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.

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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 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 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 es-

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

[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.

sential 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.

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[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).

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 $t \geq \tau$, 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 Figure 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 outcomes) 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.

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[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.

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.

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[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.

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 equations (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

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

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

$$\max_{j=1,2,3}\left\{\overline{\Pr}_{x,j}^q(\bar{e}, \mathbf{p}) \cdot V_{x,j}^q(\bar{e}, \bar{\mathbf{p}}) + \left[1 - \overline{\Pr}_{x,j}^q(\bar{e}, \mathbf{p})\right] \cdot V_{x,j}^n(\bar{e}, \bar{\mathbf{p}}) + \epsilon_j\right\}, \tag{6}$$

where ϵ_j is i.i.d. extreme value preference shocks for each occupation. The values of working normally or from home ($\iota = n, q$) for a skill-occupation combination x-j, $V_{x,j}^\iota$, are defined in equations (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 group 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.

$$\frac{\bar{S}_i}{1-\delta_i} = [1 - v_i(I^*)] S_i$$

$$\frac{\bar{I}_i}{1-\delta_i} = v_i(I^*)S_i + (1-\gamma_i)(1-m_i)I_i$$

$$\frac{\bar{R}_i}{1-\delta_i} = \gamma_i(1-m_i)I_i + R_i$$

The parameter δ_i is the baseline death rate, and $v_i(I^*)$ 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 $v_i(I^*)$, 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

$$I^* = I - QI_q, \quad 0 \leq Q \leq 1, \tag{7}$$

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 $v_i(I^*)$ differ across groups according to:

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

where $\bar{v}_i$'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]

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[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 **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.

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 sympotmatic 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 equation (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 countries, 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

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

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

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 Figure 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 v_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.

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.

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[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.

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

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
$v_{l,j}$	[0.3174, 0.0838, 0.4383]	Exposure index in Aum et al. (2020c)
$v_{h,j}$	[0.1456, 0.0000, 0.2118]	for SK employment structure
$v_{l,j}$	[0.3083, 0.0570, 0.3644]	for UK employment sturcture
$v_{h,j}$	[0.1397, 0.0000, 0.2606]	(normalized to have mean v_o and $v_{h,1}=0$)
v_q	$=v_o/7$	Reduce social contact to 1 day a week in quarantine
v_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
(η_y, η_o)	[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
	Dec 22, $t=0$	No detection	$(\tau_a, \tau_s) = 0$	$Q = 0$, no quarantines
SK	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	$(\tau_a, \tau_s) = (0, 0.3)$	$Q = 0.55$
			$\tau_1 = 0.0001 + 0.0299 \cdot \frac{t-63}{91-63}$	
			$\tau_2 = 0.03 + 0.27 \cdot \frac{t-91}{160-91}$	

Table 1: Epidemiology and Policy Parameters

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

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

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 $\bar{\rho}_{x,j}$ 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

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

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 Figure 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 ($\tau_a = 0$) 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 Figure 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

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[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.

[22]We blow up model masses by each country's age 15+ population to match integer counts in the data.
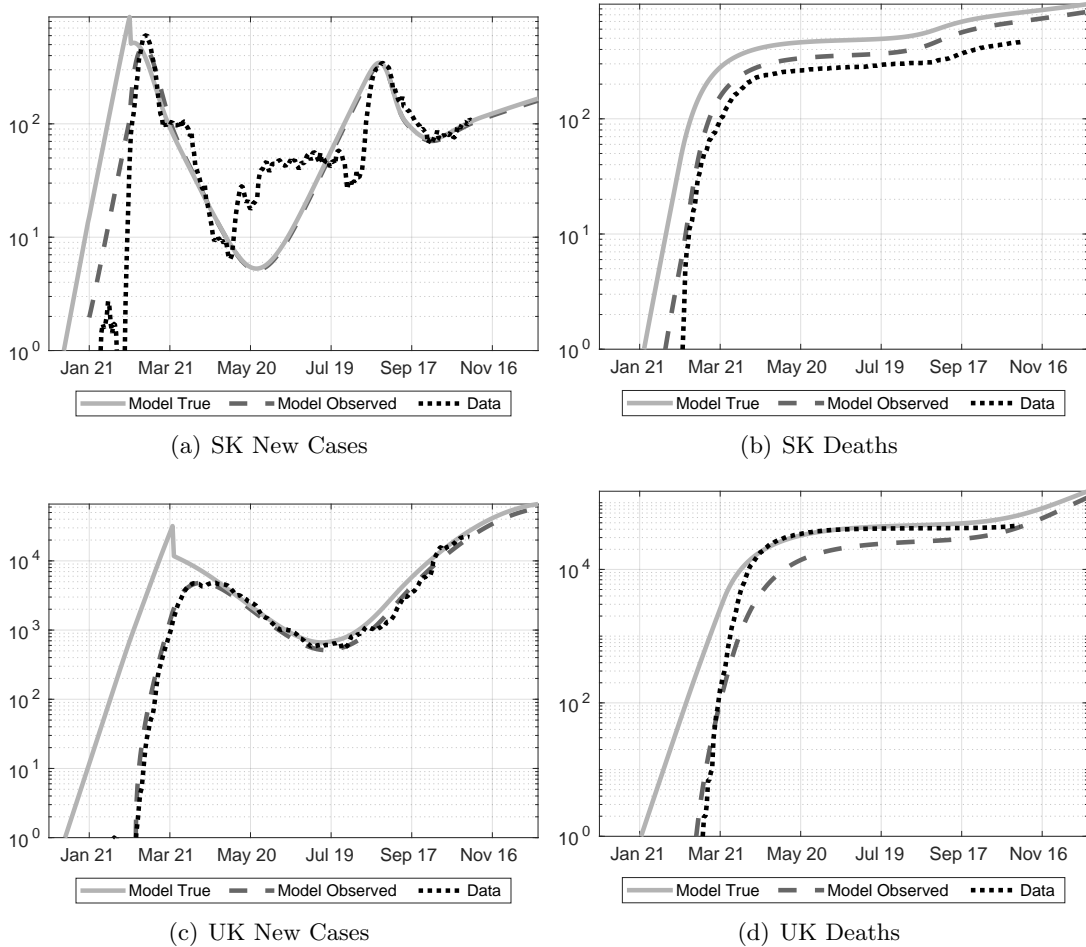
Fig. 1: SIR Model vs. Data, SK and UK

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.

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]

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[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 Figure 9 shows that SK's infection curve plateaus at 500 new cases a day in Dec 2021. UK's 2nd wave
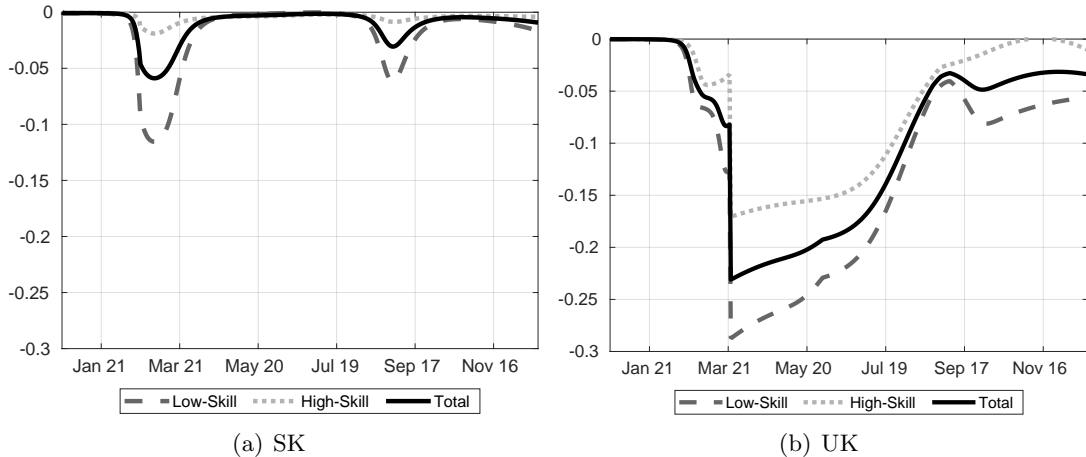
Fig. 2: GDP Losses: SK vs UK
Model implied GDP from 22 Dec 2019 to 21 Dec 2020. GDP is in log-deviations from the 2019 steady state and not per capita, so includes GDP losses from COVID-19 deaths (the working-young have a zero natural death rate).

2.2 GDP and Inequality

What are the economic effects of the containment policies? Figure 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 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

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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.

[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 Figure 9 show that GDP losses again reach about 8 percent next summer even without a second lockdown.
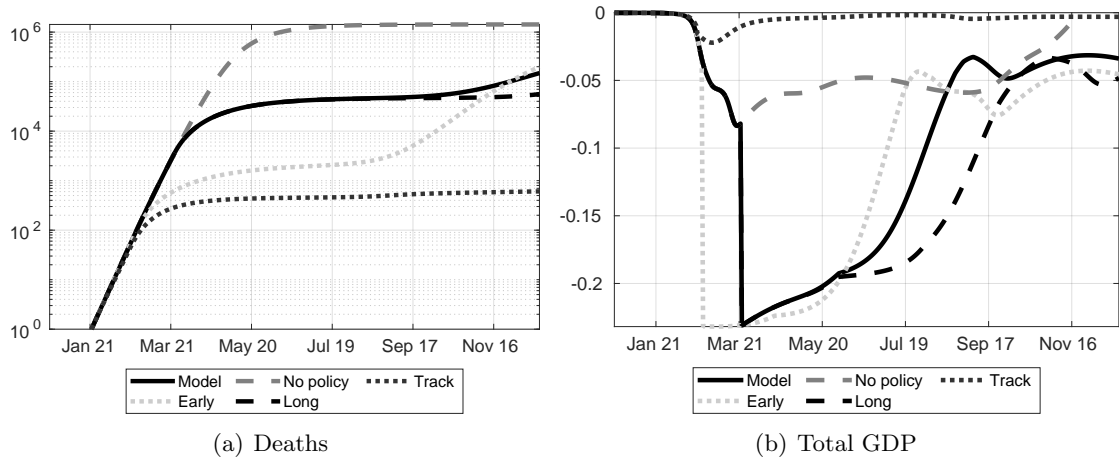
| (a) Deaths | (b) Total GDP |

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.

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 Figure 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
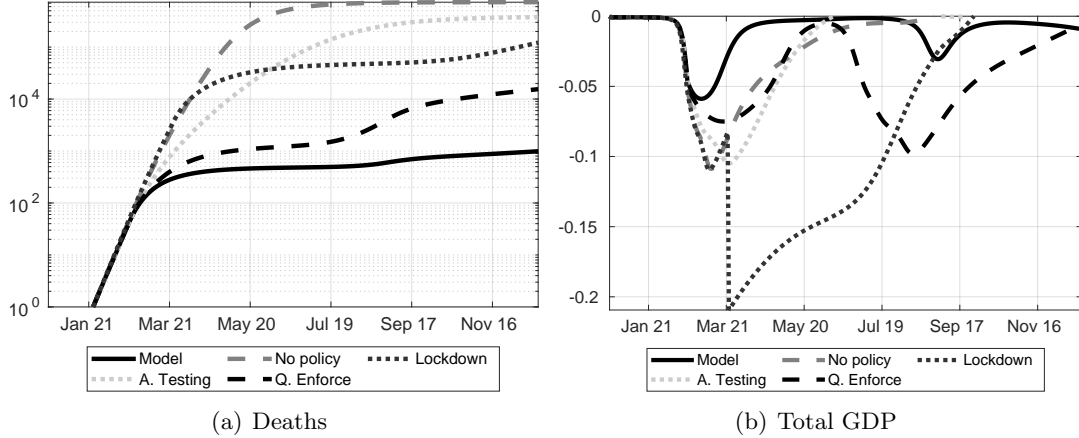
| (a) Deaths | (b) Total GDP |

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.

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 Figure 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 Figure 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,

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[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.

(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 policy"), deaths pass 700,000 by October with a 10 percent drop in GDP at peak infecton. 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.

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Online Appendix

A   Related Literature

Our paper belongs to the new strand of literature that incorporates the SIR epidemiology model by Kermack et al. (1927) or its variants into economic environments. Our innovation on the epidemiology side is to consider asymptotic carriers, which is crucial in the evaluation of testing policies, and heterogeneous infection rates by worker type, which can alter the spread of the virus depending on which people are quarantined. For the production structure, we use a simplified version of our existing work on sector/occupational heterogeneity in Lee and Shin (2017), and refer to Aum et al. (2020b) to guide our choice of work-from-home productivity differences across skill-occupations, as well as which jobs are more "essential" in the event of a lockdown.

Insofar as we focus on the quantitative impact of virus containment policies to gauge the interaction between economic activities and the epidemic, our paper is related to the more theoretical papers such as Alvarez et al. (2020), Eichenbaum et al. (2020), Garriga et al. (2020) and Piguillem and Shi (2020) that analyze optimal quarantine policies considering similar trade-offs. In particular, Piguillem and Shi (2020) is closest to our work in that theirs is the only other model that is calibrated to actual data moments (Italy), and highlights the effectiveness of testing policy under the possibility of asymptotic carriers. We expand on such papers by considering a more elaborate heterogeneous-agent equilibrium model of production in which people voluntarily choose to self-quarantine themselves out of fear and are unaware of their own infection status without testing. We also consider different dimensions of government-enforced quarantines—ordering people to stay home is different from enforcing that order, e.g. lockdown orders vs. SK-style digital tracking.

The potential importance of voluntary self-quarantine in response to the epidemic is also emphasized in Farboodi et al. (2020) and Chudik et al. (2020). The latter argues that self-quarantine is unlikely to lower infection rates unless the epidemic approaches very high levels, so that mandated social distancing could be required to flatten the epidemic curve, which we find to be true in our calibration. We focus on the quantitative impact on GDP and inequality, while Chudik et al. (2020) focus on the estimation of the epidemiology parameters.

We explicitly model the fact that high levels of voluntary self-quarantine lead to GDP losses, as well as how self-quarantine interacts with various policy options, concluding that the combination of testing and tracking is more effective from both the economic and the epidemiological perspective. To our knowledge, this paper is the first quantitative analysis that explicitly fits 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.

B Observed Epidemiological States

We define the mass of the infected who are unconfirmed, after infection and recovery take place but before testing is done at the end of the period:

$$\hat{I}_i = \bar{I}_i - (1 - \delta_i)(1 - m_i)(1 - \gamma_i)c_i,$$

where c_i is the mass of the confirmed infected at the beginning of the period. Similarly, we define the mass of the recovered who are unconfirmed, after infection and recovery take place but before testing is done at the end of the period:

$$\hat{R}_i = \bar{R}_i - (1 - \delta_i)\left[\gamma_i(1 - m_i)c_i + r_i\right],$$

where r_i is the mass of the confirmed recovered at the beginning of the period. A person is confirmed recovered either if he tests negative after having tested positive or if his recovery is confirmed by an antibody test.

Then at the end of a period, after tests are administered, the mass of the unconfirmed without symptoms $\bar{a}_i^0$ and the mass of the unconfirmed with symptoms $\bar{s}_i^0$ for each group i are

$$\bar{a}_i^0 = (1 - f_i)\bar{S}_i + (1 - \omega\tau^a)(1 - \eta_i)\hat{I}_i + (1 - \mathbb{I}_{AB}\omega\tau^a)(1 - f_i)\hat{R}_i, \tag{11a}$$

$$\bar{s}_i^0 = f_i\bar{S}_i + (1 - \omega\tau^s)\eta_i\hat{I}_i + (1 - \mathbb{I}_{AB}\omega\tau^s)f_i\hat{R}_i, \tag{11b}$$

where f_i is the probability of getting sick (symptomatic) when susceptible or recovered and η_i is the probability of getting sick when infected. Fractions τ^a and τ^s of the asymptomatic unconfirmed and the symptomatic unconfirmed are tested, respectively, and ω is the probability that the test correctly detects the virus. The indicator function $\mathbb{I}_{AB}$ is one if antibody tests are available and zero otherwise. The mass of the asymptomatic unconfirmed $\bar{a}_i^0$ consists of (i) the susceptible who are not sick, (ii) the asymptomatic unconfirmed infected who get either untested or get a false negative result, and (iii) the asymptomatic unconfirmed recovered who get either untested or get a false negative result for antibody, if antibody tests are available. Similarly, the mass of the symptomatic unconfirmed $\bar{s}_i^0$ is the sum of (i) the sick susceptible, (ii) the symptomatic unconfirmed infected who are untested or given false positive, and (iii) the symptomatic unconfirmed recovered who are untested or tested false negative for antibodies.

The masses of the confirmed infected $\bar{c}_i$ and the confirmed recovered $\bar{r}_i$ after testing at the end of the period are

$$\bar{c}_i = (1 - \delta_i)(1 - m_i)(1 - \gamma_i)c_i + \omega\left[\tau^a(1 - \eta_i) + \tau^s\eta_i\right]\hat{I}_i, \tag{12a}$$

$$\bar{r}_i = (1 - \delta_i)\left[r_i + \gamma_i(1 - m_i)c_i\right] + \mathbb{I}_{AB} \cdot \omega\left[\tau^a(1 - \eta_i) + \tau^s\eta_i\right]\hat{R}_i. \tag{12b}$$

Obviously, c_j and r_j are zero from $t = 0$ to $t = \tau$, since the virus hits at time 0 and testing begins (in the evening of) time τ. The mass of the confirmed infected is the previous period's mass net of death and recovery, plus the newly confirmed of the unconfirmed infected. The mass of the confirmed recovered is the previous period's mass net of death, plus those of the confirmed infected who recover this period (and test negative) and, when antibody tests are available, the newly confirmed of the unconfirmed recovered.

South Korea	Self-employed	Employer	Manager	Worker
Low-skill industries	1,922	922	75 (6,853)	7,751 (2,058)
High-skill industries	1,287	495	269 (9,023)	10,999 (2,956)
United Kingdom	Self-employed	Employer	Manager	Worker
Low-skill industries	2,046	412	1,591 (5,701)	14,023 (2,570)
High-skill industries	1,826	257	1,132 (6,616)	9,982 (3,397)

Table 2: 2019 Employment and Average Monthly Wage

Self-employment: single employer-employee. Employer: self-employed with non-zero employees. Manager: employees in a managerial position. Employment in thousands and monthly wage in parentheses in 2019 USD.
Source: SK, Economically Active Population Survey 2019, additional wage information from the Survey on Labor Conditions; UK, Annual Population Survey 2019, additional wage information from the Annual Survey of Hours and Employment. Unpaid family workers and workers above age 65 are excluded.

C   Economic Data and Parameters

For SK, the low-skill industries (l) are: Households as employers; Accommodation & food; Agriculture; Arts, entertainment & recreation; Health & social work; Other services; Administrative & support services; Real estate; Wholesale & retail. The high-skill industries (h) are: Construction; Transportation & storage; Education; Public administration & defense; Water supply, sewerage, waste management & remediation activities; Manufacturing; Mining & quarrying; Extraterritorial organizations; Information & Communication; Professional & scientific; Finance & insurance; Electricity, gas, steam and air conditioning supply. For UK, the low-skill industries (l) are: Households as employers; Accommodation & food; Agriculture; Wholesale & retail; Arts, entertainment & recreation; Administrative & support services; Other services; Health & social work; Real estate; Manufacturing; Transportation & storage. The high-skill industries (h) are: Education; Water supply, sewerage, waste management & remediation activities; Public administration & defense; Construction; Professional & scientific; Information & Communication; Electricity, gas, steam and air conditioning supply; Finance & insurance; Mining & quarrying; Extraterritorial organizations.

SK EAPS is a monthly panel, similar to the US Current Population Survey. For employment shares, we take the mean over occupations and industries in all months of 2019. EAPS only contains wage information in its August supplement, and only collects wage information from a sample of workers. Official wage data for SK is published by the SLC, but only average wages by industry and by occupation are publicly available (i.e., detailed wage data by industry×occupation is unavailable). Thus, we adjust industry-occupation specific wages in EAPS so that average wages by industry and occupation are consistent with SLC, and then

Parameter	Value		Description
	South Korea	United Kingdom	
L_y	1	1	Mass of young
L_o	0.2432	0.3711	Mass of old
$L_{l,j}^0$	[0.0810, 0.0420, 0.3268]	[0.0654, 0.0641, 0.4484]	Initial employment share
$L_{h,j}^0$	[0.0543, 0.0322, 0.4637]	[0.0584, 0.0444, 0.3192]	by industry/occupation
$\psi_{l,j}^0$	[0.6836, 0.6675, 0.6433]	[0.6780, 0.6721, 0.6427]	Home productivity discounts
$\psi_{h,j}^0$	[0.7687, 0.7801, 0.7605]	[0.7723, 0.7798, 0.7648]	by industry/occupation
$\phi_{l,j}^0$	[0.4850, 0.5711, 0.5207]	[0.6532, 0.6710, 0.5986]	Sick productivity discounts
$\phi_{h,j}^0$	[0.5819, 0.9967, 0.8722]	[0.9368, 0.9975, 0.8976]	by industry/occupation
$z_{l,j}$	[1.2586, 1.0 1.0]	[1.0529, 1.0, 1.0]	Effective productivities
$z_{h,j}$	[2.0566, 1.3, 1.3]	[1.3117, 1.3, 1.3]	by industry/occupation
κ	0.0861	0.0884	Sickness disutility
α_l, α_h	[0.2996, 0.1747]	[0.2406, 0.2133]	Manager wage share by industry
θ	0.4133	0.5172	Low-skill wage share in final good prod
σ	0.0323	0.0345	Scale parameter, EV distribution for home-work choice
$\mu_{l,j}$	[0, -0.6467, 1.7461]	[0, -0.0141, 2.1442]	Location parameter, EV distribution
$\mu_{h,j}$	[0, -0.5137, 2.5460]	[0, -0.2657, 1.9116]	for occupation choice
ν	1/365		Can switch occupation once a year

Table 3: Economic Parameters

average over high- and low-skill industries and non-managerial occupations using 2019 EAPS employment as weights, to obtain the moments in Table 2.

UK APS complements the monthly Labour Force Survey (LFS), also similar to the CPS. Many versions are available, so we take the January-December annual version. However, wage information is heavily top-coded in the LFS. Official wage data for the UK is published by the ASHE, but only average wages by industry and by occupation are publicly available. Thus, we adjust industry-occupation wages in APS so that average wages by industry and occupation are consistent with ASHE, and then average over high- and low-skill industries and non-managerial occupations using 2019 APS employment as weights, to obtain the moments in Table 2.

For each country, we calibrate a subset of the economic parameters as follows. First, we initialize employment shares, $L_{x,j}^0$ by skill and by assuming the self-employed ($j = 1$) and workers ($j = 3$) in the model respectively correspond to the self-employed with no employees and to the non-manager employees in EAPS/APS, and managers ($j = 2$) in the model to the employers and the employees in managerial positions in EAPS/APS. Employment shares are shown in the second panel of Table 3.

Given individuals' productivities $\psi_{x,j}$, computed from Aum et al. (2020c), we calibrate $z_{x,j}$, $\phi_{x,j}$, κ, α_x and θ as follows. Suppose that there is no epidemic, so the fear factor is irrelevant. Also suppose that there is no preference shock, neither for work-from-home decisions nor occupation choices.

1. We normalize manager-worker productivities to be equal and set high-skill workers to be

30 percent more productive than low-skill workers.[30] We then choose the self-employed productivity, $z_{x,1}$, so that they are indifferent between staying self-employed or becoming a manager.

2. The sick productivities $\phi_{x,j}$ are chosen so that all individuals are indifferent between commuting and working from home when sick, and the sickness disutility parameter κ to its maximum possible value for the $\phi_{x,j}$'s to be well-defined (between 0 and 1).

3. Now everyone is indifferent between commuting and working from home when sick, so we assume that only high-skill self-employed and managers choose to work from home when sick. Then we can compute the manager share parameter α_x to match manager wage shares computed from Table 2. We can also set θ to match the low-skill income wage share in Table 2, assuming that in the data, the mean wages of the self-employed and employers are equal to managers'.

The results are shown in the third and fourth panels of Table 3.

Given these parameter values, we then simulate the economy with no epidemic to find a steady state. We assume that the i.i.d. preference shocks for the work-from-home choice are drawn from an extreme value distribution with mean zero and scale parameter σ. For the extreme value distributions from which occupational preference shocks $\epsilon_{x,j}$ are drawn, we normalize the scale parameter to one and the self-employment location parameters to $\mu_{x,1} = 0$. We calibrate σ and the remaining location parameters $(\mu_{x,2}, \mu_{x,3})$, those for becoming a manager or worker, are as follows:

1. Choose σ, the scale parameter, so that 11.12 percent of all individuals work from home in the pre-pandemic steady state, consistent with the average share of time spent home while working in ATUS 2014-2018.

2. Choose $\mu_{x,2}, \mu_{x,3}$, to match initial employment shares $L_{x,j}^0$ in the initial steady state.

Last, once we calibrate the steady state, we arbitrarily assume that only fraction $\nu = 1/365$ of individuals get the opportunity to switch occupations (once per year on average). These parameters are summarized in the bottom panel of Table 3.

D   Epidemiology and Policy Parameter Details

The parameters in Table 1 in the main text are calibrated as follows:

1. Assume a natural death rate of 0 for the young, and a 2-percent annual death rate for the old, based on average mortality rates in SK and UK.

2. Uniformly set a recovery rate of $\gamma = 1/14$ for the young, so that the infected remain infectious for two weeks on average. We then assume that it takes twice as long for the old to recover, that is $\gamma_o = 1/28$ (Tenforde et al., 2020; Voinsky et al., 2020).

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[30]These normalizations are innocuous, since in our model, the productivity parameters are not separately identified from the manager share α_x and the low-skill share θ.

3. Set COVID mortality rates to each country's CFR as of October 30, 2020, computed from SK KCDA and UK DHSC data. While SK has a much lower value for age 65+ at 11.8 percent compared to UK's 15.2 percent, the CFR for age 15-64 is one-thirtieth of the old's in both countries.

4. Infection rates by skill and occupation are computed from the exposure index of Aum et al. (2020c), which is an average measure of "proximity to others" and "exposure to diseases" in O*NET. These measures are provided at the 3-digit occupation level, which we average for each of the six skill-occupations corresponding to our model using hours-employment weights from ACS 2014-2018. Since the unit of these measures has no meaning, we shift the average so that the lowest exposure (for high-skill managers) is 0, and normalize its mean to be equal to v_o, the infection rate of the old. Infection rates are more or less the same between the young and old, according to available data from SK KCDA and UK DHSC. Overall, high-skill jobs exhibit lower infection rates in both SK and UK, which may capture the fact that they require less social interaction in the workplace (according to our O*NET measures) and that they are in better health in general with better healthcare (Case and Deaton, 2020).

5. We fix the infection rate of those in quarantine to $1/7$ of v_o. This assumes that a person in quarantine makes one day worth of social contact per week compared to the average person who commutes.

Once these assumptions are made, there are three remaining parameters that determine the progression of the pandemic absent any policy intervention: the average COVID-19 infection rate v_o, which is also the old's infection rate; the initial date the coronavirus breaches the country, and the initial mass of the infected on that day (I_0). Since the latter two are not separately identified (we can always choose an earlier date assuming a lower mass of the initially infected, or the other way around), we set the initial date to December 22, 2019, a month before SK starts publishing infection counts. Thus, confirmed cases start appearing on $\tau = 29$. Then we make the following assumptions on the testing technology, as well as the fraction of individuals who fall sick with or without the virus:

1. The rate of false negatives is $1 - \omega = 0.2$ for the tests (Yang et al., 2020).

2. Approximately 70 and 40 percent of age 15-64 and 65+ are asymptomatic with COVID-19 $(\eta_y, \eta_o) = (0.3, 0.6)$, according to Mizumoto and Chowell (2020) and Davies et al. (2020).

3. Assume that 3 percent of the young and old are sick when uninfected, in line with evidence on the annual incidence of influenza and other respiratory illnesses (`https://www.gov.uk/government/statistics/annual-flu-reports`).

The progression of coronavirus and policies in SK unfolded as follows.

Jan 20-21 First confirmed case. Thus $\tau = 29$ for SK.

Feb 19-20 Shincheonji outbreak, daily confirmed cases surge and SK intensifies testing and tracking ($t = 60$).
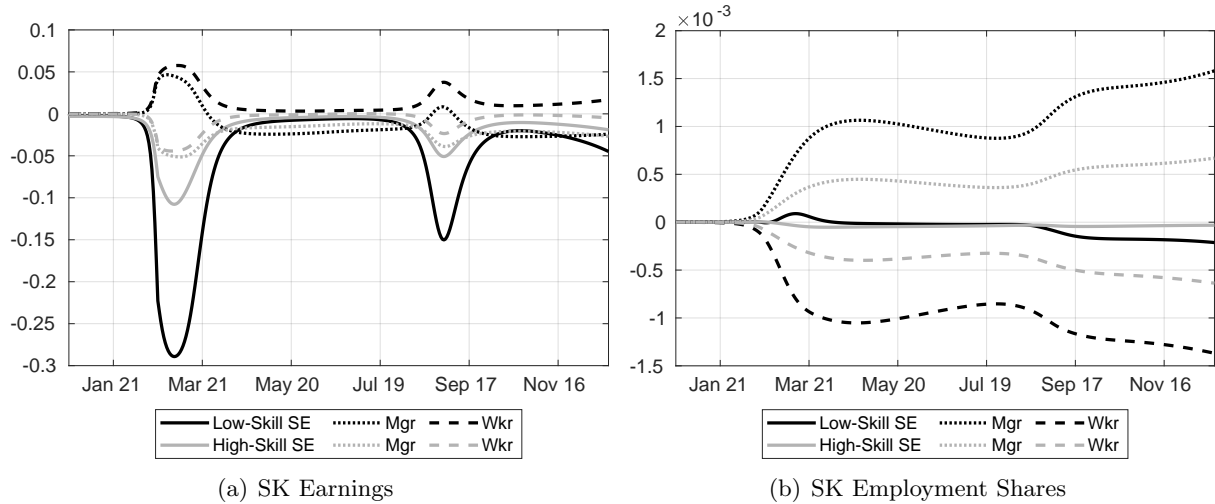
25

(a) SK Earnings

(b) SK Employment Shares

Fig. 5: Dynamics by Skill-Occupation Group, SK

SE: Self-employed, Mgr: Managers, Wkr: Workers. The left panel is log-deviations in per person earnings from the 2019 steady state, and the right panel is the changes in employment shares.

Apr 18 Social distancing measures eased, mass test and tracing system complete ($t = 59$).

Aug 15 New social distancing measures announced for Seoul after local outbreaks following street demonstrations on Aug 15 ($t = 235$).

Sep 13-Oct 12 Restrictions lifted, including in Seoul ($t = 264$).

The progression of coronavirus and policies in UK unfolded as follows.

Feb 1 First confirmed case. Thus $\tau = 41$ for UK.

Feb 10 First quarantine. Health secretary announces strengthened quarantine policies ($t = 50$).

Feb 23-25 Cases begin to rise and testing capacity raised in response ($t = 64$).

Mar 15-23 Prime Minister announces the possibility of, then implements, a lockdown ($t = 92$).

May 30 Health secretary announces mass testing target met, tracing system goes live ($t = 160$).

E   Detailed Dynamics by Skill and Occupation

Figure 5(b) shows that employment shares in SK remain nearly constant, consistent with available monthly EAPS data in 2020. This implies that the fear factor is barely operational for individuals to switch jobs (from the steady state shares at $t = 0$). However, earnings losses still vary considerably by occupation. The self-employed stand to lose the most both because of a higher fear factor (since they have higher infection rates, they stay home more) and the tracking policy (as more of them are infected, more are enforced to stay home). But the policy is strong enough so that the fear factor wears off quickly. In contrast, low-skill workers' earnings are in fact slightly higher upon policy impact, since they are forced to work while others do not. But since they face higher rates of infection, they instead switch out to become self-employed or
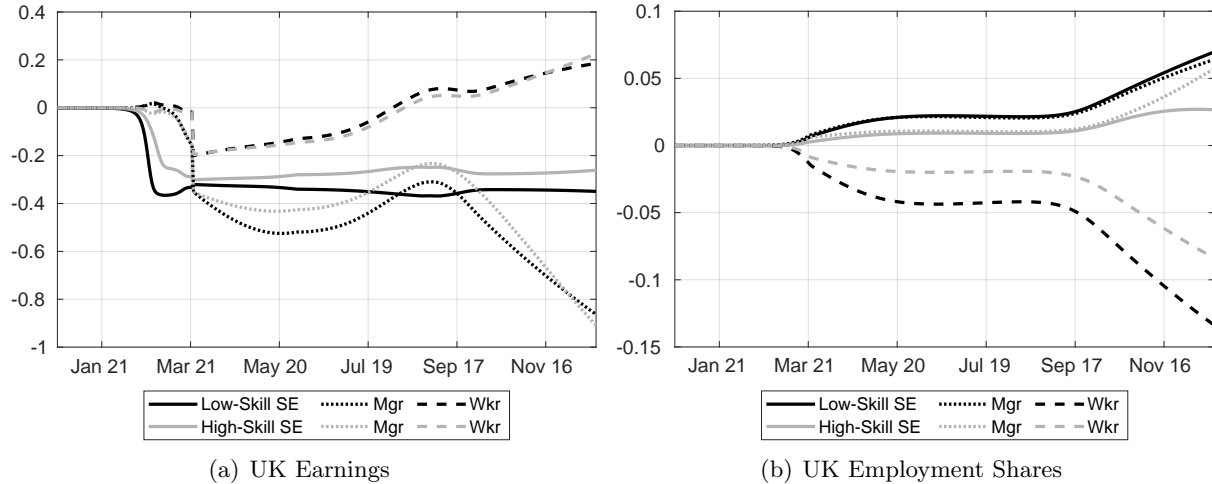
26

Fig. 6: Dynamics by Skill-Occupation Group, UK

SE: Self-employed, Mgr: Managers, Wkr: Workers. The left panel is log-deviations in per person earnings from the 2019 steady state, and the right panel is the changes in employment shares.

managers as the disease progresses over time. Despite the small magnitude both in the data and the model, these model-predicted employment share changes by skill and occupation are in fact qualitatively in line with January to March changes (initial case to peak daily cases) in the EAPS as well.

The changes in Figure 6 for the UK are more dramatic, but it is still the low-skill self-employed who lose the most early on, with both low- and high-skill managers losing the most with the lockdown as the disease progresses. Despite the large loss in earnings, self-employed shares go up: At very high rates of infection, workers value the option to stay home more than their earnings, so switch toward self-employment, as shown in Figure 6(b). And because so many workers switch to self-employment or managers, workers' relative wages go up in equilibrium, a form of compensating differential. Thus, the rise in workers' earnings in Figure 6(a) must be viewed with caution. Although we do not explicitly model unemployment, workers' switch into self-employment and then staying home would show up exactly as unemployment (or furloughs) in the data. Workers in our model who switch their jobs to self-employment experience a persistent 40-percent drop in earnings. The low earnings they make in self-employment can be viewed as unemployment benefits or other government subsidies that are issued universally.

F More Tables and Figures

UK	Lockdown	No policy	Track	Early	Long
Deaths	65253	1424800	573	31402	47501
GDP	-11.0	-4.8	-0.5	-12.2	-13.0

SK	Track	No policy	Lockdown	A. Testing	Q. Enforce
Deaths	837	729641	65403	356228	10933
GDP	-1.2	-2.0	-8.4	-2.2	-4.7

Table 4: Deaths and GDP through October 2020

UK and SK cumulative deaths and average GDP losses from January to October 2020. "Lockdown" is UK's baseline policy, "Track" is SK's baseline policy, "No policy" is doing nothing, "Early" is if UK had implemented the same lockdown but on the earlier date SK implemented its policy, "Long" is an extension of the lockdown by 90 days, "A. Testing" is if SK had tested as aggressively, but with quarantine enforcement at UK's lockdown levels ($Q = 0.55$), and "Q. Enforce" is if SK had tested and enforced quarantines as aggressively, but without any asymptomatic testing. Death counts are cumulative. GDP is in average log-point deviations from the 2019 steady state and not per capita, so includes GDP losses from COVID-19 deaths.
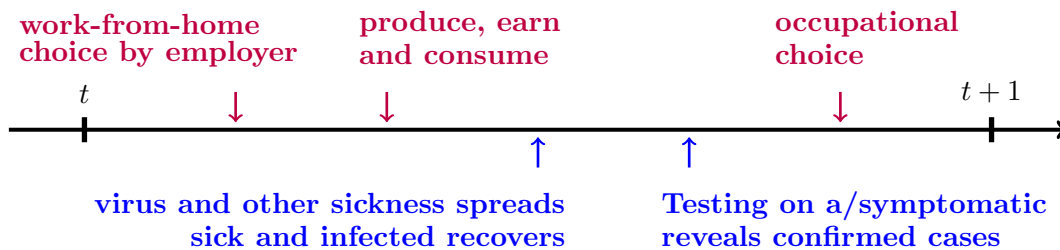

Fig. 7: Model Timeline
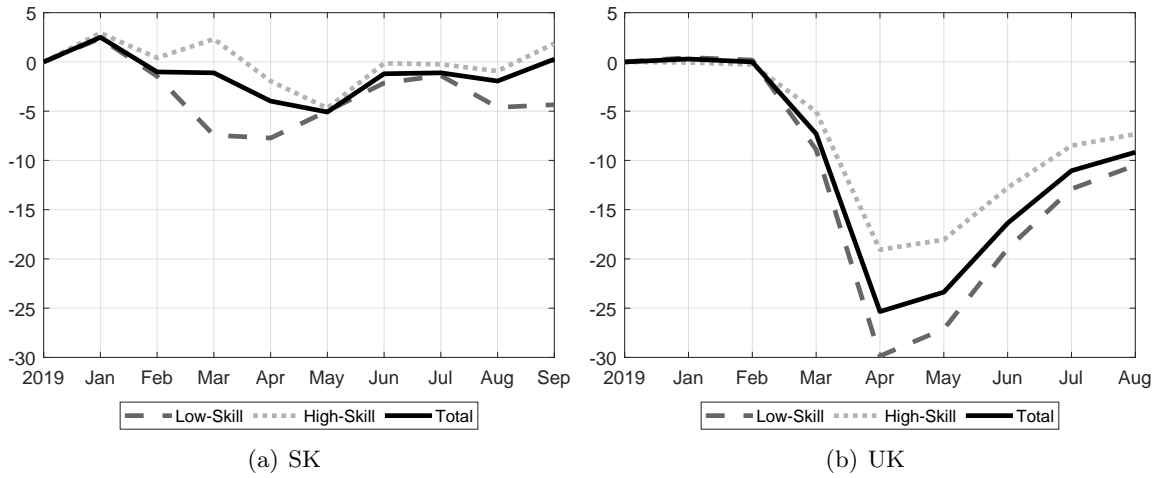
(a) SK   (b) UK

Fig. 8: Production Data, SK and UK

Percentage point deviation of industrial production (for SK) or GDP (for UK) from the average level in 2019. High and low represent the nominal-GDP weighted average of respective industries. See Appendix C for the list of high and low industries for each country.
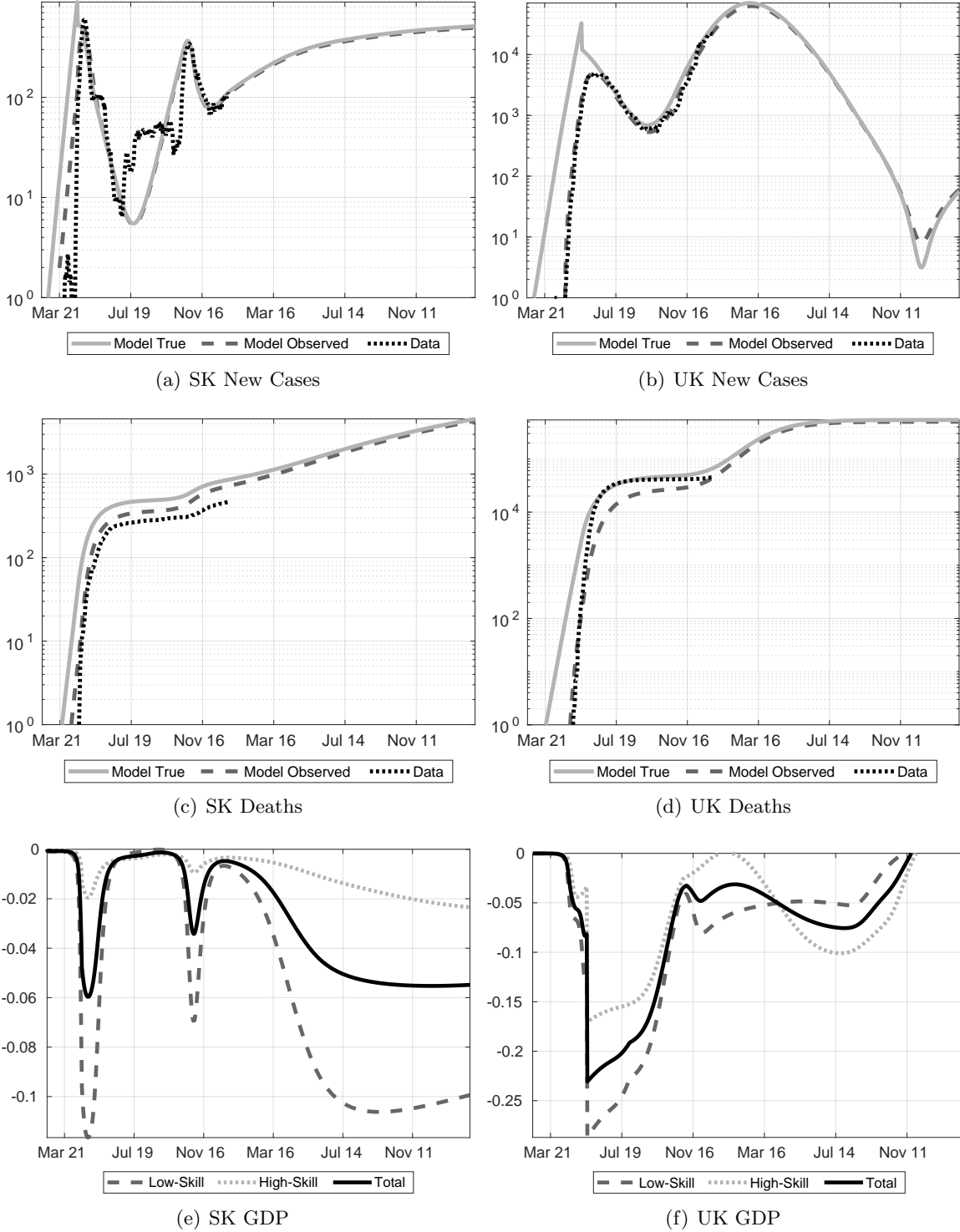
Data source: Statistics Korea and UK ONS.

(a) SK New Cases

(b) UK New Cases

(c) SK Deaths

(d) UK Deaths

(e) SK GDP

(f) UK GDP

Fig. 9: Two-year Projections, SK and UK

New case and cumulative death counts are in log-10 scale, from December 22, 2019 to December 21, 2021. "Observed" corresponds to confirmed cases in the model. GDP is in log-deviations from the 2019 steady state and not per capita, so includes GDP losses from COVID-19 deaths. UK's second rise in infections in December 2021 is explained by the fear factor no longer driving people to self-quarantine. But this "third wave" is short-lived and small, as the population reaches herd immunity.

Data source: SK KCDA and UK DHSC. Data counts in 7-day rolling averages.