

# THE MACROECONOMIC CONSEQUENCES OF STIMULATING OFFLINE CONSUMPTION DURING COVID-19\*

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December 31, 2020

## ABSTRACT

This paper theoretically analyzes the macroeconomic consequences of a new fiscal policy implemented in South Korea during COVID-19, “Korean Economic Impact Payment (KEIP)” program, that aims to stimulate offline consumption in order to support offline retailers. In doing so, we modify a SIR-macro model widely used in the recent literature on the COVID-19 crisis by explicitly distinguishing online- and offline consumption goods. Benchmark analysis predicts that (1) there are positive effects on key macro variables at the impact while progress of the epidemic hardly changes and (2) the transfer multiplier from the KEIP is estimated to be about 0.5 at the impact, a value with what we expect from the usual neo-classical business cycle model.

*JEL classification:* E10, E21, E32, E62, I10

*Keywords:* SIR-macro model, COVID-19 Crisis, Offline consumption, Fiscal policy

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\*The authors thank the anonymous referees for helpful suggestions and comments. Shim acknowledges the financial support from Yonsei University (Yonsei University Future-leading Research Initiative of 2020 (2020-22-0088)). Hye Rim Yi provided excellent research assistance

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# 1 INTRODUCTION

Is government spending, particularly a transfer policy targeting offline retailers, an effective tool to stimulate an economy during the COVID-19 crisis? This paper aims to provide an answer to this traditional question in a timely manner in the sense that the negative economic impact of the ongoing COVID-19 pandemic has been huge. In April 2020, International Monetary Fund (IMF) projected the annual growth rate of the world economy to contract -3% from a year ago and then revised the estimate to -4.9% in October 2020, which reflects the fact that the negative effect of the pandemic on the aggregate economy is worse than initially predicted. Because of the infectious nature of COVID-19, especially during social interactions, it has particularly affected offline retailers. Figure 1 shows the market Business Sentiment Index (henceforth BSI) of small business owners in South Korea between June 2019 and September 2020, which plummeted during the first large outbreak in February 2020.

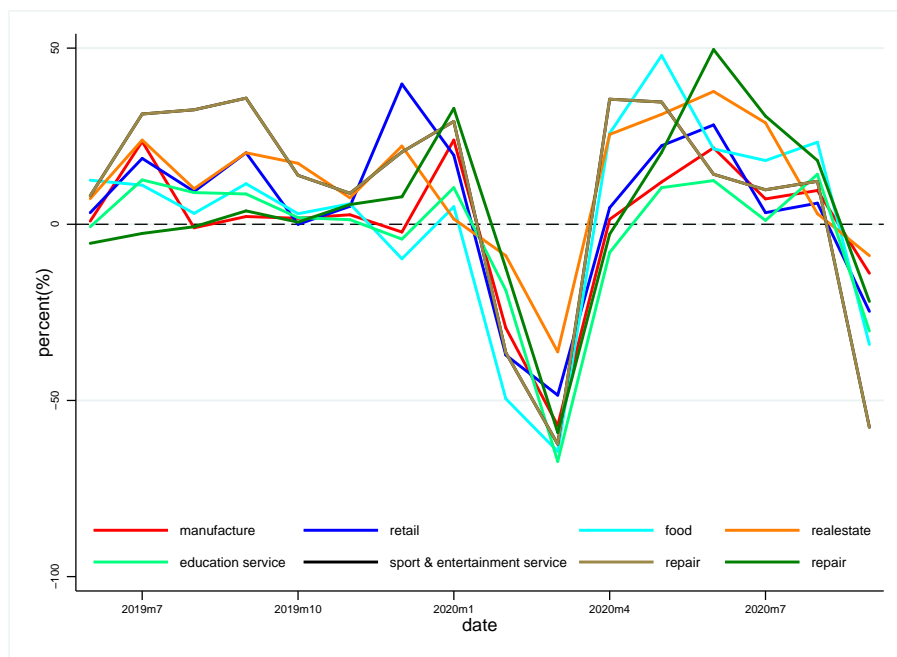


Figure 1: Small Business Owners' Market BSI: 2019.06 – 2020.09 (Source: Statistics Korea)

Given that about 30% of workers are employed in small business in South Korea (Statistics Korea, 2018)<sup>1</sup>, the COVID-19 crisis has had a large negative effect on the labor market and hence the aggregate economy: According to a 2020 second-quarter report released by the Statistics Korea, monthly average consumption expenditure plummeted 6% in the first quarter (Figure 2).

<sup>1</sup>In addition, about 25% of workers were self-employed in 2019 according to OECD.

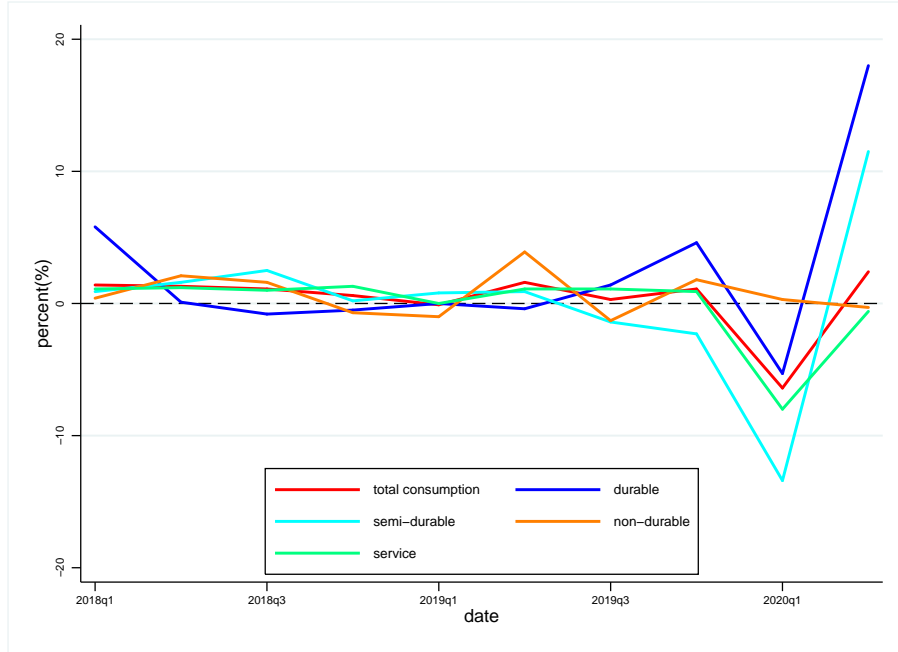


Figure 2: Monthly Average Consumption Expenditure in South Korea (Source: Statistics Korea)

As a result, the government of South Korea implemented several countercyclical policy measures, including a policy to aid offline retailers: “Korean Economic Impact Payment (hereafter KEIP)” was directly transferred to all households, with a maximum transfer of KRW 1,000,000 (about USD 880 (10/21/2020)) to each household. An important feature of this transfer is that its usage was restricted to offline stores and it should have been used between May and August 2020, indicating that this policy is transitory and would have a large effect during the second quarter of 2020. Figure 2 clearly shows that growth rate of total consumption bounces back to 2.7% in the second quarter from a quarter ago, and this pattern is not restricted to a particular consumption category.

The above figure, however, does not necessarily imply that the policy is truly effective in stimulating consumption (and hence boosting the aggregate economy), as we must take into account the shock identification problem. Given that data on the aggregate economy has not yet been accumulated enough to conduct empirical exercises for a policy evaluation in a timely manner, the natural step we should take is to conduct a thought experiment with an appropriate macro model, which is the purpose of this paper. In doing so, we introduce a SIR-macro<sup>2</sup> model, a neo-classical growth model incorporated with epidemiology, which has been widely used in the recent literature that studies the macroeconomic

<sup>2</sup>Following the literature, SIR stands for susceptible, infected, and recovered or removed, respectively.

implication of COVID-19 pandemic.<sup>3</sup> In contrast to existing works, we explicitly distinguish online- and offline consumption goods and consider a (fiscal) policy that targets offline consumption, which potentially has a perverse effect on the contagion through more social interactions required to purchase offline consumption goods. In particular, we assume that online- and offline consumption goods are imperfect substitutes to each other while only consumption at the offline stores can affect infection probabilities.

Our main findings under benchmark calibration can be summarized as follows. First, KEIP might boost GDP, consumption, and investment while the effect is temporary. Second, transfer multiplier, the extent of increases in GDP with one unit increase by the government transfer, is estimated to be about 0.50 at the impact. This is in line with previous findings on the government spending multiplier with neo-classical growth model (Ramey (2011)). Third, the infection rate and other variables related to health status barely change with the implementation of the policy. These findings are robust to (1) different parameter values and (2) different tax schemes.

The remainder of this paper is organized as follows. A model for policy evaluation is introduced in Section 2. In Section 3, we study the effect of policies. Section 4 provides a battery of robustness checks and Section 5 concludes the paper.

## 2 A BENCHMARK SIR-MACRO MODEL

This section introduces the model, which is a version of Eichenbaum, Rebelo, and Trabandt (2020) to make our analysis comparable to the previous literature. The most important deviation from the literature is that we distinguish consumption goods by marketplaces from which the goods are purchased: Goods can be either purchased from online markets such as Coupang<sup>4</sup> and Amazon (online consumption goods) or/and from offline retailers (offline consumption goods).

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<sup>3</sup>Since Atkeson (2020) introduced an SIR model to study implications of the COVID-19 on the macroeconomy, literature on the COVID-19 adopting epidemiology into a neo-classical growth model, a SIR-macro model, has flourished: Eichenbaum, Rebelo, and Trabandt (2020) showed that monopolistic competition is a key factor to reproduce the positive co-movement of consumption and investment observed during the pandemic. Jones, Philippon, and Venkateswaran (2020) analyze inconsistencies in incentives engaging in mitigation policies during the COVID-19 between social planners and private agents. Alvarez, Argente, and Lippi (2020) estimated the effectiveness of testing for COVID-19 in implementing lockdown policies. A group of researchers further analyzes aggregate effects of the pandemic by adopting the idea that COVID-19 affects specific sectors of the economy (see Bigio, Zhang, and Zilberman (2020), Guerrieri, Lorenzoni, Straub, and Werning (2020), and Caballero and Simsek (2020) as examples).

<sup>4</sup>Coupang is an e-commerce giant in South Korea whose market share was about 24% between January and early March 2020 (<https://pulsenews.co.kr/view.php?year=2020&no=387856>).

**2.1 MODEL SETUP** In this section, we introduce key ingredients of our model one by one.

**Epidemic.** We first describe the epidemic of a COVID-19 virus, by closely following the modified SIR model proposed by Eichenbaum, Rebelo, and Trabandt (2020). In this model economy, probabilities of being infected depend on agents' economic decisions. Suppose that the economy is initially at a steady-state with no infection. After the COVID-19 outbreak, population at time  $t$ , which is normalized to one, is then divided into the following four groups: susceptible people ( $S_t$ ) who have not yet been infected by a virus, infected people ( $I_t$ ) who have been infected by the virus, recovered people ( $R_t$ ) who survived from the infection and acquired immunity, and deceased people ( $D_t$ ) who died from the infection. Moreover, we additionally denote newly infected people as  $T_t$ .

We assume that agents in this economy are rational hence they are well aware of the initial state of infection and the population dynamics described below. At the initial state, right after getting into a pandemic, we assume that a fraction  $\epsilon$  of the population is infected by the virus. In case of South Korea,  $I_0$  becomes positive right after it saw its first confirmed COVID-19 case on January 20:

$$I_0 = \epsilon.$$

The rest of the population who has not yet been infected remains as susceptible people:

$$S_0 = 1 - \epsilon.$$

This is because the first outbreak lowers the number of susceptible people by the number of newly infected people,  $\epsilon$ .

Consumers can be infected through three different channels. First, they can be infected when they consume (consumption channel). In particular, we follow the idea of Bigio, Zhang, and Zilberman (2020) that final goods can be purchased in two different ways. A consumer can purchase the final good either from an online shopping mall such as Amazon (online consumption ( $C_t^o$ )), and/or from offline retailers (offline consumption ( $C_t^n$ )). We then assume that susceptible consumers can be infected from offline consumption that requires consumers to meet other people who may be infected at the marketplace while online consumption does not influence the infection rate. Second, susceptible people can become infected while they are working because of social interaction with their colleagues (labor channel). Third, they can meet infected people through random interactions unrelated to the aforementioned

economic activities (random channel). Then, the number of newly infected people at time  $t$  is given by the following transition function:

$$T_t = \underbrace{\pi_1(S_t C_t^{s,n})(I_t C_t^{i,n})}_{\text{consumption channel}} + \underbrace{\pi_2(S_t N_t^s)(I_t N_t^i)}_{\text{labor channel}} + \underbrace{\pi_3 S_t I_t}_{\text{random channel}} \quad (2.1)$$

Each  $\pi_j$  for  $j = 1, 2, 3$  denotes the probability of being infected from each channel ( $\sum_j \pi_j = 1$ ); each  $\pi_j$  determines the extent to which a susceptible can be infected from the particular channel  $j$ . In Section 2.2, we describe how  $\pi_j$  is calibrated. The number of people newly infected from offline consumption is given by  $\pi_1(S_t C_t^{s,n})(I_t C_t^{i,n})$ , the number from working is given by  $\pi_2(S_t N_t^s)(I_t N_t^i)$ , and the number from random interactions unrelated to economic activities is given by  $\pi_3 S_t I_t$  where superscript  $s$  (resp.  $i$ ) denotes susceptible (resp. infected) workers. The number of susceptible people at time  $t + 1$  is then determined as follows:

$$S_{t+1} = S_t - T_t \quad (2.2)$$

The number of infected people at time  $t + 1$  is the sum of the number of infected people who is not recovered ( $\pi_r I_t$ ) or dead ( $\pi_d I_t$ ) and the number of newly infected people at time  $t$ :

$$I_{t+1} = (1 - \pi_r - \pi_d)I_t + T_t \quad (2.3)$$

The number of recovered people at time  $t + 1$  is the sum of the number of recovered people at time  $t$  and the number of infected people who just recovered,  $\pi_r I_t$ .

$$R_{t+1} = R_t + \pi_r I_t \quad (2.4)$$

Lastly, the number of deceased people at time  $t + 1$  is the sum of the number of deceased people at time  $t$  and the number of infected people who just died,  $\pi_d I_t$ .

$$D_{t+1} = D_t + \pi_d I_t \quad (2.5)$$

**Household.** Since we are interested in the aggregate dynamics, we assume that there is a representative household with a measure one family members so that the idiosyncratic income risk that arises

from different health status can be perfectly shared within the household. In order to distinguish the behavior of each household from the aggregate economy, we use a lowercase letter to indicate the variable determined at the household level while we use a capital letter to indicate the variable determined at the aggregate level. The household maximizes its lifetime utility given as follows.<sup>5</sup>

$$U = \sum_{t=0}^{\infty} \sum_{j=s,i,r} \beta^t \cdot j_t \cdot \frac{1}{1-\xi} \left[ c_t^j - \theta \cdot \frac{(n_t^j)^{1+1/\psi}}{1+1/\psi} \right]^{1-\xi} \quad (2.6)$$

where  $s_t, i_t$  and  $r_t$  denote the measure of family members who are susceptible, infected, and recovered at time  $t$ .  $\beta \in (0, 1)$  is the discount factor and  $\psi > 0$  is the Frisch labor supply elasticity.  $n_t^j$  denotes labor supply of each type  $j$ ,  $\theta > 0$  is the parameter that governs disutility from working,  $\xi$  is the preference parameter that governs overall concavity of the utility function.

In the benchmark model, the utility function takes the form of Greenwood–Hercowitz–Huffman preference (hereafter GHH preference), following Greenwood, Hercowitz, and Huffman (1988). Our choice of the utility function is supported by recent empirical evidence. With (transitory) increases in income that do not directly affect the wage rate, labor supply would become lower if there exists a wealth (income) effect. According to Coibion, Gorodnichenko, and Weber (2020), the CARES Act, a stimulus package of the U.S. that includes a one-time transfer to all qualified adults up to USD 1,200, was not associated with any changes in labor supply, implying that the wealth effect from the transfer was not substantial. While the GHH preference does not satisfy the balanced growth path property, we focus on the short-run effect of the policy on the aggregate economy and hence this problem is not crucial for our analysis. In the Appendix, we compare predictions from our benchmark model with those obtained from an alternative model in which the utility function takes the form of the King-Plosser-Rebelo (KPR) specification.

We assume that  $c_t^j$ , consumption of each household member  $j$ , is given by

$$c_t^j = (\mu^{1/\sigma} (c_t^{j,o})^{1-1/\sigma} + (1-\mu)^{1/\sigma} (c_t^{j,n})^{1-1/\sigma})^{\sigma/(\sigma-1)}$$

where  $c_t^{j,o}$  denotes online consumption and  $c_t^{j,n}$  denotes offline consumption, respectively. Throughout the paper, we assume that online and offline consumption goods are imperfect substitutes with each

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<sup>5</sup>We follow Eichenbaum, Rebelo, and Trabandt (2020) to setup the objective function of the household.

other ( $\sigma > 1$ ). This nests the case in which both goods are perfectly substituted with each other as a special case ( $\sigma \rightarrow \infty$ ). Moreover, offline consumption consists of private consumption ( $c_t^{j,n,p}$ ) and public consumption ( $c_t^{j,n,g}$ ). In particular, offline consumption good is a composite of two types of goods:

$$c_t^{j,n} = \begin{cases} \left( (c_t^{j,n,p})^{1-1/\eta} + (c_t^{j,n,g})^{1-1/\eta} \right)^{\eta/(\eta-1)} & \text{if } 0 < \eta < \infty \\ c_t^{j,n,p} + c_t^{j,n,g} & \text{if } \eta = \infty \end{cases} \quad (2.7)$$

where  $\eta$  represents the elasticity of substitution between private- and public offline consumption.

Public offline consumption takes positive values when the government gives a lump-sum transfer to the household and zero otherwise:

$$c_t^{n,g} = \begin{cases} G & \text{if } G > 0 \\ 0 & \text{if } G = 0 \end{cases} \quad (2.8)$$

For policy experiments,  $G$  is set to match a quarter of total consumption of each household in a week, which corresponds to the size of KEIP.<sup>6</sup>

The household faces the following budget constraint:

$$s_t(c_t^{s,o} + c_t^{s,n,p} + c_t^{s,n,g}) + i_t(c_t^{i,o} + c_t^{i,n,p} + c_t^{i,n,g}) + r_t(c_t^{r,o} + c_t^{r,n,p} + c_t^{r,n,g}) + x_t + tax_t = w_t(s_t n_t^s + i_t n_t^i + r_t n_t^r) + r_t^k k_t \quad (2.9)$$

where susceptible, infected, and recovered family members choose their own consumption and hours worked, respectively. Variable  $x_t$  denotes household investment and  $tax_t$  is tax collected by the government to support the transfer payment, which will be specified later.  $r_t^k$  denotes the rate of return from physical capital and  $w_t$  is the wage rate.

We further assume that adjusting investment incurs some costs and the corresponding law of motion for capital takes the following form:

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<sup>6</sup>In particular, average consumption expenditure of a family of four in South Korea is about KRW 3.72 million per month (Statistics Korea, 2019), which is about four times the transfer from KEIP to such a family (KRW 1 million).



$$k_{t+1} = x_t(1 - \phi_t) + (1 - \delta)k_t$$

where  $\delta \in (0, 1)$  is the rate of depreciation and  $\phi_t$  denotes cost of investment adjustment:

$$\phi_t = \frac{\kappa}{2} \left( \frac{x_t}{x_{t-1}} - 1 \right)$$

where  $\kappa > 0$ .

Now, the fraction of newly infected family is given by:

$$\tau_t = \pi_1(s_t C_t^{s,n})(I_t C_t^{i,n}) + \pi_2(s_t n_t^s)(I_t N_t^i) + \pi_3 s_t I_t \quad (2.10)$$

where the household takes aggregate offline consumption ( $I_t C_t^{i,n}$ ) and hours worked ( $I_t N_t^i$ ) of infected people as given.

The fraction of the household that is susceptible, infected, and recovered at time  $t + 1$  can be described as follows, which is equivalent to the epidemic of the virus explained earlier ( $\tau_t$  denotes the fraction of newly infected family):

$$s_{t+1} = s_t - \tau_t \quad (2.11)$$

$$i_{t+1} = (1 - \pi_r - \pi_d)i_t + \tau_t \quad (2.12)$$

$$r_{t+1} = r_t + \pi_r i_t \quad (2.13)$$

**Firms.** A final good,  $Y_t$ , is produced by a representative firm that maximizes its profit:

$$\Pi_t = AK_t^{1-\alpha} N_t^\alpha - w_t N_t - r_t^k K_t \quad (2.14)$$

where  $\alpha \in (0, 1)$  is the labor share,  $A > 0$  denotes TFP level,  $N_t$  is aggregate hours worked, and  $K_t$  is aggregate capital.

**Government.** In order to be consistent with the actual policy implemented in South Korea, we assume that the fiscal authority provides a one time lump-sum transfer to the household and the transfer can be used only for offline consumption. Therefore, in the benchmark analysis, we assume that the government

transfer is provided as a form of (public) offline consumption and it is given once at  $t = 10$ , after two months of the outbreak. While the transfer can be financed through the lump-sum tax, labor income tax, and/or capital income tax, we consider the lump-sum tax scheme in the benchmark analysis. In particular, we assume that the government collects the tax about two years later and it is collected for a year (between period 120 and 171) to smooth out the effect of the taxation on aggregate outcomes when the tax is collected. Hence, the government satisfies the dynamic budget balance, denoted as  $\sum_{t=120}^{171} \Delta_t tax_t = G$  where  $\Delta_t$  is the discount factor for tax.<sup>7</sup> The robustness of our finding to different tax schemes are also analyzed and results are reported in Section 4.

**Equilibrium.** In the competitive equilibrium, each agent solves its maximization problem introduced above. The fractions of people in the family who are susceptible, infected and recovered are the same as the corresponding fraction in the population:

$$s_t = S_t, i_t = I_t, \text{ and } r_t = R_t$$

Labor market clears:

$$s_t n_t^s + i_t n_t^i + r_t n_t^r = N_t$$

Goods market also clears:

$$AK_t^{1-\alpha} N_t^\alpha = C_t + X_t$$

where the aggregate supply of capital  $K_t$  equals to  $k_t$ , i.e.,  $K_t = k_t$  and,  $C_t$  and  $X_t$  indicate aggregate consumption and investment, respectively.

$$C_t = s_t(c_t^{s,o} + c_t^{s,n,p} + c_t^{s,n,g}) + i_t(c_t^{i,o} + c_t^{i,n,p} + c_t^{i,n,g}) + r_t(c_t^{r,o} + c_t^{r,n,p} + c_t^{r,n,g})$$

where  $G = s_t c_t^{s,n,g} + i_t c_t^{i,n,g} + r_t c_t^{r,n,g}$  and

$$X_t = x_t$$

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<sup>7</sup>Main results are preserved when we assume different timings for taxation (as long as tax is collected later) and/or tax is collected with shorter horizon. For  $\Delta_t$ , we use the steady state yearly interest rate (6%) to determine the size of the lump-sum tax to finance  $G$ .

Finally, law of motion for aggregate capital satisfies

$$K_{t+1} = X_t(1 - \phi_t) + (1 - \delta)K_t$$

**2.2 CALIBRATION** For parameterization, we take two strategies: For parameters that are well-calibrated in the previous literature, we use previously calibrated values. For other key parameters that are newly introduced into our model, we calibrate them to match several important moments observed in South Korea. Table 1 reports the parameter values used in the benchmark analysis.

We first note that each period in the model corresponds to a week. We choose the same parameter values for the rate of depreciation,  $\delta$ , and the weekly discount factor,  $\beta$ , used in Eichenbaum, Rebelo, and Trabandt (2020). In addition, we revise the coefficients in the adjustment cost for investment as suggested in Katayama and Kim (2018) on a weekly basis. Following Bigio, Zhang, and Zilberman (2020), we set  $\sigma$ , a parameter governing the substitutability between two types of consumption goods, as 1.8. We set  $\mu$  as 0.1250 to match the total transaction value of online shopping mall before the COVID-19 crisis, worth KRW 135 trillion, which is about one-eighth of total consumption expenditure of households in South Korea. For  $\eta$ , the parameter that governs the substitutability between private- and public offline consumption, we do not have a well-established estimate due to the lack of data since the COVID-19 outbreak. Thus we choose the value of  $\eta$  to match the micro evidence recently found in the literature: Kim, Koh, and Lyou (2020) estimate MPC (marginal propensity to consume) from KEIP using credit card data in South Korea and report the benchmark value as 0.244. We choose the parameter value as  $\eta = 2.985$  by targeting their estimate of MPC.<sup>8</sup>

$A = 0.9552$  and  $\theta = 0.2777$  are chosen so that each worker spends 38 hours per week for market work and corresponding weekly income to be USD 31,838/52 in the pre-epidemic steady state. We set the labor share,  $\alpha$ , as 0.655, which is consistent with the value in the pre-epidemic steady state in South Korea. We set the value of  $\xi$  to be lower than one so that the value of life becomes positive. Frisch labor supply elasticity is calibrated to be one, a value widely adopted in the macro labor literature (Chang and Kim (2006)).

Lastly, parameters describing the epidemic of COVID-19 virus are chosen to closely follow Eichen-

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<sup>8</sup>Coibion, Gorodnichenko, and Weber (2020) estimate the response of private consumption to public transfer from the government in the U.S. (CARES act) as about 0.4. Our finding is both qualitatively and quantitatively similar when  $\eta$  is chosen to match the MPC in the U.S ( $\eta = 2.45$ ). Results are available upon request.

baum, Rebelo, and Trabandt (2020). They set the mortality rate to be 0.2 percent based on data for South Korea for people younger than 65 years. Each infected person takes on average 14 days to either recover or die from the infection. Hence, the probabilities of being either recovered or deceased in one time period are,  $\pi_r + \pi_d = 7/14$ , and,  $\pi_d = 0.002 * (7/14)$ . In addition, Eichenbaum, Rebelo, and Trabandt (2020) set  $\pi_1, \pi_2$ , and  $\pi_3$  to  $3.1949 \times 10^{-7}$ ,  $1.5693 \times 10^{-4}$ , and 0.4997, respectively. These values imply that, during the pandemic, 1/6 of the virus transmissions come from (offline) consumption, 1/6 come from the workplace and the remaining 2/3 come from activities unrelated to economic activities.

Table 1: Calibration

Parameter	Value	Description
$A$	0.9552	TFP level
$\beta$	$0.98^{1/52}$	Discount factor (weekly)
$\alpha$	0.655	Labor share
$\theta$	0.2777	Disutility from working
$\psi$	1	Frisch labor supply elasticity
$\sigma$	1.8	Elasticity of substitution between consumption goods
$\eta$	2.985	Elasticity of substitution between public and private consumption
$\mu$	0.1250	Share of online consumption
$\delta$	0.06/52	Rate of depreciation for capital (weekly)
$\kappa$	1.0939/39	Coefficient in adjustment cost for investment
$\xi$	0.5	Coefficient for GHH preference
$\pi_d$	0.001	Probability of dying (weekly)
$\pi_r$	0.499	Probability of recovering (weekly)
$\pi_1$	$3.1949 \times 10^{-7}$	Virus transmission rate through consumption
$\pi_2$	$1.5693 \times 10^{-4}$	Virus transmission rate through working
$\pi_3$	0.4997	Virus transmission rate through random interaction
$\epsilon_0$	0.001	Initial infection

### 3 AGGREGATE EFFECTS OF KEIP

In this section, we present key results from our model under the benchmark calibration. Following Eichenbaum, Rebelo, and Trabandt (2020), we solve for the deterministic path of the model economy using Dynare.<sup>9</sup> Time horizon is set to be 200 weeks (about 4 years) and we assume that the economy is hit by a positive shock to  $\epsilon$  at time zero so that the economy enters into the epidemic.

**3.1 THE IMPACT OF AN EPIDEMIC** We first examine if the model can generate patterns of an epidemic.

Figure 3 plots the population dynamics in percent of the initial population during the epidemic. The

<sup>9</sup>We modify the dynare code provided by Mathias Trabandt (Link: <https://sites.google.com/site/mathiastrabandt/home/research>).

epidemic ends after almost 55 percent of the initial population is infected (ratio of susceptible people to total population declines from 100% to 45%), which results from our assumption that herd immunity is accomplished when 55 percent of the initial population is infected. In our setting, the infection culminates around 32 weeks later from the initial state.

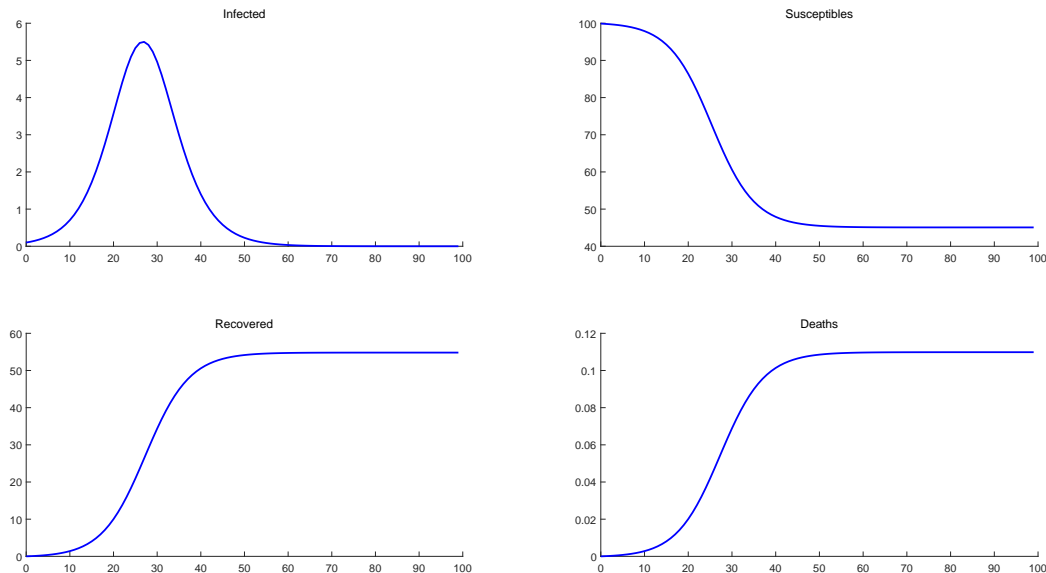


Figure 3: Progress of Epidemic in Model Economy

Figure 4 plots impulse response functions (henceforth IRFs) of aggregate variables during the pandemic, as a percentage deviation from the initial steady state. As is expected, output, consumption, and hours worked show substantial drops during the epidemic. Similarly to Eichenbaum, Rebelo, and Trabandt (2020), investment in this economy first drops but then climbs up for some periods, which is a caveat of our model. This comes from the fact that consumption in this model economy drops a lot due to possible infection from the consumption channel.<sup>10</sup>

In Figure 5, we distinguish consumption and labor supply behavior based on health status of the workers.<sup>11</sup> As can be easily predicted, susceptible people significantly reduce his/her offline consumption and hours worked because of possible infection from such activities. This type of worker reduces his/her

<sup>10</sup>While Eichenbaum, Rebelo, and Trabandt (2020) showed that (1) a neo-classical model with imperfect competition and (2) New-Keynesian feature might resolve this co-movement problem, we find that this problem is not resolved even in the model with imperfect competition.

<sup>11</sup>One caveat of this model is that it predicts that the labor supply and consumption of infected workers increase. This is because lowered labor supply of the susceptible workers due to possible infection from working pushes up the wage rate and it increases labor supply (and hence consumption) of the infected workers.

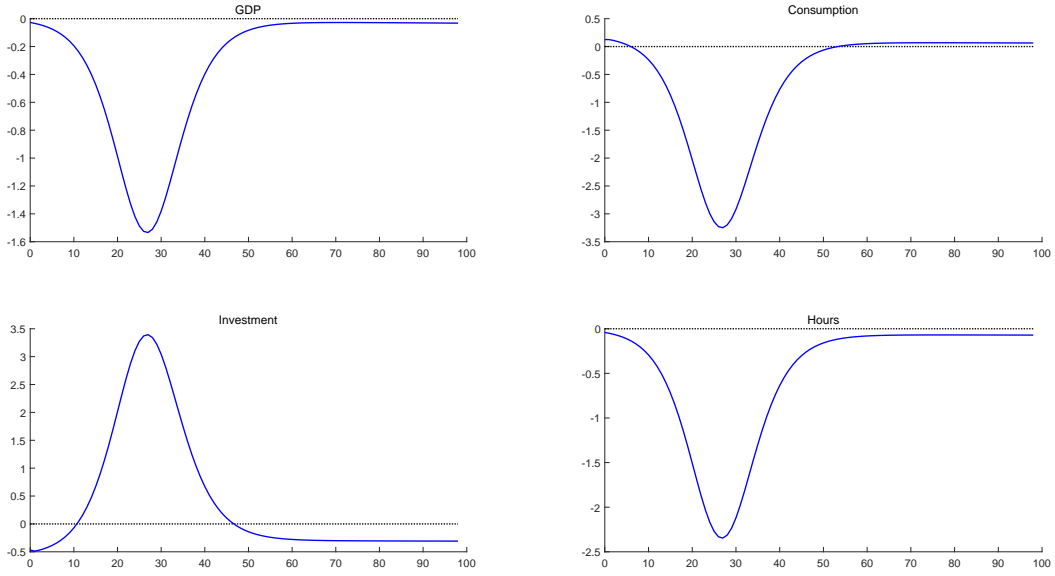


Figure 4: Effects of an Epidemic on Key Macro Variables

online consumption as well, while it declines much less than offline consumption does. This is because online consumption does not affect the infection rate and hence a fraction of offline consumption is substituted by online consumption, a finding consistent with the data: Figure 6 plots sales indices (growth rate from the same month of the previous year) for each consumption category in South Korea. It clearly shows that sales index of online shopping has increased in the first quarter of 2020 while other consumption categories have experienced negative or near zero growth rate during the same quarter.

**3.2 EFFECTS OF KEIP: BENCHMARK RESULT** In this section, we introduce main findings of this paper. In particular, we consider a policy experiment in which the lump-sum transfer is given to the household as a public offline consumption at  $t = 20$ , 5 months after the outbreak of COVID-19<sup>12</sup>, and the government imposes a series of lump-sum taxes to finance the transfer between period 120 and 171.

We first consider an extreme case in which online- and offline consumption goods are perfect substitutes of each other ( $\eta \rightarrow \infty$ ). Figure 7 and 8 describe the IRFs of macro variables under the policy experiment. It is clear that implementation of the fiscal policy does not have any effect on the progress of the epidemic as well as the dynamics of macro variables. This is an intuitive result; a household perfectly substitutes private offline consumption with public offline consumption.

<sup>12</sup>This is to match the fact that KEIP was given around 20 weeks after COVID-19 outbreak in South Korea. However, the period at which the transfer is provided does not affect the main results of the simulation.

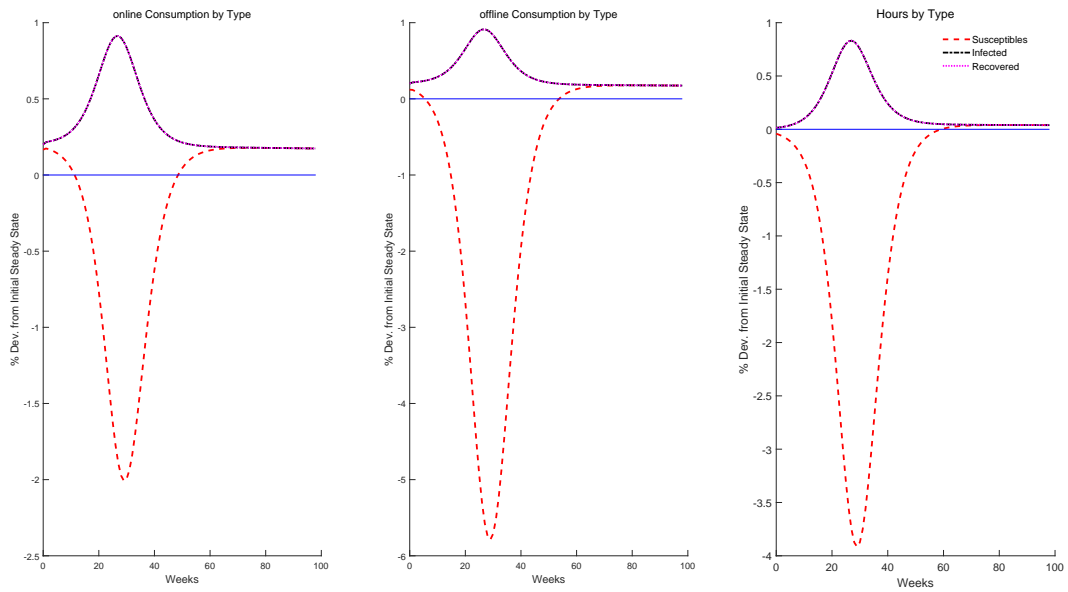


Figure 5: Effects of an Epidemic: Comparison by Type of Workers

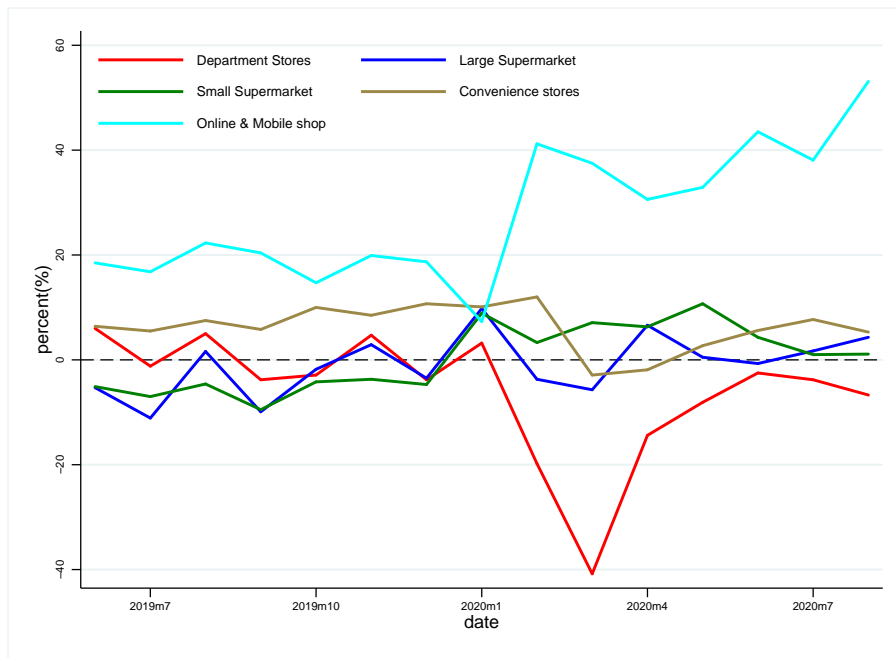


Figure 6: Online vs. Offline Consumption: Data (Source: Statistics Korea)

As we discussed above, however, consumption dynamics described in Figure 8 do not match the pattern observed in the data from South Korea (Kim, Koh, and Lyou (2020)) and also the evidence in the U.S. from the CARES act (Coibion, Gorodnichenko, and Weber (2020)). In order to resolve

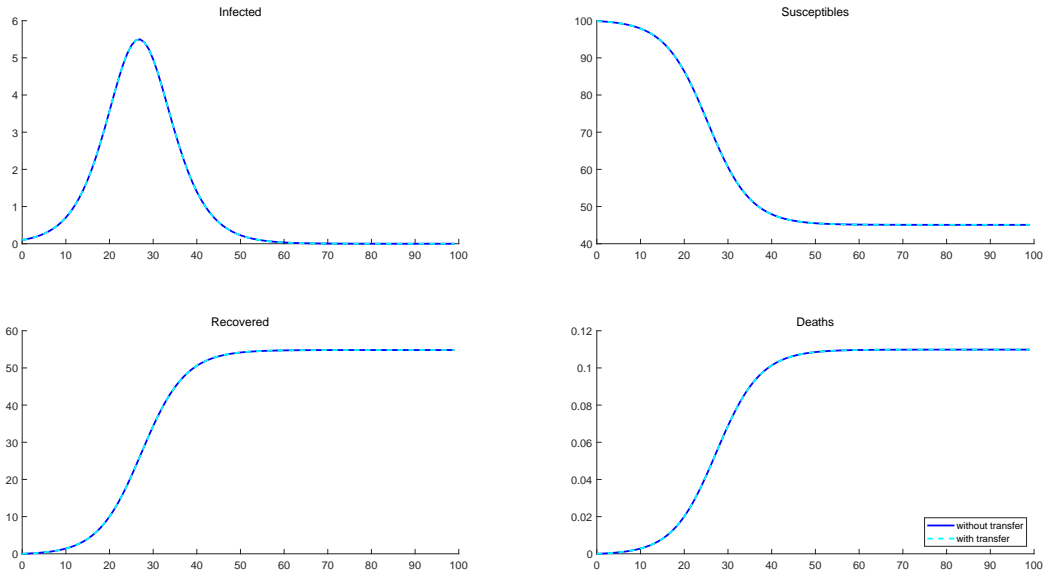


Figure 7: Effects of a Transfer with  $\eta \rightarrow \infty$ : Epidemics

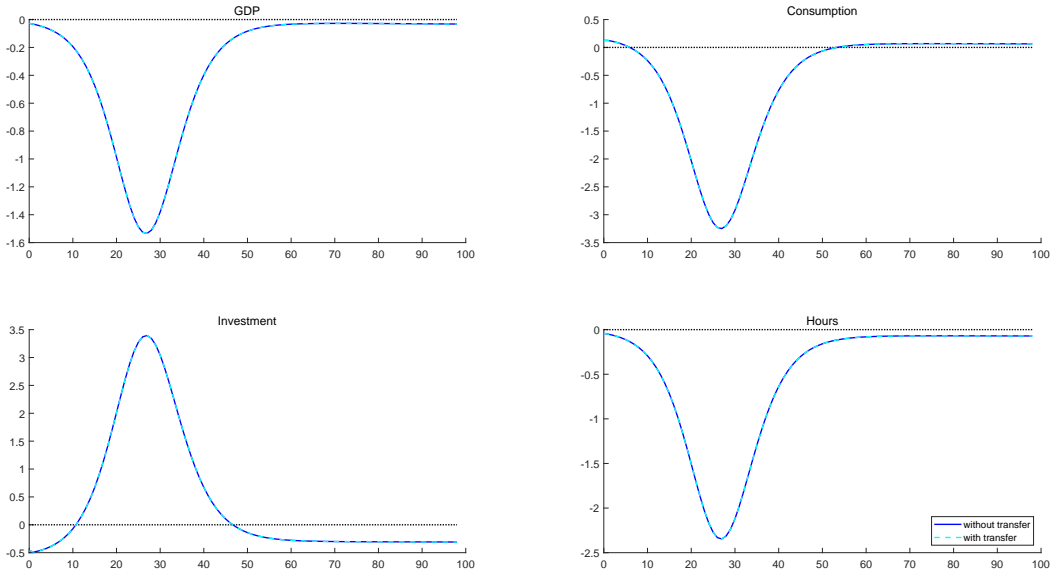


Figure 8: Effects of a Transfer with  $\eta \rightarrow \infty$ : Aggregate Variables

this problem, we instead use the benchmark value for  $\eta$  reported in Table 1 so that private- and public offline consumptions are imperfect substitutes to each other in the subsequent analysis.

Figure 9 plots the IRFs of macro variables under imperfect substitutability between the two offline



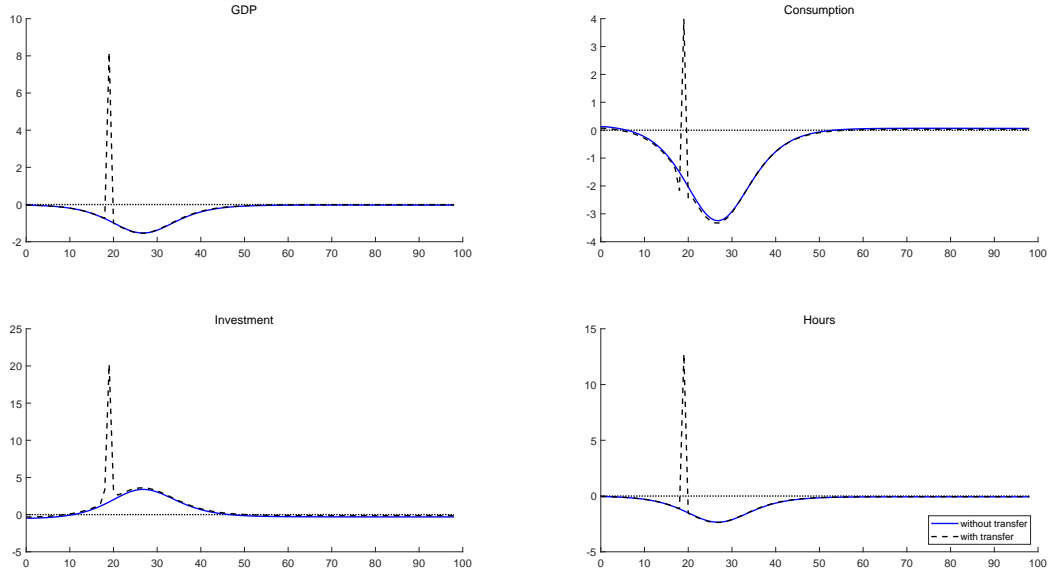


Figure 9: Effects of a Transfer on Aggregate Variables: Benchmark Results

consumption goods. We first note that response of aggregate consumption to the transfer is the moment targeted to set  $\eta$  hence it is not surprising that it spikes up after the transfer is provided to the household at period 20: Hours worked and investment also spike up in order to follow the increased demand for consumption and to clear the goods market over time. The short-lived effect of the KEIP is not surprising given that the KEIP is implemented only at  $t = 20$  so that the shock itself is very transitory. In this benchmark economy, the impact spending multiplier, the extent of output response to increases in transfer, is estimated to be about 0.48, a value consistent with the usual multiplier reported in the literature (see Ramey (2011) for an extensive review of the literature). A potential cost of this policy to boost offline consumption is that it might cause a faster epidemic due to more social interactions. Figure 10 plots the progress of the epidemic and it shows that the change in the path of the epidemic with the implementation of the lump-sum transfer is negligible in the benchmark case. Summarizing observations from Figure 9 and 10, we can conclude that KEIP can boost the economy, at least in the very short-run, without significantly increasing the infection rate. The effectiveness of the policy measured by the transfer multiplier, however, is not that large.

**3.3 COUNTERFACTUAL EXPERIMENTS** In this section, we conduct two counterfactual experiments: First, we consider an experiment in which the lump-sum transfer is only allowed to purchase online

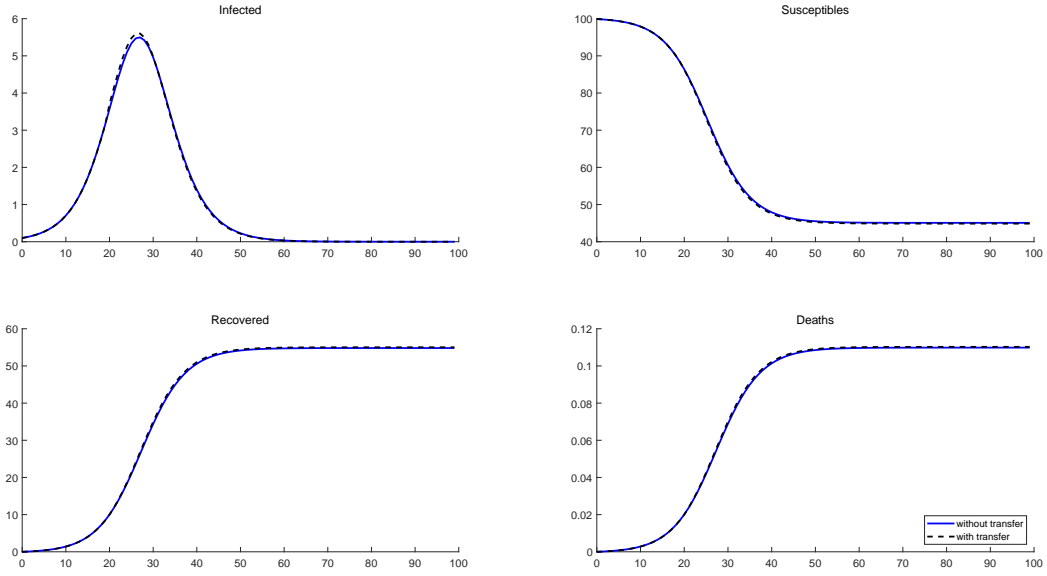


Figure 10: Effects of a Transfer on Progress of the Epidemic: Benchmark Results

goods instead of offline goods since online shopping does not affect the infection probability. Second, we change the infection probabilities due to shopping at the offline store to quantitatively measure the importance of possible interactions from (offline) consumption on the aggregate economy.

**Online Transfer.** While the offline transfer might be useful to help small retailers, it has the potential to increase the probability of the agent becoming infected as offline consumption requires social interaction. In order to further analyze this issue, we conduct a counterfactual experiment by considering an alternative fiscal policy to restrict the transfer to online consumption. Figure 11 and Figure 12 plot the IRFs of key variables under different types of lump-sum transfers. At the impact, aggregate consumption increases more under the alternative transfer policy while its effect on GDP is smaller due to lower investment and lower hours worked (Figure 11). Aggregate consumption increases more under the alternative policy because online consumption does not increase the infection rate. However, working longer hours to boost the supply of final goods is not preferred by workers since it increases the infection probability. Hence, greater consumption substitutes out investment instead of stimulating production in this economy. As a result, the transfer multiplier is estimated to be about 0.28, about 60% of the multiplier obtained under the benchmark policy. As is expected, numbers of infected people becomes slightly lower under the alternative policy (Figure 12) while the difference is negligible. Overall,

our model suggests that targeting offline consumption instead of online consumption is a more effective transfer policy.

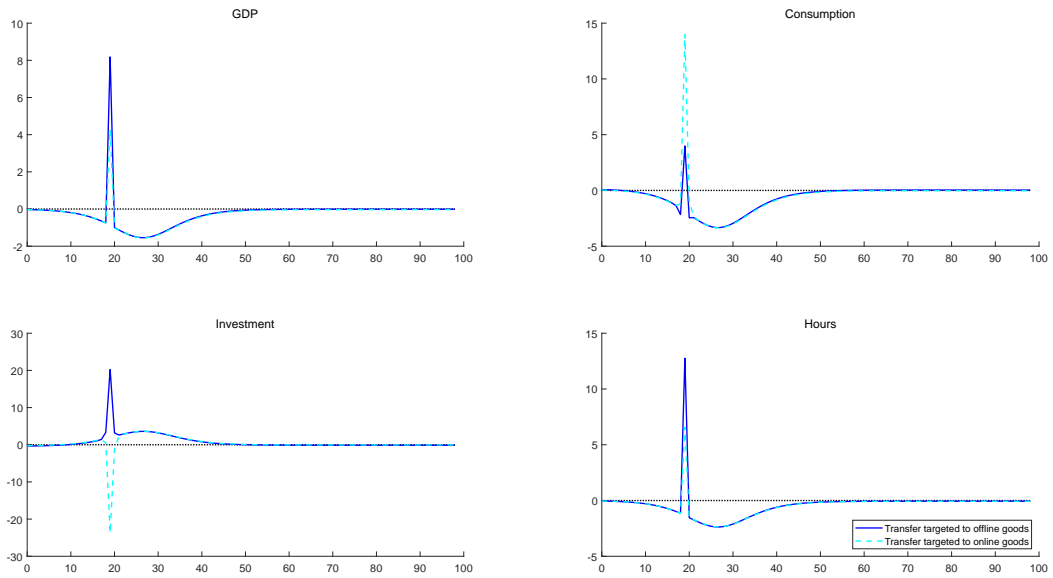


Figure 11: The Effect of a Transfer: Online vs. Offline Transfer

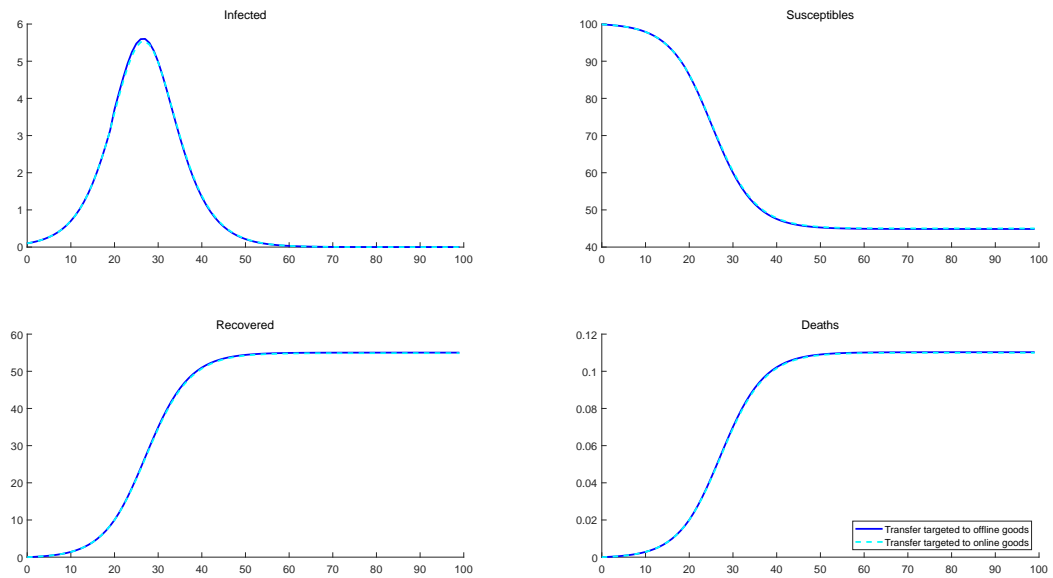


Figure 12: The Effect of a Transfer: Online vs. Offline Transfer

**Different Infection Probabilities.** One natural follow-up question would be if the aggregate effects of

KEIP would change if the infection probability from offline consumption is different from the benchmark analysis. In order to answer to this question, we conduct policy experiments by assigning different probabilities to  $\pi_1$  that governs the infection rate from offline consumption and present the IRFs of key variables in Figure 13 and Figure 14. In particular, we choose  $\pi_1$  to lower the probability of infection from offline consumption to 1/12 (solid blue line; infection probability from working is kept constant while that from non-economic activities increases to ensure the sum of all probabilities is equal to one) and to increase it to 3/12 (dotted red line; infection probability from working is kept constant while that from non-economic activities decreases to ensure the sum of all probabilities is equal to one). Two observations are remarkable. First, overall responses of key macro variables vary significantly following the impact (Figure 13), implying that the macroeconomic effects of the transfer policy targeting offline markets depend crucially on the probability structure. However, responses of the variables and the estimated transfer multipliers are similar at the impact (when the transfer is provided to the household); in any cases, the multiplier is estimated to be about 0.48. Second, the infection rate also changes significantly as the probability structure changes. For instance, the infection rate increases by about 1% point as the probability of being infected from consumption becomes lower from 1/6 to 1/12. This is because the lower infection probability from offline consumption makes the household consume more, resulting in more social interactions at the equilibrium and hence higher infection rates. In summary, this exercise shows the importance of estimating the correct infection probability when estimating the overall effects of the fiscal policy during the pandemic.

## 4 ROBUSTNESS CHECKS

In this section, we conduct two robustness checks to confirm if our findings are robust to (1) different values for key parameters (Section 4.1) and (2) different tax schemes (Section 4.2).

**4.1 DIFFERENT VALUES FOR  $\eta$**  In the benchmark analysis, we set  $\eta$  as 2.985 to match recent micro evidence (Kim, Koh, and Lyou (2020)).  $\eta$  is the key parameter in our policy experiment as it is the elasticity of substitution between private- and public offline consumption goods. Given that there is no consensus on the value of this parameter yet, it is natural to verify if our findings are preserved with different values for  $\eta$ . Figure 15 plots the IRFs of key macro variables; as the elasticity of substitution ( $\eta$ ) between two offline goods declines, responses of GDP, consumption, investment, and hours worked

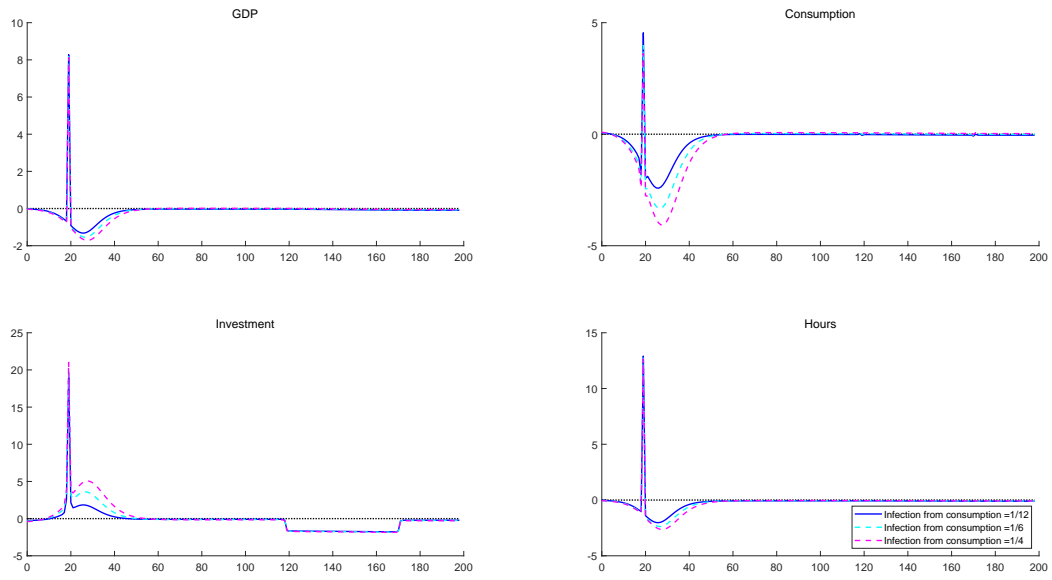


Figure 13: The Effect of a Transfer by Infection Probability according to Offline Consumption

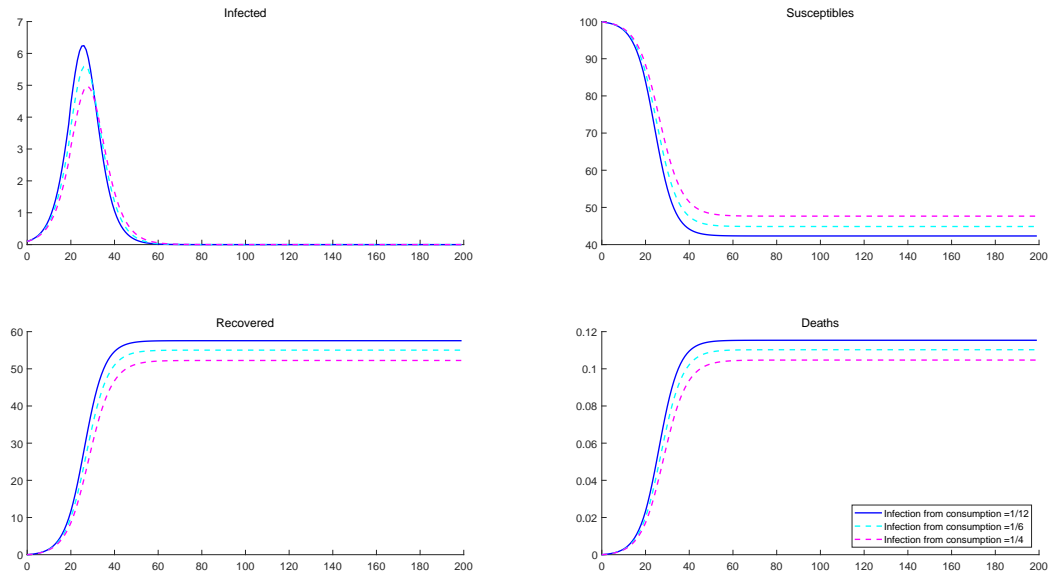


Figure 14: The Effect of a Transfer by Infection Probability according to Offline Consumption

all become greater for the same size of the transfer. This is an intuitive result because a lower  $\eta$  implies that public offline goods become relatively more complementary to private offline consumption goods. In addition, the transfer multiplier significantly increases (resp. decreases) as  $\eta$  becomes lower (resp.

greater): The impact multiplier becomes 2.70 when  $\eta$  is half of the benchmark value while becomes 0.17 when  $\eta$  is twice of the benchmark value. However, as is observed in Figure 16, this greater effect comes at a cost. The infection rate becomes higher and the timing to arrive at the maximum point of infection rate gets faster as the substitutability becomes lower.

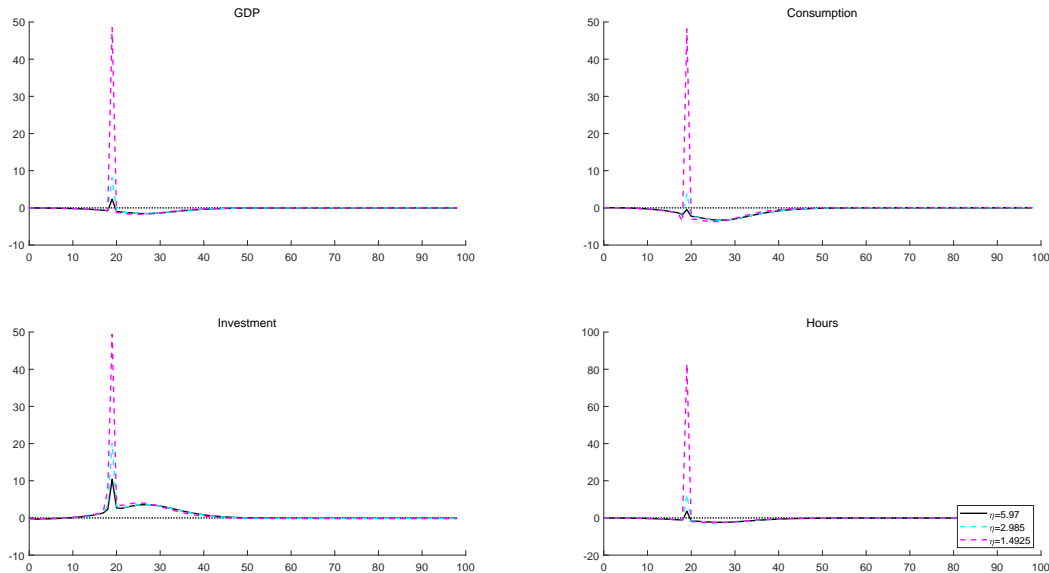


Figure 15: Effects of a Transfer on Aggregate Dynamics: Role of  $\eta$

**4.2 ALTERNATIVE TAX SCHEMES** In the benchmark analysis, we considered the case in which a lump-sum tax is implemented on consumers to finance KEIP. In this section, we further study if our findings are robust to different tax schemes, including labor income tax and capital income tax. In particular, we modify the budget constraint, equation (2.9), to incorporate labor income tax as  $tax_t = (1 - \tilde{\tau}_t)w_t(s_t n_t^s + i_t n_t^i + r_t n_t^r)$  and capital income tax as  $tax_t = (1 - \tilde{\tau}_t)r_t k_t$  where  $\tilde{\tau}_t$  is the tax rate.

Figure 17, 18 and Figure 19, 20 show the IRFs of key variables when labor income tax and capital income tax is respectively imposed on the household. The tax rate is set to be 0.55% (labor income tax) and 1% (capital income tax), and be levied for a year (between period 120 and 171, 52 weeks) in order to satisfy the government budget constraint. Importantly, a different tax policy does not have any impact on the progress of epidemic as well as the aggregate economy. This observation indicates that our finding is robust to changes in tax scheme.

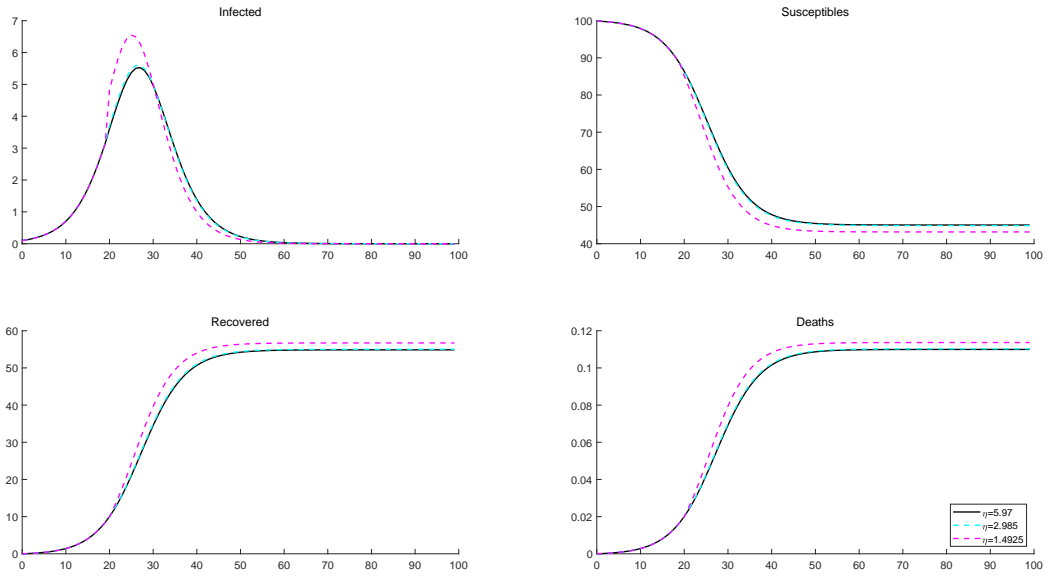


Figure 16: Effects of a Transfer on Epidemic Progress: Role of  $\eta$

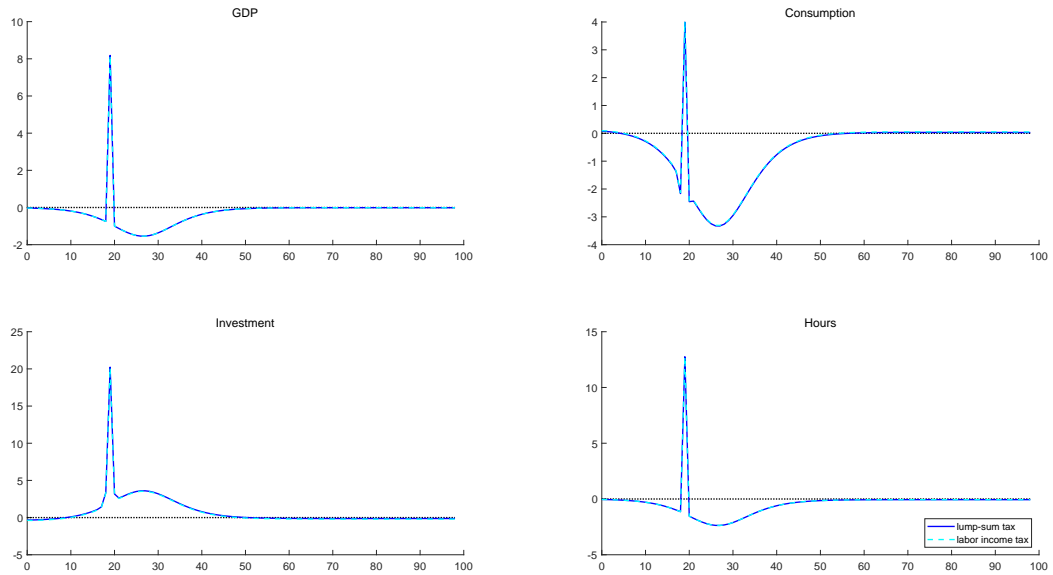


Figure 17: Effects of a Transfer: Labor Income Tax

## 5 CONCLUSION

In this paper, we study the macroeconomic consequences of a policy, “Korean Economic Impact Payment (KEIP)” program, implemented in South Korea in early 2020 by utilizing a modified SIR-macro model.

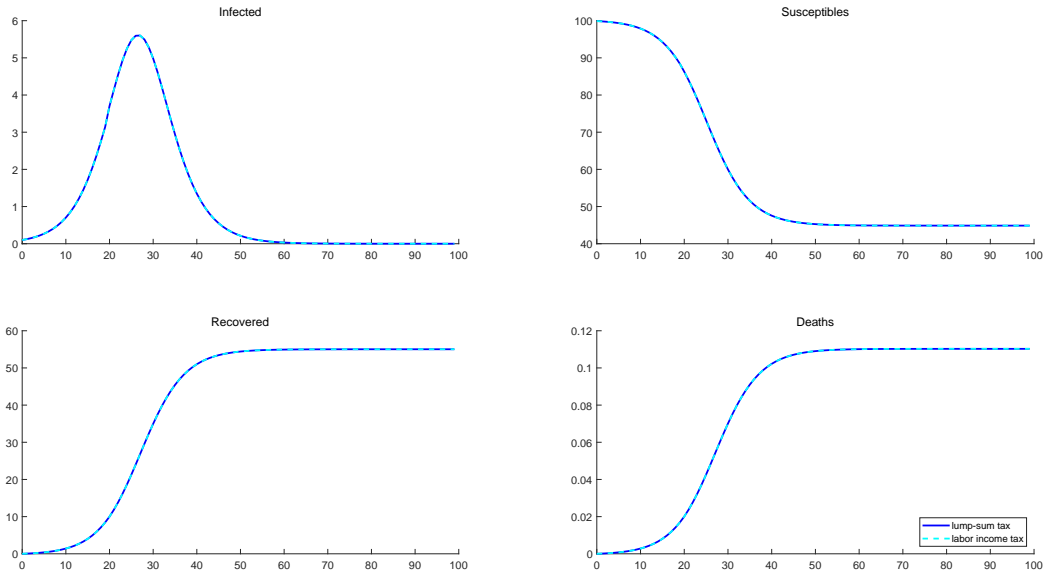


Figure 18: Effects of a Transfer: Labor Income Tax

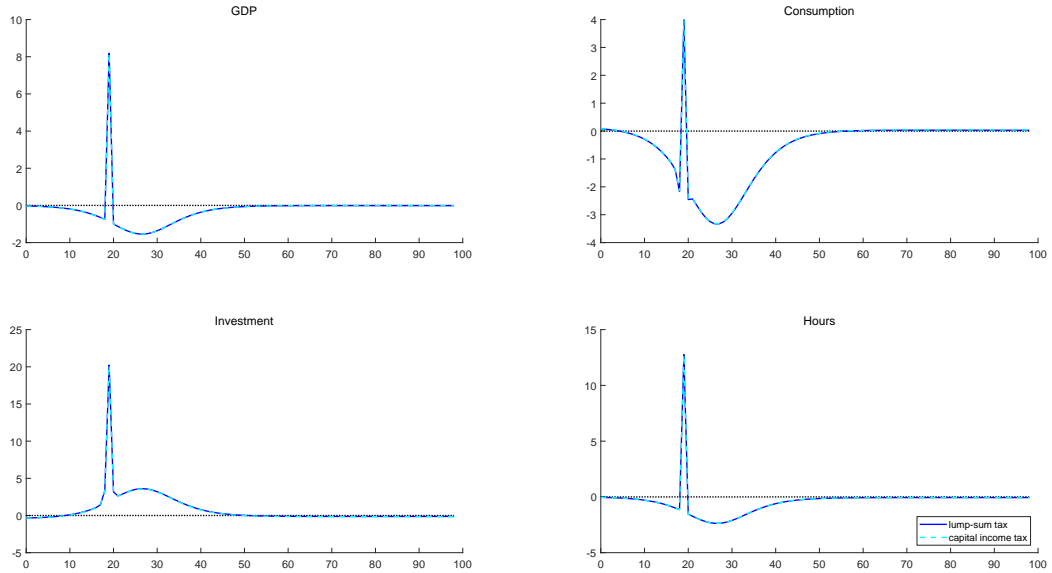


Figure 19: Effects of a Transfer: Capital Income Tax

In particular, we explicitly distinguish online- and offline consumption goods to analyze the aggregate effects of KEIP program. Our main findings indicate that (1) the policy is effective in stimulating the aggregate economy with the predicted transfer multiplier being about 0.5 at the impact, but (2) it can



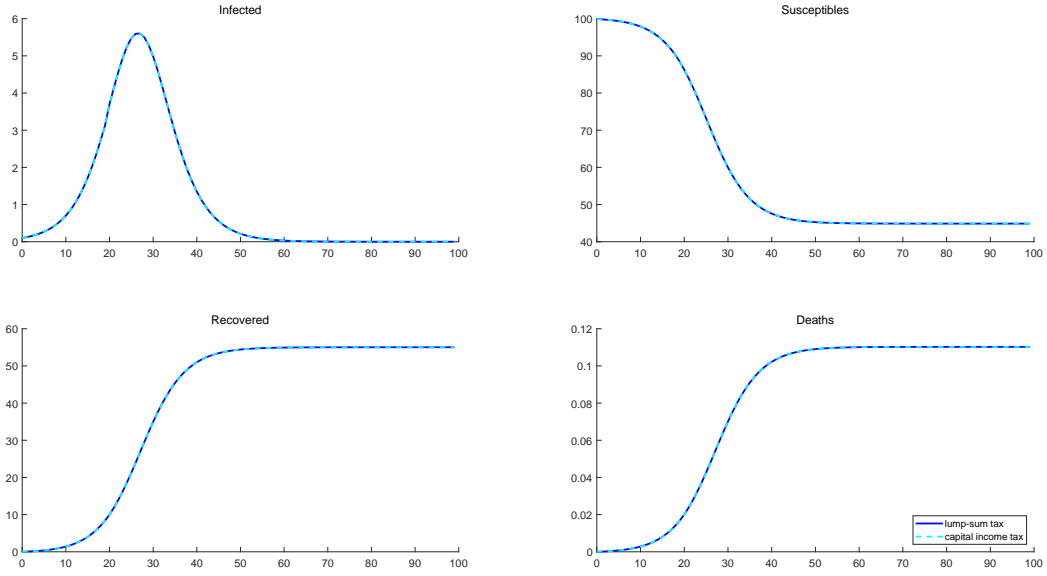


Figure 20: Effects of a Transfer: Capital Income Tax

potentially worsen the pandemic. Hence, our work takes the first step to understand aggregate effects of fiscal policies during the pandemic by providing theoretical predictions that can be used as benchmark results for future researches.

While our findings have important policy implications on the Korean economy, we would like to note that there are several caveats in our analysis. First, we do not take heterogeneity in wealth and/or income into account. The MPC of low income households is usually known to be higher and this might affect our finding. Second, some key parameters of our model are chosen to match moments that have not yet been well-established. For example, we choose the value of  $\eta$  to be in line with recent works, which have not yet been published. Third, as is already pointed out in Section 3.1, investment in our model economy has a co-movement problem. We leave extension of the model to incorporate these issues as future works.

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## APPENDIX. ALTERNATIVE UTILITY SPECIFICATION

In this appendix, we provide justification of our assumption on the utility function. In doing so, we solve the model using King-Plosser-Rebelo (KPR) preference instead of GHH preference. Figure 21 and Figure 22 plot the dynamics of key variables under different assumptions on the preferences: Under KPR preference, there are very large drops in consumption while investment shows a huge jump. Hours and output drop on impact. Hence, the aggregate dynamics in this model economy is inconsistent with the data: First, private consumption increases with KEIP as Kim, Koh, and Lyou (2020) find. Second, hours worked is not associated with the government transfer (Coibion, Gorodnichenko, and Weber (2020)). This is because the wealth effect is important in the KPR preference and thus household drops hours worked in response to the lump-sum transfer, leading to large drops in consumption as well.

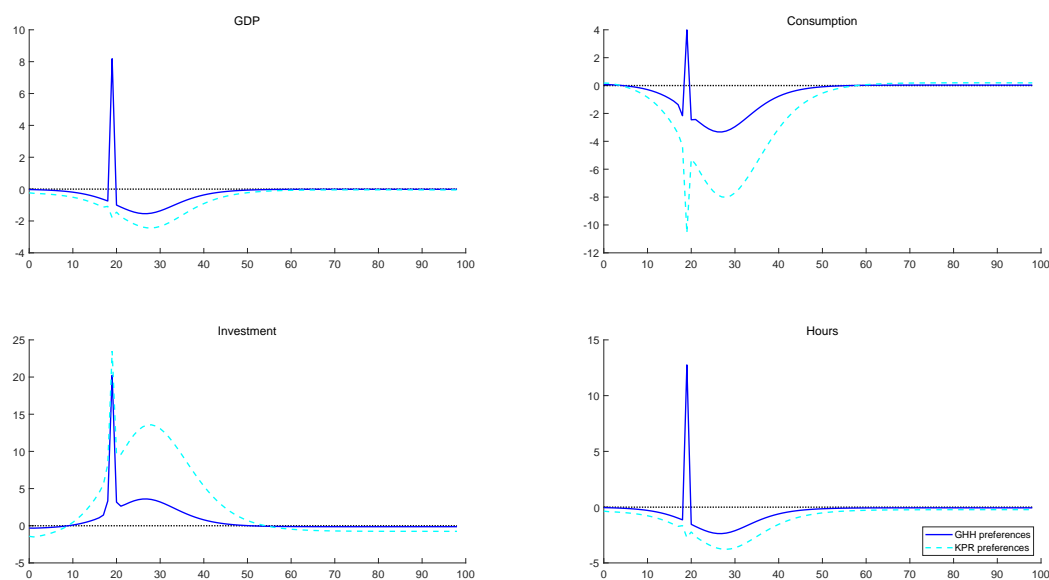


Figure 21: Effects of a Transfer: GHH vs. KPR Preferences

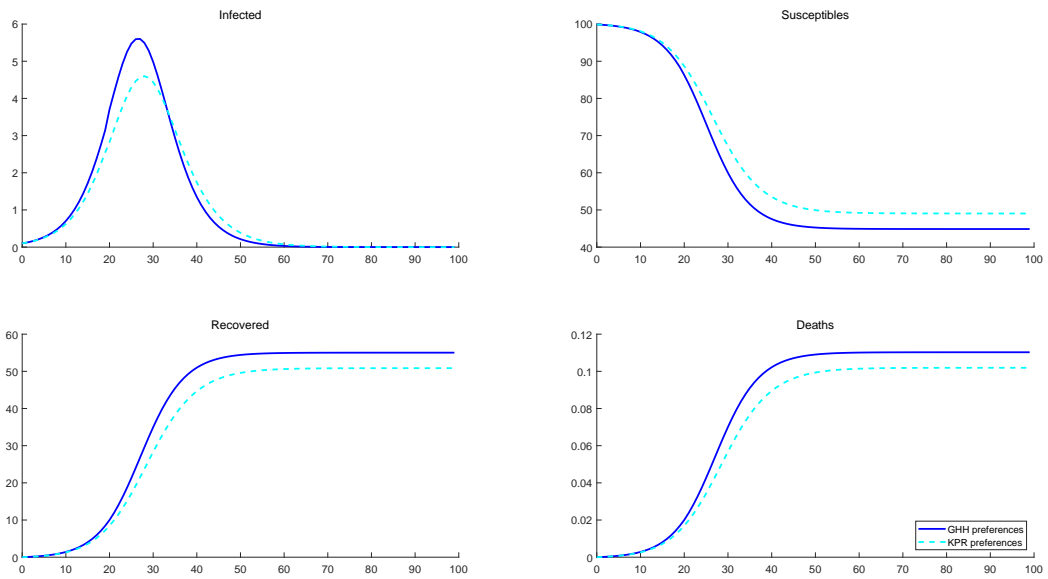


Figure 22: Effects of a Transfer: GHH vs. KPR Preferences