volumes of occupation changes at the daily frequency, and can be thought of as the standard search frictions.

The occupation choice is myopic: People choose their occupation *for tomorrow* that would maximize their utility *today*. This is a static choice but the fear factor captures a notion of continuation value. They also assume that they will work from home with the same probability as the fraction of people who stayed home today by x, j, e, but they have updated information of their status $\bar{e}$ from testing, and also the realized market clearing prices of today, $\bar{\mathbf{p}}$. Specifically, the occupation choice is

$$\max_{j=1,2,3}\left\{\overline{\Pr}^q_{x,j}(\bar{e},\mathbf{p})\cdot V^q_{x,j}(\bar{e},\bar{\mathbf{p}}) + \left[1-\overline{\Pr}^q_{x,j}(\bar{e},\mathbf{p})\right]\cdot V^n_{x,j}(\bar{e},\bar{\mathbf{p}}) + \epsilon_j\right\}, \quad (6)$$

where ϵ_j is i.i.d. extreme value preference shocks for each occupation. The values of working normally or from home ($\imath = n, q$) for a skill-occupation combination x-j, $V^{\imath}_{x,j}$, are defined in Eqs. (3) and (4). The realized price vector $\bar{\mathbf{p}}$, which clears the market and is used for occupation choice, is different from the price $\mathbf{p}$ that enters the work-from-home probabilities.

1.3. The epidemiological model

The epidemic side of our model is a heterogeneous-agent version of the SIR model. There are eight distinct groups to keep track of: six skill-occupation groups working normally, all the young people working from home (in quarantine), and the old. While the economic side of the model keeps track of who works normally or from home for each skill-occupation group, the epidemiological law of motion applies equally to all the young working from home, regardless of their skill or occupation.

True epidemiological states For each of the eight groups indexed by i, we denote the masses of people in each true epidemiological state as S_i (susceptible), I_i (infected), R_i (recovered), and use bars to denote the masses at the end of the period. Let I^* denote the mass of the infected who are not isolated. True epidemiological states evolve as follows.

$$\begin{aligned}
\tfrac{\bar{S}_i}{1-\delta_i} &= [1-\upsilon_i(I^*)]S_i \\
\tfrac{\bar{I}_i}{1-\delta_i} &= \upsilon_i(I^*)S_i + (1-\gamma_i)(1-m_i)I_i \\
\tfrac{\bar{R}_i}{1-\delta_i} &= \gamma_i(1-m_i)I_i + R_i
\end{aligned}$$

The parameter δ_i is the baseline death rate, and $\upsilon_i(I^*)$ the group-specific infection rate as a function of I^*. The recovery rate is γ_i, and added mortality from the virus m_i. In essence, we have eight separate SIR models for the eight groups, linked only by the fact that infection rates depend on I^*, the total mass of non-isolated infected individuals across all groups. The dependence itself is group-specific, hence $\upsilon_i(I^*)$, capturing the fact that sectors differ in how often their customers may infect their workers. It also captures the obvious fact that people in quarantine are both less likely to get infected and infect others.

True epidemiological states are not observed, so people do not know their infection status without testing. Even then, we allow for false negatives. Furthermore, testing is often symptoms-based, but the infected can be asymptomatic while the susceptible and even the recovered may display similar symptoms (from the flu, for example). So someone who was infected and recovered without testing will always remain unconfirmed.[12] The laws of motion for the observed epidemiological states are explained in Appendix B.

Infection rates Let I (with no subscript) denote the total mass of infected in the population, $I \equiv \sum_i I_i$, and Q the effectiveness of government quarantines, so the mass of the infected who actually spread the virus is

$$I^* = I - QI_q, \quad 0 \leqslant Q \leqslant 1, \quad (7)$$

where I_q is the mass of infected in the quarantine group, $i = q$. In this setup, Q is a policy variable that controls the *intensive margin* of quarantine policies.[13] For example, the government can check if people in quarantine are actually staying home by means of digital tracking or by police-enforced lockdowns. Given I^*, infection rates $\upsilon_i(I^*)$ differ across groups according to:

$$\upsilon_i(I^*) = \bar{\upsilon}_i \cdot \frac{I^*}{N},$$

where $\bar{\upsilon}_i$'s are positive constants and N is the population size. So infection rates depend only on the total mass of the infected, net of those effectively quarantined.[14]

1.4. Government policies

We consider three distinct types of government policies in the model.

1. **Testing** The government sets the fractions of asymptomatic and symptomatic people who are tested in each period, which we denote by τ^a and τ^s, respectively. Testing the asymptomatic can be viewed as "tracing," a policy that tests everyone who has come into contact with a positively confirmed person.
2. **Quarantine/Tracking** Quarantines are imposed on the symptomatic and confirmed ($e \in \{s^0, a^c, s^c\}$). Tracking means an effective enforcement of quarantine, as measured by the variable Q in (7). Effective tracking ensures that those who should be home are indeed staying home and not infecting others. If $Q = 1$, all the people working from home (I_q) are staying home and not infecting anyone. If $Q = 0$, all the people working from home actually go around socializing and infecting others.
3. **Lockdown** A lockdown forces people to work from home, as operationalized by $\rho_{x,j}$ in Eq. (5). If large enough a share of people voluntarily self-quarantine, this policy is not binding. A lockdown mandates that certain people work from home (*extensive margin*) but does not automatically ensure that they do not go out socializing and infecting others (*intensive margin*). The latter is captured by Q above.

2. Quantitative analysis: SK vs UK

Our benchmark calibration will target both SK and UK data on daily new infections (tested positive) and their path of GDP from Dec 2019 to October 2020, and the model is run forward to December 2020.[15] All calibrated parameters that are not directly taken from the data are assumed to be the same between the two coun-

[12] This would change with antibody testing, which we consider in the working paper version (Aum et al., 2020b).

[13] The government cannot observe anyone's true epidemiological state either. The enforcement applies equally to everyone in quarantine (group $i = q$).

[14] In the working paper version, we allowed the disutility of the fear from infection, χ, to depend on the entire distribution of the masses of infected across all groups (a vector $\mathbf{I}$, whose i-th element is the mass of infected in group i), to capture how groups interact with one another. Apart from the challenge that we lack the data to identify differential rates of intra- and inter-group transmissions, we found that it makes little quantitative difference.

[15] Appendix Fig. 9 shows 2-year simulations assuming no further policy change or advance in vaccines/treatments.

tries, with the exception of the policy variables. We then assess the effect of the policies through various counterfactual exercises.

2.1. Calibration

Economic parameters All economic parameters are calibrated separately to each country, assuming a steady state in 2019 (pre-COVID). We fix the mass of the young (ages 25–64) to 1 at time 0, and the old (age 65+) to 0.26 and 0.37, according to 2019 population estimates for SK and UK, respectively.[16] SK wage and employment shares are computed from the Economically Active Population Survey (EAPS), with additional wage information from the Survey on Labor Conditions (SLC). UK wage and employment shares are computed from the Annual Population Survey (APS), with additional wage information from the Annual Survey of Hours and Employment (ASHE). For each country, we classify industries into a low- or a high-skill sector based on average wages so that the former comprises approximately 50 percent of employment. We also consider both employers and employees in managerial positions in the data as managers in our model. The resulting summary statistics are shown in Appendix Table 2. Using wage shares computed from the table, we can fix the low-skill and manager share parameters θ and α_x.

In Aum et al. (2020c), we computed the average fraction of time spent working from home for a detailed list of industries and occupations in the American Time Use Survey (ATUS) from 2014 to 2018. From this data, we construct ψ_{xj}, the wage discount factor for working from home, using mean hours-employment in the American Community Survey (ACS) from 2014 to 2018 as weights. Low-skill industries generally have a lower work-from-home index, and so do workers compared to the self-employed and managers. We then scale both low- and high-skill productivities so that low- and high-skill sector GDP losses upon impact of a lockdown are consistent with UK's GDP drop in March and April, shown in Appendix Fig. 8.

The sick productivity parameters ϕ_{xj} and utility cost κ are computed by assuming indifference between commuting and working from home when sick before the realization of the work location preference shock ϵ_ι in (2). The scale parameter of the extreme value distribution from which ϵ_ι's are drawn is calibrated so that 11 percent of the workforce works from home pre-COVID, the average between 2014–18 in ATUS (Aum et al., 2020c).[17]

Steady-state employment shares in the model are fit to the data by choosing skill-occupation specific location parameters for the extreme value distribution that govern the preference shocks ϵ_j in (6). The resulting parameters and more calibration details are in Appendix C.

Epidemiology parameters As shown in Table 1, all epidemiology parameters are kept equal between SK and UK except the mortality rate, which is set to each country's case fatality rate (CFR) as of October 30, 2020, which is lower in SK.[18] The skill-occupation-specific infection rates υ_i are taken from the exposure indices in Aum et al. (2020c), normalized so that the lowest rate is zero (for high-skill managers) and R_0 is 3.9. This is the R_0 that matches the initial rise of virus-induced deaths. The other epidemiology parameters are based on what is known about COVID-19, according to the sources in Appendix D.

[16] Data available from Statistics Korea and the UK Office for National Statistics (ONS).

[17] We use ATUS for both SK and UK rather than country-specific surveys, since ATUS is used to compute the time-country consistent work-from-home indices.

[18] Given that we almost perfectly replicate each country's path of infection, the resulting death counts are also closely replicated. At least some of the low CFR in SK must be due to factors exogenous to our mode, such as underlying health status, medical systems, social interaction patterns and so on.

Policy variables We assume that exactly one person is infected on December 22, 2019 in each country, and that the date of the first confirmed case in the data is the day testing commences in the model.[19] From that point on, SK quarantines all untested symptomatic and confirmed ($e \in \{s^0, a^c, s^c\}$), while UK waits two more weeks to start quarantines. Test probabilities (τ^a, τ^s) and quarantine enforcement Q change whenever the government implements a new policy, and their values are calibrated to match the path of newly confirmed cases.

For the UK, we specify the lockdown function $\rho_{x,j}(e)$ in Eq. (5) as

$$\rho_{x,j}(e) = \begin{cases} \max\{\bar{\rho}_{x,j} \cdot \varphi(t; t_\lambda, T_\lambda, \lambda), \bar{Q}\} & \text{if} e \in \{s^0, a^c, s^c\} \\ \bar{\rho}_{x,j} \cdot \varphi(t; t_\lambda, T_\lambda, \lambda) & \text{otherwise}, \end{cases} \tag{8}$$

where φ is a sigmoid function that declines from 1 to 0 with start and end dates $[t_\lambda, T_\lambda]$:

$$\varphi(t, t_\lambda, T_\lambda, \lambda) = \max\left(0, \min\left\{\left[1 + \left(\frac{t - t_\lambda}{T_\lambda - t}\right)^\lambda\right]^{-1}, 1\right\}\right) \tag{9}$$

and λ measures how long the lockdown remains effective.[20] The constant $\bar{\rho}_{xj}$ vary by skill-occupation since some jobs are more essential than others, which we compute using data from Palomino et al. (2020). The constant $\bar{Q}$ is the effectiveness of stay-at-home advisories, and for lack of better evidence we set $\bar{Q} = Q$, the enforcement parameter in (7). For SK, enforcement policies are parameterized as $Q \cdot \varphi(t; t_Q, T_Q, \lambda_Q)$, with Q and (t_Q, T_Q, λ_Q) changing whenever a new policy is implemented.

Finally, the fear factor itself plays a similar role as policy: If people fear infection enough, they will voluntarily stay home, and more so when infection rates are high. This reduces the spread of the virus but also drags the economy down. For simplicity, we assume that

$$\chi_i(I^*, e) = \begin{cases} 0 & \text{if} e \in \{a^r, s^r\} \\ \bar{\chi} \cdot \upsilon_i(I^*) & \text{otherwise} \end{cases} \tag{10}$$

where the constant $\bar{\chi}$ measures the fear factor. We calibrate $\bar{\chi}$ so that SK's GDP drops by 6 percent at the trough despite not locking down, in line with Appendix Fig. 8. More details are in Appendix D.

The resulting epidemiology, policy and fear factor parameters are in Table 1. Test rates are chosen to match daily new cases, so the mass of people tested should not be taken literally: As a policy, it measures the availability of tests. In SK, the government traces and tests all individuals who came into contact with a confirmed person for free, and private tests cost less than USD 40, which is reimbursed if tested positive. This made testing available to everyone regardless of symptoms. Thus we set testing rates to $\tau_a = \tau_s$ in SK from January 20 onward. The high Q in SK captures its highly-effective digital tracking system coupled with generous subsidies during quarantine, and heavy but means-tested fines (including imprisonment) for non-compliance. Such policies may have been infeasible had infections grown larger.

In contrast, tracing was rather ineffective in the UK, with only 20 percent of contacts identified and even less complying to self-quarantines.[21] So we set $Q = \bar{Q}$ at a relatively lower level, even during the lockdown. Moreover, testing is still symptoms-based ($\tau_a = 0$)

[19] The first date of infection is not separately identified from the initial mass of the infected.

[20] Thus, λ may also measure how people's willingness to comply decays over time.

[21] https://www.gov.uk/government/collections/nhs-test-and-trace-statistics-england-weekly-reports.

Table 1
Epidemiology and Policy Parameters.

Parameter	Value	Description		
δ_y	0	Young daily natural death rate		
δ_o	5.48e-05	Old annual natural death rate of 2 percent		
γ_y	1/14	Young recover in 2 weeks		
γ_o	$\gamma_y/2$	Old recover in 4 weeks		
m_o	[0.0042,0.0054]	Age 65 + CFR of [11.8,15.2] in SK,UK as of 30 Oct 2020		
m_y	$=m_o/30$	Age 15–65 CFR of [0.4,0.5] in SK,UK as of 30 Oct 2020		
$\upsilon_{l,j}$	[0.3174, 0.0838, 0.4383]	Exposure index in Aum et al. (2020c)		
$\upsilon_{h,j}$	[0.1456, 0.0000, 0.2118]	for SK employment structure		
$\upsilon_{l,j}$	[0.3083, 0.0570, 0.3644]	for UK employment sturcture		
$\upsilon_{h,j}$	[0.1397, 0.0000, 0.2606]	(normalized to have mean υ_o and $\upsilon_{h,1} = 0$)		
υ_q	$=\upsilon_o/7$	Reduce social contact to 1 day a week in quarantine		
υ_o	0.2786	Old infection rate to match $R_0 = 3.9$		
I_0	[2.6, 2.3]$\times$1e-08	1 person infected on Dec 22nd ($t = 0$)		
$\bar{\chi}$	5000	Fear factor: 6 percent GDP drop in SK at peak infection		
ω	0.8	20 percent false negatives (Yang et al., 2020)		
$f_y = f_o$	0.03	Sick without COVID: annual respiratory illnesses		
$\left(\eta_y, \eta_o\right)$	[0.3,0.6]	Young and old infected with symptoms (Davies et al., 2020)		
$\rho_{l,j}$	[0.7463, 0.7101, 0.6891]	Fraction locked down from Palomino et al. (2020)		
$\rho_{h,j}$	[0.9014, 0.8179, 0.7992]	for SK employment structure (only for counterfactuals)		
$\rho_{l,j}$	[0.7370, 0.7456, 0.7303]	for UK employment structure		
$\rho_{h,j}$	[0.9598, 0.8135, 0.7818]			
λ	4	UK lockdown: [April,August] year-on-year GDP drop [-24,-10]%		
t_λ, T_λ	[92,362]	UK lockdown: start and end dates		
(τ_a, τ_s)	[timeline below]	Test rates for a/symptomatic		
$Q = \bar{Q}$	[timeline below]	Tracking policy		
Country	Date	Event	Testing	Quarantines
SK	Dec 22, $t = 0$	No detection	$(\tau_a, \tau_s) = 0$	$Q = 0$, no quarantines
	Jan 20, $t = 29 = \tau$	First detection	$(\tau_a, \tau_s) = (0, 0.03)$	$Q = 0.1$
	Feb 20, $t = 60$	Shincheonji outbreak	$(\tau_a, \tau_s) = \tau_1$	$Q = q_1$
	Apr 18, $t = 116$	Social restrictions eased	$(\tau_a, \tau_s) = 0.8$	$Q = q_2 + (q_1 - q_2) \cdot \varphi_2$
	Aug 15, $t = 235 = \tau$	New restrictions on Seoul	$(\tau_a, \tau_s) = 0.8$	$Q = q_3 + (q_2 - q_3) \cdot \varphi_3$
	Sep 13, $t = 264$	Seoul restrictions eased	$(\tau_a, \tau_s) = 0.8$	$Q = q_4 + (q_3 - q_4) \cdot \varphi_4$
			$\tau_1 = 0.03 + 0.77 \cdot \frac{t-59}{116-59}$	$q_1 = 0.94$
				$q_2 = 0.61, \varphi_2 = \varphi(116, 235, 3)$
				$q_3 = 0.90, \varphi_3 = \varphi(235, 265, 2)$
				$q_4 = 0.78, \varphi_4 = \varphi(265, 323, 2)$
UK	Dec 22, $t = 0$	No detection	$(\tau_a, \tau_s) = 0$	$Q = 0$, no quarantines
	Feb 1, $t = 41 = \tau$	First detection	$(\tau_a, \tau_s) = (0, 0.0001)$	$Q = 0$, no quarantines
	Feb 10, $t = 50$	First quarantine	$(\tau_a, \tau_s) = (0, 0.0001)$	$Q = 0$
	Feb 24, $t = 64$	Testing system commences	$(\tau_a, \tau_s) = (0, \tau_1)$	$Q = 0.0$
	Mar 23, $t = 92 = t_\lambda$	Lockdown	$(\tau_a, \tau_s) = (0, \tau_2)$	$Q = 0.55$
	May 30, $t = 160$	Test/Tracing complete	$(\tau_a, \tau_s) = (0, 0.3)$	$Q = 0.55$
			$\tau_1 = 0.0001 + 0.0299 \cdot \frac{t-63}{91-63}$	
			$\tau_2 = 0.03 + 0.27 \cdot \frac{t-91}{160-91}$	

and not readily available even for many people with symptoms at the moment of writing, despite high levels of testing conducted.

The results of our calibration are shown in Fig. 1 up to December 2020.[22] There are several points to note. First, the figures are in log-scale, so SK has 2 to 3 orders of magnitude fewer infections and deaths than the UK.[23] Second, fluctuations in the model represent changes in policy, which do not perfectly align with the data but track its general path. Third, model deaths are slightly higher and lower for SK and UK, respectively. Since we use empirical CFR's, the discrepancies may be due to empirical differences in demographics over time, but it may also be because SK, with low infections, undercounted some COVID deaths while UK, with high infections, was more careful with post-mortem COVID testing. Finally, the model captures that both SK's testing and tracking effectively "flattened the curve" in the spring, but UK infections rising again as the lockdown wears out.[24]

2.2. GDP and inequality

What are the economic effects of the containment policies? Fig. 2 gives an answer by plotting low-skill, high-skill and total GDP (not per capita, to capture the deaths from the virus). SK's GDP loss from February to March is 6 percent. In the data, industrial production fell by 3.5 percent from February to March (year-on-year, seasonally adjusted), reaching a trough of 6 percent in May.[25] While each country's (monthly, year-on-year) GDP drop was a target moment, note that UK GDP already drops by nearly 8 percent even before the lockdown in mid-March, which is partly due to the weak quarantine policies before the lockdown but mostly due to the fear factor. This drop is in line with the economic effect of

[22] We blow up model masses by each country's age 15 + population to match integer counts in the data.

[23] As a result, SK infections appear to fluctuate more, driven by small, local outbreaks in the data. In contrast, local outbreaks are barely visible in the UK due to the large aggregate number of infections.

[24] Appendix Fig. 9 shows that SK's infection curve plateaus at 500 new cases a day in Dec 2021. UK's 2nd wave peaks at 60,000 new cases a day in March 2021, but with half a million cumulative deaths.

[25] The exact timing of SK's GDP drop comes a bit later, which is likely due to behavioral and industrial propagation, in addition to international influences, all absent from our model.

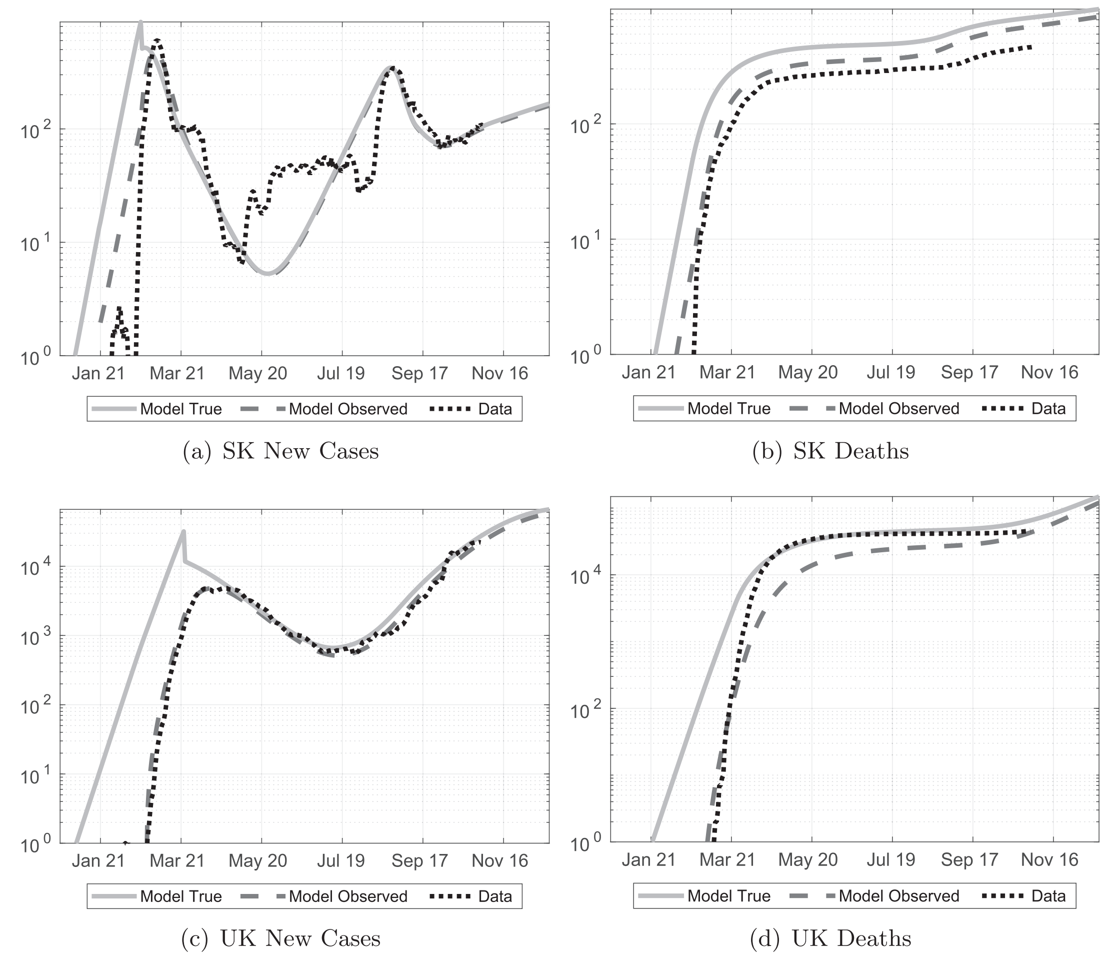


Fig. 1. SIR Model vs. Data, SK and UK. All figures are in log-10 scale, from December 22, 2019 to December 21, 2020. "Model True" corresponds to the true number of COVID infections and deaths, which are not observable and has no data counterpart, and "Observed" to cases and deaths confirmed by tests in the model. "Data" is cases and deaths confirmed by test in the real world. Death counts are cumulative. *Data source*: Korea Center for Disease Control and Prevention Agency (KDCA) and UK Department of Health and Social Care (DHSC). Data counts in 7-day rolling averages.

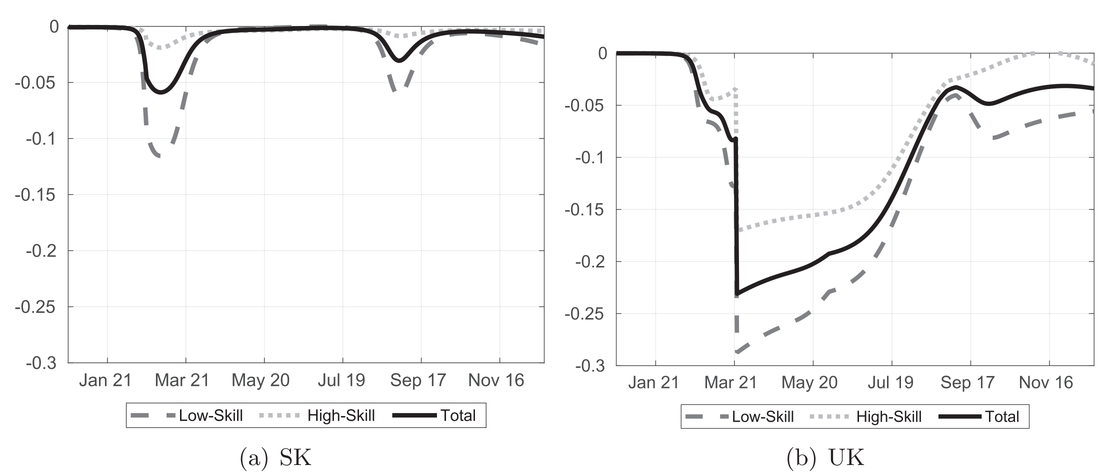
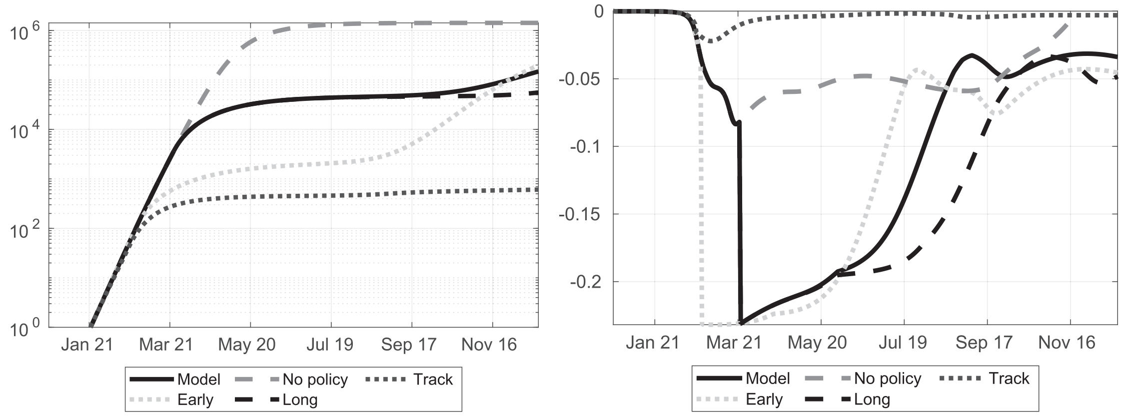


Fig. 2. GDP Losses: SK vs UK. Model implied GDP from 22 Dec 2019 to 21 Dec 2020. GDP is in log-deviations from the 2019 steady state and not per capita, so includes GDP losses from COVID-19 deaths (the working-young have a zero natural death rate).



(a) Deaths

(b) Total GDP

Fig. 3. UK Counterfactual Policies. "Model" is UK's baseline lockdown policy. "No policy" is doing nothing, and "Tracking" is if UK had followed SK's policy exactly, including its timing. "Early" is if UK had implemented the same lockdown, but at the earlier date SK implemented its policy. "Long" is an extension of the lockdown by 90 days. Death counts are cumulative. GDP is in log-deviations from the 2019 steady state and not per capita, so includes GDP losses from COVID-19 deaths.

infections we estimate *in the absence of lockdowns* (Aum et al., 2020a).[26] Since the lockdown weakens over time, GDP recovers through September, but then as the virus further progresses, GDP begins to fall again due to the fear factor.[27] The fear factor is also why GDP falls between February and March in SK. However, the fact that GDP remains more or less constant afterward, even during the local outbreak in August, implies that SK's policy successfully contained the virus so that the fear factor is no longer binding for most people.

More important, the drop in low-skill GDP is much larger than high-skill GDP. This is because the low-skill are less productive from home. Even as high-skill GDP recovers, low-skill GDP continues to drop because low-skill workers face higher risks of infection at work and are thus more sensitive to fear at very high infection rates. In Appendix E, we detail earnings and employment paths by skill and occupation. For both countries, and especially for the UK, the low-skill losses come from the self-employed losing earnings and from fewer people remaining workers. (Workers do not make commute/work-from-home decisions and ordered by managers, so to avoid infection risks they switch occupations.) These patterns are qualitatively consistent with the data from SK and UK—see Aum et al. (2020a) and the references therein.

2.3. Counterfactual policy analysis

How effective were each country's policies? What made SK's policy work, and would it work for other countries as well? Could an early or longer lockdown have contained UK's outbreak better? We address these questions by simulating the paths under alternative policy responses. The cumulative death counts and average GDP losses from all counterfactuals are summarized in Appendix Table 4.

UK Fig. 3 compares UK's baseline lockdown policy against the hypothetical outcomes of (i) doing nothing, (ii) implementing SK's policy, including the exact dates of implementation, (iii) an earlier lockdown, and (iv) a longer lockdown. Without any intervention ("No policy"), deaths pass a million by July, and GDP losses are still large at about an average of 5 percent from January to October, because of the fear factor. If the UK had instead implemented SK's testing and tracking policy ("Track"), the epidemic would have been contained early on with fewer than 600 deaths, with an even smaller GDP drop than SK of about 0.5 percent (due to differences in employment structure). This shows that SK's policy would have been effective in other countries.[28]

But is it the SK policy itself, or its early reaction (in February rather than March) that leads to successful containment? To find out, we simulate a path in which the lockdown is implemented at the same time that SK intensified its testing policies ("Early"). While an early lockdown is effective in preventing the spread of the virus and thus deaths upon impact, its efficacy wears off over time, and eventually both cumulative death counts and GDP losses reach the same level as the baseline lockdown by mid November.

Of course, the reason an early lockdown becomes ineffective is partly due to the decay of its intensity, which we built into the model in (8). The decay can stand for civil disobedience, but also weak enforcement. So in Fig. 3 ("Long"), we additionally simulate the paths of infections and GDP if the lockdown were extended by 90 days—given the sigmoid function (9), this means the lockdown remains strict for an extra 45 days. Through October, the extended lockdown would have saved 18,000 of the more than 65,000 cumulative deaths by reducing the peak infection. This reduction in deaths comes with a 45-day delay in GDP recovery, but also prevents the fear factor from taking over in the medium run, so average GDP losses are only about 2 percentage points higher through October.[29]

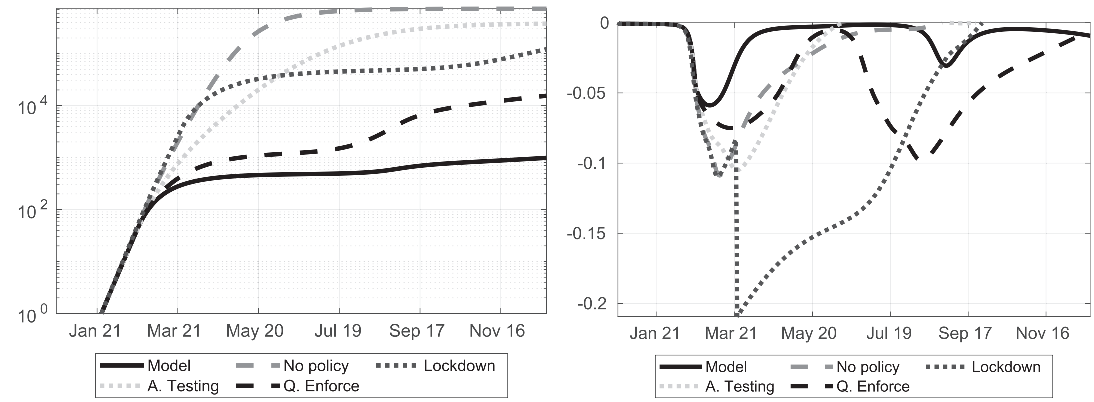
SK Fig. 4 compares SK's baseline tracking policy against the hypothetical outcomes of (i) doing nothing, (ii) implementing UK's lockdown, including the exact dates of implementation, (iii) the same testing policy as baseline, but with quarantine enforcements only at UK's lockdown level of $Q = 0.55$, and (iv) the same testing and quarantine enforcement policies, but without testing any asymptomatic (no tracing). Without any intervention ("No pol-

[26] Sheridan et al. (2020) also find strong economic contractions in the absence of lockdowns in Sweden. They also find that consumption patterns differ by age depending on whether people stay home voluntarily or by government mandate. While our model also implies that one's consumption is lower when more people stay home due to equilibrium effects, it misses the difference by age.

[27] Two-year simulations in Appendix Fig. 9 show that GDP losses again reach about 8 percent next summer even without a second lockdown.

[28] In our model, the enforcement parameter Q also captures people's compliance with quarantine above and beyond the enforcement itself. For example, it could be that social norms in SK explain effective enforcement. However, lockdowns also require compliance, and to the extent that we cannot measure how well people would comply with quarantines vs. lockdowns, we do not make this distinction in our quantitative analysis.

[29] According to the model simulation, the actual UK policy brings about even more deaths and GDP losses due to the fear factor after October. The extended lockdown not only saves more lives, but also costs *less* in terms of GDP.



(a) Deaths (b) Total GDP

Fig. 4. SK Counterfactual Policies. "Model" is SK's baseline tracking policy. "No policy" is doing nothing, and "Lockdown" is if SK had followed UK's policy exactly, including its timing. "A. Testing" is if SK had tested as aggressively, but with quarantine enforcement at UK's lockdown levels ($Q = 0.55$). "Q. Enforce" is if SK had tested and enforced quarantines as aggressively, but without any asymptomatic testing. Death counts are cumulative. GDP is in log-deviations from the 2019 steady state and not per capita, so includes GDP losses from COVID-19 deaths.

icy"), deaths pass 700,000 by October with a 10 percent drop in GDP at peak infection. With a UK-style lockdown ("Lockdown"), deaths pass 65,000 by October, and GDP drops by 21 percent upon impact, similar to the model prediction for the UK baseline.

More interesting, asymptomatic testing with UK's level of quarantine enforcement ("A. Testing") reduces deaths by more than 350,000 compared to doing nothing, but is less effective than a lockdown, although average GDP losses from January to October are relatively small at 2.2 percent compared to 8.4 percent under a lockdown. It turns out that the effectiveness of SK's pandemic containment comes from quarantine enforcement: Even without any asymptomatic testing, strict enforcement ("Q. Enforce") arrests deaths at 10,000 with an average GDP loss of 5 percent through October.

3. Concluding remarks

We presented a quantitative economic-epidemiological model of the COVID-19 pandemic. As more data becomes available and helps us improve our calibration, our model of heterogeneous skills and occupations with observable and unobservable health status can serve as a laboratory for assessing how different policies have affected and will affect economic and health inequality as we continue to battle the pandemic. In particular, the dimensions of heterogeneity in our model can readily capture the salient features of various social insurance policies implemented during the pandemic. We leave the quantitative evaluations of such policies for future research.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version at https://doi.org/10.1016/j.jpubeco.2020.104354.

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