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Social Distancing, Labor Supply, and Income Distribution†

By DUKSANG CHO*

The effects of social distancing measures on income distributions and aggregate variables are examined with an off-the-shelf heterogeneous-agent incomplete-market model. The model shows that social distancing measures, which limit households' labor supply, can decrease the labor supply of low-income households who hold insufficient assets and need income the most given their borrowing constraints. Social distancing measures can therefore exacerbate income inequality by lowering the incomes of the poor. An equilibrium interest rate can fall when the social distancing shock is expected to be persistent because households save more to prepare for rising consumption volatility given the possibility of binding to the labor supply constraint over time. When the shock is expected to be transitory, in contrast, the interest rate can rise upon the arrival of the shock because constrained households choose to borrow more to smooth consumption given the expectation that the shock will fade away. The model also shows that social distancing shocks, which diminish households' consumption demand, can decrease households' incomes evenly for every income quantile, having a limited impact on income inequality.

Key Word: Covid-19, Income Distribution, Labor Supply, Social Distancing
JEL Code: D31, E21, E43, J20

I. Introduction

The COVID-19 economic crisis is distinguished from earlier crises in that the recent economic turmoil was derived from a pandemic. To counteract the infectious disease, the South Korean government has imposed preventive measures, termed 'social distancing', including bans on gathering and restrictions on businesses.

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This paper studies the economic impacts of the social distancing measures implemented in South Korea in the midst of the COVID-19 pandemic. I specifically focus on a prominent feature of social distancing shocks: the constrained labor supply.

The social distancing measures have restricted the labor supply of households. Businesses that rely on face-to-face interactions are forced to shut down during the day or to close late at night to contain the spread of the coronavirus. The number of persons employed in the face-to-face service sector fell sharply immediately after the outbreak of the pandemic in March of 2020, decreasing by more than 4.7% on average since then[1] and accounting for almost all of the decrease in the number of employed persons in South Korea.[2] Given the fact that aggregate employment variables are in general lagging over the business cycle, the immediate decrease in employment variables concentrated on the face-to-face service sector implies that the observed constrained labor supply is not only the result but also a source of the shock. If the decline in employment is a cause of the economic turmoil, the social distancing measures can be understood as a supply shock.[3]

To study the economic repercussions of the social distancing measures, I use an off-the-shelf heterogeneous-agent incomplete-market model (Aiyagari, 1994; Guerrieri and Lorenzoni, 2017; Achdou *et al*., 2020) to examine changes in households' optimal behaviors, their income distributions, and aggregate variables.

The model shows that a labor supply constraint, which limits the maximum level of the household labor supply, can decrease the income of poor households who must earn the most and increase income inequality by thickening the left side of the tail of the household income distribution.

The joint distribution of households' asset holdings and labor productivity is endogenously determined in the model. Most low-income households have low labor productivity and hold insufficient assets in the initial steady-state distribution given a borrowing constraint. They choose to supply longer hours for work due to an income effect. When the social distancing shock arrives, however, these households cannot increase their labor supply due to the binding labor supply constraint, and they suffer from declining incomes. In contrast, households with sufficient asset holdings choose to supply shorter hours for work than low-income households and thus are less likely to bind to the labor supply constraint. Given that most of these rich households have high labor productivity in the initial steady-state distribution, the labor supply constraint has a smaller impact on the incomes of rich, productive households.

The effects of the labor supply constraint on households' income distribution are in line with the observed data of South Korea in 2020. Figure 1 presents changes in households' market incomes by income quintile in 2020 from Household Income and Expenditure Trends of Statistics Korea. We observe that households' market income, representing the sum of their labor and business income, declines for every

[1]Year-on-year percent change for the period from March of 2020 to February of 2021.

[2]See the left panel of Figure A1 in the Appendix for year-on-year changes in the number of employed in South Korea by sector.

[3]The right panel of Figure A1 in the Appendix shows that the economically inactive population increased sharply in March of 2020 and increased by 3.6% on average for the period from March of 2020 to February of 2021. Because households determine whether or not to enter the labor market, the rising economically inactive population implies that the aggregate labor supply was reduced due to the social distancing measures.

quintile and that the lower the income quintile is, the greater the decrease in the market income is. Households in the first quintile experience a significant amount of market income shock (-9.1%), while those in the fifth quintile show a small drop (-0.4%), despite the fact that the social distancing measures were imposed regardless of the household income quintile. With a labor supply constraint calibrated to mimic the observed aggregate data of South Korea in 2020, the model produces changes in household incomes by income quantile comparable to the observed data in Figure 1.

The model also suggests that the effects of the labor supply constraint on aggregate variables depend on households' expectations. When the labor supply shock is expected to be permanent, households' permanent incomes decline significantly and they choose to consume less and save more given the possibility of binding to the labor supply constraint over time. Thus, the interest rate can fall immediately with the shock. When the labor supply shock is expected to be transitory, in contrast, constrained households choose to borrow more in order to smooth their consumption, while unconstrained households scarcely change their consumption and saving decisions given the expectation that the shock will fade away. Therefore, interest rates can rise directly after the arrival of the shock. In both cases, aggregate consumption drops due to the constrained labor supply.

Two other features of social distancing shocks, in this case asymmetric declines in sectoral production and constrained consumption demand, are examined as to whether these shocks can increase income inequality among households. First, the model shows that sectoral asymmetry is not essential to generate skewed changes in the household income distribution. Whether or not the labor supply constraint shock is applied to all households or only to households in the face-to-face sector does not change the qualitative result of the rising income inequality. This is true because in the model, the rising income inequality due to the labor supply constraint stems from changes in the income distribution within a sector in which households are subject to the labor supply constraint, not from the difference between sectors.

Second, households decrease their face-to-face consumption such as spending on clothing, dining out, or accommodation, due to their voluntary social distancing with the fear of infection as well as the restriction imposed by mandatory social distancing

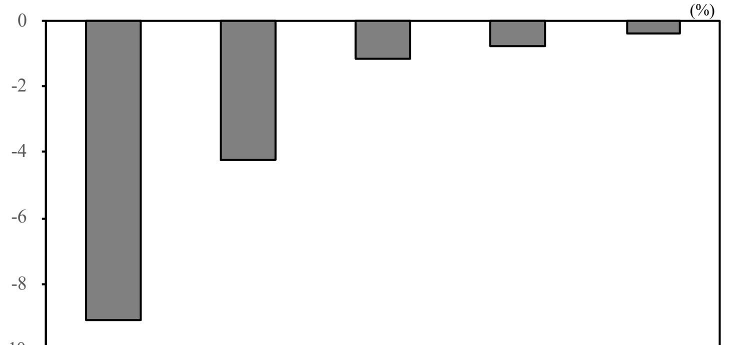


FIGURE 1. CHANGES IN HOUSEHOLDS' LABOR AND BUSINESS INCOMES BY INCOME QUINTILE IN 2020

Source: KOSIS (Last Access Date: 2021. 3. 19). YoY changes in income are calculated by aggregating quarterly income data given the lack of yearly income data in Household Income and Expenditure Trends, Statistics Korea.

measures. The model shows that the economic impacts of this constrained consumption demand are similar to those of a standard aggregate demand shock. When households' marginal utility of consumption decreases due to the constrained consumption demand, households want to consume less and aggregate consumption drops. Households save more and the aggregate interest rate can fall. The consumption demand shock reduces every household's labor supply in equilibrium and cannot generate the skewed changes in income by income quintile observed in Figure 1; hence, the effects of the shock on the household income distribution are limited. This suggests that the increased income inequality observed in Figure 1 was more likely to derive from the labor supply constraint rather than from the constrained consumption demand.

Many studies examine the economic impacts of COVID-19 by combining macroeconomic and epidemiological models (e.g., Eichenbaum *et al*., 2020; Kaplan *et al.,* 2020). They shed light on how an economy reacts to the large-scale transmission of an infectious disease and examine the economic impacts of severe measures such as a national lockdown. Given that the numbers of confirmed cases and deaths related to COVID-19 have remained at limited levels in South Korea,[4] however, most of the economic shock stemmed from the preventive, less severe measures compared to the situations in other countries. In this paper, a standard macroeconomic model that does not depend on an epidemiological mechanism is used to focus on changes in economic agents' behaviors with several preventive social distancing measures in South Korea.

The rest of this paper proceeds as follows. In Section 2, the model is introduced with specific forms of social distancing shocks. In Section 3, the effects of a labor supply constraint on households' optimal decisions, income distributions, and aggregate variables are examined. Other features of social distancing, such as sectoral asymmetry and constrained consumption demand, are studied in Section 4. Lastly, Section 5 concludes the paper.

II. Model

A. *Economic Environment*

An economy consists of a continuum of infinitely lived households who are heterogeneous in their idiosyncratic labor productivity z, assets a, and sector $j \in \{\text{Face-to-face (FF), Contact-free (CF)}\}$. The FF sector is assumed to be more vulnerable to an infectious disease and is hit hard by social distancing measures, whereas the CF sector is assumed not to be directly affected by the social distancing measures. Suppose that households in the FF sector cannot move to the CF sector, and vice versa.[5] Let the share of the FF sector households α and that of the CF

[4]The total numbers of confirmed cases and deaths per 100,000 of the population in South Korea are 193.24 and 6.99, respectively, as of March 22, 2021. These numbers are greater by ten-fold in major advanced economies: 8,911.71 and 162.17 in the U.S. and 3,183.46 and 89.17 in Germany, for instance (World Health Organization, https://covid19.who.int/).

[5]Although extreme rigidity of movement across sectors is assumed in this paper, sectoral mobility could be an important issue because long-lived shocks concentrated in the FF sector can be mitigated by reallocating resources

sector be $(1-\alpha)$. The only asset traded in the economy is a risk-free bond, and each household can borrow up to an exogenous limit such that the household's assets must satisfy

$$a_t \geq \underline{a}.$$

With this borrowing constraint and incomplete markets, each household faces an uninsurable income risk given its idiosyncratic labor productivity shock.

Each household chooses its consumption flow $c_{j,t}$ and labor supply flow $n_{j,t}$ to maximize its preference, represented by the discounted expected utility function over an infinite time horizon,

$$E_0 \int_0^{\infty} e^{-\rho t} \left\{ \psi_{c,t} \frac{c_{j,t}^{1-\gamma}}{1-\gamma} + \psi_n \frac{(1-n_{j,t})^{1-\eta}}{1-\eta} \right\} dt,$$

where $\rho > 0$ is the time discounting rate, $\gamma > 0$ and $\eta > 0$ are respectively the coefficients of the relative risk aversion and the curvature of utility from leisure governing the Frisch elasticity of the labor supply, and $\psi_{c,t} > 0$ and $\psi_n > 0$ are likewise the coefficients of consumption and leisure. $\psi_{c,t}$ is initially normalized to 1, but it can be reduced due to social distancing shocks, decreasing the marginal utility of consumption. The time endowment is normalized to 1.

Household assets a evolve according to the following law of motion,

$$\dot{a}_t = z_t n_{j,t} + r_t a_t - c_{j,t},$$

where r_t is the interest rate and $z_t n_{j,t}$ represents consumption goods produced by the household using a linear technology. The idiosyncratic labor productivity shock z_t evolves stochastically over time following an Ornstein-Uhlenbeck process while reflecting barriers $\{\underline{z}, \overline{z}\}$ such that

$$d \ln z_t = \theta(\mu - \ln z_t)dt + \sigma dW_t,$$

$$dz_t = \left\{ \theta(\mu - z_t) + \frac{1}{2}\sigma^2 \right\} z_t dt + \sigma z_t dW_t,$$

where $\theta > 0$, μ, and $\sigma > 0$ are parameters, and W_t denotes a Wiener process. The second equation of the shock process is derived from the first equation with Ito's lemma. The Ornstein-Uhlenbeck process is used because it is a continuous-time analogue of the discrete-time AR(1) process, which has been commonly used to describe idiosyncratic labor productivity shocks in the literature.

into the CF sector.

Lastly, the labor supply of households is constrained up to an exogenous limit, as follows:

$$n_{j,t} \leq \bar{n}_{j,t}$$

The labor supply constraint $\bar{n}_{j,t}$ is initially set to 1, at which no households bind, but it will be tightened to capture social distancing measures. When the social distancing measures intensify to curb the spread of a disease, business hours are limited and $\bar{n}_{j,t}$ can decrease in sector j.

B. *Equilibrium*

Given a sequence of interest rates and social distancing shocks, $\{r_t, \bar{n}_{j,t}, \psi_{c,t}\}$, let $c_{j,t}(z,a)$ and $n_{j,t}(z,a)$ denote the optimal consumption and labor supply flows at time t of a household in sector j with productivity z and assets a. Given $c_{j,t}(z,a)$ and $n_{j,t}(z,a)$, a household's assets a_t evolve according to the above law of motion. Let $g_{j,t}(z,a)$ denote the joint distribution of idiosyncratic productivity and the assets of households in sector $j \in \{FF, CF\}$ at time t. The transition of $g_{j,t}(z,a)$ over time is fully determined by the function $c_{j,t}(z,a)$ and $n_{j,t}(z,a)$. Equilibrium is defined as follows.

Definition. Given the initial distributions $\{g_{j,t=0}(z,a)\}_{j\in\{FF,CF\}}$, equilibrium is a sequence of interest rates $\{r_t\}$, a sequence of social distancing shocks $\{\bar{n}_{j,t}, \psi_{c,t}\}$, a sequence of consumption and labor supply flows $\{c_{j,t}(z,a), n_{j,t}(z,a)\}$, and a sequence of joint distributions of labor productivity and assets $\{g_{j,t}(z,a)\}_{j\in\{FF,CF\}}$ such that

(i) $c_{j,t}(z,a)$ and $n_{j,t}(z,a)$ are optimal given $\{r_t, \bar{n}_{j,t}, \psi_{c,t}\}$,
(ii) the joint distributions $\{g_{j,t}(z,a)\}_{j\in\{FF,CF\}}$ are consistent with the optimal consumption and labor supply flows, and
(iii) the asset market clears,

$$0 = \alpha \int_{\underline{a}}^{\infty} \int_{\underline{z}}^{\bar{z}} a g_{FF,t}(z,a) dz da + (1-\alpha) \int_{\underline{a}}^{\infty} \int_{\underline{z}}^{\bar{z}} a g_{CF,t}(z,a) dz da.$$

The optimal consumption and labor supply flows of households are derived from the following system of equations for $j \in \{FF, CF\}$:

$$\begin{aligned} \rho v_{j,t}(a,z) = {} & \max_{\{c_t, n_t\}} \psi_{c,t} \frac{c_{j,t}^{1-\gamma}}{1-\gamma} + \psi_n \frac{(1-n_{j,t})^{1-\eta}}{1-\eta} + \lambda_t(\bar{n}_{j,t} - n_{j,t}) \\ (HJB) \qquad & + (z n_{j,t} + r_t a - c_{j,t}) \cdot \partial_a v_{j,t}(a,z) + \partial_t v_{j,t}(a,z) \\ & + \mu(z) \cdot \partial_z v_{j,t}(a,z,t) + \frac{1}{2}\sigma^2(z) \cdot \partial_{zz} v_{j,t}(a,z), \end{aligned}$$

$$(BC)\quad \partial_a v_{j,t}(\underline{a},z) \geq \psi_{c,t}(zn_{j,t}(z,\underline{a}) + r_t\underline{a})^{-\gamma},$$

$$(FP)\quad \begin{aligned}\partial_t g_{j,t}(a,z) &= -\partial_a\{s_{j,t}(a,z)\cdot g_{j,t}(a,z)\} - \partial_z\{\mu(z)\cdot g_{j,t}(a,z)\}\\ &\quad + \frac{1}{2}\partial_{zz}\{\sigma^2(z)\cdot g_{j,t}(a,z)\},\end{aligned}$$

$$(Saving)\quad s_{j,t}(a,z) = zn_{j,t}(z,a) - r_t a - c_{j,t}(a,z),$$

$$(PDF)\quad 1 = \int_{\underline{a}}^{\infty}\int_{\underline{z}}^{\overline{z}} g_{j,t}(z,a)dzda,$$

$$(Assets)\quad \begin{aligned}0 &= \alpha\int_{\underline{a}}^{\infty}\int_{\underline{z}}^{\overline{z}} ag_{FF,t}(z,a)dzda\\ &\quad + (1-\alpha)\int_{\underline{a}}^{\infty}\int_{\underline{z}}^{\overline{z}} ag_{CF,t}(z,a)dzda.\end{aligned}$$

The above system of equations is solved numerically with a solution method introduced by Achdou *et al*. (2020) and its companion website (Moll, 2021).

C. *Calibration*

Baseline parameters are calibrated to match the Korean economy before the COVID-19 pandemic and are presented in Table 1. Time is discretized by a half quarter, 0.125 year. The borrowing constraint $\underline{a}$ is arbitrarily set to -0.5, which is slightly larger than the average yearly labor income in the initial steady state. The

TABLE 1—PARAMETER VALUES

Parameter	Explanation	Value	Target
$\underline{a}$	Borrowing constraint	-0.5	Arbitrary choice, slightly larger than the average yearly labor income
ρ	Time discounting rate	0.073	Interest rate r = 2.5%
γ	Curvature of the consumption utility function	2.0	Within the standard values in the literature
η	Curvature of the leisure utility function	1.47	Weighted average of Frisch elasticity = 1
ψ_n	Coefficient of leisure preference	2.45	The share of hours worked of the time endowment = 42.3%
θ	Coefficient of the idiosyncratic labor productivity process governing autocorrelation	0.09	Persistence of wage process in Floden and Linde (2001)
μ	Coefficient of the idiosyncratic labor productivity process governing the average value	0	Mean value of productivity normalized to 1
σ	Coefficient of the idiosyncratic labor productivity process governing the standard deviation	0.22	Variance of wage process in Floden and Linde (2001)
α	Share of the FF sector households	0.34	The share of employed persons in the FF sector in 2019

time discounting rate ρ is chosen to yield a yearly interest rate of 2.5% in the initial steady state. The relative risk aversion parameter γ is assumed to be 2.0, which is within the standard choices in the macroeconomics literature. The curvature of the leisure utility function η is 1.47, which matches the weighted average of Frisch elasticity to 1.0.[6] The coefficient of consumption preference is normalized to 1 in the initial steady state,[7] and that of leisure preference is 2.45 to match the average hours worked for households as 42.3% of their time endowment.[8] The labor supply constraint $\overline{n}_j$ for all sectors is set to 1 in the initial steady state,[9] at which no households are constrained. The continuous-time Ornstein-Uhlenbeck process parameters, θ and μ, are calibrated by matching the wage process in Floden and Linde (2001).[10] Lastly, the share of FF sector households is chosen to be 0.34 given that the share of those employed in the FF sector was 34% in 2019 in South Korea (Statistics Korea).[11]

Figure 2 presents households' policy functions in the initial steady state economy. The horizontal axes indicate household asset holdings a. Solid lines and dashed lines refer to the policy functions of households with high labor productivity ($z = 1.5$) and those with low labor productivity ($z = 0.5$), respectively.[12] The optimal labor supply functions are presented in the panel on the left in Figure 2. Thin and thick lines represent the labor supply (the share of time endowment) and the effective labor supply (the labor supply multiplied by labor productivity), respectively. Note that the effective labor supply is equal to labor income given the linear technology assumption in the model.

Longer hours for work are supplied either by households with insufficient assets due to an income effect or by households with greater labor productivity due to a substitution effect. For most values of a, the substitution effect dominates, and high-productivity households supply longer hours for work. As a is low enough, however, the income effect dominates and low-productivity households supply longer hours for work than high-productivity households. As households approach the borrowing constraint, borrowing for them becomes more restricted, and they depend more on labor income to smooth consumption. While high-productivity

[6]Given that labor supply elasticity has substantial heterogeneity in both the cross-section and over the business cycle (e.g., Attanasio *et al.*, 2018), I arbitrarily set the value to 1.0, which is within the range widely used in the literature.

[7]The coefficient of consumption preference changes over time due to the constrained consumption demand in Section 4.

[8]Time for sleep and personal care per week is assumed to be 70 hours. The average hours worked for those employed is 41.5 hours per week in 2019 in South Korea according to Statistics Korea. Thus, the share of hours worked of the time endowment is $41.5/(168-70) = 0.423$.

[9]The labor supply constraint changes over time due to the social distancing measures in Sections 3 and 4.

[10]Although Floden and Linde (2001) report idiosyncratic risks of the U.S. and Sweden, I follow their estimates because I cannot find reliable estimates of households' idiosyncratic risks for South Korea. The S80/S20 income quintile share in the model in the initial steady state, which is the share of all income received by the top quintile divided by the share of the first, is 5.9. Because the observed S80/S20 disposable income quintile share of South Korea in 2018 is 6.5 (OECD income distribution database; https://stats.oecd.org), the model seems to have lower levels of idiosyncratic risk than in the targeted Korean economy before the COVID-19.

[11]The face-to-face sector as defined here includes (1) wholesale and retail trade; (2) transportation and storage; (3) accommodation and food service activities; (4) arts, sports, and recreation related services; and (5) membership organizations, repair and other personal services.

[12]Two productivity levels are presented among others for expositional purposes. The model has a continuous labor productivity space, which is discretized into 16 grid points from $z_{min} = 0.37$ to $z_{max} = 2.72$ for the numerical computation.

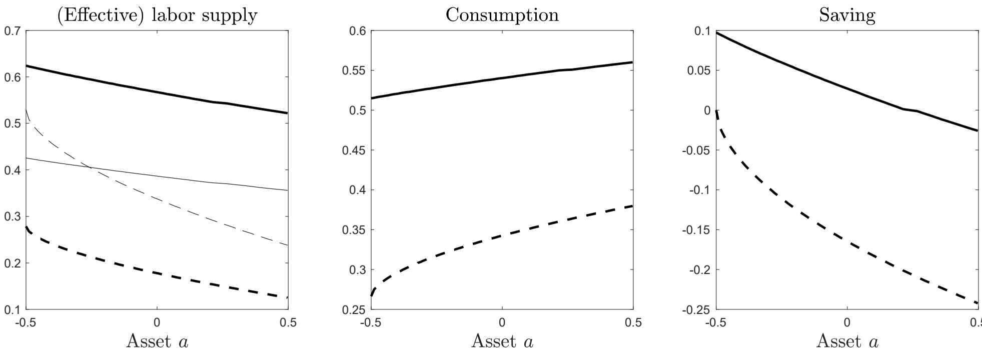


FIGURE 2. POLICY FUNCTIONS IN THE INITIAL STEADY STATE

households can earn sufficient labor income and even save the remaining income after consumption, low-productivity households cannot earn sufficient labor income to smooth consumption and need to increase their labor supply steeply. Note that the low-productivity households' consumption policy function shows steeper concavity for low values of a in the middle panel.

In the model, a household with low labor productivity successively for a long enough time hits the borrowing constraint because this household always chooses to borrow to consume. With this finite probability of hitting the borrowing constraint, the marginal distribution of asset holdings is bimodal, one peak at the borrowing constraint and another peak around at $a = 1$ due to precautionary savings. Figure A4 in the Appendix presents the endogenous marginal distributions of assets and labor productivities in the initial steady state. A sizable share of households can be found on the left side of the marginal asset distribution in the initial steady state. These households could be more susceptible to the labor supply constraint limiting the maximum hours for work, as discussed in the following section.

III. Constrained Labor Supply

Among the major social distancing measures implemented by the South Korean government to counteract COVID-19 are restrictions on business hours in the face-to-face (FF) sector. Depending on the level of the corresponding social distancing scheme, the government forces business sites with a high risk of infection to shut down or close at night. The government also imposes bans on gathering, which can decrease the maximum amount of effective labor supply and production in the FF sector. These restrictions are captured in the model by lowering the labor supply constraint in the FF sector, $\overline{n}_{FF,t}$.

To examine the effects of tightening the labor supply constraint, we assume that $\overline{n}_{FF,t}$ is reduced to 0.4 at $t = 0.125$, which is 68% of the largest optimal labor supply (0.584) in the initial steady state at $t = 0$.[13] This shook decreases the output

[13]A household's optimal labor supply does not exceed 0.584 in the initial steady state and thus $\bar{n}_{FF} > 0.584$ is not binding in the initial steady state.

of the FF sector by 8.8% for the first year after the arrival of the shock in the model, which is comparable to a 9.3% (YoY) decrease in the FF sector service production for the period from February of 2020 to December of 2020 in South Korea. We assume that the labor supply constraint shock is unanticipated at $t = 0$, but the sequence of shocks is fully anticipated from $t = 0.125$. Given the fact that production in the other sectors have remained intact or recovered rapidly in 2020, as shown in Figure A3 in the Appendix, we assume that the labor supply constraint for the contact-free (CF) sector never binds over time such that $\overline{n}_{CF,t} = 1$ for all t.

In South Korea, employment and production in the FF sector fell sharply on February of 2020 and has remained stagnant since then without a sign of recovery,[14] which makes the persistent labor constraint shock a plausible assumption for the long-lasting social distancing measures. Specifically, the following labor constraint shock process is assumed:

$$\overline{n}_{FF,t} = 0.584 - (0.584 - 0.4) \cdot \frac{\exp\left(\frac{(T-t)}{\tau}\right)}{\exp\left(\frac{(T-1)}{\tau}\right)} \quad \textit{for } t \geq 0.125,$$

where $\tau > 0$ is a parameter governing the mean lifetime of the shock and T is the last period that is long enough for $\overline{n}_{FF,t}$ to converge to the initial level. As households expect the social distancing measures will last longer, τ becomes larger. In the next section, a permanent shock with $\tau = \infty$ is examined as an extreme case, after which a transitory shock with $\tau = 2$ is investigated.

A. *Case of a Permanent Shock*

Suppose that the labor supply constraint lasts forever ($\tau = \infty$). Figure 3 shows how households' optimal policy functions change with the permanent labor supply constraint. Dashed lines correspond to the policy functions in the initial steady state ($t = 0$). Solid lines show the values immediately after the arrival of the shock ($t = 0.25$), in which thick and thin solid lines refer to FF and CF sector households, respectively. Both a low ($z = 0.5$, bottom lines) and a high ($z = 1.5$, top lines) level of labor productivity are presented.

The effective labor supply of households who hold insufficient assets is binding to $\overline{n}_{FF,t}$, as indicated by the flattened thick solid lines in the left panel of Figure 3. Given the expectation that the labor supply of FF sector households is binding to $\overline{n}_{FF,t}$ over time, these households choose to supply longer hours for work and increase their precautionary savings when their labor supply constraint is not binding.

The expected permanent income of the FF sector households decreases with the constraint and these households are therefore forced to cut their average consumption

[14]See Figures A1 and A2 in the Appendix.

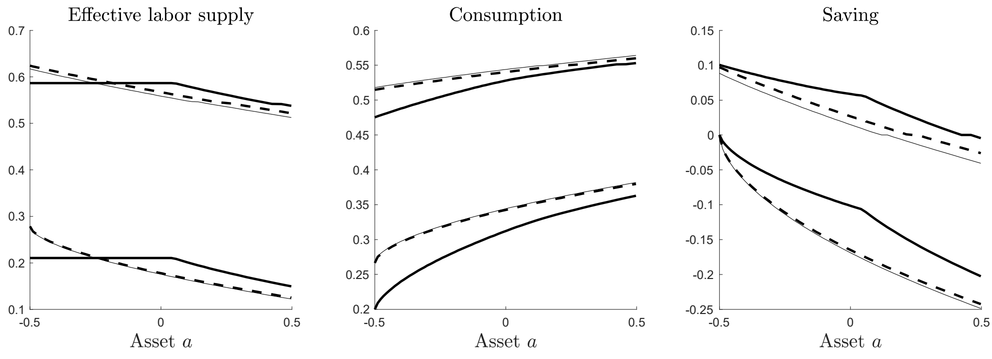


FIGURE 3. POLICY FUNCTIONS WITH A PERMANENT LABOR CONSTRAINT SHOCK

level, which can be seen in the middle panel. Their optimal consumption decisions become more concave. This implies that their consumption volatility over time increases given the idiosyncratic productivity shocks, causing their precautionary saving motive also to rise. The savings of FF sector households, thus, increase for all a in the right panel.

In contrast to FF sector households, CF sector households enjoy the fall of the equilibrium interest rate due to the increased savings of the FF sector households. Thus, the CF sector households, as indicated by thin solid lines, slightly decrease their labor supply in the left panel, increase consumption in the middle panel, and decrease savings in the right panel.

Changes in aggregate variables over time are presented in Figure 4. Units of the vertical axes are the percentage deviations from the initial steady state, except for the right panel of the interest rate, where units of the vertical axis are the percentage-point interest rate level. Note that the aggregate consumption in this economy is equal to the aggregate output (GDP) because the net aggregate saving is zero.

We can observe that both the GDP in the left panel and interest rates in the right panel fall immediately when the shock to $\overline{n}_{FF,t}$ arrives at $t = 0.125$. The labor supply constraint shock decreases the expected permanent income of FF sector households and hence aggregate consumption plunges. As explained above, FF sector households, who hold insufficient assets, cannot supply their optimal hours

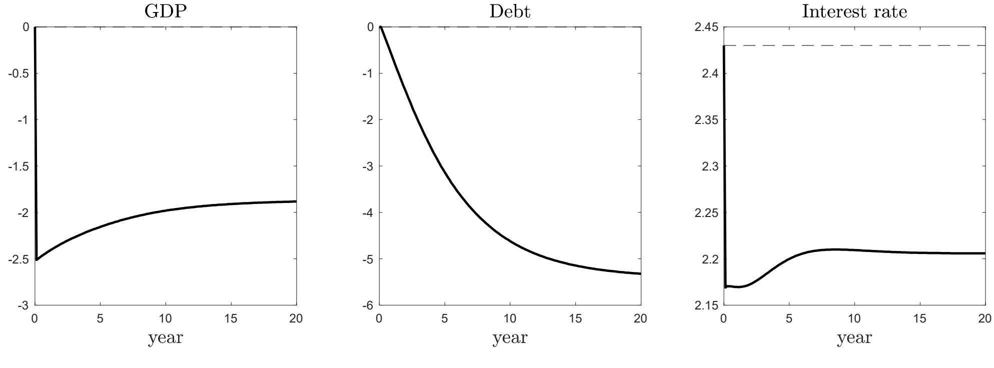


FIGURE 4. AGGREGATE VARIABLES WITH A PERMANENT LABOR CONSTRAINT SHOCK

for work due to the social distancing measures; they decrease their consumption steeply and hence save more or borrow less to prepare for the rising consumption volatility. Other FF sector households, who hold sufficient assets, also anticipate binding to the constraint over time and save more in order to smooth consumption. These increased savings of FF sector households push down the equilibrium interest rate. Note that consumption by FF sector households decreases more than their income due to the rising precautionary saving motive and that the aggregate debt continues to fall over time until FF sector households accumulate their optimal levels of precautionary savings. GDP is also suppressed until that time.

Distributional effects of the social distancing measures can be observed in Figure 5. Similar to the figures above, dashed lines represent the initial steady state distribution, and thick and thin solid lines refer to the distributions of the FF sector households and those of the CF sector households immediately after the shock at $t = 0.25$, respectively.

The labor income distribution of the FF sector households, indicated by the thick solid line in the left panel, shifts to the left while its right tail remains mostly intact. This leftward shift mainly derives from households whose labor supply levels are constrained by the social distancing shock. Note that in Figure 3, FF sector households whose labor supply is not restricted indeed increase their labor supply due to a precautionary saving motive. The capital income distributions for all households in the middle panel barely changes, but the right tails of the distributions are slightly pushed down due to the decline in the interest rate. Overall, the total income distribution of FF sector households in the right panel shows a leftward shift, while the corresponding right tail remains mostly unchanged.

This increase in income inequality indicated by the thickening of the left tail of the household income distribution in the model is in line with observations in South Korea in 2020. Figure 6 shows the changes in household income by income decile. Incomes of the first and the second deciles decrease by 13.8% and 9.8%, respectively, comparable to that in the first quintile (-9.1%) in Figure 1. The model also generates uneven decreases in income; the lower the decile is, the more the income decreases. The two highest income deciles in Figure 6 show significantly smaller changes, -1.2% for the ninth decile and -2.2% for the tenth decile. In sum, given the labor supply constraint, the model can generate quantitatively plausible numbers indicating the rising income inequality.

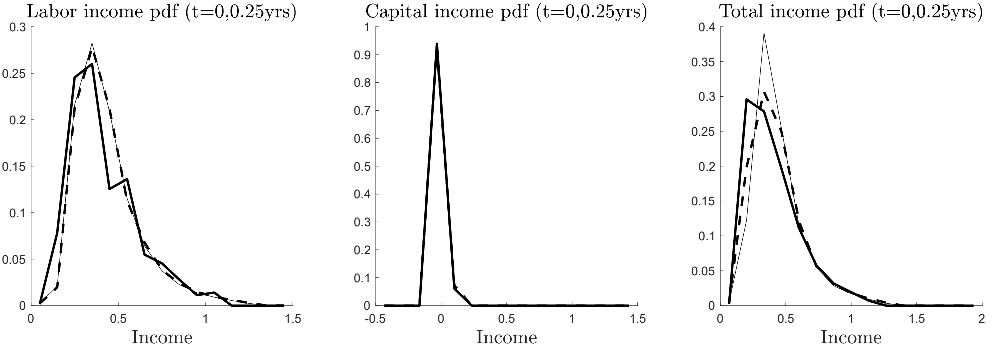


FIGURE 5. INCOME DISTRIBUTIONS WITH A PERMANENT LABOR CONSTRAINT SHOCK

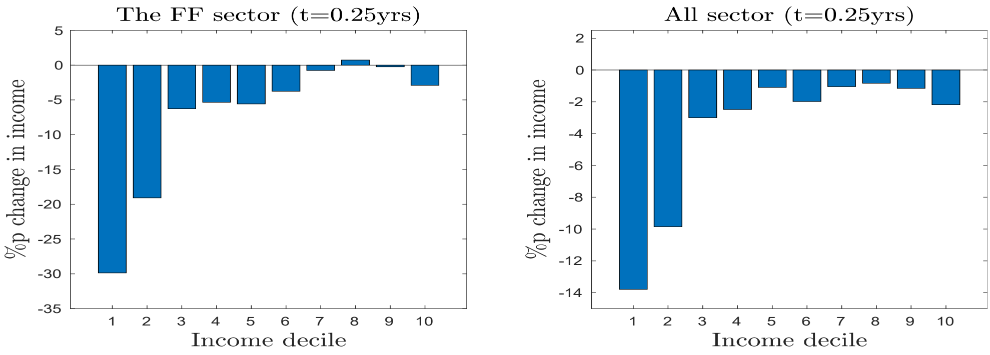


FIGURE 6. CHANGES IN INCOME BY INCOME DECILE WITH A PERMANENT LABOR CONSTRAINT SHOCK

B. *Case of a Transitory Shock*

In this section, we consider the case of a transitory shock. Here, we assume that the labor supply constraint in the FF sector $\overline{n}_{FF,t}$ is reduced to 0.4 at $t = 0.125$ and that $\overline{n}_{FF,t}$ recovers to its initial level exponentially past that point with $\tau = 2$.

Changes in households' policy functions are presented in Figure 7. Dashed lines, thick solid lines, and thin solid lines refer to the initial steady state policy functions, the FF sector households' policy functions immediately after the arrival of the shock at $t = 0.25$, and the CF sector households' policy function at $t = 0.25$, respectively. The bottom and top lines represent households with low labor productivity ($z = 0.5$) and high labor productivity ($z = 1.5$), respectively.

Because the shock is transitory, the expected permanent income of households changes little. Only low-productivity FF sector households holding insufficient assets are forced to cut their consumption sizably, as they cannot earn sufficient labor income due to the labor supply constraint shock, as indicated in the bottom left of the middle panel in Figure 7. High-productivity FF sector households with insufficient assets, however, do not reduce their consumption despite the fact that they are also binding to the labor supply constraint, as they can earn sufficient labor income to smooth consumption. The panel on the right shows that these households save less and smooth consumption given the expectation that the shock is transitory.

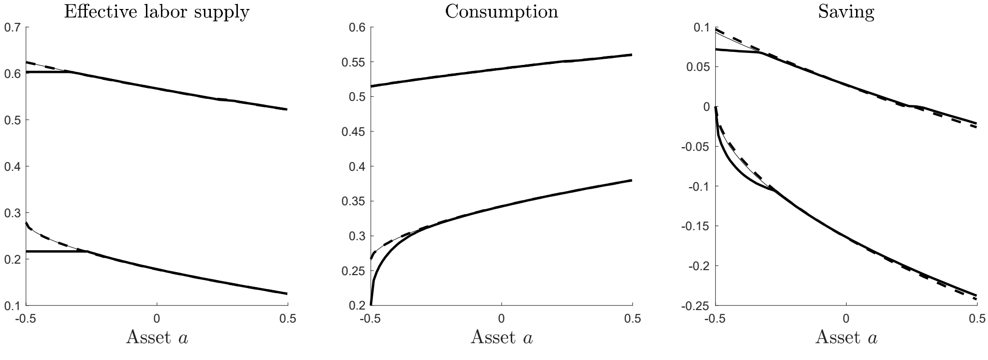


FIGURE 7. POLICY FUNCTIONS WITH A TRANSITORY LABOR CONSTRAINT SHOCK

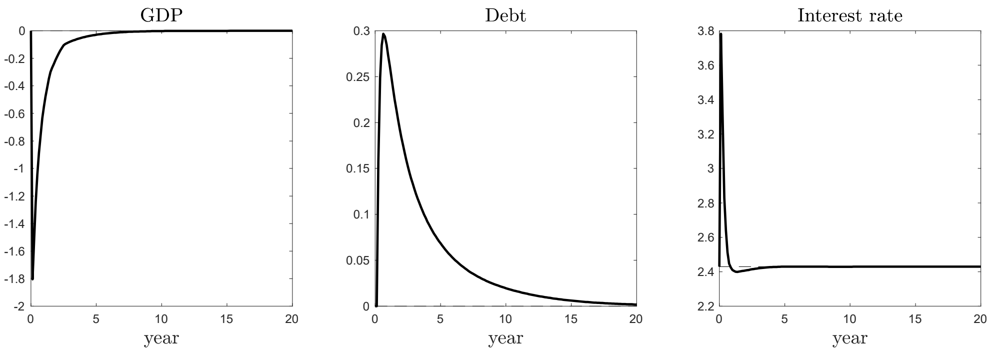


FIGURE 8. AGGREGATE VARIABLES WITH A TRANSITORY LABOR CONSTRAINT SHOCK

In contrast, FF sector households with sufficient assets, whose labor supply is not binding, increase their savings slightly due to a rising precautionary saving motive as well as the increased equilibrium interest rate, which will be explained below.

Figure 8 shows the changes in aggregate variables over time. Units of the vertical axes are the percentage deviations from the initial steady state, except for the right panel of interest rates, where units of the vertical axis are the interest rate level. When the shock hits the economy at $t = 0.125$, GDP falls and the interest rate increases. Given the sizable population of households who are net debtors or have small levels of assets in equilibrium,[15] the main driver of the change in the interest rate is the decrease in savings or increase in borrowing by households with insufficient assets. This rising demand for borrowing increases the aggregate debt in the middle panel and pushes up the equilibrium interest rate in the right panel.[16] Note that the rising aggregate debt level is deleveraged and converges to the initial level much more slowly than other aggregate variables, such as the GDP and interest rate, which implies that the distributional impacts of the social distancing shock can last longer even after the shock itself is dissipated.

Similar to the previous permanent labor supply constraint shock, the transitory labor constraint shock also increases the dispersion of income distributions. In Figure 9, dashed lines indicate the income distributions in the initial steady state, and thick and thin solid lines refer to the income distributions of the FF and the CF sector households, respectively, at $t = 0.25$. The thick solid line in the panel on the left shifts to the left with its right tail fixed because low-income households in the FF sector cannot increase their labor supply due to the constraint. In contrast to the previous case, however, the right tails of the capital income distributions in the middle panel are inflated owing to the rising interest rate.

Figure 10 shows that the lower the income decile is, the greater the decrease in households' income becomes, similar to the previous case of the permanent shock. The only qualitative difference between the permanent and transitory cases is that the highest income quantile households benefit from the rising capital income in the

[15]Figure A4 in the Appendix shows the marginal distributions of the initial steady state.

[16]See Figure A5 in the Appendix for the impact of the shock on interest rates with different values of τ. The responses of the interest rate converge from that with a transitory labor supply constraint shock to that with a permanent shock as τ increases.

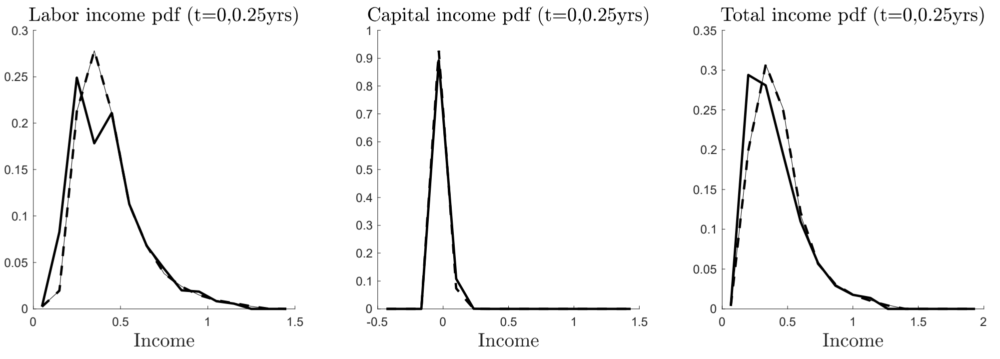


FIGURE 9. INCOME DISTRIBUTIONS WITH A TRANSITORY LABOR CONSTRAINT SHOCK

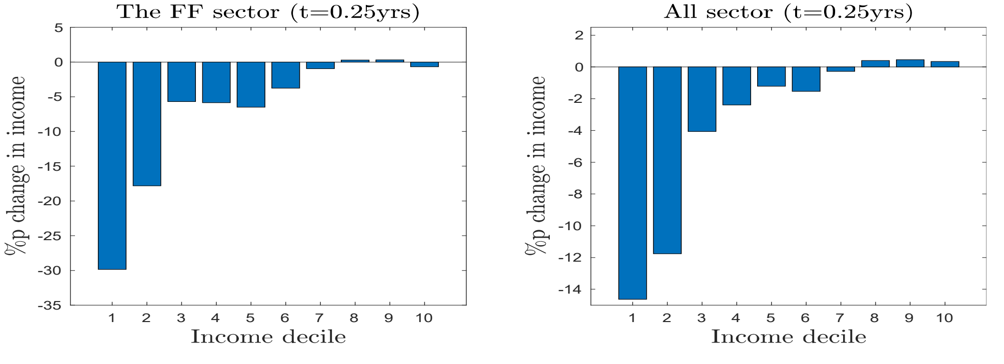


FIGURE 10. CHANGES IN INCOME BY INCOME DECILE WITH A TRANSITORY LABOR CONSTRAINT SHOCK

transitory case, as indicated by the increases in income of the eighth, ninth, and tenth income deciles in Figure 10.

IV. Sectoral Asymmetry and Constrained Consumption Demand

In the previous section, the labor supply constraint is applied only to FF sector households, whose population share α is 34% in the baseline calibration. Although the rising income inequality in the model derives from changes in income within the FF sector households, a part of the result still may stem from the sectoral asymmetry of the labor supply constraint in the model. To address this issue, we examine the effects of symmetric shocks by assuming that both $\overline{n}_{CF,t}$ and $\overline{n}_{FF,t}$ are reduced to 0.4 at $t = 0.125$ and then converge exponentially to the initial level with $\tau = 2$.

Figures 11 and 12 present changes in households' optimal behaviors and changes in households' total income by income decile, respectively. As shown in these figures, every result with the symmetric constraint ($\overline{n}_{CF,t} = \overline{n}_{FF,t} = 0.4$ at $t = 0.125$) is nearly identical to that with the asymmetric constraint ($\overline{n}_{CF,t} = 1$ for all t), which can be seen in Figures 7 and 10. The only prominent difference between the two

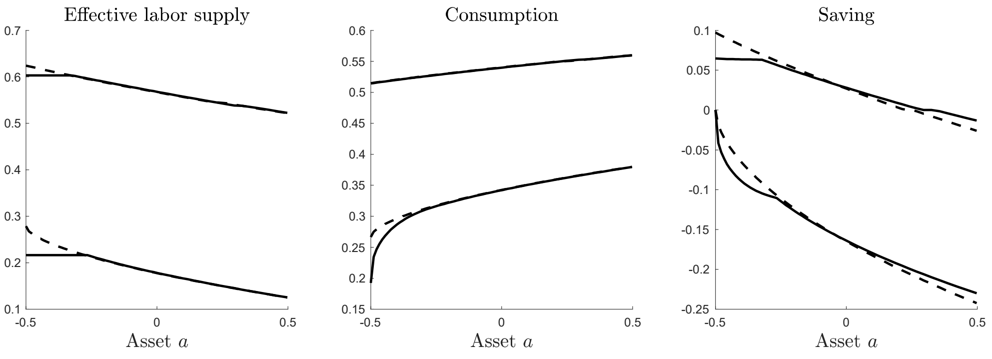


FIGURE 11. POLICY FUNCTIONS WITH A SYMMETRIC, TRANSITORY LABOR CONSTRAINT SHOCK

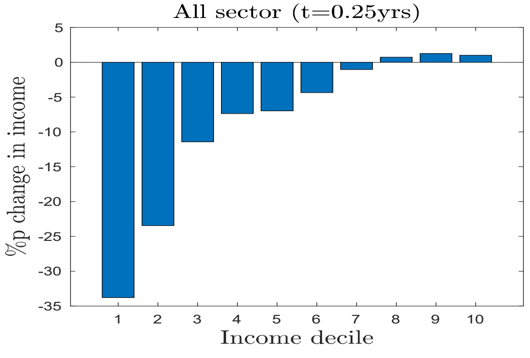


FIGURE 12. CHANGES IN INCOME BY INCOME DECILE WITH A SYMMETRIC, TRANSITORY LABOR CONSTRAINT SHOCK

cases is the size of the responses; this stems from the differences in how many households are subject to the constraint.

Lastly, we consider another prominent feature of social distancing shocks: distorted consumption demand. As households have decreased outdoor activities and avoided face-to-face interactions, their sectoral consumption changed abruptly in 2020.[17] These changes in consumption behaviors imply that households cannot optimize their consumption basket as before and are thus likely to experience a decline in the marginal utility of consumption with the shrinking feasible consumption set (Carroll *et al.*, 2020). In this case, the social distancing measures could be understood as a demand shock.

To capture this consumption demand shock, we assume that the consumption preference coefficient, $\psi_{c,t}$, is decreased by 8% at $t = 0.125$ and is recovered

[17]The left panel of Figure A3 in the Appendix shows that monthly sales index of semi-durable goods, mostly apparels, decreased by 32% due to restricted outings in March of 2020 compared to the corresponding month of the previous year, while sales of durable goods increased in 2020. The composite consumer sentiment index (CCSI) also decreased sharply right after the outbreak of COVID-19 and has shown a slow recovery thus far as of February of 2021. The panel on the right in Figure A3 shows that the shares of households' nominal consumption expenditures changed abruptly in 2020. Expenditures of the face-to-face sector include households' consumption abroad. Note that households have been effectively prohibited from traveling abroad since March of 2020, and their overseas consumption fell sharply; this represents one of the sizable components of household consumption in South Korea.

exponentially with $\tau = 2$ past that point.[18] We also assume that the shock is unanticipated at $t = 0$ but is fully anticipated from $t = 0.125$. The size of the shock is chosen to match the observed difference of -2.4%p (YoY) in the growth rate of the monthly retail sales index for the period from February of 2020 to December of 2020.[19]

With this transitory consumption demand shock, every household reduces its consumption, saves more with unused income, and supplies shorter hours for work to enjoy more leisure. As can be seen in Figure 13, households who hold sufficient assets decrease their consumption more than households who hold insufficient assets, as rich households have a lower marginal utility of consumption and are more sensitive to the diminishing marginal utility of consumption. This is in stark contrast to the results from the labor supply constraint shocks observed in Figures 3 and 7. As households consume less and save more, aggregate consumption (GDP) falls, aggregate debt shrinks, and the interest rate falls, which can be seen in Figure A6 in the Appendix.

The effects of the constrained consumption demand shock on labor income distributions are not asymmetric in that every household reacts to the demand shock in the same way. Figure 14 shows that the demand shock decreases income for every

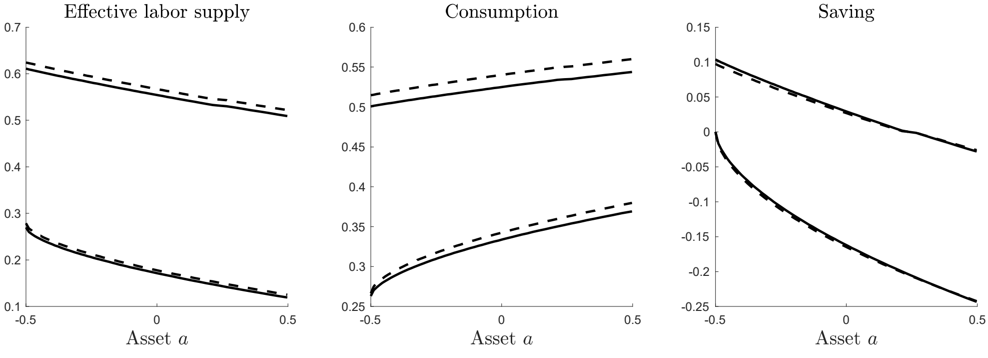


FIGURE 13. POLICY FUNCTIONS WITH A CONSTRAINED CONSUMPTION DEMAND

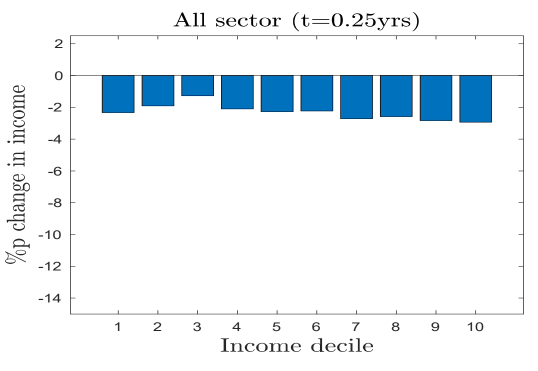


FIGURE 14. CHANGES IN INCOME BY INCOME DECILE WITH A CONSTRAINED CONSUMPTION DEMAND

[18]The shock process of $\psi_{c,t}$ is defined as follows: $\psi_{c,t} = 1 - 0.08 \cdot \frac{\exp\left(-\frac{(t-T)}{\tau}\right)}{\exp\left(-\frac{(1-T)}{\tau}\right)}$ for $t \geq 0.125$.

[19]This preference shock lowers aggregate consumption by 2.45% in the model for the first year after the shock, comparable to observed data.

income decile. This implies that the constrained consumption demand by itself cannot readily explain the observed rise in income inequality during the COVID-19 pandemic, which features larger decreases in incomes of poor households.

V. Conclusion

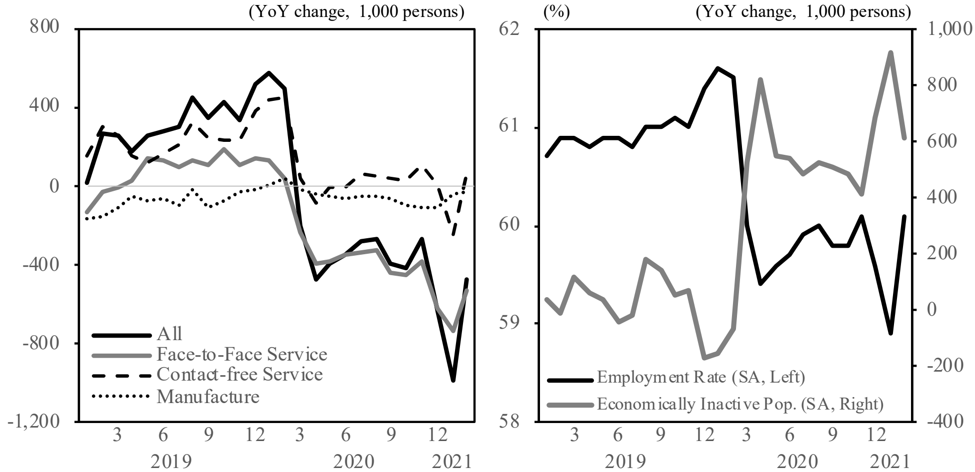
This paper sheds light on how the constrained labor supply imposed by social distancing measures can increase households' income inequality despite the fact that social distancing per se is not directly related to households' income levels. An off-the-shelf heterogeneous-agent incomplete-market model is used to show that the labor supply constraint can increase the income inequality of households by mainly restricting the labor supply of low-income households, who need income the most due to their insufficient asset holdings given a borrowing constraint. The rising income inequality in the model derives from changes in the income distribution within the face-to-face sector, in which households are subject to the constraint.

The model also shows that households' expectations about the longevity of the social distancing measures affect the responses of aggregate variables such as the equilibrium interest rate. If households expect a persistent labor constraint shock, they cut their consumption and save more in order to prepare for the increased consumption volatility in the long run, and the interest rate can tumble. In contrast, when a labor constraint shock is expected to be transitory, households smooth their consumption by borrowing more, and the interest rate can shoot up due to the growing aggregate debt in the short run. This implies that we can observe an interest rate hike with a recovery of consumption at the time when the expectation that social distancing measures will end forms.

Given the observation that poor households asymmetrically suffer from decreases in income due to social distancing measures, a government transfer scheme could be an effective complementary measure. In future research, several policies could be examined with the model to find an optimal transfer scheme that alleviates the side effects of social distancing measures.

To focus on the direct effects of labor supply shocks due to mandatory social distancing measures, this paper abstracts from sectoral differences in consumption goods. This parsimonious modeling choice leaves many questions unanswered. For instance, voluntary social distancing due to the fear of infection can asymmetrically decrease consumption demand in the face-to-face sector and result in a collapse in the labor demand level in this sector. This demand shock channel could be quantitatively important and potentially intertwined with the labor supply shock channel. Krueger *et al*. (2020) argue that the COVID-19 shocks concentrated in the face-to-face sector could be substantially mitigated if households elastically shift their consumption across sectors. On the other hand, Guerrieri *et al*. (2020) show that sectoral supply shocks concentrated in the face-to-face sector can trigger an extra aggregate demand shortage given that the degree of substitution across sectors is low enough or that the intertemporal elasticity of substitution is high enough.

APPENDIX

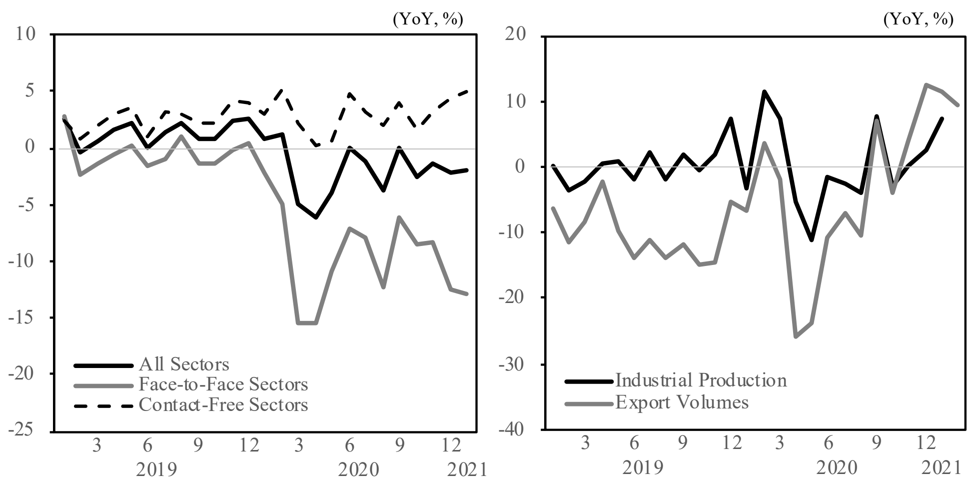


(a) Changes in the number of employed (b) Employment rate and the Econ. Inactive Pop.

FIGURE A1. EMPLOYMENT VARIABLES

Note: The face-to-face sector includes (1) wholesale and retail trade; (2) transportation and storage; (3) accommodation and food service activities; (4) arts, sports, and recreation related services; and (5) membership organizations, repair and other personal services. The contact-free sector includes all other categories.

Source: KOSIS (Last Access Date: 2021. 3. 19). All employment variables are monthly and were acquired from the Economically Active Population Survey, Statistics Korea.

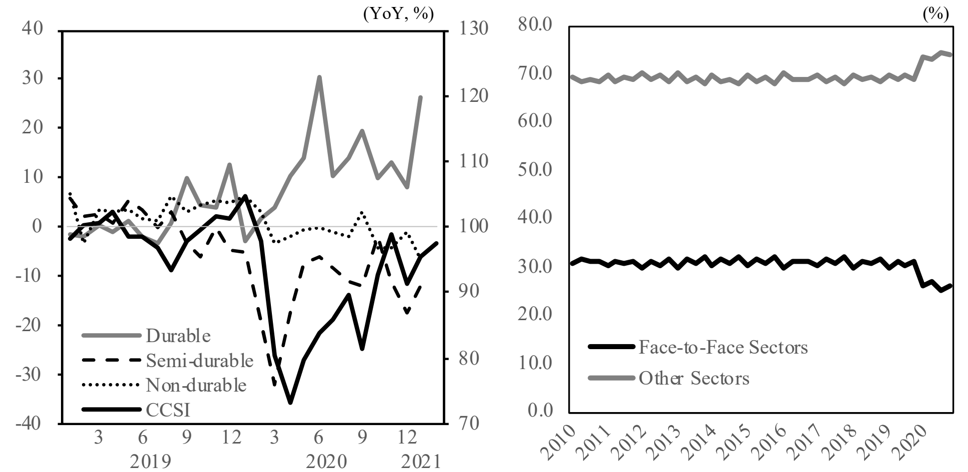


(a) Service production by sector (b) Industrial production and export volumes

FIGURE A2. SERVICE AND INDUSTRIAL PRODUCTION

Note: The face-to-face sector includes (1) wholesale and retail trade; (2) transportation and storage; (3) accommodation and food service activities; (4) arts, sports, and recreation related services; and (5) membership organizations, repair and other personal services. The contact-free sector indicates all other categories.

Source: KOSIS; KITA (Last Access Date: 2021. 3. 19). Monthly indices of service productions by sector in the left panel are acquired from the Monthly Service Industry Survey, Statistics Korea. Monthly industrial production index and export volumes in the panel on the right are acquired from Monthly Survey of Mining and Manufacturing, Statistics Korea and from KITA, respectively.



(a) Retail sales indices and CCSI

(b) Share of HH's sectoral nominal consumption expenditure

FIGURE A3. RETAIL SALES, COMPOSITE CONSUMER SENTIMENT INDEX (CCSI), AND THE SHARE OF HOUSEHOLDS' SECTORAL NOMINAL CONSUMPTION EXPENDITURES

Note: Face-to-face sectors are defined by the sum of sectors experiencing decreases in 2020 exceeding a standard deviation of one and a half.

Source: KOSIS; ECOS (Last Access Date: 2021. 3. 19). Monthly retail sales indices and CCSI data in the left panel are acquired from the Monthly Service Industry Survey, Statistics Korea and from the Consumer Survey Index, Bank of Korea, respectively. The share of households' sectoral nominal consumption expenditures in the panel on the right is calculated with data acquired from Final Consumption Expenditure of Household by Purpose, Bank of Korea.

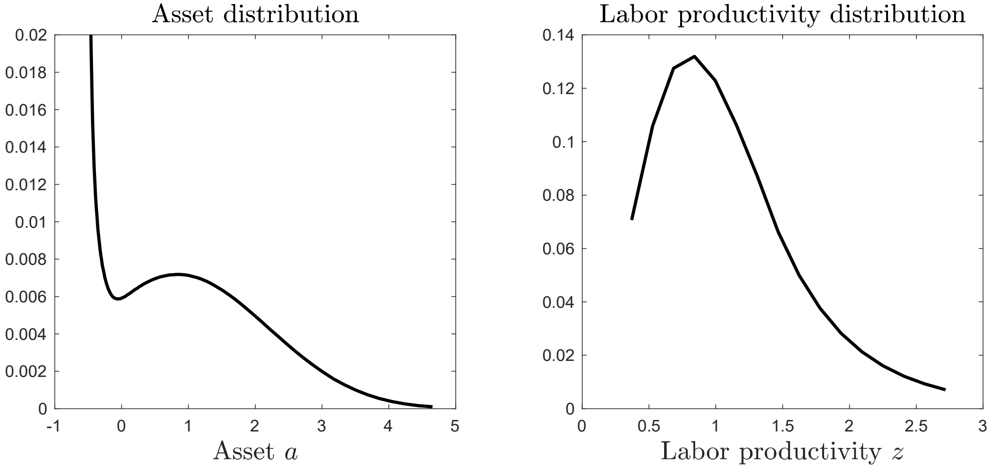


FIGURE A4. MARGINAL DISTRIBUTIONS IN THE INITIAL STEADY STATE

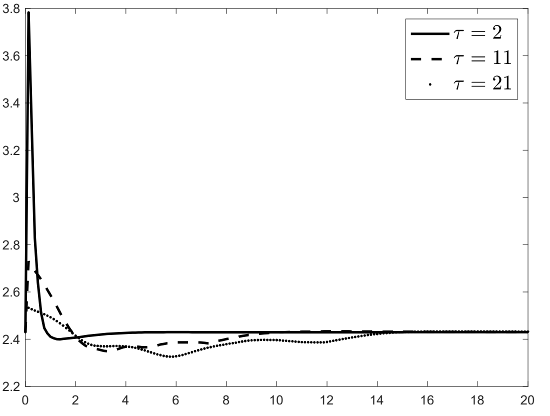


FIGURE A5. CHANGES IN INTEREST RATE RESPONSES FROM TRANSITORY TO PERMANENT SHOCKS WITH MEAN LIFETIME τ

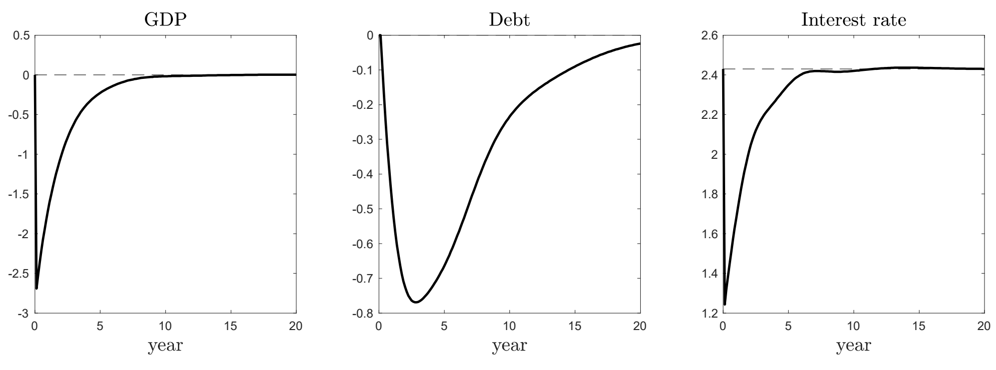


FIGURE A6. AGGREGATE VARIABLES WITH A CONSTRAINED CONSUMPTION DEMAND

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Who's Hit Hardest? The Persistence of the Employment Shock by the COVID-19 Crisis†

By JOSEPH HAN*

The persistence of the employment shock by COVID-19 has various policy implications during the pandemic and beyond it. After evaluating the impact of the health crisis at the individual level, this study decomposes employment losses into persistent and transitory components using the observed timing of the three major outbreaks and subsequent lulls. The estimation results show that while face-to-face services were undoubtedly hit hard by the COVID-19 crisis, the sectoral shock was less persistent for temporary jobs and self-employment. Permanent jobs in the hard-hit sector showed increasingly large persistent losses through the recurring crises, indicating gradual changes in employer responses. The persistent job losses were concentrated on young and older workers in career transitions, whose losses are likely to have long-term effects. These results suggest that targeted measures to mitigate the persistent effects of the employment shock should take priority during the recovery process.

Key Word: COVID-19, Employment Shock, Job Losses, Persistence, Heterogeneity
JEL Code: E24, J21, J63

I. Introduction

The COVID-19 crisis in 2020 had unprecedented impacts on the labor market. Although the spread of the novel coronavirus is predicted to recede in 2021 once a significant portion of the population is vaccinated, there remains a substantial amount of uncertainty over how long the pandemic will continue. It is also likely that the labor market impacts of the health crisis will outlast the pandemic. It is necessary to assess the impacts of the COVID-19 crisis to understand this unusual crisis and to identify particularly vulnerable groups during the pandemic and beyond it.

A distinctive feature of the pandemic-induced recession, besides the sheer size of

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its labor market impact, can be found in the temporal dimension. First, the impacts on the labor market were highly concentrated in the initial phase. Immediately after the initial outbreak, the number of jobs plummeted at an unprecedented speed. Second, the employment shocks due to the COVID-19 crisis consisted of persistent and transitory components. Although employment partially recovered after the initial outbreak had calmed down, the rebound was far short of the pre-pandemic level, showing signs of persistence. To fully understand the unequal burden of the pandemic, it is necessary to assess the persistence of the employment losses caused by the COVID-19 crisis.

In addition to the common patterns across many countries, the COVID-19 crisis in Korea has several interesting characteristics. First, there were three major COVID-19 outbreaks in 2020, all of which subsided within a short period. The repeated experiences of a short-lived outbreak and a subsequent lull provide an opportunity to better identify the persistence of employment losses caused by the COVID-19 crisis. Second, the actual number of confirmed cases remained relatively low without official lockdowns owing to the targeted testing and quarantine strategy based on contact tracing, but the impacts on the labor market were still significant. Social distancing measures combined with strong voluntary alertness effectively contained the spread of the coronavirus *and* human activities. Except for occasional clustered cases, most people just reduced social activities without actual infections around them, outcomes that were advantageous for distinguishing the economic effects of the health crisis from the effects of the infectious disease *per se* (e.g., sick leaves, absences for family care, and excess mortality).

This study evaluates the impact of the COVID-19 crisis on employment from monthly survey data in Korea. For the impact evaluation, counterfactual outcomes are constructed for each subdivided group based on simple assumptions. While there is more than one way to construct counterfactual outcomes, the evaluated impacts provide a reasonable reference point from which to evaluate the national-level shock. Subsequently, the employment shocks by the COVID-19 crisis are decomposed into their persistent and transitory components by utilizing the observed events of the three major outbreaks and the subsequent recovery periods as the source of identification.

Decomposing the employment losses due to COVID-19 yields the following findings at the aggregate level. First, while job losses underestimate the employment shocks caused by COVID-19, extra losses at the intensive margin (i.e., hours worked) were largely transitory. The transitory component is mostly related to a distinctive feature of the COVID-19 employment shocks, i.e., the unusual increase in temporary closures and leaves. Second, while face-to-face services were hit hard during this pandemic, the employment shock on the sector was less persistent compared to those on other sectors. Within the face-to-face service sector, the employment shocks on temporary and self-employed jobs were particularly less persistent at both margins of employment – even compared to similar jobs in other services. These results lead to a mixed conclusion about the persistence of the employment shock overall by COVID-19: while employment shocks by the COVID-19 were largely transitory, they were highly persistent in some dimensions, particularly regarding permanent jobs in the face-to-face service sector.

The analyses of individual heterogeneity show that the persistently affected workers in the face-to-face service sector are mostly young or older workers who are in transition into or out of their career jobs. Particularly, men in their 40s and 50s had persistent job losses in that sector, although these losses were masked by simultaneous increases in temporary jobs and self-employment in another sector. Combined with previous findings on the persistent effects of job losses, these workers are likely to remain as particularly vulnerable groups during the post-pandemic recovery. While women in their 30s also experienced large and persistent job losses, their channel differed. In contrast, less-educated workers, who were among the hard-hit group during the initial shock, showed much less persistent job losses.

This study is closely related to the growing body of work on the labor market impact of the COVID-19 crisis. The initial studies focused on the nature of the COVID-19 crisis and its heterogeneous impacts during the initial phase. For example, high-income households reduced consumption and local service jobs disappeared (Chetty *et al*., 2020). Hourly jobs in low-wage services disappeared rapidly (Bartik *et al*., 2020), and small firms halted new hiring (Campello, Kankanhalli, and Muthukrishnan, 2020). The initial impacts were concentrated on older workers, women, youth, Hispanics, and less-educated workers compared to previous recessions (Bui, Button, and Picciotti, 2020; Montenovo *et al*., 2020) and on workers in low-work-from-home or high physical-proximity jobs who are likely less educated and earn lower incomes (Mongey, Pilossoph, and Weinberg, 2020).

Later studies naturally focus on the reopening and (first) recovery process. After reopening, employment recovered to some extent but partially and selectively. Employment losses after reopening were still concentrated among lower wage workers (Cajner *et al*., 2020). Cheng *et al*. (2020) note that the employment recovery was largely due to workers who were recalled to a previous employer, and new employment matches slowly arose for hard-hit workers. Small firms rehired their previous workers but their employment remained low compared to the pre-pandemic level, particular for the service sector (Kurmann, Lalé, and Ta, 2020). Costa Dias *et al.* (2020) emphasizes active labor market policies for reallocating workers to sectors with better prospects during the recovery process.

This study evaluates the labor market impact of COVID-19 in Korea from the beginning of the crisis and provides additional evidence of the impact of COVID-19 on the Korean labor market using a different methodology from those in concurrent studies (e.g., Aum, Lee, and Shin, 2021b; Lee and Yang, 2021). In particular, this study systematically decomposes the employment losses due to COVID-19 into their persistent and transitory components using the repeated temporal variation observed in Korean data, providing useful information about the recovery process. While confirming previous findings, this study also presents new findings, such as the increases in persistent job losses in face-to-face services through the recurring crises and for those in persistently vulnerable groups, all of which are relevant for labor market policies during the recovery process.

The rest of this paper is organized as follows: Section 2 describes the COVID-19 crisis in Korea, and Section 3 explains the data and the methodology. Section 4 discusses the decomposition of employment losses into persistent and transitory components, and Section 5 presents the estimation results. Section 6 provides concluding remarks.

II. The COVID-19 Crisis in Korea

Judging by the number of confirmed cases alone, the intensity of the COVID-19 crisis in Korea has been relatively mild. However, there have been three major outbreaks, and the impacts on the labor market were significant in each case.

The COVID-19 crisis began relatively early in Korea. The first confirmed case of the novel coronavirus (2019-nCoV) was on January 20, 2020. After a while, the first major outbreak began in mid-February, mostly in the Daegu-Gyeongbuk area. The first and largest cluster of infections started to emerge on February 18. Although the first shock was concentrated to a local area, social distancing measures were implemented across the nation, from February 29 to May 5, to block the spread of the coronavirus. While there were no official lockdowns, the targeted testing and quarantine strategy based on contact tracing was highly effective for the containment of the coronavirus (Aum, Lee, and Shin, 2021a).

The second major outbreak was from mid-August to late September. The number of confirmed cases increased across the nation, although the origin of the outbreak was likely Seoul. The government implemented enforced social distancing measures starting on August 16 for Seoul and surrounding areas and starting on August 23 for the entire nation. After a relatively short period, the number of confirmed cases receded significantly. However, the social distancing measures continued until October 11, as one of the two major holiday seasons in Korea, *Chuseok*, was from September 30 to October 2. The government lifted these measures approximately one week after the holiday season.

The third major outbreak started in late November, without notably clustered cases. The social distancing measures were raised to a higher level on November 24 for the Seoul metro area and on December 8 for other regions. With the end of another major holiday season, *Seol*, the social distancing measures were loosened on February 15, 2021. The number of confirmed cases decreased, but the spread of the coronavirus continued at a level between 300 and 500 confirmed cases per day through late March.

This study defines the periods of the COVID-19 outbreak and the subsequent lull from the officially announced dates of enforced social distancing measures (Figure 1). As the decisions on social distancing measures were based on the predicted intensity of the COVID-19 crisis, I use the dates of these measures rather than the dates matching the actual intensity levels of the COVID-19 crisis. First, the starting dates of an unusual increase in confirmed cases are nearly exogenous. The dates of enhanced social distancing measures closely follow those dates with a lag of one or two weeks. In the main analyses, whether we use the starting dates of clustered cases or the implementation dates of enhanced social distancing measures is immaterial. Second, while the ending date of an outbreak is important, the observed intensity of COVID-19 as measured by the number of confirmed cases is an endogenous variable affected by social distancing measures. Furthermore, the changes in social distancing measures may also have affected the labor market significantly, given that those measures were highly effective.

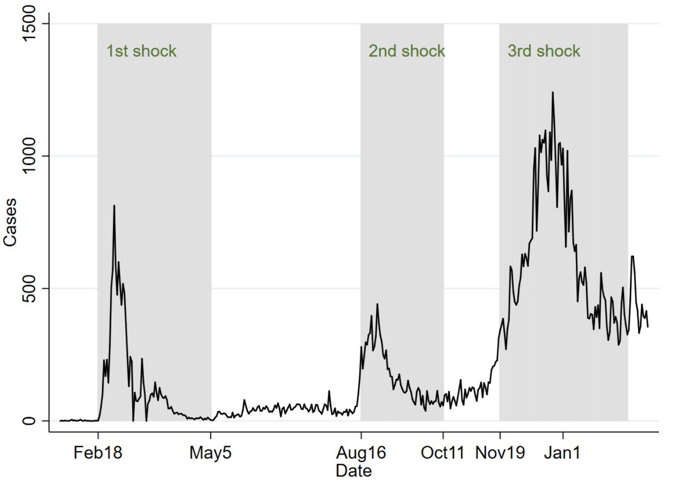


FIGURE 1. THE COVID-19 CRISIS IN KOREA

Note: All daily confirmed cases from the Ministry of Health and Welfare. The shared areas indicate the periods of enforced social distancing.

TABLE 1—A BRIEF HISTORY OF SOCIAL DISTANCING MEASURES IN KOREA

Phase	Period	Major contents / Exceptions
(Initial) Social Distancing	Feb 29~Mar 21	Government-initiated campaigns (mostly voluntary)
Enhanced Social Distancing	Mar 22~Apr 19	Business/school closures Prohibition of crowded gatherings and events (mandated)
Eased Social Distancing	Apr 20~May 5	Partial lifting of restrictions on facilities with relatively low risk
Distancing in Daily Life	May 6~Aug 22	Personal and community guidelines *Social distancing (Level 2) in SMA: Aug 16~Aug 22
Social Distancing (Level 2~2.5)	Aug 23~Oct 11	Prohibition of unnecessary social gatherings *"Enhanced" social distancing (Level 2.5) in Seoul metropolitan area (SMA): Aug 30~Sep 13
Social Distancing (Level 1)	Oct 12~Dec 7	Personal and community guidelines *Social distancing (Level 2) in SMA: Nov 24~Dec 7
Social Distancing (Level 2~2.5)	Dec 8~ Feb 14, 2021	Prohibition of unnecessary social gatherings *"Enhanced" social distancing (Level 2.5) in SMA: Dec 8~Feb 14
Social Distancing (Level 1.5)	Feb 15, 2021~	Partial restrictions on high-risk facilities. *Social distancing (Level 2) in SMA: Feb 15~

Note: 1) Social distancing in three levels (Jun 28~Nov 6): 1, 2, and 3, 2) Social distancing in five levels (Nov 7~): 1, 1.5, 2, 2.5, and 3.

III. Data and Methodology

A. *Data: Economically Active Population Survey*

The economically active population survey (EAPS, hereafter) provided by Statistics Korea, interviews a representative sample of the entire population residing in Korea on a monthly basis. While the survey is officially announced and widely used for economic analyses, there exists an important limitation in that it does not provide household and/or individual identifiers.[1] Owing to this data limitation, this study focuses on changes at the level of subdivided-demographic groups (by gender, age, and final education).[2]

Several characteristics of the survey are particularly noteworthy. First, its sample size (about 60,000 people ages 15 and older) is relatively large compared to the population size; on average, each person in the survey represents approximately 750 people in the population.[3] Second, each household is surveyed for consecutive 36 months, and approximately three percent of the sample is replaced each month. Third, the EAPS asks about the activities during the reference week, which is the week (from Sunday to Saturday) that includes the 15th day of the month. Fourth, the EAPS does not have information on individual earnings. Although a supplementary survey in August contains such information, month-to-month variations in earnings are not observed.

B. *Methodology: The Impact of COVID-19 on Employment*

To evaluate the impacts of COVID-19 on labor market outcomes, strong identification assumptions are inevitable. Reduced-form approaches with minimal identification assumptions, such as difference-in-differences (DD) analyses, are not very useful for identifying the impact of the COVID-19 crisis at the national level due to the difficulty in finding a suitable control group.[4]

This study constructs a short-term counterfactual trajectory of each labor market outcome without COVID-19 based on simple assumptions commonly used in the literature. The construction of an individual-level counterfactual outcome is performed in three stages. First, for each subgroup defined by invariant characteristics (g) and age (a), the average outcome (e) in period $t+1$ ($e_{g,a,t+1}$) is predicted by the average employment outcome of the group in period t ($e_{g,a,t}$). For example, the average employment outcome of males who graduated from a 4-yr program at a university and are 35 years old can be predicted by the average outcome of identically aged males whose education status was also the same in the previous year, as a counterfactual case without COVID-19.[5] This counterfactual prediction is based on an identification assumption that differences across cohorts are negligible within a narrow range of birth years (i.e., $\hat{e}_{g,b+1,t+1} = e_{g,b,t}$ where b is a birth year).[6] This identification assumption is widely used in micro-level evaluation studies as well as macro-level prediction studies, as the age-time-cohort effects cannot be

[1]The identifiers were provided before 2004.

[2]Final education is categorized into five groups: less than high school graduate, high school graduate, college graduate from a 2-3 year program, college graduate from a 4-5 year program, and holder of a post-graduate degree.

[3]The corresponding ratio for the CPS in the U.S. is about 2,500.

[4]DD analyses are still useful for identifying the impact of the intensity of COVID-19 at the level of local labor markets; for example, it is natural to compare labor market outcomes between relatively hard-hit regions and other regions with regional fixed effects. However, it should be noted that DD estimates are not likely to reflect the persistent impact of the COVID-19 crisis, particularly those common across the nation.

[5]Regarding the validity of this identification assumption, see Figure A1 in the Appendix.

[6]If cohort effects are large compared to time effects, alternative assumptions such as constant aging effects across cohorts under negligible time effects ($e_{g,a+1,t+1} - e_{g,a,t} = e_{g,a+1,t} - e_{g,a,t-1}$) provide better approximations.

separately identified.[7] This prediction method requires modifications for a time horizon longer than a year due to base effects, but it works reasonably well for a shorter horizon.

Second, from the predicted group averages combined with actual population changes observed in the data, it is possible to construct a population-driven trajectory in the labor market outcome at a more aggregated level (e.g., $\hat{E}_t = \sum_{g,a} \hat{e}_{g,a,t} P_{g,a,t}$). This trajectory reflects "supply-side changes," as it is constructed under the assumption that the average outcomes for subgroups are unchanging and can be explained only by the changes in population structure.

Third, the difference between the actual and predicted outcomes just before the COVID-19 pandemic ($u_{t_0} = E_{t_0} - \hat{E}_{t_0}$), a prediction error, is subtracted from all individual-level differences using a DD framework. This term reflects "(residual) demand-side changes" such as a cyclical component in the labor demand, industry-level demand changes, and the effects of various governmental interventions that existed just before the COVID-19 pandemic. For any reason, it is likely to persist for several months or more (Figure 2). While a prediction model for this term is important for an employment outlook (e.g., Jeong and Kim, 2017), it requires many more assumptions pertaining to the trajectories of other macroeconomic variables. For simplicity, this term is assumed to be constant throughout the pandemic period, which is up to a year in the data. While the constancy of the unpredicted change is unlikely to hold true over the long term, it serves as a reasonable short-term approximation here, especially because the unpredicted change in employment was rising to a peak just before the COVID-19 crisis (Figure 2). This assumption provides a useful reference point given the substantial uncertainty about macroeconomic forecasting.

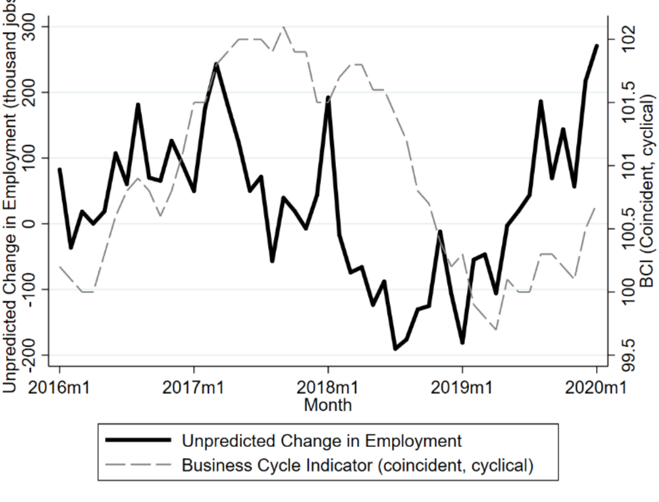


FIGURE 2. UNPREDICTED JOB CHANGES AND BUSINESS CYCLES

[7]I use five-year age groups (11 groups: 15-19, 20-24, ..., 60-64, 65 or more) instead of the yearly age to reduce the number of empty cells. However, the results are nearly identical regardless of the choice of age unit.

The "invariant characteristics" defining a group could include the industry or employment type in the previous year if individual-level panel data are given. With repeated cross-sectional data, it is not possible to use those variables in the definition of a group. However, it is still possible to construct industry and employment type-specific outcomes for each group. Then, the same procedure described above can be applied to each industry-by-type outcome. The second stage in that case aggregates the individual-level (group-level) predicted outcomes at each industry-by-employment type cell (c) across the population (e.g., $\hat{E}_t^c = \sum_{g,a} e_{g,a,t}^c P_{g,a,t}^c$). The third stage subtracts the forecasting error term just before the COVID-19 pandemic (e.g., $u_{t_0}^c = E_{t_0}^c - \hat{E}_{t_0}^c$) from all differences in subsequent periods.

C. *Adjustments for Senior Citizen Jobs Created by the Government*

The government creates a considerable number of jobs for senior citizens aged 65 or more.[8] These jobs, mostly temporary jobs lasting less than a year with less than 15 hours per week, are provided for the purpose of alleviating poverty among the elderly. While these 'senior jobs' were also severely affected by the COVID-19 crisis, it is better to analyze the impact of the health crisis on them separately because they are directly created by the government. Furthermore, some movements in senior jobs are for purely administrative reasons (e.g., changes in the timing of initiating those projects each year). To eliminate fictitious changes in employment due to government-initiated jobs, all jobs in the sector of public administration and healthcare and welfare held by workers older than 65 are omitted from the analyses of this study. In other words, workers with those jobs are treated as non-employed and their hours worked are counted as zero. However, this does not affect the results from industry or employment type-specific analyses.

D. *Adjustments for Weekly Hours Using Election-day Variations*

Weekly hours worked can be significantly affected by changing holidays during the reference week. For example, an unusual holiday in the reference week can significantly underestimate weekly hours worked by approximately 5-7% for the month (in a monthly survey), which is far from negligible even at the annualized level. A few holidays in Korea have a changing day of the week because they fall on a specific date on the solar calendar. Two major holiday seasons, *Seol* and *Chuseok*, are on specific dates on the lunar calendar – they can even sometimes appear on a different page of the solar calendar compared to the previous year.

This study uses previous election-day variations in weekly hours worked to control for hour changes in 2020 due to changing holidays. In 2020, there were two unusual holidays; one is April 15, which was the election day for the parliament, and the other was August 15, a national holiday, which was on a Saturday in 2020 (it was on a Thursday in 2019). By using the similar framework explained above, the differences between actual and predicted hours are estimated for each demographic group. The estimated group-level differences in hours worked during the previous

[8]The government also supports jobs for citizens between 60 and 64 of age. However, those jobs are mostly market-based; they are included in the analyses.

election days[9] are used to adjust the predicted weekly hours in 2020.

It is also important to consider concurrent institutional changes. Maximum working hours were reduced to 52 hours per week starting in 2018. Prior to this reform, it had been (implicitly) 68 hours per week. The reform was implemented stepwise according to firm size, and the new mandate was applied to medium-sized enterprises with 50 to 299 employees from January of 2020. To eliminate the impact of the institutional changes, this study uses only working-hour variations within the newly restricted range by replacing weekly hours worked exceeding 52 with the new maximum hours in all years.

E. *The Impact of the COVID-19 Crisis on Employment at the Aggregate Level*

From the EAPS data using the methodology described above, this subsection provides an outline of employment losses at the aggregate level by graphs. The next section discusses in detail the definition of persistence in this study, its identification, and the estimation results.

Although the intensity of the COVID-19 crisis was relatively mild in Korea, this health crisis had a large and impressive impact on the labor market. Figure 3 shows the labor market impact of the health crisis, which aggregates the individual-level impacts over the entire population. The three shaded areas are the three major COVID-19 outbreaks. The three graphs correspond to job losses, job losses including temporary layoffs (i.e., employed but not worked during the reference week), and the losses in full-time equivalents (FTEs), which is the total (adjusted) hours worked divided by the predicted averages without COVID-19.

At the initial outbreak that appears in the employment data from March to April of 2020, the number of jobs plummeted immediately in Korea, similar to other countries. The job losses were approximately 3% of the predicted number of jobs in mid-April without the COVID-19 crisis. However, job losses may underestimate the actual shock on employment, as many labor relations continued with zero hours. The losses in jobs with positive hours worked were more than twice those of job losses at approximately 6.3% of the predicted number of those jobs in mid-April. The difference between the two measures during the first outbreak of COVID-19 reflects the unprecedented increase in temporary closures or leaves, a distinctive feature of this pandemic-driven employment shock. However, temporary layoffs are not the entire story of the adjustment at the intensive margin. The reduction in hours worked, in addition to temporary closures or leaves, was also significant, as shown by the significant differences between job losses, including temporary layoffs and FTE losses, throughout the pandemic period. FTE losses reached 8.1% of the predicted hours in mid-April.

[9]Specifically, I estimated the average changes in group-level working hours during the two recent nationwide election days (the parliamentary election day of April 13, 2016 (Wed) and the election for all local governments on June 13, 2018 (Wed) in a difference-in-differences framework, using these estimates to adjust weekly hours for the reference weeks with the unusual holidays in 2020.

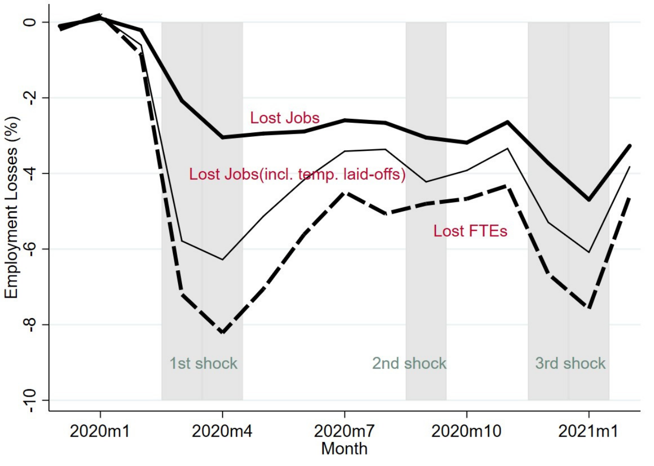


FIGURE 3. EMPLOYMENT LOSSES DURING THE COVID-19 CRISIS

Note: Employment losses are evaluated by calculating the difference between actual and predicted outcomes without the COVID-19 pandemic. The aggregate-level losses are calculated by summing up the individual-level differences based on the group-level predictions for each period. The unusual working-hour variations in April and August are adjusted by using estimates of previous election-day variations at the demographic group level, as explained in the data and methodology section. Lost jobs (incl. temp. layoffs) denote losses in jobs with positive hours, including the unprecedented increase in temporary layoffs, mostly through temporary closures and leaves.

During the first lull from May to August of 2020, the government implemented various measures to boost the economy. The most notable measure was the stimulus payment for all individuals, roughly 200,000 KRW per person.[10] The stimulus payment, for which the government allocated 14.3 trillion KRW in total (0.75 percent of the 2019 GDP), was paid in early May mostly into credit/debit card accounts. Furthermore, the third supplementary budget, a 35.1 trillion KRW package, was approved by the parliament on July 3. The government announced the implementation of 75 percent of the supplementary budget within three months from July to October. While evaluating the employment effect of these government transfers is beyond the scope of this study, the expanded government transfers are highly likely to have boosted employment during the period of expedited implementation.[11] In particular, the spikes in July are likely to reflect the boosting effects of the government transfers. Nonetheless, the recovery in employment losses was slow overall, showing a sign of persistence.

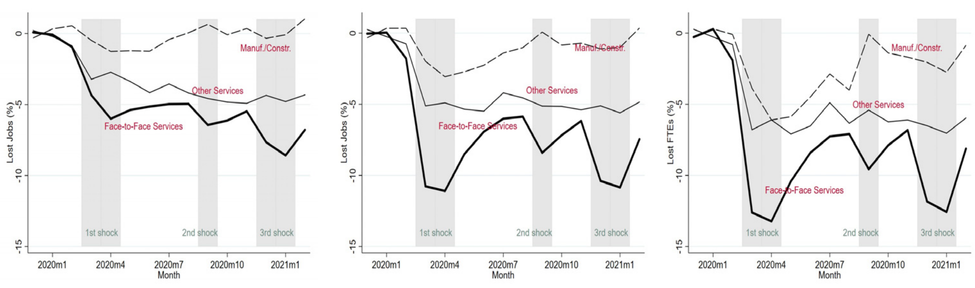
A closer look by industry and employment type shows two important patterns about the first outbreak and the subsequent lull. First, the face-to-face service sector[12] was the sector hardest hit, but the losses in that sector were concentrated during the

[10]The actual amount was based on the number of household members: 400,000 KRW for a single-person household, 600,000 KRW for a two-person household, 800,000 KRW for a three-person household, and 1,000,000 KRW for a household with four people or more.

[11]The employment inducement coefficient was 10.6 per billion KRW in 2017 and 10.1 in 2018 according to the Bank of Korea. Based on the 2018 coefficient, if the final demand had increased by 35.1 trillion KRW, the total employment (including all direct and indirect effects) would have increased by 355,000 jobs, approximately 1.3 percent of the total number of jobs predicted in 2020.

[12]The face-to-face service sector is broadly defined by six industries at the one-digit level (21 categories) available in the EAPS data: arts, sports and recreational activities; education; personal services; restaurants and lodging; transportation; and wholesales and retails.

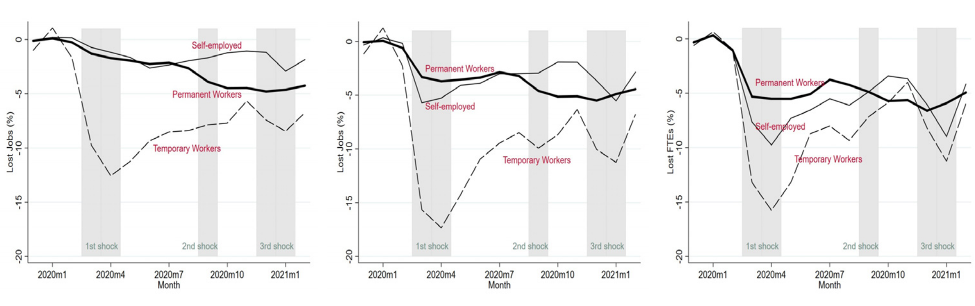
outbreaks. Figure 4 shows that the employment losses of the face-to-face sector were greater than those of other sectors. However, the gap between the service sector and the other sectors became much smaller after the outbreak, suggesting that the extra losses in this sector were transitory. Second, temporary workers were severely hit by the COVID-19 outbreak, but their speed of recovery was also rapid (Figure 5). Although the employment losses of those workers remained to some extent, a significant portion of the losses disappeared. Conversely, permanent workers appear to have been mostly unaffected at the extensive margin, although they also experienced large reductions in hours worked. However, their losses appear to be much more persistent. Self-employed workers were similar to permanent workers at the extensive margin but similar to temporary workers at the intensive margin.



(a) Jobs (b) Jobs with positive hours (c) FTEs

FIGURE 4. EMPLOYMENT LOSSES DURING THE COVID-19 CRISIS: BY INDUSTRY

Note: Employment losses are evaluated by calculating the difference between actual and predicted outcomes without the COVID-19 pandemic. Aggregate-level losses are calculated by summing up the individual-level differences based on the group-level predictions and subdivided by industries and employment types. The face-to-face service sector is defined by six industries at the broadest level: arts, sports and recreational activities; education; personal services; restaurants and lodging; transportation; and wholesales and retails. Other services include all other service industries except for public administration and healthcare and welfare. Some industries, such as public administration, health and welfare; electricity, gas and water; and agriculture and fisheries, are not shown in the graphs, although they are included in the figure for aggregate employment losses.



(a) Jobs (b) Jobs with positive hours (c) FTEs

FIGURE 5. EMPLOYMENT LOSSES DURING THE COVID-19 CRISIS: BY EMPLOYMENT TYPE

Note: Employment losses are evaluated by calculating the difference between actual and predicted outcomes without the COVID-19 pandemic. Aggregate-level losses are calculated by summing up the individual-level differences based on the group-level predictions and subdivided by industries and employment types. Employment types are permanent workers (with a labor contract equal to or exceeding a year), temporary workers (less than a year), and the self-employed (including unpaid family workers who work more than 18 hours per week).

At the second outbreak that should have appeared in the EAPS data in September, the aggregate employment losses appear to be very small by any standard (Figure 3). A closer look at the employment losses, however, reveals that there was substantial heterogeneity across sectors and job types. First, the face-to-face service sector was significantly affected by the second outbreak by any standard (Figure 4). Second, certain sectors, such as manufacturing and construction, were in rapid recovery, masking the negative impacts on face-to-face services. This is likely due to the expanded government transfers during this period, as explained above. Third, while the face-to-face service sector was the industry hardest hit during the COVID-19 outbreaks, Figure 4 shows that the additional employment shock on the face-to-face service sector was likely transitory. The extra employment losses in the face-to-face services compared to those associated with other services mostly disappeared once the COVID-19 outbreaks subsided. Fourth, permanent jobs decreased by any standard during this period (Figure 5). This is not likely due to the statistical definition of temporary layoffs in the EAPS data, which counts unpaid temporary layoffs as employed for up to six months, as all measures move in the same direction. Fifth, temporary jobs and self-employment did not decrease much, unlike during the first outbreak (Figure 5). This provides indirect evidence that the aggressive expansion in government transfers increased labor hours for those in temporary jobs and for the self-employed, given that permanent jobs decreased during this period. Furthermore, the number of temporary jobs with positive hours decreased, showing that there were at least some temporary layoffs among them. This suggests higher-order heterogeneity at the industry-by-type level.

During the second lull from October to November, the face-to-face service sector rebounded again. However, the employment losses of the sector remained a level similar to that during the previous lull, confirming the existence of persistent losses. The employment losses of other sectors also continued.

At the third outbreak, the employment losses were intense, particularly at the extensive margin. All three measures of employment declined together with only small differences (Figure 3). The relatively large adjustment at the extensive margin during the third shock is associated with the decreased number of temporary layoffs. It appears that employers responded to the shock by terminating labor relations, unlike in the first shock. Other patterns resemble those in the previous outbreaks. Figure 4 reconfirms that the face-to-face service sector was severely hit during the third outbreak by any standard, and those extra employment losses were transitory. Figure 5 reconfirms that temporary and self-employed workers were also severely hit during the third outbreak but that their employment losses were transitory.

Although the third outbreak relented by mid-February, the number of confirmed cases remained between 300 and 500 per day, similar to the previous peaks. The employment losses rebounded rapidly, partly owing to the announcement of the vaccination plan which was to start on February 26, 2021. Nevertheless, a large portion of the employment losses remained during the third lull at a level similar to those in the previous lulls, suggesting that the negative impacts will continue at least for a while.

IV. Decomposition into Persistent and Transitory Components

In addition to the individual-level heterogeneity in the initial employment shock due to COVID-19, it is important to understand the persistence of the heterogeneous impacts. For example, the sizes and contents of income and job support programs during the recovery process will significantly differ depending on the persistence of the employment losses for each group. The optimal macroeconomic policies are also likely to differ depending on the persistence of the shock (e.g., Gallant *et al*., 2020).

While there is more than one way to analyze the persistence of the employment shock by COVID-19, this study decomposes the employment losses into persistent and transitory components for each group because the size of the persistent component matters.

$$
\begin{aligned}
\Delta\hat{E}_{it} &= \phi_{g(i)} + (D_t^P + D_t^T)\alpha_{g(i)} + D_t^T \beta_{g(i)} + \varepsilon_{it} \\
&= \phi_{g(i)} + D_t^P \alpha_{g(i)} + D_t^T(\alpha_{g(i)} + \beta_{g(i)}) + \varepsilon_{it}
\end{aligned}
\tag{1}
$$

In the above equation, $\Delta\hat{E}_{it}$ is the predicted employment losses of individual i at period t from the information available before the pandemic ($\Delta\hat{E}_{it} = E_{it} - \hat{E}_{it}$), D_t^T is an indicator of all COVID-19 outbreaks, and D_t^P is an indicator of the lulls after the COVID-19 outbreaks.

The first line decomposes the impact of the COVID-19 crisis into four parts. The first term on the right-hand side is the pre-pandemic heterogeneity at the group level. The second term, $(D_t^P + D_t^T)\alpha_g$, is the persistent component, which is the employment losses throughout the pandemic. This component is identified from the observed recovery periods after the COVID-19 outbreaks ($D_t^P = 1$). The third term is the transitory component ($D_t^T \beta_g$), which is the extra losses during the outbreaks in addition to the persistent component. The last term is an idiosyncratic error term, which includes traditional measurement errors. The second line simply rearranges the persistent and transitory components on the first line. It becomes clear that the persistent component is identified by the observed recovery periods ($D_t^P = 1$).

This measure of persistence, the average impact after the shock period, is closely linked to previous studies on the persistent impacts of job losses (Jacobson, LaLonde, and Sullivan, 1993; Stevens, 1997; Chan and Stevens, 2001; Davis and von Wachter, 2011) or on graduating during a recession (Kahn, 2010; Oreopoulos, Von Wachter, and Heisz, 2012; Han, 2018). As in these previous studies, the identification of persistence comes directly from observed events. In normal times, the indicators of shock and recovery periods are specific to the individual and are mostly unobserved. During the COVID-19 crisis, which is a common shock, those indicators are observed for all individuals.

Finally, the persistent component requires a cautious interpretation. The persistent component may also be decomposed into two parts: the effect of the pandemic (δ) and the persistent effect of COVID-19 outbreaks (ψ). With the observations after the pandemic ($D_t^C = 0$), those two effects are separately identified. This cannot be done for now, but previous findings on the persistence of job losses for certain groups

($\psi_{g(i)}$) can provide partial information on such effects.

$$D_t^P \alpha_{g(i)} = D_t^P (D_t^C \delta_{g(i)} + \psi_{g(i)}), \tag{2}$$

where D_t^C is an indicator of the entire COVID-19 pandemic period.

V. Estimation Results

All estimates in this section should be interpreted as percentage point changes in the ratio of the employed to the relevant population, as all regression equations are estimated at the individual level with population weights. A full-time equivalent (FTE) job in this section is defined by the individual-level outcome divided by the predicted group average to make the percentage point changes comparable to the other measures of employment change.

A. *Decomposition at the Aggregate Level*

he results at the aggregate level are largely consistent with the graphs presented in the previous section, but the decomposition into persistent and transitory components provides additional information. First, employment losses are persistent at both the extensive and intensive margins. Table 2 shows that the persistent component in employment losses is sizable by any standard: a 1.7%p decrease in jobs, a 2.3%p decrease in jobs with positive hours worked, and a 3.1%p decrease in FTEs. The difference between the first two measures, which indicates temporary layoffs, is 0.6%p. This suggests that many "temporary" layoffs continued over an extended period after the outbreaks. Some service industries were continuously affected by the ban on international travel and large gatherings. Furthermore, the demand for local services recovered very slowly, which can be verified from service production and consumption indices.[13] The difference between the last two measures, which reflects hour reductions except for temporary layoffs, is 0.8%p. This shows that the hourly adjustment at the intensive margin other than temporary closures or leaves was also significant and persistent.

Second, the transitory component in employment losses is small at the extensive margin and large at the intensive margin, which is unsurprising given the strong employment protection in Korea. However, the difference in the transitory component across measures is mostly explained by the difference between the first two measures, 0.7%p, showing that approximately 56% of those temporarily laid off during the outbreaks returned to work.[14] The difference between the last two measures was very small, less than 0.1%p. This shows a distinct characteristic of the employment shock

[13]Consumption of durables increased rapidly, masking the slow recovery in service consumption. According to the Economic Statistics System by the Bank of Korea, service consumption decreased by 5.2%, 6.8%, 7.7%, and 9.5% from the first to last quarters of 2020 (year on year), while consumption of durables increased by 0.0%, 18.6%, 16.6%, and 10.3%, respectively.

[14]It is not identified whether or not they were recalled to the same employer.

TABLE 2—EMPLOYMENT LOSSES DURING THE COVID-19 CRISIS: AT THE AGGREGATE LEVEL

	(1) Job	(2) Job	(3) Job($h > 0$)	(4) Job($h > 0$)	(5) FTE	(6) FTE
Persistent component (α)	-0.017***		-0.023***		-0.031***	
	(0.003)		(0.003)		(0.003)	
× First shock		-0.017***		-0.024***		-0.033***
		(0.002)		(0.003)		(0.004)
× Second shock		-0.018***		-0.022***		-0.027***
		(0.003)		(0.003)		(0.004)
× Third shock		-0.020***		-0.022***		-0.027***
		(0.003)		(0.003)		(0.004)
Transitory component (β)	-0.002*		-0.009***		-0.010***	
	(0.001)		(0.002)		(0.001)	
× First shock		0.002		-0.011***		-0.012***
		(0.002)		(0.003)		(0.003)
× Second shock		-0.001		-0.003*		-0.002
		(0.002)		(0.002)		(0.002)
× Third shock		-0.006***		-0.011***		-0.015***
		(0.002)		(0.002)		(0.002)
Group FE	Y	Y	Y	Y	Y	Y
N	833,142					
$\bar{\gamma} = \alpha/(\alpha + \beta)$	0.88		0.71		0.75	

Note:1) All specifications are weighted by the population weights, 2) Groups are defined the gender-by-age-by-education level, 3) COVID-19 shocks refer to the three major outbreaks: the first from March to April, the second from late-August to September, and the third from December to January of, 2021, 4) Standard errors are clustered at the demographic group level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

due to the health crisis.

Third, the recurring employment shocks due to the three COVID-19 outbreaks and subsequent lulls showed similar patterns in terms of persistent components, but their transitory components were quite different. The transitory component during the first shock was almost zero at the extensive margin but was much larger at the intensive margin (column 2 in Table 2), which suggests that many firms perceived the health crisis as temporary at the first outbreak. The second shock had very small transitory components through all measures (column 4 in Table 2), an outcome related to the expansionary fiscal policies during the same period. The transitory component was salient across all employment measures (column 6 in Table 2), which also suggests changes in employer responses.

B. *Demand Side Heterogeneity: By Industry and Employment Type*

Aggregate-level analyses may hide important heterogeneity at the firm or firm-by-contract level, as implied by Figures 4 and 5. To investigate the demand-side heterogeneity, this subsection decomposes the employment outcome into industry-by-employment type cells. This exercise provides partial answers to questions such as which groups were persistently hit by the unusual crisis and why their losses were more persistent.

The estimations results confirm the patterns in Figure 4 and 5 with additional information. The common patterns across all measures (Tables 3, 4, and 5) are as follows. First, the persistent components estimated in each industry-by-type outcome

TABLE 3—JOB LOSSES DURING THE COVID-19 CRISIS: BY INDUSTRY AND EMPLOYMENT TYPE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Face-to-Face Services			Other Services			Manuf./Constr.		
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
Persistent component (α)	-0.007***	-0.004**	-0.002	-0.003*	-0.001	-0.000	-0.001	-0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Transitory component (β)	-0.000	-0.002**	-0.001	0.000	0.000	0.000	-0.000	-0.000	0.000*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\overline{\gamma} = \alpha/(\alpha+\beta)$	0.98	0.69	0.79	1.03	1.03	-	0.66	0.53	0.49
By shock period Persistent × First shock	-0.005***	-0.005***	-0.002	-0.002	-0.002*	-0.000	-0.000	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
× Second shock	-0.009***	-0.004*	-0.002	-0.004**	-0.001	-0.000	-0.002	0.000	0.001*
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
× Third shock	-0.010***	-0.003	-0.003	-0.004*	-0.001	-0.000	-0.001	0.000	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Transitory × First shock	0.002*	-0.002	-0.000	0.001	-0.000	0.000	-0.001	-0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
× Second shock	0.000	-0.002	-0.000	0.000	0.000	0.000	0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
× Third shock	-0.000	-0.003***	-0.000	-0.000	-0.001	0.000	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Group FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	833,142								

Note: 1) All specifications are weighted by the population weights, 2) Groups are defined at the gender-by-age-by-education level, 3) COVID-19 shocks refer to the three major outbreaks: the first from March to April, the second from late-August to September, and the third from December to January of 2021, 4) Face-to-face services are defined by six industries at the level provided by the EAPS data: arts, sports and recreational activities; education; personal services; restaurants and lodging; transportation; and wholesale and retail jobs. Other services include all other service industries except for public administration and healthcare and welfare, 5) Standard errors are clustered at the demographic group level. * p < 0.1, ** p < 0.05, *** p < 0.01.

were salient for all types of jobs in face-to-face services and permenant jobs in other services. While the former is obviously due to social distancing measures and the fear of infection, the latter is not, suggesting the need for further analyses on worker-side heterogeneity. This is explained in the next subsection.

Second, the transitory components of the employment losses in the face-to-face service sector were also large and statistically significant, outcomes mostly explained by temporary jobs and self-employment within the sector. While temporary workers were hit hard by the employment shocks by COVID-19, their employment recovered rapidly during the lulls due to low hiring and firing costs.[15] Changes in self-employment at the intensive margin are explained by the wide discretion in working hours.

Third, by shock period, the persistent component becomes larger in the latest shock for the permanent jobs in service sectors, which is consistent with the explanation that employers' responses to the employment shock due to COVID-19 changed during the crisis. Accumulated losses during the longer-than-expected crisis may have led to hiring cuts (particularly for small firms), dismissals for managerial

[15]The Labor Standards Act mandates employers to save a month's salary (or 30 days) each year for severance pay (regardless of the reason for job separation). This is only applicable to permanent workers.

TABLE 4—JOB LOSSES INCLUDING TEMPORARY LAYOFFS: BY INDUSTRY AND EMPLOYMENT TYPE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Face-to-Face Services			Other Services			Manuf./Constr.		
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
Persistent component (α)	-0.008***	-0.005***	-0.004**	-0.004**	-0.002	-0.000	-0.002	-0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Transitory component (β)	-0.001*	-0.004***	-0.003***	0.000	-0.000	0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\overline{\gamma} = \alpha/(\alpha+\beta)$	0.88	0.56	0.53	1.04	0.83	4.00	0.90	0.51	0.22
By shock period Persistent × First shock	-0.006***	-0.006***	-0.004**	-0.003**	-0.002*	-0.000	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
× Second shock	-0.009***	-0.005**	-0.003	-0.004**	-0.001	0.000	-0.002	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
× Third shock	-0.010***	-0.004	-0.004**	-0.004*	-0.001	-0.000	-0.001	0.000	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Transitory × First shock	-0.000	-0.005***	-0.004***	0.001	-0.001	-0.000	-0.001	-0.001	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
× Second shock	-0.000	-0.003***	-0.001	0.000	-0.000	0.000	(0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
× Third shock	-0.001	-0.005***	-0.002***	-0.000	-0.001	0.000	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Group FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N					833,142				

Note: See Table 3 notes.

TABLE 5—FTE LOSSES DURING THE COVID-19 CRISIS: BY INDUSTRY AND EMPLOYMENT TYPE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Face-to-Face Services			Other Services			Manuf./Constr.		
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
Persistent component (α)	-0.010***	-0.005**	-0.005**	-0.005**	-0.001	-0.000	0.002	-0.002	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Transitory component (β)	-0.002**	-0.004***	-0.004***	0.000	-0.001	-0.000	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
$\overline{\gamma} = \alpha/(\alpha+\beta)$	0.83	0.55	0.54	1.06	0.58	0.74	1.12	0.81	14.00
By shock period Persistent × First shock	-0.009***	-0.006***	-0.005***	-0.004**	-0.001	-0.000	-0.002	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
× Second shock	-0.011***	-0.004	-0.004	-0.005**	-0.002	-0.000	-0.002	-0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	.002)	(0.002)	(0.001)
× Third shock	-0.011***	-0.004	-0.006**	-0.005**	-0.001	-0.001	-0.001	-0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	.002)	(0.002)	(0.001)
Transitory × First shock	-0.002	-0.004**	-0.006***	0.001	-0.002	-0.000	0.000	-0.001	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
× Second shock	-0.000	-0.003***	-0.002**	0.000	0.000	0.000	0.002*	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
× Third shock	-0.002**	-0.005***	-0.003***	-0.000	-0.001	0.001	-0.002*	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Group FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N					833,142				

Note: See Table 3 notes.

reasons, and business closures, all of which can affect the number of permanent jobs. The persistent component became smaller for temporary jobs in service sectors, which is also consistent with the changes over time in employer responses.

Differences among the three different measures of employment are also noteworthy. First, the differences between the first two measures (Tables 3 and 4), which indicate temporary layoffs, are observed in relation to the face-to-face service sector – the persistent components for self-employment and the transitory components for the temporary jobs and self-employment. These differences mean that temporary workers in this sector who retained their jobs with zero hours (temporary layoffs) were rehired in the same sector[16] once the outbreak subsided, but many self-employed workers stayed at zero hours even after the outbreak.

Second, the differences between the last two measures (Tables 4 and 5) (i.e., hour adjustments except for temporary layoffs) are notable for the persistent component of the permanent jobs in the two service sectors and the transitory component of self-employment in the face-to-face service sector. This indicates that permanent jobs were relatively more protected (i.e., continued with reduced working hours), although the protection became weaker during the latest shock (i.e., temporary layoffs). In addition to the strong employment protection by labor laws, firms may have wanted to retain and utilize those workers with high skills and/or those who were a successful match. Also, many self-employed workers responded to the crisis by reducing their working hours rather than using the temporary closure strategy, owing to the fixed costs associated with closing and reopening a business.

C. *Worker-side Heterogeneity: By Gender, age, and Education*

This subsection extends the empirical investigation in the previous subsection by further delving into individual heterogeneity. When the employment shock due to COVID-19 is particularly strong for certain sectors (e.g., the face-to-face service sector) or employment types (e.g., temporary jobs), the employment shock is naturally heterogeneous across individuals as the compositions of sectors or employment types differ across demographic groups. Furthermore, it is also possible that the employment shocks are particularly strong for certain demographic groups, for reasons unrelated to industry or employment types.

Table 6 reports the estimation results considering the group-level heterogeneity of the employment shock. While employment losses by demographic groups are well-documented,[17] some patterns found in this study are worth highlighting. First, young men (ages 15-29) were among the groups hardest hit throughout this pandemic period. This group had large and persistent employment losses according to all three measures (columns 1, 3, and 5). Second, women, particularly those in their 30s and 50s, were also persistently hit by the pandemic. Their employment losses were large and persistent by any standard (columns 1, 3, and 5). Third, less

[16]It is not identified whether or not they were recalled to the same employer.

[17]For example, the employment of young people (ages 15-29) in Korea declined from the very beginning of the pandemic (Han, 2020). The employment of women also dropped disproportionately more, which was a common phenomenon across countries during this pandemic (e.g., Albanesi and Kim, 2021; Alon *et al*., 2020; Alstadsæter *et al*., 2020; Bui, Button, and Picciotti, 2020; Cheng *et al*., 2020; Russell and Sun, 2020; Sevilla and Smith, 2020).

TABLE 6—PERSISTENCE OF EMPLOYMENT LOSSES DURING THE COVID-19 CRISIS

	(1) Job	(2) Job	(3) Job(h > 0)	(4) Job(h > 0)	(5) FTE	(6) FTE
Persistent component × Men × 15-29	-0.039***	-0.037***	-0.041***	-0.040***	-0.045***	-0.039***
	(0.011)	(0.010)	(0.011)	(0.010)	(0.012)	(0.010)
× Men × 30-39	-0.018***	-0.016***	-0.024***	-0.021***	-0.035***	-0.029***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
× Men × 40-49	-0.005	-0.003	-0.012*	-0.009	-0.024***	-0.018**
	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
× Men × 50-59	-0.007	-0.005	-0.019***	-0.017**	-0.037***	-0.032***
	(0.006)	(0.008)	(0.006)	(0.007)	(0.006)	(0.007)
× Men × 60+	-0.002	-0.003	-0.006	-0.008	-0.016	-0.015
	(0.006)	(0.007)	(0.006)	(0.006)	(0.012)	(0.010)
× Women × 15-29	-0.012**	-0.009	-0.018***	-0.017**	-0.020***	-0.015*
	(0.005)	(0.007)	(0.006)	(0.007)	(0.005)	(0.009)
× Women × 30-39	-0.037***	-0.034***	-0.038***	-0.035***	-0.042***	-0.036***
	(0.010)	(0.009)	(0.007)	(0.007)	(0.010)	(0.008)
× Women × 40-49	-0.018*	-0.015*	-0.027***	-0.023***	-0.032***	-0.024**
	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
× Women × 50-59	-0.031***	-0.029***	-0.037***	-0.035***	-0.054***	-0.049***
	(0.005)	(0.007)	(0.006)	(0.008)	(0.007)	(0.010)
× Women × 60+	-0.014***	-0.017**	-0.017***	-0.022***	-0.017***	-0.018*
	(0.004)	(0.008)	(0.004)	(0.008)	(0.006)	(0.010)
× LT HSG		0.005		0.008		0.005
		(0.008)		(0.007)		(0.009)
× HSG		-0.005		-0.006		-0.010*
		(0.005)		(0.005)		(0.006)
× CLG (2-Yr)		-0.011		-0.010		-0.017*
		(0.010)		(0.009)		(0.010)
× Grad Sch.		0.016		0.008		0.004
		(0.021)		(0.018)		(0.020)
Transitory component × Men × 15-29	-0.006*	-0.003	-0.010***	-0.011***	-0.008***	-0.008***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
× Men × 30-39	-0.004	-0.003	-0.010***	-0.010***	-0.009**	-0.009***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
× Men × 40-49	0.001	0.003	-0.003	-0.003	-0.004	-0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
× Men × 50-59	-0.005***	-0.003	-0.009***	-0.009***	-0.010**	-0.010**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)
× Men × 60+	-0.000	0.002	-0.006***	-0.007**	-0.007***	-0.008**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
× Women × 15-29	-0.012*	-0.010	-0.017**	-0.017**	-0.017***	-0.018***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)
× Women × 30-39	0.000	0.001	-0.013***	-0.013**	-0.014***	-0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)
× Women × 40-49	-0.001	0.001	-0.015***	-0.015***	-0.018***	-0.018***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)
× Women × 50-59	-0.000	0.002	-0.012***	-0.012***	-0.012***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)
× Women × 60+	0.001	0.003	-0.005	-0.006	-0.007	-0.008*
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
× LT HSG		-0.002		0.002		0.002
		(0.003)		(0.004)		(0.004)
× HSG		-0.004		-0.001		-0.002
		(0.003)		(0.003)		(0.002)
× CLG (2-Yr)		0.002		0.002		0.002
		(0.004)		(0.004)		(0.004)
× Grad Sch.		-0.002		0.003		0.006
		(0.005)		(0.006)		(0.009)
Group FE	Y	Y	Y	Y	Y	Y
N	833,142					

Note:1) All specifications are weighted by the population weights, 2) Groups are defined at the gender-by-age-by-education level, 3) The final education statuses are classified into five categories: less than high school graduate, high school graduate, college graduate from a 2-3 year program, college graduate from a 4-5 year program, and holder of a post-graduate degree, 4) Standard errors are clustered at the demographic group level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

educated workers, even after controlling for gender and age, showed persistent employment losses at the intensive margin (column 6). Fourth, while some groups such as young people (ages 15-29) and men in their 50s had relatively large transitory components in their job losses (column 1), all estimates became small and insignificant if controlling for their education level (column 2). This suggests the transitory job losses were mostly related to low educational status. This is also supported by alternative estimates of persistence reported in Table A4 in the Appendix.[18]

The results above may simply reflect the compositional effects from the sector- or type-specific shock. A further decomposition by industry-by-employment type can help to control for these effects. Through a comparison across demographic groups within each cell, it is possible to identify which groups are particularly affected by the COVID-19 crisis. Table 7 summarizes the decomposition results by focusing on only the qualitative aspects (see Appendix Tables A1, A2, and A3 for full estimation results).[19]

First, the persistent losses of permanent jobs in the face-to-face service sector are statistically significant at the ten percent level among young men, men in their 40s and 50s, and women in their 50s. These groups are mostly in transition into or out of their careers.[20]

Although the labor demand in the face-to-face service sector may at least partially rebound after the pandemic, the hysteresis of the employment shock by the COVID-19 crisis will exist in various forms. Firm closures and capital-labor substitutions such as unmanned systems introduced in the hard-hit service sector during the health crisis will reduce labor demand beyond the pandemic, particularly for older workers. The increase in labor demand will mostly come from newly established firms, whose labor compositions will be different from those of previous firms (Barth *et al.*, 2017). The quality of newly found jobs during the recession is also likely to be lower than those in normal times (Haltiwanger *et al.*, 2018).

The job losses for middle-aged and older workers during the COVID-19 crisis, many of whom move out of their career jobs, are predicted to have persistent effects (e.g., Jacobson, LaLonde and Sullivan, 1993; Stevens, 1997; Davis and von Wachter, 2011; Chan and Stevens, 2001; Amior and Manning, 2018). Given the rigidities in the Korean labor market, these persistent effects for displaced workers are likely stronger than those found in relatively flexible labor markets.

The job losses for young men will disappear with new hiring during the recovery process. However, the unlucky cohorts graduating during the pandemic are likely to have long-lasting effects over their lifetime in various dimensions (e.g., Kahn, 2010; Oreopoulos, Von Wachter and Heisz, 2012; Schwandt and Von Wachter, 2019). Graduates during the previous recessions in Korea experienced persistent negative effects on their labor market outcomes. Additional negative effects were found in

[18]Appendix Table A4 estimates the following equation,

$$(\Delta\hat{E}_{g,t} - \phi_g) = \gamma_g \times (\Delta\hat{E}_{g,t-1} - \phi_g) + \nu_{g,t}, \nu_{g,t} \sim N(0, \sigma_g^2), \forall t \quad s.t. D_t^P = 1,$$

where D_t^P is an indicator of the lulls after the COVID-19 outbreaks.

[19]Because the estimates are interpreted as percentage point changes, additional rescaling for conversion to a percent is required for a quantitative comparison across demographic groups.

[20]The retirement age from a career job is distributed around the early 50s, except for a small number of workers with jobs secured until mandatory retirement.

TABLE 7— PERSISTENT EMPLOYMENT LOSSES DURING THE COVID-19 CRISIS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Face-to-Face Services			Other Services			Manuf./Constr.		
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
Jobs									
Men, 15-29	−**	−***	−	−	−	−	−	−	+
Men, 30-39	+	+	−***	−	+*	+	−	+	+
Men, 40-49	−***	+	+	−	−	+	−	+**	+**
Men, 50-59	−*	+	+	−	−	−	+	+	−
Men, 60+	−	+	−**	−	+	+*	−	−	+
Women, 15-29	−	−***	+	+	+	−	+	−	−
Women, 30-39	−	−	−	−***	−	+	+***	−**	+***
Women, 40-49	−	−*	+	−	−	−	−	+	+
Women, 50-59	−*	−	−**	−	−	−	−	−	−*
Women, 60+	+	+	−	+	−***	−	−**	+	+
Jobs (h>0)									
Men, 15-29	−**	−***	−	−	−	−	+	−	+
Men, 30-39	+	+	−***	−	+*	+	−*	+	+
Men, 40-49	−***	+	+	−	−	+	−	+*	+
Men, 50-59	−**	+	+	−	−	−	−	+	−
Men, 60+	−	+	−***	−	+	+	−	−	+
Women, 15-29	−	−***	−	−	+	−	+	+	−
Women, 30-39	−	−*	−	−**	−	+	+***	−**	+***
Women, 40-49	−	−***	+	−	−	−	−	+	+
Women, 50-59	−*	−	−***	−	−	−	−	−	−
Women, 60+	+	−	−	+	−***	−	−**	−	+
FTEs									
Men, 15-29	−**	−***	−	−	−	+	+	−	+
Men, 30-39	−	+	−**	−	+*	+	−*	−	−
Men, 40-49	−***	+	−	−	−	+	−	+	+
Men, 50-59	−**	+	+	−	−	−	−	−	−**
Men, 60+	−	+	−*	−	+	+	−	−	+
Women, 15-29	−	−***	−	−	+	−	+	+	−
Women, 30-39	−	−	−***	−***	−	+	+**	−**	+***
Women, 40-49	−	−	+	−	−	−	−	+	+
Women, 50-59	−***	−	−***	−	−	−	−	−	−**
Women, 60+	+	−	−	−	−	−	−*	+	+

Note:1) Standard errors are clustered at the demographic group level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, 2) See Tables A1, A2, and A3 in the Appendix for more details.

earnings by high school graduates and employment in large firms by college graduates (Han, 2018).

Second, the persistent job losses of women in their 30s were the most salient in relation to permanent jobs in other services. There exists a clear difference from other persistently hit workers, whose employment losses were concentrated in the face-to-face service sector. This supports the contention that the employment losses borne by these women may have been the supply-driven types, as none of the other demographic groups in this sector showed clear employment losses by any employment measure. As suggested by previous studies, this may have been due to school closures and the uneven burden of childcare (Alon *et al*., 2020; Russell and Sun, 2020; Sevilla and Smith, 2020). However, it is uncertain how much the effects of mothers' employment losses during the COVID-19 crisis are likely to persist beyond the pandemic, particularly when those mothers are highly educated and voluntarily quit their jobs.

Third, although the employment losses of young women (ages 15-29) were relatively less overall, Table 7 shows that they also experienced persistent job losses in the face-to-face services. They worked more in other services compared to the predicted level without the COVID-19 crisis, although the increases in the employment rate are not statistically significant. Combined with the job losses of women in their 30s in the same sector, it is feasible that young women partially filled the sudden vacancies of those women who voluntarily quit, contributing to the rapid recovery of the overall employment of young women. However, the group-level estimates provide at best speculative evidence of this possibility, and future work is therefore required.

VI. Concluding Remarks

This study evaluated the labor market impacts of the COVID-19 crisis in Korea using monthly survey data and decomposed the employment losses using the observed events of the three major COVID-19 outbreaks and the subsequent recovery periods. The persistent component of the employment losses during the COVID-19 crisis was large by any measure of employment, with "temporary" layoffs and hourly reductions continued after the outbreaks.

The groups hit hard by the COVID-19 crisis changed during the crisis. While the face-to-face service sector was clearly the hardest-hit industry, employment losses in this sector were less persistent. Within this sector, the employment shocks on temporary and self-employed workers were relatively transitory. The persistent job losses of permanent jobs in that sector increased through the recurring crises, suggesting gradual changes in employer responses.

At the individual level, the persistent job losses in the face-to-face sector were the most salient among young and older workers who are mostly in the transition into or out of their career jobs. Particularly, men in their 40s and 50s experienced large and persistent job losses in hard-hit sectors, although their losses were masked by simultaneous increases of temporary jobs and self-employment in the manufacturing and construction sector. While women in their 30s also experienced persistent job losses, their employment shock came from a different channel. In contrast, the job losses of less-educated workers were much less persistent.

Although this study is not without limitations, it provides useful information on the recovery process beyond the pandemic. Particularly, it identifies persistently vulnerable groups during the pandemic. While there remains a substantial amount of uncertainty about the persistence of the employment losses beyond the pandemic, the pandemic-induced job losses are predicted to have persistent effects over an extended period, given previous findings in the literature. With special attention to the employment situations of these workers, labor market policies during the recovery process will need to prioritize (re)activating those with persistent employment losses and mitigating the lasting effects of the pandemic.

APPENDIX

TABLE A1—JOB LOSSES DURING THE COVID-19 CRISIS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Face-to-Face Services			Other Services			Manuf./Constr.		
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
P × M × 15-29	-0.016**	-0.016***	-0.002	-0.003	-0.002	-0.001	-0.000	-0.002	0.001
	(0.006)	(0.006)	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)	(0.005)	(0.001)
× M × 30-39	0.004	0.007	-0.015***	-0.012	0.005*	0.002	-0.011	0.000	0.001
	(0.006)	(0.006)	(0.004)	(0.010)	(0.003)	(0.002)	(0.008)	(0.002)	(0.001)
× M × 40-49	-0.018***	0.002	0.002	-0.003	-0.003	0.001	-0.004	0.009**	0.005**
	(0.007)	(0.004)	(0.007)	(0.007)	(0.003)	(0.003)	(0.007)	(0.004)	(0.002)
× M × 50-59	-0.008*	0.001	0.011	-0.002	-0.001	-0.002	0.000	0.002	-0.004
	(0.005)	(0.002)	(0.008)	(0.004)	(0.003)	(0.004)	(0.007)	(0.007)	(0.003)
× M × 60+	-0.005	0.001	-0.003**	-0.000	0.004	0.002*	-0.000	-0.005	0.001
	(0.005)	(0.004)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)
× F × 15-29	-0.012	-0.018***	0.001	0.002	0.002	-0.001	0.006	-0.000	-0.001
	(0.009)	(0.005)	(0.004)	(0.004)	(0.002)	(0.001)	(0.004)	(0.002)	(0.001)
× F × 30-39	-0.008	-0.010	-0.009	-0.013***	-0.003	0.002	0.009***	-0.006**	0.002***
	(0.006)	(0.007)	(0.007)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.000)
× F × 40-49	-0.005	-0.009*	0.003	-0.001	-0.004	-0.000	-0.003	0.001	0.002
	(0.005)	(0.005)	(0.007)	(0.004)	(0.004)	(0.002)	(0.005)	(0.004)	(0.002)
× F × 50-59	-0.006*	-0.003	-0.009**	-0.003	-0.002	-0.002	-0.001	-0.002	-0.002*
	(0.004)	(0.006)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.001)
× F × 60+	0.002	0.000	-0.003	0.000	-0.008***	-0.001	-0.003**	0.000	0.000
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T × M × 15-29	0.001	-0.006	-0.001*	0.001	0.001	0.001	-0.001	-0.000	0.000
	(0.001)	(0.005)	(0.000)	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
× M × 30-39	-0.004	-0.000	-0.002	-0.000	-0.001	-0.000	0.002	-0.000	0.002**
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
× M × 40-49	0.002	-0.001	-0.002	-0.001	0.001**	0.001	0.002	-0.002	0.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
× M × 50-59	0.001	-0.000	-0.001	-0.001	0.000	-0.001**	-0.003	-0.002	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
× M × 60+	0.001	-0.000	-0.000	-0.001	-0.002***	0.001*	-0.001	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
× F × 15-29	0.003	-0.008	-0.000	0.001	0.000	-0.001	-0.001	-0.001**	0.000
	(0.002)	(0.005)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
× F × 30-39	-0.001	-0.001	-0.001	0.001	0.000	0.000	-0.001	0.001	-0.000*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)
× F × 40-49	-0.001	-0.002*	0.001	0.001	-0.001	0.001	-0.001	-0.000	-0.001**
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
× F × 50-59	-0.002*	0.001	0.000	-0.000	-0.002*	0.000	0.000	0.001	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
× F × 60+	-0.000	-0.002*	-0.000	0.000	0.002***	0.000	0.001**	-0.001*	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Group FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N					833,142				

Note: Standard errors are clustered at the demographic group level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A2—JOB LOSSES (INCLUDING TEMPORARY LAYOFFS) DURING THE COVID-19 CRISIS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Face-to-Face Services			Other Services			Manuf./Constr.		
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
P × M × 15-29	-0.016**	-0.017***	-0.002	-0.003	-0.002	-0.001	0.000	-0.002	0.001
	(0.006)	(0.006)	(0.002)	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)	(0.001)
× M × 30-39	0.003	0.007	-0.015***	-0.012	0.005*	0.003	-0.013*	0.000	0.001
	(0.006)	(0.006)	(0.004)	(0.009)	(0.003)	(0.002)	(0.008)	(0.002)	(0.001)
× M × 40-49	-0.019***	0.001	0.000	-0.004	-0.003	0.001	-0.005	0.008*	0.003
	(0.006)	(0.004)	(0.007)	(0.008)	(0.003)	(0.003)	(0.007)	(0.004)	(0.002)
× M × 50-59	-0.011**	0.000	0.009	-0.002	-0.001	-0.003	-0.002	0.001	-0.006
	(0.005)	(0.002)	(0.008)	(0.004)	(0.003)	(0.004)	(0.007)	(0.007)	(0.003)
× M × 60+	-0.005	0.000	-0.004***	-0.001	0.003	0.002	-0.000	-0.005	0.001
	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)
× F × 15-29	-0.013	-0.019***	-0.000	-0.001	0.002	-0.001	0.005	0.000	-0.001
	(0.008)	(0.006)	(0.005)	(0.005)	(0.002)	(0.001)	(0.004)	(0.002)	(0.001)
× F × 30-39	-0.005	-0.013*	-0.011	-0.012**	-0.003	0.002	0.009***	-0.007**	0.002***
	(0.005)	(0.008)	(0.007)	(0.005)	(0.004)	(0.002)	(0.003)	(0.003)	(0.000)
× F × 40-49	-0.006	-0.011***	0.001	-0.002	-0.004	-0.001	-0.004	0.001	0.002
	(0.004)	(0.004)	(0.007)	(0.004)	(0.005)	(0.002)	(0.005)	(0.004)	(0.001)
× F × 50-59	-0.007*	-0.004	-0.011***	-0.004	-0.002	-0.001	-0.002	-0.002	-0.002
	(0.004)	(0.006)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.001)
× F × 60+	0.001	-0.001	-0.003	0.000	-0.008***	-0.001	-0.003**	-0.000	0.000
	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T × M × 15-29	-0.001	-0.009*	-0.001**	0.001	0.001	0.000	-0.001	-0.000	-0.000
	(0.002)	(0.005)	(0.001)	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
× M × 30-39	-0.006*	-0.001	-0.005***	-0.000	-0.001	-0.001	0.003	-0.001	0.002**
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
× M × 40-49	0.001	-0.001	-0.005**	-0.001	0.001*	0.001	0.002	-0.002	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
× M × 50-59	0.001	-0.001	-0.004***	-0.002	0.000	-0.001**	-0.002	-0.001	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
× M × 60+	-0.000	-0.001	-0.003***	-0.001	-0.002***	0.001*	-0.001	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
× F × 15-29	0.002	-0.011*	-0.001	0.002	-0.000	-0.000	-0.002	-0.002**	0.000
	(0.003)	(0.006)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
× F × 30-39	-0.003*	-0.005*	-0.005***	0.001	-0.000	0.000	-0.003*	0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)
× F × 40-49	-0.004**	-0.006***	-0.004	0.001**	-0.002*	0.000	-0.001	-0.001	-0.001***
	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
× F × 50-59	-0.003**	-0.003**	-0.004**	-0.000	-0.003**	0.000	0.001	0.001	0.001***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
× F × 60+	-0.001	-0.004***	-0.002*	-0.000	0.001*	0.000	0.001*	-0.001*	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Group FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N					833,142				

Note: Standard errors are clustered at the demographic group level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A3—FTE LOSSES DURING THE COVID-19 CRISIS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Face-to-Face Services			Other Services			Manuf./Constr.		
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
P × M × 15-29	-0.018**	-0.017***	-0.007	-0.003	-0.001	0.001	0.000	-0.003	0.001
	(0.007)	(0.006)	(0.005)	(0.005)	(0.002)	(0.004)	(0.004)	(0.005)	(0.001)
× M × 30-39	-0.001	0.004	-0.013**	-0.013	0.005*	0.002	-0.013*	-0.001	-0.001
	(0.006)	(0.005)	(0.006)	(0.010)	(0.003)	(0.002)	(0.007)	(0.002)	(0.001)
× M × 40-49	-0.021***	0.000	-0.002	-0.006	-0.003	0.001	-0.008	0.006	0.003
	(0.007)	(0.004)	(0.007)	(0.007)	(0.003)	(0.003)	(0.008)	(0.004)	(0.003)
× M × 50-59	-0.014**	0.000	0.008	-0.004	-0.002	-0.004	-0.005	-0.003	-0.008**
	(0.006)	(0.002)	(0.008)	(0.005)	(0.004)	(0.005)	(0.007)	(0.009)	(0.004)
× M × 60+	-0.005	0.002	-0.006*	-0.003	0.003	0.002	-0.001	-0.005	0.001
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)
× F × 15-29	-0.014	-0.021***	-0.001	-0.001	0.002	-0.001	0.005	0.000	-0.001
	(0.009)	(0.007)	(0.005)	(0.005)	(0.002)	(0.001)	(0.004)	(0.002)	(0.001)
× F × 30-39	-0.010	-0.005	-0.017***	-0.012***	-0.004	0.000	0.008**	-0.007**	0.002***
	(0.006)	(0.008)	(0.007)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)
× F × 40-49	-0.009	-0.008	0.001	-0.002	-0.007	-0.002	-0.004	0.001	0.002
	(0.006)	(0.005)	(0.008)	(0.004)	(0.005)	(0.002)	(0.005)	(0.003)	(0.002)
× F × 50-59	-0.012***	-0.002	-0.015***	-0.005	-0.005	-0.002	-0.004	-0.004	-0.003**
	(0.005)	(0.007)	(0.005)	(0.003)	(0.004)	(0.003)	(0.002)	(0.004)	(0.001)
× F × 60+	0.001	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002*	0.000	0.000
	(0.002)	(0.002)	(0.004)	(0.003)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
T × M × 15-29	-0.001	-0.007**	0.001	0.002	0.001	-0.002	-0.001	0.000	-0.000
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)
× M × 30-39	-0.006**	-0.001	-0.007***	-0.000	-0.001	-0.001	0.005	-0.002	0.002**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)	(0.004)	(0.002)	(0.001)
× M × 40-49	-0.001	-0.000	-0.007**	-0.000	0.001**	0.001	0.005	-0.001	0.000
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)
× M × 50-59	0.000	-0.001	-0.006***	-0.000	0.001	-0.001	-0.001	-0.003	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)
× M × 60+	-0.001	-0.001	-0.006***	0.000	-0.001*	0.000	-0.001	0.003**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
× F × 15-29	-0.001	-0.012*	-0.001	0.001	-0.000	-0.000	-0.001	-0.001	-0.000
	(0.002)	(0.006)	(0.001)	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.000)
× F × 30-39	-0.002	-0.005**	-0.004**	0.000	-0.000	0.001	-0.003*	0.000	-0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)
× F × 40-49	-0.005***	-0.005***	-0.006**	0.001	-0.002***	0.002	-0.000	0.000	-0.001**
	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
× F × 50-59	-0.005***	-0.005***	-0.003**	-0.001	-0.001	-0.000	0.001	0.001**	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
× F × 60+	-0.001	-0.003***	-0.003	-0.000	-0.005	0.000	0.000	-0.001**	0.002
	(0.001)	(0.001)	(0.002)	(0.000)	(0.006)	(0.000)	(0.000)	(0.001)	(0.002)
Group FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N					833,142				

Note: Standard errors are clustered at the demographic group level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

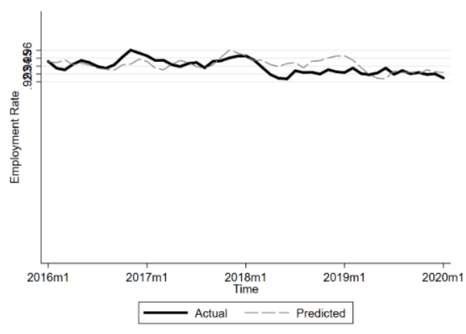
TABLE A4—PERSISTENCE OF THE EMPLOYMENT LOSSES: ALTERNATIVE ESTIMATES

	(1) Job	(2) Job	(3) Job(h > 0)	(4) Job(h > 0)	(5) FTE	(6) FTE
Lagged Impact	0.771***	0.832***	0.773***	0.765***	0.792***	0.806***
	(0.054)	(0.054)	(0.057)	(0.053)	(0.026)	(0.040)
Lagged Impact × Men × 15-29	0.149**	0.141**	0.134*	0.139**	0.134**	0.132***
	(0.070)	(0.063)	(0.072)	(0.057)	(0.052)	(0.050)
× Men × 40-49	0.164**	0.191***	0.132*	0.152*	0.137***	0.150**
	(0.063)	(0.073)	(0.076)	(0.077)	(0.048)	(0.061)
× Men × 50-59	0.076	0.067	-0.010	0.019	-0.038	-0.019
	(0.089)	(0.076)	(0.083)	(0.080)	(0.068)	(0.070)
× Men × 60+	0.099	0.082	0.015	0.021	-0.001	0.022
	(0.094)	(0.121)	(0.094)	(0.111)	(0.067)	(0.079)
× Women × 15-29	0.048	0.019	0.032	0.013	-0.050	-0.067
	(0.136)	(0.094)	(0.126)	(0.093)	(0.094)	(0.074)
× Women × 30-39	0.128**	0.071	0.023	-0.003	0.004	-0.055
	(0.062)	(0.061)	(0.071)	(0.058)	(0.057)	(0.051)
× Women × 40-49	0.190***	0.142**	0.090	0.064	0.111*	0.067
	(0.067)	(0.059)	(0.076)	(0.060)	(0.065)	(0.053)
× Women × 50-59	0.187***	0.185***	0.080	0.090*	0.096**	0.093**
	(0.061)	(0.054)	(0.060)	(0.050)	(0.047)	(0.044)
× Women × 60+	0.029	0.053	0.002	0.020	0.013	-0.019
	(0.070)	(0.080)	(0.070)	(0.064)	(0.045)	(0.050)
× LT HSG		-0.103*		-0.024		-0.042
		(0.057)		(0.048)		(0.053)
× HSG		-0.147***		-0.055		-0.055
		(0.042)		(0.038)		(0.036)
× CLG (2-Yr)		-0.005		0.075*		0.071*
		(0.030)		(0.040)		(0.043)
× GRAD		0.061		0.118*		0.106
		(0.048)		(0.060)		(0.065)
Group FE	Y	Y	Y	Y	Y	Y
N	714	714	714	714	714	714

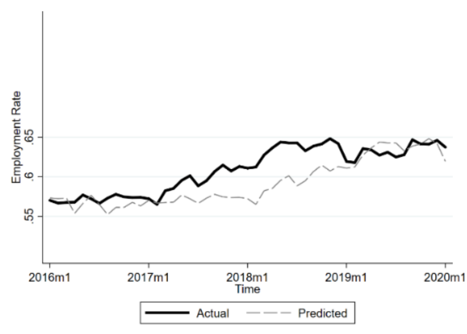
Note: 1) All that regressions are weighted by the population weights at the group level, 2) The unit of analysis is defined at the level of gender-by-age-by-education groups. The base is men in their 30s who are college graduates from a four-year program, 3) Standard errors are clustered at the demographic group level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A5—THE REFERENCE WEEK OF THE EAPS

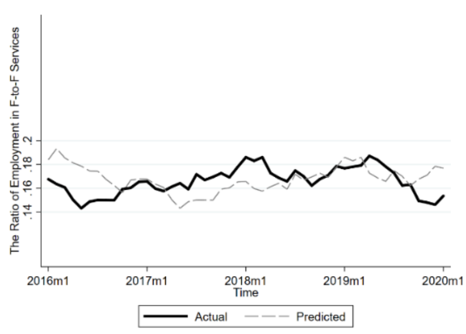
2019	Reference Week	Holidays	2020	Reference Week	Holidays	2021	Reference Week	Holidays
Jan	13-19	-	Jan	12-18	-	Jan	10-16	-
Feb	10-16	-	Feb	9-15	-	Feb	14-20	-
Mar	10-16	-	Mar	15-21	-			
Apr	14-20	-	Apr	12-18	15(Wed)			
May	12-18	-	May	10-16	-			
Jun	9-15	-	Jun	14-20	-			
Jul	14-20	-	Jul	12-18	-			
Aug	11-17	15(Thu)	Aug	9-15	15(Sat)			
Sep	15-21	-	Sep	13-19	-			
Oct	13-19	-	Oct	11-17	-			
Nov	10-16	-	Nov	15-21	-			
Dec	15-21	-	Dec	13-19	-			
Seol	Feb 4-6		*Seol*	Jan 24-26		*Seol*	Feb 11-13	
Chuseok	Sep 12-14		*Chuseok*	Sep 30-Oct 2		*Chuseok*	ep 20-22	



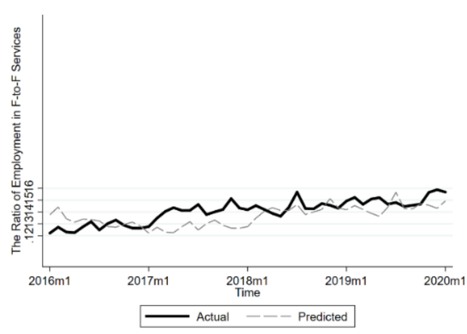
<Men, 35-39, College Graduate (4-yr)>



<Women, 35-39, College Graduate (4-yr)>



<Men, 35-39, College Graduate (4-yr)>
The Ratio of Employment in the Face-to-Face Industry to the Population



<Women, 35-39, College Graduate (4-yr)>
The Ratio of Employment in the Face-to-Face Industry to the Population

FIGURE A1. VALIDITY OF THE IDENTIFICATION ASSUMPTION

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Searching for the Cause of the Gender Gap in Employment Losses during the COVID-19 Crisis†

By JIYEON KIM*

The recession caused by the COVID-19 crisis has features that could disproportionately harm female employment. Risk of infection and social distancing measures may have disrupted jobs in face-to-face industries, which have traditionally hired more women than men. School closures and a consequent increase in childcare and homeschooling demands may have discouraged labor market participation by working mothers. Using the Economically Active Population Survey, I examine how female employment was affected by each factor. I find that the gender gap in the Employment to Non-participation (E to N) transition rates is twice as large as the gap in the Employment to Unemployment (E to U) transition rates. Women's overrepresentation in the face-to-face industries accounts for most of the gap in the E to U transition but only a third of the gap in the E to N transition. The rise in non-participation is especially pronounced among married women aged 39-44, the group most likely to have elementary-school-age children.

Key Word: COVID-19, Employment Losses, Gender Gap
JEL Code: E24, J2, J16, J21, J23

I. Introduction

The recession in 2020 caused by COVID-19 is unprecedented in many ways. In this paper, I explore one of the unique features of the pandemic recession: its disproportionate impact on female employment. It has been well documented that women, especially married women, have a lower cyclicality of employment than men (Albanesi, 2019). This is explained to some extent by a high share of female employees in jobs that are less sensitive to business cycles, such as service occupations (Albanesi and Sahin, 2018). Married women's tendency to stay employed in economic downturns in response to the increased risk of spousal job

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loss also plays a role (Ellieroth, 2019). Consequently, we usually observe a larger drop in male employment during recessions.

During the COVID-19 recession, however, a different pattern emerged. Figure 1 describes employment losses for men and women throughout the year 2020 in comparison with the 1998 recession. With year fixed effects and seasonality controlled for, the employment-to-population ratio for married women dropped much more than that for married men in March, when the number of confirmed cases of COVID-19 spiked for the first time. The difference becomes more striking considering the lower reference employment rate for married women.[1] The gap narrowed as female employment recovered more rapidly in the lull periods but

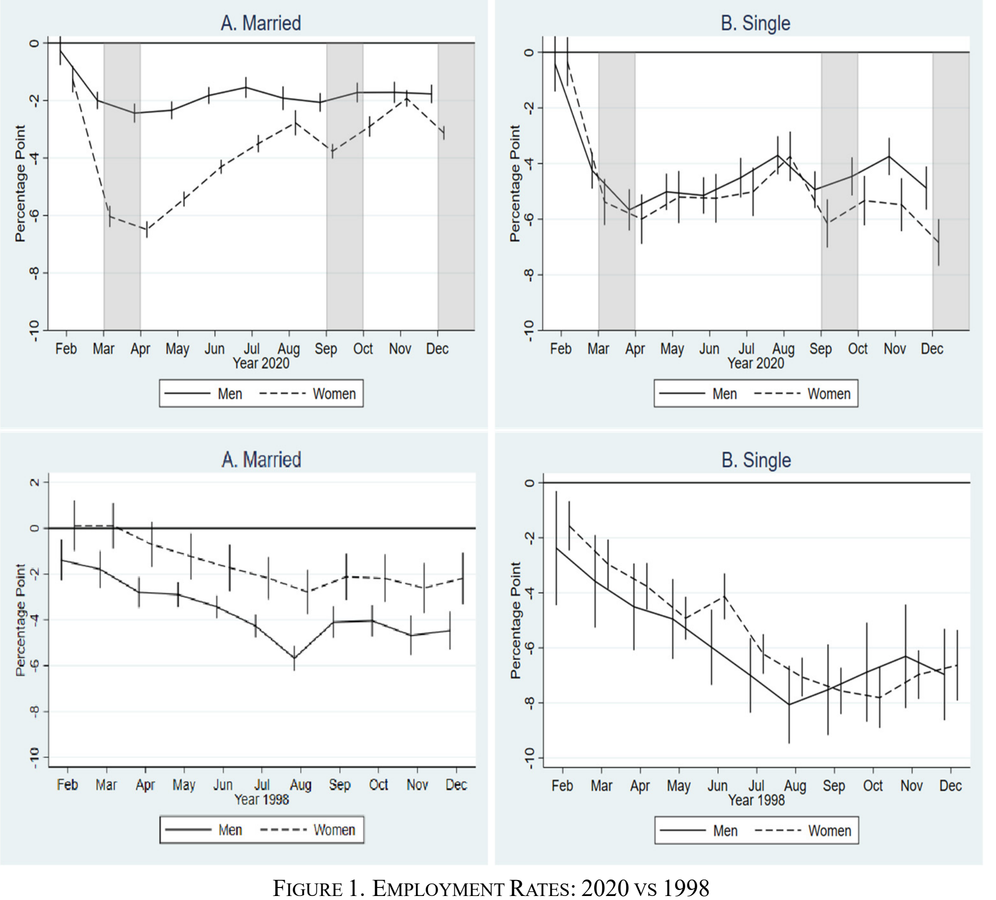

FIGURE 1. EMPLOYMENT RATES: 2020 VS 1998

Note: 1) The figure compares the 2020 and 1998 recessions in terms of their impact on employment by gender and marital status, 2) The upper (lower) figures plot changes in the share of employed individuals aged 25-54 throughout the year 2020 (1998) compared to January 2020, 3) Seasonality and year fixed effects are controlled for, 4) Error bars denote 95% confidence intervals, 5) The shaded areas indicate the periods when the first, second, and third waves of infections hit.

Source: Economically Active Population Survey, 2013-2020.

[1]The employment rate for married women in January of 2020 was 58 percent, whereas the rate for men was 94 percent. Married women lost 11 percent of employment between January of 2020 and March of 2020, while married men lost about three percent during the same period.

started to widen again with the start of the third wave of infections in December of 2020. No significant gender differences were observed between single men and women at least in the first half of the year, but the gap began to broaden starting with the second wave in September of that year. This pattern is in sharp contrast to the 1998 recession, in which men experienced a greater drop in the employment-to-population ratio than women.

The reason COVID-19 took a greater toll on female employment, unlike in previous recessions, appears to be twofold. One factor is related to the types of jobs the pandemic hit. The risk of infection and social distancing measures imposed to curb the transmission of the virus mainly disrupted jobs in the services industries. Women were more affected by this disruption because they are overrepresented in such jobs. Another important factor is the increased need for childcare at home caused by school closures. Given that it is commonly the mother who is in charge of childcare in the household, when children spend more time at home, it becomes difficult for working mothers to stay in the labor market.

In this paper, I examine both possibilities. I first document the heterogeneous impact of COVID-19 across different jobs along with the share of men and women employed. I find that jobs with a high share of female employees are most affected by the pandemic. To ascertain if this is the main reason women fared much worse than men, I explore gender differences in the outflows from employment using the individual-level data. I find that the transition from employment to non-employment (E to NE) for married women rose by an additional two percentage points from its pre-pandemic level of 1.9 percentage points compared to married men in the first wave of the pandemic. Controlling for job characteristics such as occupations, industries, and worker arrangements mitigates the gender differences, but a statistically significant gap of 0.9 percentage points remains. Decomposing the E to NE transition into the employment to unemployment (E to U) and the employment to non-participation (E to N) transition, I find that the gender gap in the E to N transition is more than twice as large as the gap in the E to U transition. Moreover, job characteristics explain most of the gap in the E to U transition but only half of the gap in the E to N transition.

The aforementioned results imply that a sizable gender difference unexplained by women's concentration in service jobs exists in labor supply behavior in response to the pandemic. As likely as it seems to be associated with added childcare responsibilities at home, it is not possible to obtain direct evidence of this due to data restrictions. Instead, I use workers' marital status and age as a proxy for having children. The largest gender gap in the E to N transition is observed among married women aged 39-44, the group most likely to have elementary school age children. Women in this group were 1.4 percentage points more likely to leave the labor force than men during the first wave of infections taking all job characteristics into account. In the other age groups, gender disparities do not exist or are mostly explained by gender differences in the job characteristics. The heterogeneity observed among parents may reflect a disproportionate increase in the childcare burden according to children's ages during the pandemic. Older children do not need as much supervision from parents. Families of preschool children who most likely need parental care the most were provided intensive governmental support such as emergency childcare services and extra child benefits. The fact that mothers of children between these age groups were most likely to drop out of the labor force during the COVID-19 crisis suggests that increased childcare needs played a sizable role in the excess drop in female employment. Since the start of the pandemic, a large body of work has examined its economic consequences from various angles. A number of papers[2] are concerned with gender differences in the labor market impact of the pandemic. Most of them focus on occupational distributions, emphasizing that female-dominated jobs tend to require employees to work in a close physical proximity to other people and are difficult to be conducted remotely, which makes them especially vulnerable to the COVID-19 shock. A few studies state that female-dominated jobs' excessive exposure to COVID-19 does not explain all of the gender disparities. Cajner *et al.* (2020) finds that even within detailed industries, women experience larger job declines than men. Adams-Prassl *et al.* (2020) point out that the gender gap persists even with job characteristics controlled for. Alon *et al.* (2020b) stress that men and women's different labor supply responses to school closures make an additional contribution to women's incremental employment losses. Albanesi and Kim (2021) show that the gender gap in employment losses is larger among parents than non-parents and that differential occupation declines do not fully account for the sharp increase in non-participation among mothers. Despite growing interest in the topic, evidence from non-US countries is still scarce.

This paper aims to fill this gap by providing evidence from the Korean labor market.

The paper is structured as follows. Section 2 documents the distributional impacts of COVID-19 across job characteristics and the share of female employees. Section 3 describes the data and methodology used in the paper. Section 4 examines the individual-level data and investigates the gender-related impact of the COVID-19 recession on outflows from employment. Section 5 discusses COVID-19's long-run implications for female employment.

II. Heterogeneous Impacts of COVID-19

Recessions in general do not affect everyone equally. This unequal impact of recessions is even more pronounced during the COVID-19 crisis. The COVID-19 recession was caused by a health crisis. The risk of infection and the ensuing social distancing measures disrupted activities that involve physical contact with other people, resulting in large employment losses in the service industries. On the other hand, jobs that can be performed at workers' home were affected less. This section documents the heterogeneous impacts of the COVID-19 recession across industries, occupations, and work arrangements.

Table 1 reports the changes in employment rates by industry during the pandemic. The Pre-COVID column reports the industry-specific employment rates in January of 2020. The industry-specific employment rates are defined as the number of individuals employed in each industry divided by the total population aged 25-54. The next four columns report the drop in the employment rate for each industry in

[2]Among others, Albanesi and Kim (2021); Mongey *et al.* (2020); Cortes and Forsythe (2020); Alon *et al.* (2020b); Cajner *et al.* (2020); Adams-Prassl *et al.* (2020).

TABLE 1—EMPLOYMENT IMPACTS OF COVID-19 BY INDUSTRY

(1) Industry	(2) Pre-COVID (%)	(3) Mar (%p)	(4) Apr (%p)	(5) Sep (%p)	(6) Dec (%p)	(7) Emp. women (%)	(8) Emp. men (%)	(9) F. share (%)
Education	5.5	-1.703	-1.480	-1.009	-1.071	12	4	68
Accommodation and food service activities	5.4	-0.650	-0.766	-0.871	-0.830	10	6	54
Human health and social work activities	6.2	-0.438	-0.503	-0.419	-0.404	16	3	81
Arts, sports and recreation related services	1.4	-0.284	-0.276	-0.170	-0.356	2	2	45
Membership organizations, repair and other personal services	3.3	-0.210	-0.329	-0.225	-0.359	5	4	47
Wholesale and retail trade	10.4	-0.208	-0.125	-0.343	-0.342	15	13	44
Business facilities management and business support services	3.2	-0.204	-0.284	-0.058	-0.065	4	4	41
Professional, scientific and technical activities	4.1	-0.195	-0.154	-0.124	-0.004	5	6	35
Manufacturing	14.2	-0.162	-0.453	-0.286	-0.343	13	23	27
Transportation and storage	3.7	-0.110	-0.210	-0.184	0.023	2	7	15
Real estate activities	1.3	-0.097	-0.159	-0.243	-0.269	2	2	44
Construction	5.5	-0.082	-0.258	-0.120	-0.128	2	11	12
Financial and insurance activities	2.7	-0.081	-0.056	-0.032	-0.074	5	3	54
Information and communication	3.2	-0.078	-0.052	-0.089	-0.060	3	5	28
Agriculture, forestry and fishing	1.1	-0.048	-0.123	-0.106	0.028	1	2	30
Electricity, gas, steam and air conditioning supply	0.2	-0.017	-0.044	0.001	-0.008	0	0	15
Activities of extraterritorial organizations and bodies	0.0	-0.003	-0.014	-0.005	0.001	0	0	32
Mining and quarrying	0.0	-0.002	-0.005	-0.012	-0.003	0	0	23
Water supply; sewage, waste management, materials recovery	0.4	0.006	-0.001	-0.022	0.023	0	1	12
Public administration and defense	2.8	0.047	0.067	0.188	0.328	3	4	35
Total	74.6	-4.5	-5.2	-4.1	-3.9	100	100	41

Note: 1) This table presents the changes in the employment rate by industries throughout the year 2020, 2) The industry-specific employment rate is computed as the ratio of workers employed in a given industry to the total 25-54 population, 3) The *Pre-pandemic* column reports the industry-specific employment rates in January of 2020, 4) *Emp. women (men)* is the percent of women employed in the given industry as a share of all employed women (men), 5) *F. share* denotes the share of female employees, 6) Industries are ranked from the most affected by COVID-19 to the least affected based on the declines in the corresponding employment rates in March of 2020, 7) Year and month fixed effects are excluded.

Source: Economically Active Population Survey, 2013-2020.

March, April, September, and December, the months associated with high numbers of confirmed cases. The year fixed effects and seasonality are controlled for. The remaining columns describe the distribution of workers by gender across industries. The Emp. women (men) column reports the percentage of women (men) employed in each industry as a share of all employed women (men). The F. share column presents the share of female employees for each industry.

The impacts of COVID-19 vary considerably by industry. The education industry shows the largest decline. In March of 2020, the employment rate of the education industry dropped by nearly two percentage points from its pre-pandemic level of 5.5 percent. At the end of the year, it remained nearly one percentage point lower than its pre-pandemic level. Accommodation and food service activities are the second worst affected, hitting a low in April of that year with a decline of 0.8 percentage points from 5.4 percent in January. Human health and social work activities are the third worst-hit industry, exhibiting a 0.5 percentage point drop in April from the corresponding January level of 6.2 percent. Table 1 also reports the pre-pandemic distribution of men and women across industries. More than a third of employed women were working in one of the three most affected industries. Twelve percent of women as opposed to four percent for men were employed in the education industry. The female share in the education industry is around 68 percent. Accommodation and food service activities (54 percent) and human health and social work activities (81 percent) also exhibit a high share of female employees

A similar pattern is observed in the analysis of occupations. The employment rate dropped the most among professional occupations, in which 30 percent of women and 23 percent of men are employed. Service occupations and clerical occupations, the second and third worst hit, are female-dominated as well, accounting for about 40 percent of female employment. More than two-thirds of those in the female workforce belong to one of the three most affected occupation groups. Among the least affected occupations are managers, skilled agricultural workers, forestry and fishery workers, and equipment, machine operating and assembly workers. These occupations account for 20 percent of male employment but only five percent of female employment.

With regard to work arrangements, the majority of the workforce, 61 percent of women and 66 percent of men, were employed full-time before the pandemic struck. The employment rate for full-time workers dropped by around two percentage points in April of 2020 from the pre-pandemic level of 47.8 percent and has remained low since. Women are disproportionately employed as part-time workers. Nineteen percent of women worked part-time pre-pandemic while only nine percent of men were classified as part-time workers. The employment rate for part-time workers declined by 1.6 percentage points in April from the corresponding pre-pandemic level of 9.8 percent. Part-time workers account for approximately 30 percent of the average employment losses in the year, much larger than their share in the workforce, at 13 percent.

The results thus far suggest that there are indeed considerable differences in employment losses caused by COVID-19 across different types of jobs and that women are more likely to be employed in jobs that experienced larger declines. The rest of the paper is devoted to understanding to what extent these differences in job characteristics account for the gender gap in the economic fallout of COVID-19.

TABLE 2—EMPLOYMENT IMPACTS OF COVID-19 BY OCCUPATION

(1) Occupation	(2) Pre-COVID (%)	(3) Mar (%p)	(4) Apr (%p)	(5) Sep (%p)	(6) Dec (%p)	(7) Emp. Women (%)	(8) Emp. Men (%)	(9) F. share (%)
Professionals and Related Workers	19.3	-2.108	-2.101	-1.639	-1.566	30	23	48
Service Workers	7.5	-0.926	-1.117	-1.122	-1.236	14	7	58
Clerks	16.5	-0.439	-0.461	-0.606	-0.392	27	19	50
Sales Workers	8.2	-0.355	-0.238	-0.246	-0.355	13	10	47
Craft and Related Trades Workers	6.7	-0.254	-0.511	-0.384	-0.359	2	14	10
Elementary Workers	6.1	-0.188	-0.348	0.253	0.199	9	8	44
Equipment, Machine Operating and Assembling Workers	8.3	-0.185	-0.307	-0.269	-0.237	4	16	13
Skilled Agricultural, Forestry and Fishery Workers	1.1	-0.07	-0.169	-0.151	0.006	1	2	26
Managers	1.0	0.003	0.027	0.07	0.054	0	2	15
Total	74.6	-4.5	-5.2	-4.1	-3.9	100	100	41

Note: 1) This table presents the changes in the employment rate by occupations throughout the year 2020, 2) The occupation-specific employment rate is computed as the ratio of workers employed in a given occupation to the total 25-54 population, 3) The *Pre-pandemic* column reports the occupation-specific employment rates in January of 2020, 4) *Emp. women (men)* is the percent of women employed in the given occupation as a share of all employed women (men), 5) *F. share* denotes the share of female employees, 6) Occupations are ranked from the most affected by COVID-19 to the least affected based on the declines in the corresponding employment rates in March of 2020, 7) Year and month fixed effects are excluded.

Source: Economically Active Population Survey, 2013-2020.

TABLE 3—EMPLOYMENT IMPACTS OF COVID-19 BY WORK ARRANGEMENT

(1) Worker type	(2) Pre-COVID (%)	(3) Mar (%p)	(4) Apr (%p)	(5) Sep (%p)	(6) Dec (%p)	(7) Emp. Women (%)	(8) Emp. Men (%)	(9) F. share (%)
Full-time employee	47.8	-1.59	-2.239	-2.18	-2.097	61	66	39
Part-time employee	9.8	-1.509	-1.574	-1.1	-0.898	19	9	60
Self-employed w/o employees	8.4	-0.756	-0.579	-0.181	-0.103	9	13	33
Self-employed w/ employees	4.1	-0.432	-0.414	-0.419	-0.363	4	7	27
Unpaid family worker	2.0	-0.133	-0.156	-0.168	-0.145	5	1	82
Day-to-day worker	2.6	-0.104	-0.264	-0.045	-0.281	2	4	28
Total	74.6	-4.5	-5.2	-4.1	-3.9	100	100	41

Note: 1) This table presents the changes in the employment rate by worker classes throughout the year 2020, 2) The class-specific employment rate is computed as the ratio of workers employed as a given status to the total population aged 25-54, 3) The *Pre-pandemic* column reports the class-specific employment rates in January of 2020, 4) *Emp. women (men)* is the percent of women who belong to the given class as a share of all employed women (men), 5) *F. share* denotes the share of female employees for each work arrangement, 6) Worker types are ranked from the most affected by COVID-19 to the least affected based on the decline of employment rates in March of 2020, 7) Year and month fixed effects are excluded.

Source: Economically Active Population Survey, 2013-2020.

III. Data and Methodology

I use monthly data from the Economically Active Population Survey between January of 2013 and December of 2020. The EAPS provides a rich set of information ranging from basic demographics to various labor market characteristics at the individual level. For the employed, the survey provides current job characteristics, such as occupations, industries, and work arrangements (full-time, part-time, or self-employed). For those who are not employed, the characteristics of the most recent job are available. The analysis focuses on the prime-age group (aged 25-54). Each respondent belongs to one of the three labor market statuses: employment, unemployment, and non-participation. Those who have a job but are temporarily laid off are classified as unemployed.

The availability of longitudinal data at the individual level is crucial when investigating transitions of labor market statuses. Although the EAPS surveys the same respondent for 36 consecutive months, it is not possible to utilize its panel structure due to the unavailability of individual identifiers. Instead, the survey provides the year and month of job separation (whether they quit or were laid off) for individuals who are currently not employed. Based on this information, I compare the time of job separation to the survey time. If a respondent's job separation time is within a month from the survey time t, I conclude that she made an employment to non-employment transition in time t.

Figure 2 displays the aggregate outflows of different demographic groups from employment throughout the year 2020. The flows are expressed as a share of the labor force in each demographic group. Women, especially married women, experienced a sharper increase in the outflow rates during the first and the second waves of infections compared to their male counterparts. In the periods between, the outflow rates for married women were lower than for married men. This could be a reverse rebound effect after the considerable outflows in March and September. The survey also provides the job start time for the employed, which can be used to analyze the inflow rates into employment. The changes in the employment inflow rates can measure the speed at which the economy recovers in periods of low infection rates. However, the job start time is not available for the self-employed, who account for 18 percent of the total employment. Especially considering the nontrivial share of self-employed workers in the service industries (30 percent), where the COVID shock is concentrated, significant bias could be generated in the analysis. For this reason, I only focus on the outflow from employment in this study.[3]

[3]Although the individual job start time is not available for all workers, it is possible to obtain the aggregate inflows into employment using the following equation:

$$NEE_t = \Delta E_t - ENE_t$$

where NEE_t is the number of newly employed workers in time t, ΔE_t denotes the changes in employment between t and $t-1$, ENE_t is the number of newly separated workers obtained from the job separation time information. Figure A1 in the Appendix plots the aggregate pattern of the inflows in the year 2020 for different demographic groups. The inflows dropped more for married women than for married men in all three waves of infections. In the periods between the waves, there are no significant gender differences. For those who are single, men and women experienced nearly identical declines in the inflows in all three waves. However, in the periods of low infections, the inflows for women recovered more rapidly than those for men.

FIGURE 2. OUTFLOW RATES FROM EMPLOYMENT

Note: 1) The figure plots changes in the percent of individuals aged 25-54 who exit employment to non-employment as a share of the labor force throughout the year 2020, compared to January 2020, 2) Seasonality and year fixed effects are controlled for. 3) Error bars denote 95% confidence intervals, 4) The shaded areas denote the periods when the first, second, and third waves of infections hit.

Source: Economically Active Population Survey, 2013-2020.

The main specification is as follows:

$$Y_{it} = \alpha + \beta Female_i + \gamma Covid_t + \delta Covid_t \times Female_i + \rho X_{it} + \eta Covid_t \times X_{it} + \omega Year_t + \psi Month_t + \varepsilon_{it} \tag{1}$$

The dependent variable Y_{it} is equal to one for individuals who make a transition from employment to non-employment between time $t-1$ and t, and zero otherwise. I regress this on the female indicator (denoted as $Female_i$), the COVID-19 indicator (denoted as $Covid_i$), which is a vector of the time dummies from February of 2020 through December of 2020, and the interaction between the female indicator and the COVID-19 indicator. The vector γ captures the impact of the pandemic recession on men's employment in each month of the pandemic year. δ, the gender difference, is a vector capturing the extra impact of the pandemic on women's employment during each pandemic month. The vector X_{it} includes a set of additional control variables regarding various job characteristics. To control for the disproportionate impact across different job types, a well-documented feature of the COVID-19 recession, I include occupation, industry, and work arrangement fixed effects as well as their interactions with the COVID-19 indicator. If most gender differences in the pandemic's impact stem from high shares of women in hard-hit jobs, an estimate of δ will not be different from zero. Year and month dummies are included as well to control for year specific effects and seasonality.

IV. Results

Table 4 reports $\hat{\delta}$ for those who are married, estimated using the linear probability model. Each column represents a different specification. Column (1) contains no additional controls other than year and month dummies. Columns (2), (3), and (4) include occupation, industry, and work arrangement fixed effects as well as their interactions with the COVID-19 indicator. Column (5) reports the most restrictive specification with all sets of controls included.

All specifications include year and month fixed effects. In March of 2020, when the country experienced the first spike of confirmed cases of COVID-19, women were two percentage points more likely to leave employment than men. As more control variables are considered, the size of the coefficients is reduced. When all controls are included, the coefficient is reduced to 0.9 percentage points, suggesting that occupation, industry, and work arrangement distribution together account for about half of the gender differences in the impact of COVID. Occupation and work arrangement alone do not explain the gender gap very much, whereas controlling for industry alone narrows the gap by a third. This implies that the difference in the industry distribution between men and women is the key to understanding the pandemic's uneven impact across gender. I do not observe gender differences in the second (September) and third (December) wave. The results for those who are single are in marked contrast to those who are married. Unlike married individuals, no gender differences are observed among single individuals, even in the version with no controls. The regression results for singles are relegated to the Appendix.

There are two working hypotheses on why the COVID-19 pandemic extracted a greater toll on female employment. One is the labor demand story. Service jobs traditionally have employed more women than men. Given that the pandemic hit those jobs harder, it is no surprise that more women lost their jobs. The other hypothesis concerns labor supply factors. As schools and nurseries closed, mothers with an increased childcare burden may have chosen to exit the labor force to take

TABLE 4—GENDER DIFFERENCES IN THE EMPLOYMENT TO NON-EMPLOYMENT TRANSITION RATES

	(1)	(2)	(3)	(4)	(5)
1st Wave * Female	0.020***	0.019***	0.013***	0.020***	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
2nd Wave * Female	-0.000	0.001	-0.001	0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
3rd Wave * Female	0.002	0.003	0.005	-0.002	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Worker Type Fixed Effects				Yes	Yes
Observations	1,421,439	1,421,439	1,421,439	1,421,439	1,421,439
R-squared	0.007	0.013	0.011	0.068	0.070
P.C.P	0.982	0.982	0.982	0.982	0.982

Note: 1) The table reports δ from equation (1), 2) The dependent variable is a binary variable for whether a respondent left employment within the past month, 3) The sample is restricted to those who are married, 4) The corresponding results for single individuals can be found in Table A1 in the Appendix, 5) OLS regressions. Robust standard errors in parentheses. P.C.P: percent correctly predicted. *** p<0.01, ** p<0.05, * p<0.1. Full regression results are available on request.

care of their children. In an attempt to isolate the role of labor demand and supply factors, I estimate the same specification for the employment to unemployment (E to U) and the employment to non-participation (E to N) transition. The E to U flow measures the rate at which employed individuals lose their jobs. The E to N flow captures voluntary job separations as well as discouraged workers. The former shows very good agreement with the labor demand factors, while the latter reflects workers' labor supply decisions.

Table 5 reports the gender gap in the E to U flows throughout the year 2020. There exists a significant gender gap of 0.6 percentage points in March, which becomes insignificant once industries are controlled for. Table 6 presents the results for the E to N flows. Around the first wave in March, the gap is more than twice as large as the gap observed from the E to U flows. Married women are 1.5 percentage points more likely to leave the labor force than married men. Controlling for industries narrows the gap by a third. However, unlike the case for the E to U flows, a significant gap of one percentage point remains. This marks a large increase given that the pre-pandemic E to N flow rates for married women is around three percent. In the most restrictive specification where not only industry but also occupation and work arrangement controls are included, the gap in March is reduced to one half but remains significant at the 10% significance level.

To summarize, the empirical evidence suggests that (1) the changes in the E to N flows contributed more to the larger drop in female employment in the first wave of infections, (2) the concentration of women in service industries explains most of the gender gap in the E to U flows but not entirely the E to N flows.

The increase in the E to N flows for married women is a unique feature that has not been seen in previous recessions. Female employment usually shows lower cyclicality than that for males (Albanesi, 2019). Analyzing pre-pandemic periods,

TABLE 5—GENDER DIFFERENCES IN THE EMPLOYMENT TO UNEMPLOYMENT TRANSITION RATES

	(1)	(2)	(3)	(4)	(5)
1st Wave * Female	0.006***	0.006***	0.003	0.007***	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
2nd Wave 2020 * Female	-0.000	-0.001	0.000	-0.000	0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
3rd Wave 2020 * Female	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Worker Type Fixed Effects				Yes	Yes
Observations	1,402,185	1,402,185	1,402,185	1,402,185	1,402,185
R-squared	0.000	0.002	0.002	0.025	0.026
P.C.P	0.995	0.995	0.995	0.995	0.995

Note: 1) The table reports δ from equation (1), 2) The dependent variable is a binary variable for whether a respondent made an employment-unemployment transition within the past month, 3) The sample is restricted to those who are married. The corresponding results for single individuals can be found in Table A2 in the Appendix, 5) OLS regressions. Robust standard errors in parentheses. P.C.P: percent correctly predicted. *** p<0.01, ** p<0.05, * p<0.1. Full regression results are available on request.

TABLE 6—GENDER DIFFERENCES IN THE EMPLOYMENT TO NON-PARTICIPATION TRANSITION RATES

	(1)	(2)	(3)	(4)	(5)
1st Wave * Female	0.015***	0.013***	0.010***	0.013***	0.007*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
2nd Wave * Female	0.000	0.001	-0.002	0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
3rd Wave * Female	0.001	0.002	0.003	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Worker Type Fixed Effects				Yes	Yes
Observations	1,414,972	1,414,972	1,414,972	1,414,972	1,414,972
R-squared	0.008	0.013	0.012	0.054	0.056
P.C.P	0.986	0.986	0.986	0.986	0.986

Note: 1) The table reports δ from equation (1), 2) The dependent variable is a binary variable for whether a respondent made an employment to non-participation transition within the past month, 3) The sample is restricted to those who are married, 4) The corresponding results for single individuals can be found in Table A3 in the Appendix, 5) OLS regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Ellieroth (2019) shows that married women's lower cyclicality is accounted for by their precautionary labor supply behavior, by which married women tend to be more attached to employment in economic downturns to compensate for their husbands' increased unemployment risks. For this reason, the E to N flows for married women decrease in recessions.

Which aspect of the COVID-19 recession causes married women to behave differently from other recessions? One possibility is the increased burden of childcare. In the spring of 2020, as the number of confirmed cases of the coronavirus continued to increase, schools throughout the country, ranging from day care centers to high-schools, were mandated to postpone the start of the spring semester. Schools were not allowed to open for in-person learning until the end of May. Most schools re-opened in June, but many students started going to school only part of the week as schools attempted to limit the number of students per classroom. This nationwide school closure heightened the need for parents to supervise and take care of their children at home. Because mothers commonly take more childcare responsibilities than fathers even in two-earner households,[4] school closures caused by the pandemic may have driven more mothers out of the labor market than fathers.

The ideal way to examine this hypothesis is to determine whether mothers experienced larger employment losses compared to women who do not have children. Unfortunately, the EAPS does not provide information about whether the respondents have children, let alone the children's ages. As an alternative, I use individuals' marital status and ages as a proxy for having children. The average age of mothers at their child's birth in the 2010s is around 32 years old.[5] Based on this

[4]According to 2019 time use survey, the wife spends three times as much time on housework as the husband in dual-earner households.

[5]Vital Statistics, 2010-2019.

TABLE 7—GENDER DIFFERENCES IN THE EMPLOYMENT TO NON-PARTICIPATION TRANSITION RATES BY AGE

	Aged 25-31		Aged 32-38		Aged 39-44		Aged 45-54	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1st Wave * Female	-0.012	-0.009	0.020**	0.011	0.028***	0.014*	0.010**	0.002
	(0.016)	(0.019)	(0.009)	(0.008)	(0.008)	(0.008)	(0.004)	(0.004)
2nd Wave * Female	-0.039**	-0.048***	0.009	0.010	-0.001	-0.000	0.003	-0.001
	(0.016)	(0.018)	(0.008)	(0.009)	(0.005)	(0.005)	(0.004)	(0.004)
3rd Wave * Female	-0.015	-0.008	-0.003	0.001	-0.004	-0.010**	0.007*	0.004
	(0.016)	(0.018)	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes		Yes		Yes		Yes
Industry Fixed Effects		Yes		Yes		Yes		Yes
Worker Type Fixed Effects		Yes		Yes		Yes		Yes
Observations	71,341	71,341	285,624	285,624	368,095	368,095	689,912	689,912
R-squared	0.013	0.053	0.012	0.048	0.009	0.054	0.006	0.069
P.C.P	0.978	0.978	0.978	0.978	0.978	0.978	0.978	0.978

Note: 1) The table reports δ from equation (1), 2) The regressions are done separately for each age group, 3) The dependent variable is a binary variable for whether a respondent made an employment to non-participation transition within the past month, 4) The sample is restricted to those who are married, 5) OLS regressions. Robust standard errors in parentheses. P.C.P: percent correctly predicted. *** p<0.01, ** p<0.05, * p<0.1.

information, I divide married individuals into four age groups. The youngest group (32 and younger) is assumed to have no children. Those who are assumed to have children are further divided into parents of younger children (under 6 years old), elementary school age children (7-12 years old), and adolescents (above 12 years old). Table 7 reports the estimates of the E to N transition for each age group. Those aged 39-44, who are most likely to be parents of children in elementary school, show the largest gender gap in the E to N flows around the first wave. With all work characteristics controlled for, married women in this age group have a 1.4 percentage point higher E to N transition rate than their male counterparts. In contrast, the results for those who do not have children show a negative and non-significant gender gap. Among the parents of children under 7 and above 12, there exists a gender gap of 1-2 percentage points, but those gaps are gone once controls for work characteristics are included. The higher rate of voluntary job separation for married women aged 39-44 is not observed among single women about the same age. Table A4 in the Appendix shows that regardless of age, there are no prominent differences in the E to N transition around the first wave between single men and women. The results in Table 7 and the fact that this pattern cannot be found among single individuals are indirect evidence supporting that added difficulties related to child supervision led to a high E to N transition among married women during the COVID-19 recession.

Why is there heterogeneity even among parents? Although school closures affected most households with young children, there is heterogeneity according to children's ages in the extent to which households were affected by this situation. First, older children who go to junior high or high schools need much less supervision from parents than younger children. In addition, the details of the government programs introduced to support working parents during the crisis varied depending on the children's ages. There is some evidence that these programs mainly benefited families of children under 7. From March through May of 2020, the government provided emergency childcare services to lessen the burden of working parents. Any child 12 years old or younger was eligible for the program, but due to capacity limits, the program prioritized younger children, leaving the parents of older children with no choice but to take care of their kids at home.[6] Families with children under 7 were also given extra child benefits, including a 400,000 won voucher they could use to offset their increased childcare costs.[7]

Despite the data limitation, the results from Table 7 are consistent with other studies using data on which detailed family information is available. Using the U.S. Current Population Survey, Albanesi and Kim (2021) show that the E to N flow rates increased more for mothers than for fathers during the pandemic and that the differences were especially sizable for single parents. Similarly, Collins *et al.* (2021) report that the largest reductions in work hours were observed among mothers with children aged 6 through 12, attributable to homeschooling demands.

The results from Table 7 highlight how the childcare burden continues to be of critical importance with regard to mothers' decisions to participate in the labor market. The fact that mothers of elementary-school-aged children are disproportionately pushed out of the labor market during the pandemic implies that they may have been excluded from the current public child care system, which focuses on providing care for younger children. An expanded system that includes older children will help parents continue their careers in situations such as the COVID-19 pandemic, which will burden them with increased family responsibilities. The high incidence of labor market exits during the pandemic also reveals the hidden costs of the school shutdowns. These actions not only deprive children of learning opportunities but also prevent parents from working, suggesting that they should be carefully implemented based on a thorough comparison between the benefits and costs. In a situation where a school shutdown is unavoidable, complementary policies such as emergency child care should be considered.

Table 8 presents the estimation results by education group. Regardless of the education level, the gender differences in the E to U flows disappear with industry controls included, except for the third wave of infections in December of 2020. At the time, less-educated women were 0.7 percentage points more likely to be unemployed than less-educated men, significant at the 1% significance level, even with industry controls. The gender differences in the E to N flows are mainly driven by those who have at least some college education. Women in this category are 1.5 percentage points more likely to exit the labor force than their male counterparts. In contrast, the E to N gap for the less-educated group is influenced by gender differences in the industry distribution, implying that the extra increase in non-participation for less-educated women is driven by discouraged workers rather than voluntary quitters. These differences based on education levels may reflect different self-insuring abilities. More-educated women likely have more household savings and their spouses' income compared to less-educated women, helping them to get by in periods of joblessness. For this reason, more-educated women may have been

[6]According to a government report published late March, 20 percent of preschool children in the Seoul area were participating in the emergency childcare program. The participation rate for elementary school students, however, was much lower, at 2.2 percent.

[7]Households with older children received a smaller voucher later in the year as school closures were prolonged.

TABLE 8—GENDER DIFFERENCES IN THE EMPLOYMENT TRANSITION RATES BY EDUCATION LEVEL

	High school or less				At least some college			
	E to U		E to N		E to U		E to N	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1st Wave * Female	0.007**	0.005	0.009*	0.006	0.006**	0.003	0.020***	0.015***
	(0.003)	(0.003)	(0.005)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
2nd Wave * Female	0.001	0.000	0.002	-0.004	-0.001	0.000	0.000	-0.001
	(0.002)	(0.003)	(0.005)	(0.006)	(0.002)	(0.002)	(0.003)	(0.004)
3rd Wave * Female	0.006**	0.007***	0.008	0.008	-0.001	-0.001	-0.002	0.002
	(0.002)	(0.002)	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.004)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects		Yes		Yes		Yes		Yes
Observations	609,040	609,040	617,285	617,285	793,145	793,145	797,687	797,687
R-squared	0.000	0.000	0.007	0.007	0.000	0.000	0.009	0.009
P.C.P	0.994	0.994	0.981	0.981	0.997	0.997	0.991	0.991

Note: 1) The table reports δ from equation (1), 2) The regressions are done separately for each education group, 3) In columns (1)-(2) and (5)-(6), the dependent variable is a binary variable for whether a respondent made an E to U transition within the past month, 4) In columns (3)-(4) and (7)-(8), the dependent variable is a binary variable for whether a respondent made a E to N transition within the past month, 5) The sample is restricted to those who are married, 6) OLS regressions. Robust standard errors in parentheses. P.C.P: percent correctly predicted. *** p<0.01, ** p<0.05, * p<0.1.

able to choose to exit the labor market in the face of increased childcare and homeschooling demands. Furthermore, relatively more-educated parents are usually more engaged with their children's education than less-educated parents (Guryan *et al.,* 2008). Faced with the unexpected halt in children's schoolwork, more-educated mothers may have responded to this situation rather actively by leaving their jobs and supervising their kids' education themselves.

V. Concluding Remarks

In this paper, I show that the COVID-19 recession disproportionately hit women. Both labor demand factors such as a high concentration of women in industries vulnerable to COVID-19 and labor supply factors such as the added childcare and homeschooling burdens due to school closures have made this recession particularly challenging for women, more so for working mothers. That said, the question arises of what the consequences of the COVID-19 recession, distinctive from previous recessions, will be. First, its unequal impacts on married women can make the recession more severe because this can disable the insurance mechanism of households against income shocks. Households insure themselves against idiosyncratic risks not only by accumulating assets but also adjusting their labor supply behavior. In two-earner households, when one spouse faces income risks, the other spouse will compensate for that risk by increasing the labor supply of the household. A recent study by Wu and Krueger (2021) finds that the presence of and labor supply adjustment by the second earner, i.e., the female in most two-earner households, both decrease considerably to the extent that the wage shocks translate into consumption. The less cyclical nature of female-dominated jobs and married women's tendency to be loosely attached to the labor market make them crucial providers of household consumption insurance. During the COVID-19 recession, however, many households lost this insurance channel, allowing more income shocks to pass through household consumption.

Second, the COVID-19 crisis produced a generation of women whose careers were halted prematurely. Human capital depreciation during spells of prolonged non-employment will hurt their future career prospects, aggravating gender disparities in the labor market. As their return to the labor market is delayed, the recovery of employment will slow down as well. Some of the jobs lost in the pandemic may not return because occupations that have suffered from large employment losses during the pandemic are highly susceptible to automation (Albanesi and Kim, 2021). One of the changes expected to continue after the COVID-19 crisis is the spread of remote working. How this trend will affect the female workforce is a controversial topic. Alon *et al.* (2020b) raises the possibility that the rise of remote work as accelerated by the pandemic could largely benefit women, as it encourages fathers to take a more active role in childcare. This can lead to a permanent shift in the traditional view of gender roles, freeing women from their conventional household duties. In addition, more flexible work arrangements of remote work could make it easier for working mothers to balance work and childcare. Unfortunately, a series of survey results appears pessimistic about this possibility; amongst the population working from home, women spend significantly more time homeschooling and caring for children than men (Adams-Prassl *et al.,* 2020), and female employees with children are less satisfied with remote working than their male colleagues and females without children (Slack survey). These survey results imply that remote work could result in an extra childcare burden laid on women, thereby diminishing their work productivity. Moreover, remote work has grown considerably more for women than men during the pandemic (Mertens *et al.,* 2021). If it is mostly working mothers seeking flexible work arrangements who choose to work remotely, these mothers may feel stigmatized and discriminated against (Albanesi and Kim, 2021) in the long run. Further investigations of these long-term consequences of COVID-19 are left for future work.

APPENDIX

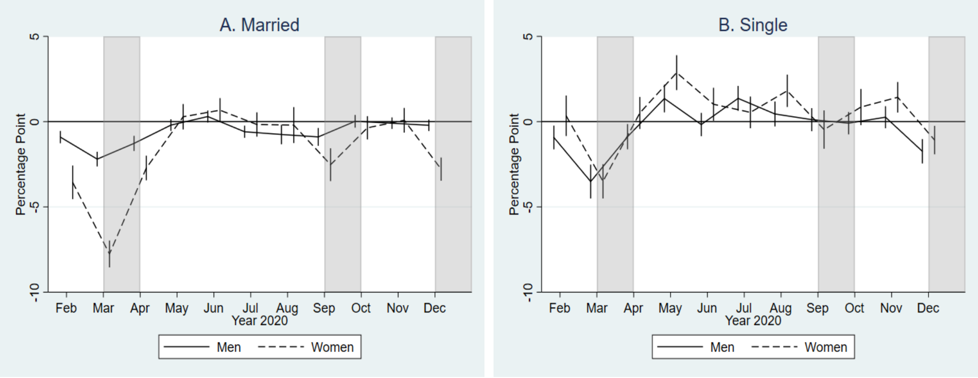

FIGURE A1. INFLOW RATES INTO EMPLOYMENT

Note: 1) The figure plots changes in the percent of individuals aged 25-54 who become employed from non-employment as a share of the labor force throughout the year 2020, compared to January of 2020, 2) Seasonality and year fixed effects are controlled for, 3) Error bars denote 95% confidence intervals, 4) The shaded areas denote the periods when the first, second, and third waves of the infections hit.

Source: Economically Active Population Survey, 2013-2020.

TABLE A1—E TO NE, SINGLE

	(1)	(2)	(3)	(4)	(5)
1st Wave * Female	0.010	0.010	0.007	0.010	0.003
2nd Wave * Female	-0.003	0.000	-0.002	-0.001	0.003
3rd Wave * Female	0.001	0.006	0.003	0.003	0.005
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Worker Type Fixed Effects				Yes	Yes
Observations	465,056	465,056	465,056	465,056	465,056
R-squared	0.002	0.010	0.008	0.070	0.073
P.C.P	0.972	0.972	0.972	0.972	0.972

Note: 1) The table reports δ from equation (1), 2) The dependent variable is a binary variable for whether a respondent left employment within the past month, 3) The sample is restricted to those who are single, 4) OLS regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A2—E TO U, SINGLE

	(1)	(2)	(3)	(4)	(5)
1st Wave * Female	0.003	0.006	0.004	0.002	0.004
2nd Wave * Female	-0.002	-0.000	-0.002	-0.001	0.001
3rd Wave * Female	0.003	0.004	0.003	0.002	0.004
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Worker Type Fixed Effects				Yes	Yes
Observations	457,221	457,221	457,221	457,221	457,221
R-squared	0.001	0.005	0.004	0.035	0.037
P.C.P	0.988	0.988	0.988	0.988	0.988

Note: 1) The table reports δ from equation (1), 2) The dependent variable is a binary variable for whether a respondent made an employment-unemployment transition within the past month, 3) The sample is restricted to those who are single, 4) OLS regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A3—E TO N, SINGLE

	(1)	(2)	(3)	(4)	(5)
1st Wave * Female	0.007	0.004	0.003	0.007	-0.001
2nd Wave * Female	-0.002	0.000	-0.000	-0.000	0.002
3rd Wave * Female	-0.002	0.002	0.000	-0.000	0.001
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Worker Type Fixed Effects				Yes	Yes
Observations	459,594	459,594	459,594	459,594	459,594
R-squared	0.001	0.007	0.006	0.052	0.054
P.C.P	0.983	0.983	0.983	0.983	0.983

Note: 1) The table reports δ from equation (1), 2) The dependent variable is a binary variable for whether a respondent made an employment to non-participation transition within the past month, 3) The sample is restricted to those who are single, 4) OLS regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A4—GENDER DIFFERENCES IN THE EMPLOYMENT TO NON-PARTICIPATION TRANSITION RATES BY AGE, SINGLE

	Aged 25-31		Aged 32-38		Aged 39-44		Aged 45-54	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1st Wave * Female	0.004	-0.008	0.009	0.010	0.002	-0.002	0.018	0.008
	(0.008)	(0.009)	(0.010)	(0.011)	(0.011)	(0.012)	(0.021)	(0.024)
2nd Wave * Female	0.005	0.016*	-0.016*	-0.020**	-0.002	-0.012	-0.008	-0.014
	(0.008)	(0.009)	(0.008)	(0.010)	(0.013)	(0.013)	(0.013)	(0.020)
3rd Wave * Female	0.003	0.008	-0.009	-0.013	-0.001	0.001	-0.011	-0.003
	(0.007)	(0.008)	(0.008)	(0.010)	(0.010)	(0.011)	(0.014)	(0.009)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes		Yes		Yes		Yes
Industry Fixed Effects		Yes		Yes		Yes		Yes
Worker Type Fixed Effects		Yes		Yes		Yes		Yes
Observations	230,549	230,549	126,825	126,825	58,530	58,530	43,690	43,690
R-squared	0.001	0.040	0.002	0.050	0.003	0.105	0.003	0.127
P.C.P	0.978	0.978	0.978	0.978	0.978	0.978	0.978	0.978

Note: 1) The table reports δ from equation (1), 2) The regressions are done separately for each age group, 3) The dependent variable is a binary variable for whether a respondent made an employment to non-participation transition within the past month, 4) The sample is restricted to those who are singles, 5) OLS regressions. Robust standard errors in parentheses. P.C.P: percent correctly predicted. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A5—GENDER DIFFERENCES IN THE E TO NE TRANSITION RATES, FULL REGRESSION RESULTS, MARRIED

	(1)	(2)	(3)	(4)	(5)
Female	0.019***	0.018***	0.021***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
February 2020	0.004*	0.015	-0.013	-0.001	-0.015
	(0.002)	(0.009)	(0.011)	(0.002)	(0.035)
March 2020	0.006**	-0.002	-0.033***	-0.000	-0.073*
	(0.002)	(0.004)	(0.007)	(0.002)	(0.041)
April 2020	0.006**	0.005	-0.019**	0.001	0.017
	(0.002)	(0.005)	(0.009)	(0.002)	(0.052)
May 2020	0.008***	0.013*	-0.011	0.005**	0.033
	(0.002)	(0.007)	(0.010)	(0.002)	(0.044)
June 2020	0.005**	0.009	-0.021***	0.003	-0.006
	(0.002)	(0.006)	(0.008)	(0.002)	(0.045)
July 2020	0.005**	-0.000	-0.004	0.003	0.067
	(0.002)	(0.002)	(0.013)	(0.002)	(0.050)
August 2020	0.005*	0.006	-0.003	-0.000	0.032
	(0.002)	(0.008)	(0.012)	(0.002)	(0.037)
September 2020	0.010***	0.001	-0.022***	0.007***	-0.053***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.009)
October 2020	0.006***	0.002	-0.024***	0.005**	-0.077*
	(0.002)	(0.002)	(0.006)	(0.002)	(0.041)
November 2020	0.008***	0.010*	-0.012	0.006**	-0.002
	(0.002)	(0.006)	(0.008)	(0.002)	(0.041)
December 2020	0.005**	0.002	0.047***	0.001	0.055
	(0.002)	(0.005)	(0.018)	(0.002)	(0.060)
February 2020 * Female	-0.000	0.002	-0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
March 2020 * Female	0.020***	0.019***	0.013***	0.020***	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
April 2020 * Female	0.005	0.006*	0.003	0.006*	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
May 2020 * Female	-0.004	-0.003	-0.003	-0.000	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
June 2020 * Female	-0.001	0.001	-0.001	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
July 2020 * Female	-0.002	0.001	-0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
August 2020 * Female	-0.006**	-0.006**	-0.008**	-0.007**	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
September 2020 * Female	-0.000	0.001	-0.001	0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
October 2020 * Female	-0.007***	-0.006**	-0.009***	-0.004	-0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
November 2020 * Female	-0.007***	-0.007**	-0.007***	-0.003	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
December 2020 * Female	0.002	0.003	0.005	-0.002	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Class Fixed Effects				Yes	Yes
Observations	1,421,439	1,421,439	1,421,439	1,421,439	1,421,439
R-squared	0.007	0.013	0.011	0.068	0.070
P.C.P	0.982	0.982	0.982	0.982	0.982

TABLE A6—GENDER DIFFERENCES IN THE E TO U TRANSITION RATES, FULL REGRESSION RESULTS, MARRIED

	(1)	(2)	(3)	(4)	(5)
Female	0.000*	-0.000	0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
February 2020	0.002	0.009	-0.003***	-0.001	-0.001
	(0.001)	(0.008)	(0.001)	(0.001)	(0.009)
March 2020	0.001	-0.002**	-0.005***	-0.001	-0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)
April 2020	0.002	-0.002*	-0.003*	-0.000	-0.023***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.009)
May 2020	0.003*	0.003	-0.000	0.001	0.011
	(0.001)	(0.004)	(0.004)	(0.001)	(0.025)
June 2020	0.001	0.003	-0.001	0.001	0.005
	(0.001)	(0.004)	(0.002)	(0.001)	(0.016)
July 2020	0.001	-0.002	0.004	-0.000	0.051
	(0.001)	(0.001)	(0.008)	(0.001)	(0.052)
August 2020	-0.001	0.007	-0.003***	-0.002*	-0.002
	(0.001)	(0.008)	(0.001)	(0.001)	(0.008)
September 2020	0.002	-0.000	-0.003**	0.001	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
October 2020	0.002	-0.000	-0.002	0.001	-0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
November 2020	0.002*	0.005	-0.001	0.001	-0.002
	(0.001)	(0.005)	(0.001)	(0.001)	(0.005)
December 2020	0.001	0.004	-0.003***	-0.001	0.000
	(0.001)	(0.005)	(0.001)	(0.001)	(0.006)
February 2020 * Female	0.001	0.002	0.000	0.000	0.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
March 2020 * Female	0.006***	0.006***	0.003	0.007***	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
April 2020 * Female	0.003	0.003*	0.001	0.003	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
May 2020 * Female	0.001	0.002	0.003	0.002	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
June 2020 * Female	-0.000	0.002	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
July 2020 * Female	0.003*	0.004**	0.004**	0.003*	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
August 2020 * Female	0.001	0.001	0.001	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
September 2020 * Female	-0.000	-0.001	0.000	-0.000	0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
October 2020 * Female	-0.002	-0.001	-0.002	-0.001	0.000
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
November 2020 * Female	-0.001	-0.001	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
December 2020 * Female	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Class Fixed Effects				Yes	Yes
Observations	1,402,185	1,402,185	1,402,185	1,402,185	1,402,185
R-squared	0.000	0.002	0.002	0.025	0.026
P.C.P	0.995	0.995	0.995	0.995	0.995

TABLE A7—GENDER DIFFERENCES IN THE E TO N TRANSITION RATES, FULL REGRESSION RESULTS, MARRIED

	(1)	(2)	(3)	(4)	(5)
Female	0.019***	0.018***	0.020***	0.014***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
February 2020	0.002	0.006	-0.010	-0.000	-0.018
	(0.002)	(0.004)	(0.010)	(0.002)	(0.034)
March 2020	0.005**	-0.000	-0.028***	0.001	-0.058
	(0.002)	(0.003)	(0.006)	(0.002)	(0.040)
April 2020	0.004**	0.007	-0.017*	0.001	0.034
	(0.002)	(0.005)	(0.009)	(0.002)	(0.051)
May 2020	0.005***	0.010*	-0.010	0.004**	0.031
	(0.002)	(0.005)	(0.009)	(0.002)	(0.044)
June 2020	0.004*	0.006	-0.020**	0.002	-0.013
	(0.002)	(0.005)	(0.008)	(0.002)	(0.046)
July 2020	0.005**	0.001	-0.009	0.003*	0.044
	(0.002)	(0.002)	(0.010)	(0.002)	(0.045)
August 2020	0.006***	-0.001	0.000	0.001	0.032
	(0.002)	(0.002)	(0.012)	(0.002)	(0.038)
September 2020	0.007***	0.002	-0.019***	0.005**	-0.047***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.009)
October 2020	0.004**	0.002	-0.022***	0.004**	-0.073*
	(0.002)	(0.002)	(0.006)	(0.002)	(0.042)
November 2020	0.005***	0.006**	-0.011	0.004**	-0.000
	(0.002)	(0.003)	(0.008)	(0.002)	(0.043)
December 2020	0.005**	-0.001	0.050***	0.001	0.053
	(0.002)	(0.002)	(0.018)	(0.002)	(0.060)
February 2020 * Female	-0.001	0.000	-0.001	0.001	0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
March 2020 * Female	0.015***	0.013***	0.010***	0.013***	0.007*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
April 2020 * Female	0.002	0.002	0.002	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
May 2020 * Female	-0.005**	-0.005*	-0.006**	-0.002	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
June 2020 * Female	-0.001	-0.001	-0.002	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
July 2020 * Female	-0.005*	-0.003	-0.005*	-0.002	-0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
August 2020 * Female	-0.008***	-0.007***	-0.008***	-0.009***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
September 2020 * Female	0.000	0.001	-0.002	0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
October 2020 * Female	-0.006***	-0.006**	-0.008***	-0.003	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
November 2020 * Female	-0.006***	-0.005**	-0.006**	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
December 2020 * Female	0.001	0.002	0.003	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Class Fixed Effects				Yes	Yes
Observations	1,414,972	1,414,972	1,414,972	1,414,972	1,414,972
R-squared	0.008	0.013	0.012	0.054	0.056
P.C.P	0.986	0.986	0.986	0.986	0.986

TABLE A8—GENDER DIFFERENCES IN THE E TO NE TRANSITION RATES, FULL REGRESSION RESULTS, SINGLE

	(1)	(2)	(3)	(4)	(5)
Female	-0.005***	0.001**	-0.002***	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
February 2020	0.005	-0.008*	-0.055***	0.004	-0.075***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.016)
March 2020	0.014**	-0.017***	-0.054***	0.004	-0.185
	(0.006)	(0.005)	(0.008)	(0.005)	(0.137)
April 2020	0.013**	0.046	-0.007	0.007	-0.120
	(0.006)	(0.058)	(0.022)	(0.005)	(0.191)
May 2020	0.009*	-0.008	-0.028	0.004	0.020
	(0.005)	(0.005)	(0.022)	(0.005)	(0.079)
June 2020	0.007	-0.007	0.012	0.001	0.108
	(0.005)	(0.004)	(0.030)	(0.005)	(0.083)
July 2020	0.006	-0.007	-0.009	0.003	0.134
	(0.005)	(0.004)	(0.021)	(0.005)	(0.114)
August 2020	0.004	0.005	-0.014	-0.001	0.056
	(0.005)	(0.015)	(0.019)	(0.005)	(0.069)
September 2020	0.017***	-0.004	-0.015	0.009*	0.030
	(0.005)	(0.005)	(0.019)	(0.005)	(0.086)
October 2020	0.003	-0.006	-0.042***	-0.001	-0.065
	(0.005)	(0.004)	(0.009)	(0.004)	(0.083)
November 2020	-0.001	-0.004	-0.013	0.003	0.044
	(0.005)	(0.004)	(0.018)	(0.004)	(0.081)
December 2020	0.007	-0.009**	0.036	-0.001	0.102
	(0.005)	(0.005)	(0.027)	(0.005)	(0.077)
February 2020 * Female	-0.006	-0.010	-0.004	-0.007	-0.012*
	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)
March 2020 * Female	0.010	0.010	0.007	0.010	0.003
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
April 2020 * Female	-0.004	0.003	-0.005	-0.003	-0.001
	(0.006)	(0.007)	(0.007)	(0.006)	(0.008)
May 2020 * Female	0.002	0.008	0.004	0.002	0.006
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
June 2020 * Female	-0.002	0.001	0.003	-0.000	0.005
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
July 2020 * Female	-0.002	-0.001	0.000	0.001	0.002
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
August 2020 * Female	-0.002	-0.004	0.001	-0.002	-0.001
	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
September 2020 * Female	-0.003	0.000	-0.002	-0.001	0.003
	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
October 2020 * Female	0.001	0.003	0.003	-0.000	0.004
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
November 2020 * Female	0.008	0.006	0.007	0.005	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
December 2020 * Female	0.001	0.006	0.003	0.003	0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Class Fixed Effects				Yes	Yes
Observations	465,056	465,056	465,056	465,056	465,056
R-squared	0.002	0.010	0.008	0.070	0.073
P.C.P	0.972	0.972	0.972	0.972	0.972

TABLE A9—GENDER DIFFERENCES IN THE E TO U TRANSITION RATES, FULL REGRESSION RESULTS, SINGLE

	(1)	(2)	(3)	(4)	(5)
Female	-0.004***	-0.002***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
February 2020	-0.003	-0.007**	-0.015***	-0.002	-0.033***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.010)
March 2020	0.006	-0.009***	-0.015***	0.001	-0.173
	(0.004)	(0.003)	(0.003)	(0.004)	(0.131)
April 2020	0.006	-0.005	0.011	0.004	-0.250
	(0.004)	(0.003)	(0.018)	(0.004)	(0.171)
May 2020	0.004	-0.004	0.011	0.001	0.078
	(0.004)	(0.003)	(0.022)	(0.004)	(0.098)
June 2020	0.000	-0.005*	0.002	-0.002	0.065
	(0.004)	(0.003)	(0.015)	(0.003)	(0.095)
July 2020	-0.000	-0.005	0.012	-0.003	0.109
	(0.003)	(0.003)	(0.017)	(0.003)	(0.119)
August 2020	-0.010***	-0.006*	-0.013***	-0.007**	-0.020***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)
September 2020	0.003	-0.003	-0.005	0.002	0.040
	(0.004)	(0.003)	(0.006)	(0.003)	(0.086)
October 2020	-0.001	-0.004	-0.011***	-0.004	-0.059
	(0.003)	(0.003)	(0.003)	(0.003)	(0.047)
November 2020	-0.003	-0.005	-0.003	-0.002	0.061
	(0.003)	(0.003)	(0.009)	(0.003)	(0.082)
December 2020	-0.002	-0.005*	-0.007	-0.005*	-0.005
	(0.003)	(0.003)	(0.006)	(0.003)	(0.039)
February 2020 * Female	0.002	0.001	0.004	0.001	0.001
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
March 2020 * Female	0.003	0.006	0.004	0.002	0.004
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
April 2020 * Female	-0.009**	-0.006	-0.009**	-0.008*	-0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
May 2020 * Female	-0.003	0.002	0.000	-0.002	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
June 2020 * Female	-0.001	0.000	0.002	-0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
July 2020 * Female	0.000	0.001	0.001	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
August 2020 * Female	0.005*	0.003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
September 2020 * Female	-0.002	-0.000	-0.002	-0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
October 2020 * Female	0.001	0.003	0.002	0.001	0.004
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
November 2020 * Female	0.003	0.006*	0.002	0.002	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
December 2020 * Female	0.003	0.004	0.003	0.002	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Class Fixed Effects				Yes	Yes
Observations	457,272	457,272	457,272	457,272	457,272
R-squared	0.001	0.005	0.004	0.035	0.037
P.C.P	0.988	0.988	0.988	0.988	0.988

TABLE A10—GENDER DIFFERENCES IN THE E TO N TRANSITION RATES, FULL REGRESSION RESULTS, SINGLE

	(1)	(2)	(3)	(4)	(5)
Female	-0.001*	0.003***	0.001**	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
February 2020	0.007*	-0.001	-0.041***	0.006*	-0.051***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.014)
March 2020	0.009**	-0.008**	-0.040***	0.003	-0.015
	(0.004)	(0.004)	(0.007)	(0.004)	(0.050)
April 2020	0.007*	0.051	-0.017	0.003	0.118
	(0.004)	(0.058)	(0.014)	(0.004)	(0.113)
May 2020	0.005	-0.004	-0.040***	0.003	-0.045***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.015)
June 2020	0.007*	-0.002	0.010	0.002	0.112
	(0.004)	(0.003)	(0.027)	(0.003)	(0.092)
July 2020	0.006*	-0.002	-0.020	0.006	0.076
	(0.004)	(0.003)	(0.013)	(0.004)	(0.090)
August 2020	0.013***	0.010	-0.003	0.006	0.072
	(0.004)	(0.015)	(0.019)	(0.004)	(0.071)
September 2020	0.015***	-0.002	-0.011	0.007*	0.012
	(0.004)	(0.004)	(0.018)	(0.004)	(0.072)
October 2020	0.004	-0.002	-0.031***	0.002	-0.016
	(0.004)	(0.003)	(0.008)	(0.003)	(0.080)
November 2020	0.002	0.001	-0.010	0.005	-0.022
	(0.003)	(0.003)	(0.016)	(0.003)	(0.016)
December 2020	0.009**	-0.004	0.043	0.004	0.139*
	(0.004)	(0.003)	(0.027)	(0.004)	(0.084)
February 2020 * Female	-0.008**	-0.011**	-0.008*	-0.009**	-0.014***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
March 2020 * Female	0.007	0.004	0.003	0.007	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
April 2020 * Female	0.005	0.009	0.003	0.004	0.006
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
May 2020 * Female	0.005	0.006	0.004	0.004	0.005
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
June 2020 * Female	-0.001	0.001	0.001	0.000	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
July 2020 * Female	-0.002	-0.003	-0.001	-0.002	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
August 2020 * Female	-0.006	-0.007	-0.002	-0.005	-0.003
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
September 2020 * Female	-0.002	0.000	-0.000	-0.000	0.002
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
October 2020 * Female	0.000	-0.000	0.001	-0.001	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
November 2020 * Female	0.005	0.001	0.005	0.003	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
December 2020 * Female	-0.002	0.002	0.000	-0.000	0.001
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects		Yes			Yes
Industry Fixed Effects			Yes		Yes
Class Fixed Effects				Yes	Yes
Observations	459,594	459,594	459,594	459,594	459,594
R-squared	0.001	0.007	0.006	0.052	0.054
P.C.P	0.983	0.983	0.983	0.983	0.983

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Korea's Inflation Expectations with regard to the Phillips Curve and Implications of the COVID-19 Crisis†

By KYU-CHUL JUNG*

This paper estimates the expectation-augmented Phillips curve, which explains inflation dynamics, in Korea. The phenomenon of low inflation in Korea has been going on for quite some time, in particular since 2012. During the Covid-19 crisis, due to low inflation expectations the operation of monetary policy was limited as the base rate approached the zero lower bound. The main objective of this paper is to estimate where and how tightly inflation expectations are anchored. It was found that long-term inflation expectations fell to around 1%, falling short of the inflation target, and that inflation expectations are strongly anchored to long-term expectations, which implies that the low inflation phenomenon is likely to extend into the future. The results also imply that even if inflation fluctuates due to temporary disturbances, it may converge to a level below the inflation target. The slight rebound of long-term expectations during the Covid-19 crisis suggests that the aggressive monetary policy may have contributed to improving economic agents' beliefs about the commitment of monetary authorities to inflation stability. This may also help long-term expectations gradually to approach the inflation target.

Key Word: Inflation Expectations, Phillips Curve, Monetary Policy
JEL Code: E31, E42, E52

I. Introduction

The continuing phenomenon of low inflation remains ongoing in Korea. Figure 1 shows the inflation targets and the actual inflation rates. Prior to 2011, inflation sometimes fell outside the range of the target temporally, but for most of the period inflation it was in line with the targeted forecasts. In contrast, since 2012 actual inflation has been below the inflation target for most of the period. Short-term

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disturbances, such as international oil price hikes, a good harvest, bird flu, and foot-and-mouth disease, may play major roles in headline inflation fluctuations. However, core inflation, which excludes food and energy, has also been gradually declining below the target since 2012.

As the phenomenon of low inflation has continued, economic agents may have lowered their inflation expectations, which have limited the operation of monetary policy. If the economy is subdued and inflation falls, the monetary authority in Korea lowers real interest rates (nominal interest rates minus inflation expectations) by cutting the key short-term nominal rate, the base rate. Given that nominal interest rates are bounded by zero, real interest rates cannot be sufficiently lowered when inflation expectations are low.

When the Covid-19 crisis occurred, the Bank of Korea cut its base rate to a level close to the lower bound. That is, due to low inflation expectations, the Bank of Korea could not sufficiently adjust real interest rates. As the base rate approached the lower bound, the Bank of Korea employed unconventional monetary policy measures, such as purchasing government bonds, whose effectiveness is uncertain and debatable. Recognizing the importance of the stable expectations, the Bank of Korea revised its “General Principles of Monetary Policy Operation” in December 2020. According to the new general principles, the Bank of Korea is supposed to consider anchoring of inflation expectations in addition to overall inflation and growth outlooks, the associated uncertainties and risks, and financial stability conditions when it assesses the path of convergence of inflation.

Stable inflation expectations themselves matter with regard to the stability of actual inflation. If expectations are well anchored, actual inflation is ensured to converge to the target even if it temporally deviates. The sustained low inflation in Korea, however, suggests that expectations may not have been well anchored. If expectations are tightly anchored to a level that differs from the target, it becomes difficult to expect inflation to converge to the target in the foreseeable future. With this motivation, the main objective of this paper is to estimate where and how tightly inflation expectations are anchored.

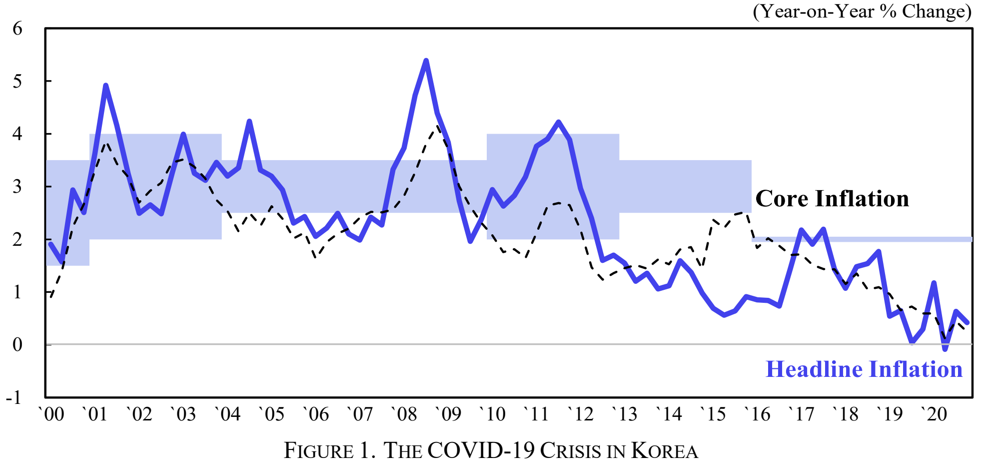

FIGURE 1. THE COVID-19 CRISIS IN KOREA

Note: Shading represents the inflation target.

Source: Statistics Korea.

Several previous studies have investigated possible decreases in the slope of the Phillips curve, inflation's responsiveness to economic fluctuations. Ball and Mazumder (2011; 2019) found that US expectations of the Phillips curve were strongly backward-looking in the past, but became more strongly linked to the Fed's inflation target recently. Based on this evidence, they concluded that inflation remained stable in the 2000s, not because the slope of the Phillips curve had decreased but because inflation expectations had been strongly anchored. Matheson and Stavrev (2013), the IMF (2013), and Blanchard, Cerutti, and Summers (2015) also analyzed the Phillips curve for the United States or for 21 countries. They also found that inflation expectations for the US were strongly anchored to long-term expectations recently.

This paper also studies variations in inflation expectations in the Phillips curve by applying the Kalman-filter model used in Matheson and Stavrev (2013), the IMF (2013), and Blanchard, Cerutti, and Summers (2015). An obvious difference is that this paper analyzes the Korean economy, which was not considered in the previous literature. A more critical departure is that this paper directly estimates long-term inflation expectations, in contrast to existing literature. For long-term expectations, Ball and Mazumder (2019) used the Fed's target level, while Matheson and Stavrev (2013), the IMF (2013), and Blanchard, Cerutti, and Summers (2015) used survey results. Considering the upward bias of survey results in Korea, using survey results as a proxy for long-term inflation expectations in the Phillips curve is limited. This paper found that while inflation expectations in Korea also show recent strongly anchored to long-term expectations, the anchored level appears to be substantially different from the target.

There have also been studies of the low inflation phenomenon in Korea from a structural point of view. Lee (2014) and Jung (2019) investigated the low inflation phenomenon, the risk of deflation, and implications for monetary policy. Lee (2014) and Cho (2018) compared Japan's economic structure and macro-policies with Korea's. Japan's monetary policy was critically examined, and policy implications were derived to prevent deflation in Korea, whose current economic structure is similar to that of Japan's in the past. Jung (2019) and Cho (2020) discussed structural issues in the Korean monetary policy management system. Although this paper does not formally analyze Korea's monetary policy, it suggests related policy implications.

This paper is organized as follows. Section II discusses the survey results on inflation expectations. Section III presents the model and data. Section IV shows the results and implications, and Section V concludes the paper.

II. Discussion of Survey Results

Inflation expectations are unobservable. This section discusses the survey results on inflation expectations. The Bank of Korea surveys the public and experts on inflation expectations. Surveys of the general public are released monthly, and surveys of experts are released through a quarterly monetary policy report. Inflation expectations refer to the rate of headline inflation over the following year. Figure 2 shows that expectations of the general public are higher than those of experts.

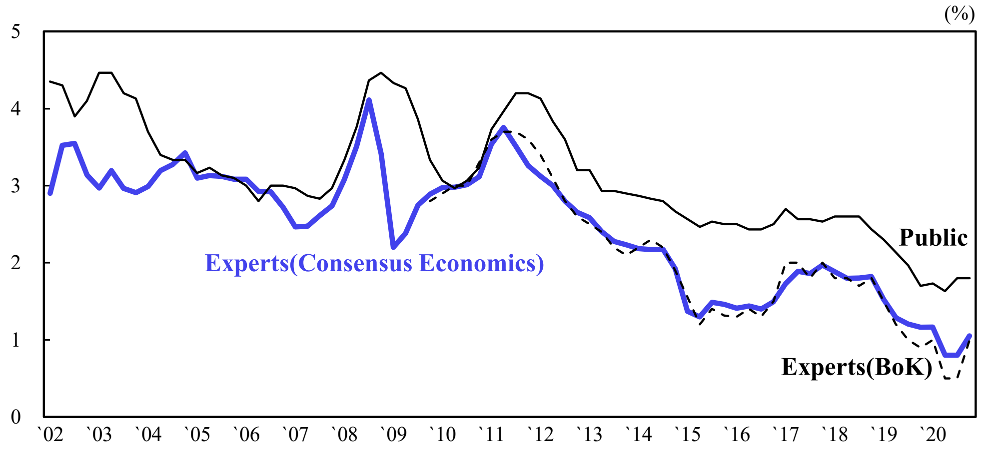

FIGURE 2. SURVEY RESULTS ON INFLATION EXPECTATIONS (ONE-YEAR-AHEAD)

Source: Bank of Korea, Consensus Economics.

Consensus Economics examines inflation expectations with experts. This survey concentrates on headline inflation, categorized into short-term (one year ahead) and long-term (five years ahead) periods. The survey results of experts by the Bank of Korea and Consensus Economics are very similar because the survey groups who take the two surveys are similar. In this paper, experts' expectations will be discussed based on the survey conducted by Consensus Economics because it has a longer time series.

First, this paper examines whether the survey results have a statistical bias. As a simple benchmark, I also examine inflation of the current period as the forecast for one-year-ahead inflation. In the first column of Table 1, when current inflation is used as a forecast for inflation expectations, an upward bias of 0.1%p is found. This can be understood as reflecting the trend in which inflation rates have declined by 0.1%p per year. Inflation expectations for the general public has an upward bias of 1.0%p compared to actual inflation, meaning that the upward bias is much greater than the expectations when using current actual inflation. The fact that there is upward bias in inflation expectations over a long period of time means that there is a limitation to predicting future inflation trends with survey results on inflation expectations of the general public. Experts' inflation expectations also showed an upward bias of 0.3%p from actual inflation rates. The bias of expert inflation expectations was smaller than that of the general public, but it was also found to be greater compared to the simple use of current actual inflation. This suggests that it is difficult even for expert groups to forecast inflation trends.

Table 1 shows the size of the average error of inflation expectations against the actual future inflation, as measured using the root mean squared error (RMSE). If current-period inflation is used as the inflation forecast, the RMSE is about 1.2%p, as presented in Table 1. Inflation expectations of the general public have an RMSE of 1.5%p, which is larger than the forecast error of the current actual inflation. This also means that the inflation expectations of the general public are less useful than the current inflation value in explaining short-term inflation fluctuations.

TABLE 1—ONE-YEAR-AHEAD INFLATION EXPECTATIONS AND ACTUAL INFLATION

Sample period		Inflation Expectations		
		Current-period actual inflation	Survey (public)	Survey (experts)
From Q1 2003 to Q4 2020	Bias (%p)	0.1	1.0	0.3
	RMSE (%p)	1.2	1.5	1.1
From Q1 2012 to Q4 2020	Bias (%p)	0.4	1.7	0.9
	RMSE (%p)	1.0	1.8	1.1

Note: One-year-ahead inflation expectations π^e_{t-4} are formed at period *t-4* and compared with actual inflation π_t at period *t*. Bias denotes the averages of forecast errors $(\pi^e_{t-4}-\pi_t)$, and the RMSE (root mean squared error) is determined using the equation $\sqrt{\Sigma^T_{t=1}(\pi^e_{t-4}-\pi_t)^2/T}$.

Source: Bank of Korea, Consensus Economics, Statistics Korea.

The bias reveals a more pronounced difference since 2012, when inflation began to fall persistently below the target. Table 1 shows that the upward bias of the inflation expectations for the general public is larger and that the RMSE is also higher. The bias of experts' inflation expectations was also relatively large. For reference, the bias of expert inflation expectations before 2012 was -0.2%p.

How can we determine why the bias of inflation expectations for the general public is high and the forecasting error is large, and what are the main factors affecting the formation of inflation expectations? Previous studies such as those by Lee (2012), Choi (2012), Lee and Choi (2015), and Nam and Go (2018) explained that the backward-looking factor in the formation of inflation expectations is important. The Bank of Korea's survey of the general public includes inflation perception as well as inflation expectations. Inflation perception comes from the results of a survey on headline inflation over the previous year. Figure 3 shows the inflation expectations of the general public, inflation perception results, and actual inflation. First, we find that there is a considerable gap between the general public's

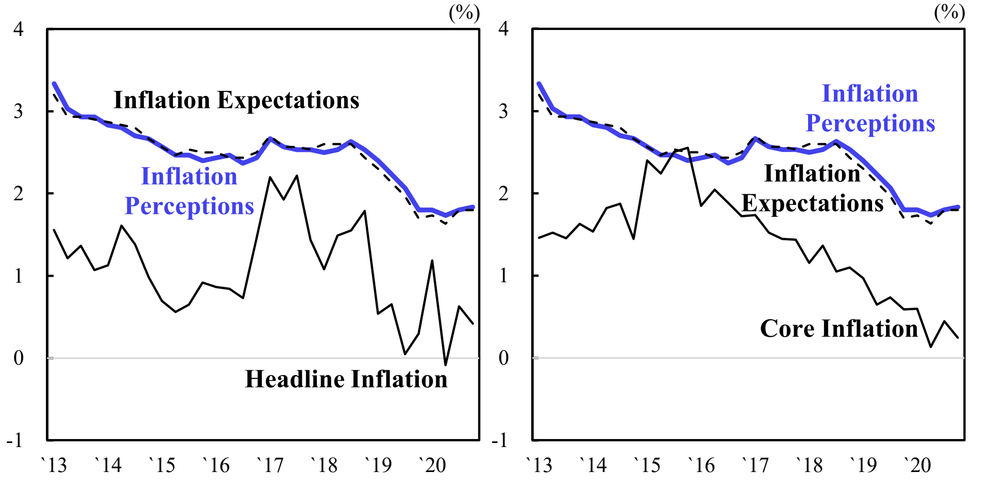

FIGURE 3. INFLATION EXPECTATIONS, INFLATION PERCEPTION, AND ACTUAL INFLATION

Source: Bank of Korea, Statistics Korea.

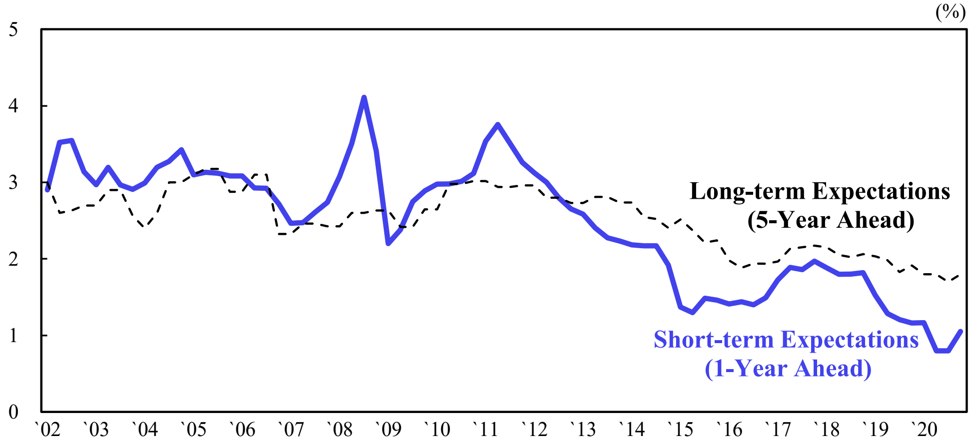

FIGURE 4. SURVEY RESULTS ON LONG-TERM AND SHORT-TERM INFLATION EXPECTATIONS

Source: Consensus Economics.

perception of inflation and actual inflation. Second, inflation expectations are strongly correlated with inflation perception, indicating that the formation of inflation expectations is backward-looking. Nam and Go (2018) reported that these features were also found in other major economies.

With regard to long-term inflation expectations, Consensus Economics surveys experts on five-year-ahead inflation expectations. Figure 4 compares the survey results on short- and long-term inflation expectations. While long-term expectations tend to fluctuate around the inflation target, short-term expectations have consistently fell short of long-term expectations, meaning that the survey respondents thought that inflation would gradually converge to the inflation target in the future. Just as there was upward bias in short-term expectations, however, long-term expectations also show some upward bias. In contrast to the experts' long-term expectations, actual inflation has been below 2% for most of the period since the second half of 2012.

The discussion covering the survey results on inflation expectations can be summarized as follows. First, the inflation expectations of survey results tended to be backward-looking. Second, the short- and long-term expectations did not correspond to the low inflation phenomenon that has appeared since 2012. Therefore, it is highly likely that the results of the inflation expectations survey did not sufficiently reflect information on the future inflation trend.

III. The Model and Data

This section explains the method used to estimate inflation expectations as reflected in the time series of actual inflation. After setting the Phillips curve model, we explain how we measure where and how strongly inflation expectations are anchored by a Kalman-filter model.

A. *Phillips Curve Model*

The Phillips curve represents how prices are determined. The specific form may vary from study to study, but in this paper, inflations are expressed as inflation expectations, demand-side pressure, and supply-side pressure. This form of the Phillips curve is also supported by a theoretical model. For example, Clarida, Galí, and Gertler (1999) derived the following Phillips curve in the dynamic stochastic general equilibrium model:

$$\pi_t = \lambda E_t[\pi_{t+1}] + \kappa \hat{y}_t + e_t,$$

where $\hat{y}_t$ denotes the GDP gap. Given that inflation expectations in Clarida, Galí, and Gertler (1999) are purely forward-looking, past inflation is not included on the right side of the Phillips curve. Woodford (2003), Christiano, Eichenbaum, and Evans (2005), however, explained that in the model in which producers index prices to past inflation, past inflation may be included in the Phillips curve.

Inflation expectations can be expressed in various forms. The simplest form is the adaptive expectations form, i.e., $\pi_t^e = \pi_{t-1}$. If economic agents believe that inflation will converge to a certain level, they may not adjust inflation expectations to one-to-one for short-term fluctuations in inflation. For example, Ball and Mazumder (2019) set inflation expectations as a weighted average of long-term inflation expectations and past short-term inflation. Economic agents' long-term inflation expectations may also change over time.

Demand pressure is usually estimated by the GDP gap. In many previous studies, demand pressure is measured by the unemployment rate gap. However, in Korea, the unemployment rate is of limited utility when used to explain economic fluctuations.[1]

According to Chun (2020), factors of global inflation can help to predict Korea's inflation. Global factors can include both global demand pressure and global supply pressure, and can be expressed as global inflation. This paper measures global factors using import price inflation.

Based on the above discussion, the Phillips curve can be set as follows:

$$\pi_t = \pi_t^e + \kappa_t \hat{y}_t + \gamma_t \hat{\pi}_{mt} + e_t,$$

where π_t denotes inflation, π_t^e inflation expectations, $\hat{y}_t$ the GDP gap, $\hat{\pi}_{mt}$ import price inflation, and e_t other factors including short-term supply factors.

Following Matheson and Stavrev (2013), the IMF (2013), and Blanchard, Cerutti, and Summers (2015), inflation expectations are set as the weighted average of long-term inflation expectations and past short-term inflation,

[1]For example, Park, Park, and Oh (2013) reported that since the global financial crisis, the relationship between the unemployment rate and business cycle in Korea had been statistically insignificant.

$$\pi_t^e = \theta_t \bar{\pi}_t + (1-\theta_t)\pi_{t-1}^4,$$

where $\bar{\pi}_t$ denotes long-term inflation expectations and π_{t-1}^4 is past inflation. θ_t represents the stability of inflation expectations or the degree of anchoring to long-term expectations. As θ_t is high, inflation is less affected by short-term factors. Finally, the Phillips curve is set in the following form.

$$\pi_t = \theta_t \bar{\pi}_t + (1-\theta_t)\pi_{t-1}^4 + \kappa_t \hat{y}_t + \gamma_t \hat{\pi}_{mt} + e_t.$$

This paper sets constraints on the coefficients following Matheson and Stavrev (2013), the IMF (2013), and Blanchard, Cerutti, and Summers (2015). Because inflation expectations are the weighted average of long-term expectations and past short-term inflation, $0 \le \theta_t \le 1$. As the widening of the GDP gap and the rise in import price inflation push up domestic inflation, $\kappa_t \ge 0$ and $\gamma_t \ge 0$. Long-term inflation expectations are unconstrained.

B. *Kalman-filter model*

This paper uses the Kalman-filter model, details of which can be found in Hamilton (1994), among others. To reflect the constraints, we consider the following transformation:

$$\begin{pmatrix} \bar{\pi}_t \\ \theta_t \\ \kappa_t \\ \gamma_t \end{pmatrix} = \begin{pmatrix} \beta_t(1) \\ \dfrac{\exp(\beta_t(2))}{1+\exp(\beta_t(2))} \\ \exp(\beta_t(3)) \\ \exp(\beta_t(4)) \end{pmatrix}.$$

For all $\beta_t \in (-\infty, \infty)$, the constraints are satisfied. The inverse transformation can be written as

$$\beta_t = \begin{pmatrix} \bar{\pi}_t \\ \ln\left(\dfrac{1-\theta_t}{\theta_t}\right) \\ \ln \kappa_t \\ \ln \gamma_t \end{pmatrix}.$$

Let $x_t \equiv (\pi_{t-1}^4, \hat{y}_t, \hat{\pi}_{mt})$ denote the predetermined exogenous variables and let

$$h(\beta_t, x_t) \equiv \frac{\beta_t(1)e^{\beta_t(2)}}{1+e^{\beta_t(2)}} + \frac{\pi_{t-1}^4}{1+e^{\beta_t(2)}} + e^{\beta_t(4)}\hat{y}_t + e^{\beta_t(4)}\hat{\pi}_{mt}.$$

Observation equations in the Kalman-filter model are $\pi_t = h(\beta_t, x_t) + e_t$, where the error term is independent and identically distributed and follows a normal distribution, $e_t \sim N(0, R)$. State equations are

$$\beta_t = \beta_{t-1} + v_t,$$

where the error term is independent and identically distributed and follows a normal distribution, $v_t \sim N(0, Q)$. The covariance matrix Q is a diagonal matrix. The state equations imply that the state variables β_t follow a random walk pattern.

In a linear Kalman-filter model, the observation equation is expressed as $\pi_t = H_t \beta_t + e_t$. In contrast, $h(\beta_t, x_t)$ is non-linear in β_t and hence the model in this paper is a non-linear Kalman-filter model. In this paper, not only is the nonlinear transformation applied to reflect the constraints, but there are also cross terms between state variables in the observation equations. To analyze the non-linear Kalman-filter model, this paper follows Simon and Chia (2002), Simon (2010), and Matheson and Stavrev (2013), among others. The key procedure is to replace H_t with the gradient of $h(\beta_t, x_t)$ with respect to β_t.

$$H_t = \left(\frac{\partial h(\beta_t, x_t)}{\partial \beta_t(1)}, \frac{\partial h(\beta_t, x_t)}{\partial \beta_t(2)}, \frac{\partial h(\beta_t, x_t)}{\partial \beta_t(3)}, \frac{\partial h(\beta_t, x_t)}{\partial \beta_t(4)} \right).$$

Taking partial derivative, I obtain

$$H_t = (\theta_t, (\overline{\pi}_t - \pi_{t-1}^4)\theta_t(1-\theta_t), \kappa_t \hat{y}_t, \gamma_t \hat{\pi}_{mt}).$$

The forward recursion of the Kalman filter includes

$$\beta_{t|t-1} = \beta_{t-1|t-1},$$

$$P_{t|t-1} = P_{t-1|t-1} + Q,$$

$$y_{t|t-1} = \theta_{t|t-1}\overline{\pi}_{t|t-1} + (1-\theta_{t|t-1})\pi_{t-1}^4 + \kappa_{t|t-1}\hat{y}_t + \gamma_{t|t-1}\hat{\pi}_{mt},$$

$$f_{t|t-1} = H_t P_{t|t-1}(H_t)^T + R,$$

$$\beta_{t|t} = \beta_{t|t-1} + P_{t|t-1}(H_t)^T (f_{t|t-1})^{-1}(y_t - y_{t|t-1}),$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}(H_t)^T (f_{t|t-1})^{-1} H_t P_{t|t-1},$$

where for any variable z_t, $z_{t_1|t_2}$ denotes the estimate for z_t of period t_1 based on information up to and including period t_2. Given the parameters (R, Q), I calculate the likelihood using the Kalman filter and then obtain the maximum likelihood estimates for (R, Q).

By Kalman filtering, I obtain $\beta_{t|t}$, which is the estimate with the information up to period *t*. The main focus of this paper is not the short-term forecasting of π_t but is instead the trends of $\bar{\pi}_t$ and θ_t per se. It is more useful to obtain estimates for $\bar{\pi}_t$ and θ_t with all available information. To obtain $\beta_{t|T}$ I apply backward recursion to the Kalman smoothing,

$$\beta_{t|T} = \beta_{t|t} + P_{t|t}(P_{t+1|t})^{-1}(\beta_{t+1|T} - \beta_{t+1|t}).$$

The backward recursion of the mean squared error matrix follows:

$$P_{t|T} = P_{t|t} + P_{t|t}(P_{t+1|t})^{-1}(P_{t+1|T} - P_{t+1|t})(P_{t|t}(P_{t+1|t})^{-1})^T.$$

C. *Data Description*

The sample period is from the first quarter in 2000 to the fourth quarter in 2020. Inflation is measured as the logarithm difference of quarterly seasonally adjusted consumer-price indices. Because the seasonally adjusted consumer price is not officially released, Census X-13 ARIMA-SEATS values are used. I multiplied the difference by 400 in each case to convert the rates into the annual percentage change. The past short-term inflation is the year-over-year logarithm difference relative to the consumer price of the previous period. This corresponds to the average quarterly inflation over the four quarters. I multiplied the difference by 100. This specification followed Matheson and Stavrev (2013), the IMF (2013), and Blanchard, Cerutti, and Summers (2015).

The GDP gap is the actual GDP(Y_t) and the potential GDP($\bar{Y}_t$). That is, $\hat{y}_t = (\ln Y_t - \ln \bar{Y}_t) \times 100$. The potential GDP is unobservable and thus needs to be estimated. This paper uses the method of Hodrick and Prescott (1997), henceforth referred to as the HP filter. Estimates of the potential GDP with quadratic time trend are also examined. Figure 5 shows the GDP gap estimates by the two methods. The overall trends of the two series are very similar, but there are some differences in the breadth of the economic fluctuations. The methods using the structural VAR model in Blanchard and Quah (1989) is widely used in the literature. Blanchard and Quah (1989) used data on the unemployment rate and GDP. In Korea, the unemployment rate is limited if used to reflect short-term economic fluctuations. Because the HP filter and the quadratic time trend model mechanically decompose the time series into trends and short-term fluctuations, the accuracy of the potential GDP estimation

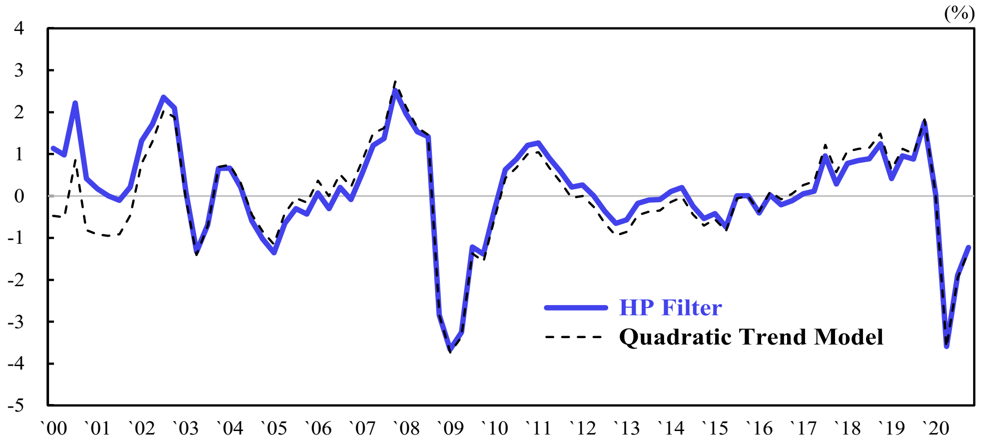

FIGURE 5. COMPARISON OF GDP GAP ESTIMATES

Source: Authors' estimates.

is debatable. In future research in this area, more rigorous estimates of the GDP gap could be used to improve the results of this paper. Therefore, when interpreting the results of this study, it is necessary to focus more on the estimation of inflation expectations rather than on the coefficient of the GDP gap.

Import price inflation is defined as the logarithm difference of seasonally adjusted import prices in Korean won relative to consumer prices in accordance with Matheson and Stavrev (2013), the IMF (2013), Blanchard, Cerutti, and Summers (2015). Import price inflation is also converted into an annual rate. The deviation from the mean is calculated by subtracting the mean value of the sample period from the time series. In a regression analysis, the mean value of the time series is often treated as a constant term. In this analysis, however, because a constant term may affect the level of inflation expectations, the mean value of the time series is subtracted.

IV. Results and Implications

A. *Linear Regressions*

Before performing the Kalman filter analysis, I undertake a linear regression analysis. This model is usually used to identify short-term inflation fluctuations. We consider the linear regression analysis below.

$$\pi_t = c + \rho\pi_{t-1}^4 + \kappa\hat{y}_t + \gamma\hat{\pi}_{mt} + e_t. \tag{1}$$

This regression model can be interpreted as meaning that the form of inflation expectations is expressed as follows:

$$\pi_t^e = c + \rho \pi_{t-1}^4. \tag{2}$$

The long-term expectations are $\bar{\pi}_t = c$ and the degree of anchoring is $\theta_t = (1-\rho)$. The other coefficients are also assumed to be invariant over time.

Table 2 shows the results of regression analysis with the sample from the first quarter of 2000 to the fourth quarter of 2020. The dependent variable is quarterly headline inflation in the annual rate. The coefficient of π_{t-1}^4 is estimated to be 0.519, which means that there is considerable inertia affecting inflation. Inflation also had a statistically significant response to the demand pressure, i.e., the GDP gap. Inflation was analyzed and found to increase by 0.056%p when import price inflation rises by 1%p, and this was found to be significant at the 1% level.

The implied degree of anchoring to long-term inflation expectations is $1 - 0.519 = 0.481$. The implied long-term inflation expectations are $1.032 / (1 - 0.519) = 2.15\%$, which is less than the average of the inflation target levels.

Table 2 also shows the result of the same analysis on core inflation. The coefficient of π_{t-1}^4 is estimated to be 0.706, indicating that the inertia of core inflation exceeded that of headline inflation. There was no significant difference between headline and core inflation outcomes with regard to the response to the GDP gap. On the other hand, for core inflation, the regression coefficient for import price inflation was small and statistically insignificant; while changes in energy prices have a strong influence on import price inflation, they are excluded from the basket of core inflation.

The implied degree of anchoring to long-term inflation expectations is $1 - 0.706 = 0.294$. The implied long-term inflation expectations are $0.579 / (1 - 0.706) = 1.97\%$, similar to the estimate using headline inflation.

The linear regression model above can be interpreted as meaning that the state variables are assumed to be constant over time. This assumption may be improper

TABLE 2—LINEAR REGRESSION ESTIMATIONS

Independent variables	Dependent variables			
	Headline inflation		Core inflation	
	(1)	(2)	(3)	(4)
Constant	1.032*** (0.222)	2.842*** (0.795)	0.579* (0.299)	2.074*** (0.387)
Time trend		-0.024** (0.010)		-0.019** (0.004)
π_{t-1}^4	0.519*** (0.076)	0.191 (0.175)	0.706*** (0.118)	0.381*** (0.135)
$\hat{y}_t$	0.282** (0.108)	0.148 (0.121)	0.277*** (0.090)	0.175** (0.082)
$\hat{\pi}_{mt}$	0.056*** (0.010)	0.059*** (0.011)	0.003 (0.013)	0.004 (0.014)
R^2	0.46	0.52	0.35	0.44
Number of observations	84	84	84	84

Note: 1) Numbers in parenthesis are Newey-West standard errors, 2) ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

considering that there was a declining trend of the inflation rate in Korea. To examine this possibility, rolling regressions were performed. The same linear regression model was analyzed with the data for 40 quarters (ten years) from period $t-39$ to period t. Figure 6 shows the results of the regression analysis. The constant term shows a clear downward trend. The coefficient of π_{t-1}^{4} did not remain stable for each time point. It is not clear whether there is a time trend in the coefficients of π_{t-1}^{4}, the GDP gap, and import price inflation. The rolling regression analysis implies that there is a downward trend in the constant term and that it is therefore necessary to include the time trend term in the linear regression model.

Reflecting the rolling regression results, inflation expectations are modified by allowing a linear time trend. Adding a time trend to the previous linear regression

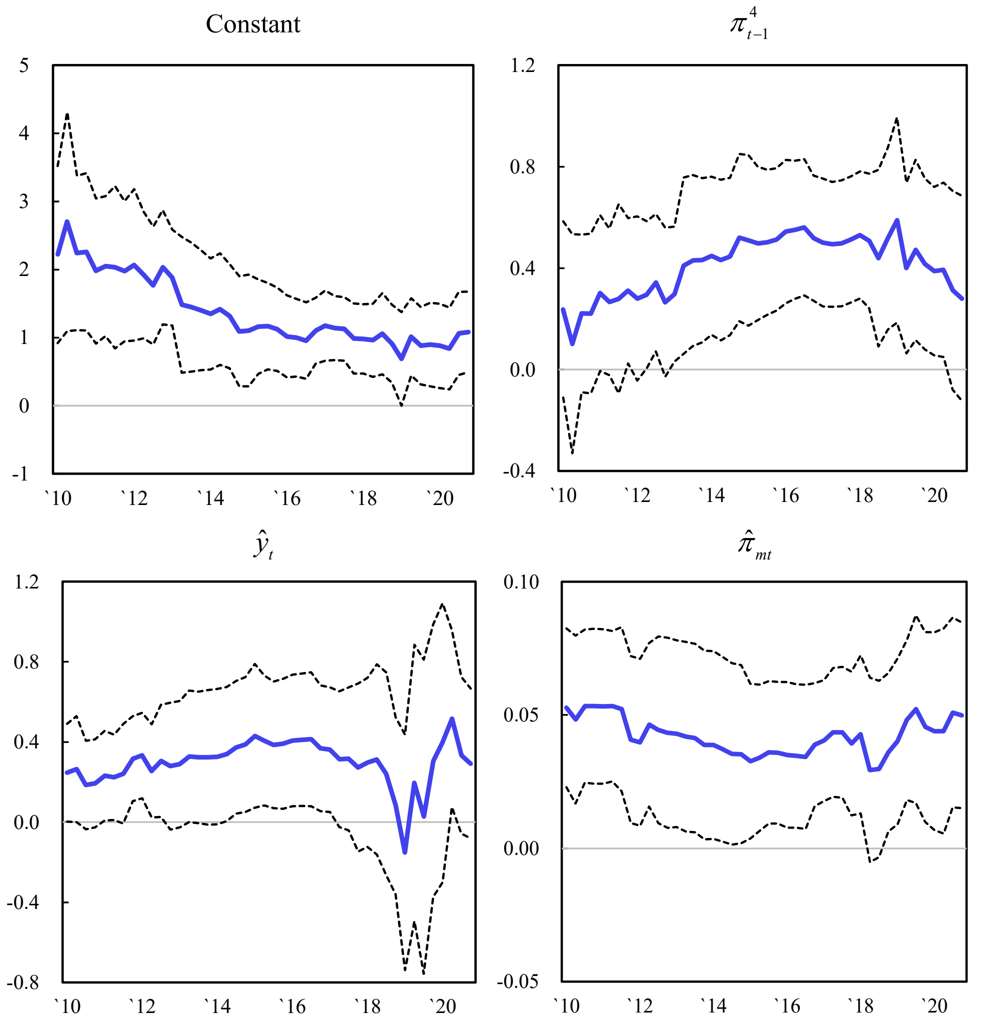

FIGURE 6. ROLLING REGRESSION COEFFICIENTS

Note: 1) The dependent variable is headline inflation, 2) The dashed line represents a 95% confidence interval using the Newey-West standard error.

yields the following regression model:

$$(3) \qquad \pi_t = c + \alpha t + \rho \pi_{t-1}^4 + \kappa \hat{y}_t + \gamma \hat{\pi}_{mt} + e_t.$$

This regression model can be interpreted as meaning that inflation expectations can be expressed as

$$(4) \qquad \pi_t^e = c + \alpha t + \rho \pi_{t-1}^4.$$

Table 2 above shows the regression analysis results. First, the coefficient of the time trend was negative and statistically significant. This result can be readily expected in that inflation has shown a downward trend. The degree of anchoring to long-term expectations $\theta = (1-\rho)$ is 0.809, which is much higher than the estimate without the time trend, at 0.481. The coefficients for π_{t-1}^4 and the GDP gap were reduced compared to those without the time trend. Meanwhile, there was no significant difference in the regression coefficient for import price inflation. Table 2 also shows the results of a regression analysis of core inflation. Similar to the analysis of headline inflation, the regression coefficient for the time trend was negative and statistically significant. The regression coefficients of π_{t-1}^4 and the GDP gap were also lower than those without the time trend.

The focus of this study is on inflation expectations. Figure 7 shows the inflation expectation outcomes estimated in the linear regression with and without the time trend. In the analysis including the time trend, the inflation expectation levels were high at the beginning of the sample period and low at the end of the analysis period. The estimates of the degree of anchoring to the long-term inflation expectations were quite different.

As the assumption of a linear time trend in inflation expectations is not firmly grounded, I will not rely on a specific time structure and will directly estimate how the long-term expectations and the degree of anchoring change over time using the Kalman-filter model.

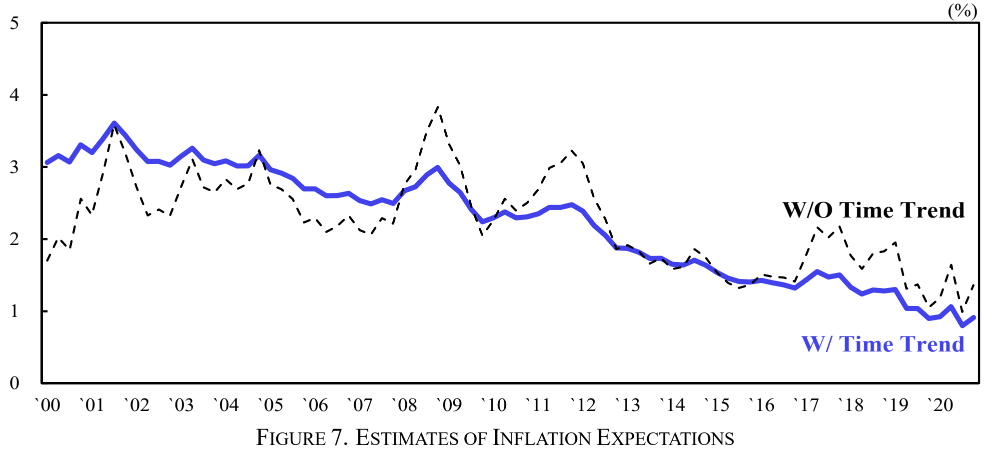

FIGURE 7. ESTIMATES OF INFLATION EXPECTATIONS

B. *Kalman Filter Analysis*

This subsection presents the analysis results of the Kalman-filter model. The first panel of Figure 8 shows that long-term expectations are on a downward trend, similar to actual inflation. Long-term expectations remained relatively stable in the mid 2% range in the mid-2000s, but since 2012 the decline of long-term expectations has been remarkable and they have remained below the inflation target. Recently, long-term expectations rebounded slightly and were in the low 1% range. Figure 8 shows that the estimates with the alternative GDP gap measure, de-trended using a quadratic time trend model, are qualitatively similar to the baseline estimates.

To check the robustness of the results, estimation for the sample excluding the Covid-19 crisis is conducted; a marked decline in long-term expectations since 2012 has been maintained (Results are available upon request). In summary, the rate of decline in long-term expectations has accelerated since 2012, and recently it remains in the low 1% range, which is much lower than the Bank of Korea's inflation target of 2%.

Figure 8 shows that the degree of anchoring of inflation to long-term expectations has risen consistently and is estimated to be around 0.9 at the time of this writing. The estimates with the alternative GDP gap measure show a similar trend. The IMF (2013) also found that inflation has been strongly anchored to long-term expectations. It reported that the median of the degree of anchoring for 21 economies had been rising and, depending on the specification for unemployment gap measures, they reached 0.84-0.93 at the end of 2011.

Given the results of low long-term expectations and high degree of anchoring to them, Korea's low inflation since 2012 is not a case in which temporal factors lowered actual inflation with high inertia. Instead, economic agents have lowered their long-term expectations, whose role in the determination of inflation has been greater. The results here imply that low inflation can persist into the future even if actual inflation temporarily rises due to short-term disturbances.

Figure 8 shows the coefficients of the GDP gap and import price inflation, although they are not the main focus of this study. The coefficient for the GDP gap in the baseline estimation was slightly above 0.3, similar to the coefficient in the rolling regression. It did not exhibit clear time trend in either the baseline or the alternative estimation.[2] The coefficient of import price inflation was around 0.07 at the end of 2020, which is close to the estimation in the linear regression model. The coefficient exhibited an upward trend after the global financial crisis. Note that the coefficient in the rolling regression also had a slight upward trend more recently. This result is in line with Park and Park (2014), who found that the explanatory power of global factors with regard to inflation in Korea had increased since the global financial crisis. The estimation results for the sample excluding the Covid-19 crisis were not qualitatively different (Results are available upon request).

[2]In the baseline specification, κ_t is estimated to be constant over time because the estimated variance of the innovation of β_3 is close to zero. The result is, however, not robust because, in the alternative specification, κ_t is estimated to fluctuate.

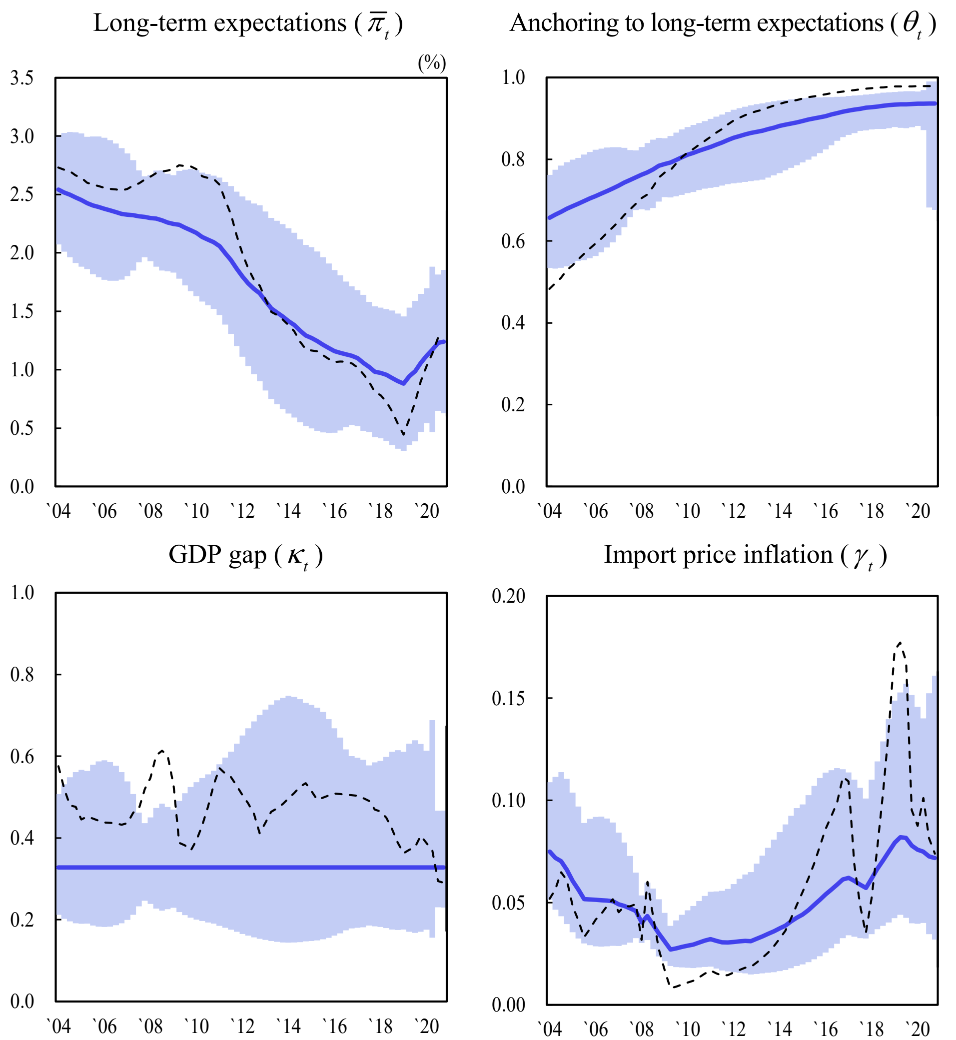

FIGURE 8. RESULTS OF THE KALMAN FILTER ANALYSIS

Note: 1) The solid line represents estimates using the GDP gap with the HP filter (baseline) and shading represents one standard error band, 2) The dashed line represents estimates using the GDP gap with a quadratic time trend (alternative specification).

C. *Comparison among Various Inflation Expectations*

How different are the long-term inflation expectations estimated through the Kalman filter and the survey results of the experts' long-term expectations? Figure 9 shows the experts' long-term expectations, which were taken from Consensus Economics' five-year-ahead inflation expectations. The experts' long-term expectations did not significantly deviate from the inflation target. As with the short-term expectations, however, experts' long-term inflation expectations were also upwardly biased compared to actual inflation. In other words, even if the experts' long-term inflation expectations survey results remain high, long-term expectations

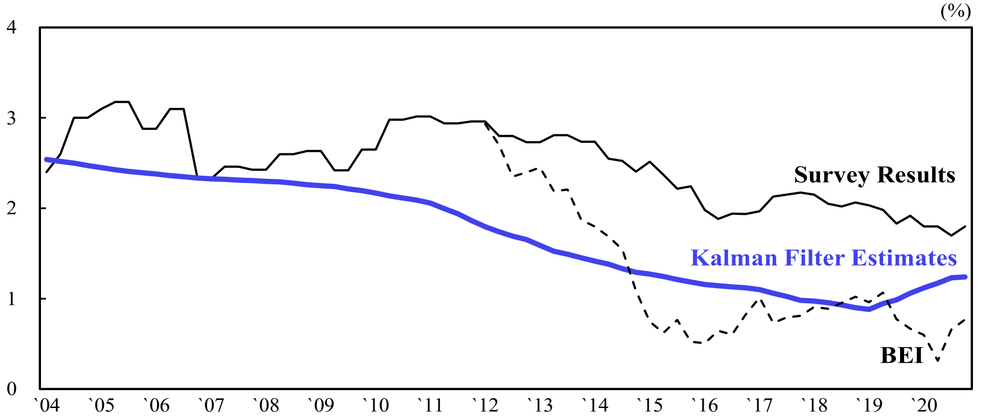

FIGURE 9. LONG-TERM EXPECTATIONS - SURVEY RESULTS, FINANCIAL MARKET ESTIMATES, AND KALMAN FILTER ESTIMATES

Note: BEI represents break-even inflation in 10-year treasury bonds.

Source: Consensus Economics, Bloomberg, author's calculations.

as reflected in actual inflation can significantly fall short of this level.

As another reference, the break-even inflation (BEI), measured as the yield difference between the 10-year treasury bond and an inflation-protected bond with the same maturity, can be considered. BEI is interpreted as inflation expectations assessed by financial market participants. The series begin at the end of 2011. Figure 9 shows that BEI also has declined rapidly since 2012, remaining around 1%, similar to the Kalman filter estimates.

D. *Implications of the Covid-19 Crisis*

During the Covid-19 crisis, the Bank of Korea cut its base rate from 1.25% to 0.5% by 0.75%p. The Bank of Korea lowers the real interest rate (base rate minus inflation expectations) by lowering the nominal interest rate, affecting the real economy. Because nominal interest rates have a zero lower bound, the real interest rate is constrained by inflation expectations. Figure 10 shows the estimated real interest rate (solid line) and the hypothetical real interest rate (dashed line), which is calculated by assuming, all other things being equal, that long-term expected inflation remains at the inflation target of 2%; i.e., $\pi_t^e = \theta_t \cdot 2\% + (1-\theta_t)\pi_{t-1}^4$. Had the real interest rate been lower with high inflation expectations, the recession would have been less severe. In cases where a large nominal interest rate cut is required, such as during the Covid-19 crisis, the level of inflation expectations acts as a major constraint on the implementation of monetary policies.

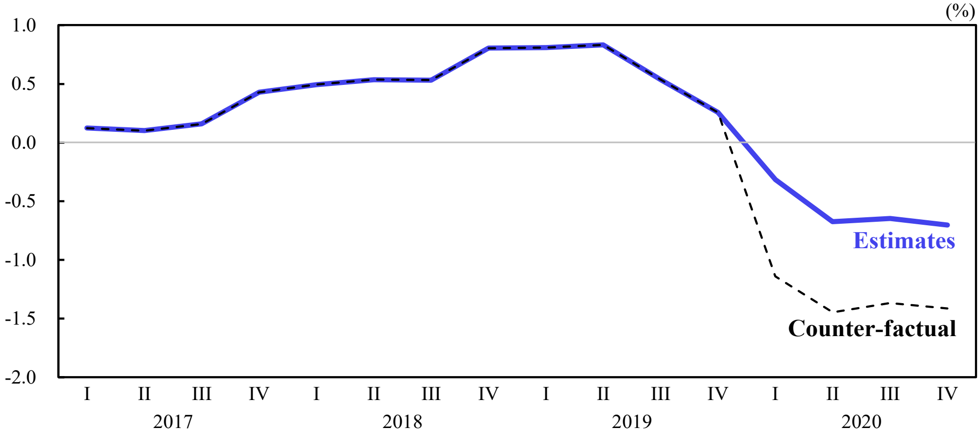

FIGURE 10. REAL INTEREST RATES

Note: Counter-factual inflation expectations are calculated assuming that long-term inflation expectations are identical to the inflation target of 2%.

Source: Authors' estimates.

V. Concluding Remarks

This paper examined where and how tightly inflation expectations are anchored in the Phillips curve, finding that the dynamics of inflation expectations have changed significantly since 2012. Long-term expectations fell to around 1%, short of the inflation target for an extended time. Moreover, inflation expectations are strongly anchored to long-term expectations, implying that the phenomenon of low inflation will persist into the future. This paper did not formally analyze why the inflation dynamics changed around 2012. As Jung (2019) and Cho (2020) claimed, one possibility is that financial stability was added as a monetary policy goal at the end of 2011, and despite the fact that inflation significantly deviated from the target below, the Bank of Korea was reluctant to lower the base rate for fear of financial imbalances.

As expectations for a recovery from the Covid-19 crisis emerge and accommodating monetary and fiscal policies continue, there are concerns about a surge in the inflation rate. The results of this paper suggest that as inflation expectations are strongly anchored at the 1% level, even if inflation fluctuates due to temporary disturbances, it may converge again to a level below the inflation target.

Long-term expectations have rebounded slightly since 2020. Due to the continued low inflation phenomenon, there was criticism that the Bank of Korea's inflation management was too passive. During the Covid-19 crisis, the Bank of Korea lowered its base rate promptly and implemented unconventional monetary policies. It is still too early at the time of this writing to evaluate the monetary policy implemented by the Bank of Korea in Covid-19 crisis, but the slight rebound in long-term expectations suggests that the aggressive monetary policy may have contributed to improving economic agents' beliefs about the monetary authority's commitment to inflation stability and may have helped long-term expectations gradually to approach the inflation target.

This paper has many limitations. The GDP gap was estimated somewhat mechanically rather than by an econometric model. A more rigorous estimation of the GDP gap may be helpful for more precise and robust estimations for inflation expectations. Also in future work, the factors that affect inflation expectations should be examined closely. During the Covid-19 crisis, the Bank of Korea faced the zero lower bound and implemented an unconventional monetary policy for the first time. The effectiveness, including side effects, of such a monetary policy should also be evaluated.

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The Impact of COVID-19 Regional Cash Subsidies on the Sales of Local Businesses in South Korea†

By MEEROO KIM AND YOON HAE OH*

This paper examines the impact of the regional cash subsidies which were granted in some districts in addition to the national universal stimulus payment in South Korea related to the COVID-19 pandemic. We evaluate the effects of the cash distribution per resident on aggregate credit and debit card sales and sales by industry using the difference-in-difference method. The increment in card spending due to the cash subsidy is about 1.58%p in total, and this effect is concentrated within a single month. The consumption stimulating effect is prominent among (semi)-durable goods that do not require close interactions between customers and sellers. In contrast, the effect is relatively small in the high-contact face-to-face service sectors and restaurants, areas the COVID-19 pandemic hit directly. On the other hand, some service sectors where customers could wear face masks, such as education and fitness, experienced a substantial sales boost due to the cash subsidy.

Key Word: COVID-19, Stimulus Payment, Cash
JEL Code: D12, E21, H12

I. Introduction

Starting in late February of 2020, when the number of COVID-19 (coronavirus disease 2019) confirmed cases rose rapidly in Daegu and Gyeongsangbuk-do, household consumption fell sharply in South Korea. Therefore, like other governments such as the U.S. and Japan, the South Korean government provided an emergency COVID-19 relief fund (EDRF) to all households in May of 2020 to mitigate the economic disruption caused by the COVID-19 pandemic.

At around the same time, most metropolitan governments and municipal governments also provided various additional subsidies to residents. For example, some regions gave cash to residents, while most local governments granted subsidies

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by means of paper gift cards or magnetic prepaid cards. Some districts, including nine "Gu" areas in Busan, Namyangju-si in Gyeonggi, Donghae-si, and Sokcho-si in Gangwon-do, provided cash to residents. This study analyzes whether local small businesses' sales increased more in areas with additional cash subsidies than in areas without any additional payments from local governments apart from the EDRF.

The EDRF was the first national universal stimulus payment policy in South Korea. Thus, evaluating the impact of the national EDRF policy could be meaningful. Moreover, the total amount of the additional local stimulus payments was smaller than the nationwide EDRF total amount. However, this study mainly focuses on regional governments' cash payment policies, and not the national EDRF payment, to analyze whether the cash subsidy flowed to residential, small businesses by way of sales.

Analyzing payment by regional governments has the advantage of distinguishing the effects of specific payment methods. The primary goal of the stimulus payment policy is to support households' income and boost the sales of small businesses, which dropped distinctly due to the COVID-19 pandemic. Hence, in preparing the stimulus payment policy in early 2020 in South Korea, determining which payment methods to use was one of the major issues, along with the payment targets. Accordingly, the national EDRF and most local governments' subsidies were paid as local currency coupons with several limitations to their use. First, the validation period was short as three to four months. Second, gift cards or prepaid cards and credit card coupons were valid only within the recipients' residency areas. Third, the payments were only available in specific sectors and excluded department stores and online malls. These limitations were established to increase the effectiveness of the policy, preventing the subsidy from flowing into saving accounts or online shopping malls, where sales increased even after the outbreak of COVID-19.

However, as most households consume a large portion of their living expenses within their residential areas, even a cash subsidy could flow to local small businesses. Chetty *et al.* (2020) also report that small businesses' revenues increased after the U.S. government provided a stimulus payment as cash. It is costly to issue certificates/coupons and to establish a system that distinguishes transactions within a residential area and in specific sectors. Furthermore, for consumers, it is confusing to attempt to determine where the coupons would be accepted. On the other hand, providing subsidies as cash can be an economical and straightforward payment method. However, cash payments were regarded as an ineffective method in the policy design absent any empirical evidence.

We utilize the combined credit and debit card sales of eight prominent card companies in Korea. We find that businesses in regions with additional cash subsidies experienced significantly more card sales compared to areas without additional support. Thus, a simple payment in the form of cash can also increase business sales in residential areas, without high administrative expenses and/or consumer inconveniences. Some local governments paid subsidies as local consumption vouchers in a similar period, and comparing the policy impact between coupon payments and cash payments would be more informative. However, this approach was not plausible here, as voucher consumption data pertaining to local governments were not available.

Moreover, analyzing the effect of regional cash payments can evaluate the impact of the stimulus payment in a more robust way than analyzing the national EDRF subsidy. Several studies have reported the impact of the EDRF stimulus payments in South Korea. However, as it is challenging to find an appropriate control group (excluded as recipients), various methods have been tested, with varying results. Hong (2020) and W. Lee *et al.* (2020) utilize consumption in the previous year (2019) as a type of control sample, reporting marginal propensity to consume (MPC) as 76.2% and 65.4~78.2%, respectively.[1] However, this approach can severely overestimate the consumption boosting impact, as it cannot control factors that significantly facilitate consumption only in the period after the policy in 2020, which was not present in 2019.[2]

Kim and Oh (2020) utilize the synthetic control method by Abadie and Gardeazabal (2003) to construct control groups from the sales of sectors that do not accept EDRF coupons. They report that the increment ratio in nationwide card spending among sectors that accept consumption vouchers relative to the total amounts of funds injected is in the approximate range of 26.2~36.1%. On the other hand, Kim *et al.* (2020) report that the MPC of Seoul residents within six weeks is 24%. They utilize Shinhan card spending by non-Seoul residents within the Seoul area as a control group.

In this study, we compare the card sales of the regions' businesses with additional cash subsidies to the sales of areas without any local governmental support, which is a distinct control group. Thus, we can utilize the difference-in-difference method as a traditional setting.

This study also investigates how the impact of the cash subsidy differs by industry. In a situation where the pandemic is still spreading, the effect of the stimulus payment can be asymmetric according to how each business requires personal interaction to transact. In this case, even with the increased income, households may not significantly increase their consumption in the high-contact service sectors, while the damage by COVID-19 was concentrated in these sectors. We estimate the policy's heterogeneous effects in different industries, i.e., face-to-face services, restaurants, (semi)-durable goods such as clothes and furniture, essential goods, and education/fitness services, among others.

This study also uses the number of confirmed COVID-19 cases by district (Si/Gun/Gu) as a control variable and analyzes whether the effect of the cash subsidy on local business sales is asymmetric according to the degree of the spread of the pandemic. This approach is also distinct from other in the literature.

The rest of this paper is structured as follows. Section 2 reviews related studies and the features of the regional stimulus payments in South Korea. Section 3 presents the data and the empirical strategy. The descriptive statistics and regression results are presented in section 5, Section 6 concludes the paper.

[1]Hong (2020) analyze daily Shinhan Card sales, and W. Lee *et al.* (2020) use quarterly data of household incomes and expenditure survey results from Statistics Korea

[2]The decreased number of confirmed COVID-19 cases, tax exemptions for the purchase of new automobiles, and large-scale discount promotions could be among these factors. Therefore, it is necessary to select a control group from the same period which experiences other factors other than the EDRF policy.

II. The COVID-19 Crisis in Korea

A. *Literature Review*

This study is closely related to the literature on evaluations of stimulus payments policy in response to COVID-19. Previously, a stimulus payment policy providing cash or consumption coupons was implemented in many countries to induce an economic recovery after a recession. Several studies of these stimulus payments report that such a policy partially promotes consumption, as households spend part of the increased income (Agarwal *et al.,* 2007; Johnson *et al.,* 2006; Parker *et al.,* 2013; Kan *et al.,* 2017).

Several studies investigate the impact of the U.S. CARES Act stimulus payments with individual transaction data (Baker *et al.,* 2020; Chetty *et al.,* 2020; Misra *et al.,* 2020) Previous studies analyze the heterogeneous impact of the policy by industry and income level. Karger *et al.* (2020) report that non-needy individuals spend 23% of the payment within two weeks, while those living 'hand-to-mouth' spend 70% of the payment. Baker *et al.* (2020) also report that low-income households increased consumption within ten days after the cash payment. They also point out that the consumption of preserved food increased considerably. Chetty *et al.* (2020) report that the impact of the US CARES Act payments was larger in sectors requiring little physical interaction. Kim *et al.* (2020) report that card sales increased less in areas with higher average incomes or more confirmed COVID-19 cases, analyzing the impact of the EDRF through Seoul citizens' card consumption levels. The impact is also lower in sectors which experienced larger sales decreases after an outbreak of COVID-19. Kim and Oh (2020) also report using a synthetic control method that the consumption-boosting effect of the EDRF is greater in durable goods and essential goods, while the impact is smaller in restaurants or in-person service sectors.

This study is similar to previous studies as we also investigate the heterogeneous effects of the stimulus payment by industry. Nonetheless, it is distinct in that we focus on the effects of cash payments on local business sales. T. Lee *et al.* (2020) investigate the impact of cash payments through survey data on 1,386 EDRF cash recipients and report that consumption increased by 21.7%. However, T. Lee *et al.* (2020) did not distinguish the consumption-boosting impact within and outside of residential areas. This study is also similar to that by Chetty *et al.* (2020) as they investigated the effect of cash payments according to zip-code-level business revenue. However, this comparison between regions with additional cash payments and areas without any regional relief funding is distinguished from the study of Chetty *et al*. (2020).

B. *Policy Review*

From May 11 (the 20th week) of 2020, the COVID-19 EDRF was provided to most households in South Korea, and existing welfare recipients such as basic livelihood security funds, basic pensions, and pensions for the disabled were paid in cash a week earlier (May 4, the 19th week). The amount of the payment increases with the number of people in a household by KRW 200,000, varying from KRW

400,000 (single-member households) to KRW 1,000,000 (families with four or more). Except for welfare recipients who received cash, the payment was in the form of local consumption vouchers with many restrictions based on sectors, regions, and dates. To boost the sales of local small businesses, the Korean government limited the industries or sectors that could accept the vouchers. For instance, online retailers were excluded, as they did not suffer damage with the increased sales after COVID-19. Department stores or large retailers such as E-mart (similar to Walmart in the U.S.) and Costco could not accept the vouchers either, as they are not small businesses needing protection. Entertainment venues such as pubs and karaoke bars were also excluded, as promoting these sectors may have increased the risk of infection. The vouchers were accepted at local stores in residential areas. This was done to prevent a situation in which the subsidy would be concentrated in large metropolitan areas with more and better shopping conditions than in less populated areas. The payments expired at the end of August of 2020, and this was done to boost consumption more effectively.

At the same time, most metropolitan counties and local city authorities provided additional subsidies, and the type of payment mainly was consumption vouchers such as the EDRF again with region, sector and period restrictions.

In this way, most of the EDRF was paid in the form of local consumption coupons, and the portion of cash recipients stood at only 12.9% out of KRW 14.2 trillion. Additionally, KRW 1,800 million was paid by metropolitan city or provincial governments and KRW 2,700 million by local municipal governments. The reason for designing a large amount of money in the form of a coupon with many restrictions stems from an agreement that payment in cash would not increase the sales of local small businesses significantly. However, the hypothesis that payment in the form of cash does not help revitalize local business has not been empirically tested, although high issuance costs are required during the process of designing consumption, and consumers' choices are limited.

Therefore, this study aims to analyze whether local business sales were boosted in regions where households receive a 'cash' transfer. Table 1 shows the amounts of cash support and the time of the payment in each region. KRW 50,000 to KRW 200,000 per person was distributed, equivalent to KRW 800,000 for a household

TABLE 1—AMOUNTS OF CASH SUPPORT AND TIME OF PAYMENT

Province	District	Subsidy per person (KRW)	Date of payment
Busan	Busanjin-gu	50,000	4. 8.
Busan	Buk-gu	50,000	5. 29.
Busan	Gangseo-gu	50,000	4. 27.
Busan	Gijang-gun	100,000	3. 28.
Busan	Jung-gu	100,000	5. 20.
Busan	Nam-gu	50,000	4. 22.
Busan	Sasang-gu	50,000	4. 16.
Busan	Seo-gu	50,000	5. 6.
Busan	Yeongdo-gu	50,000	4. 22.
Gangwon-do	Donghae-si	200,000	6. 3.
Gangwon-do	Sokcho-si	200,000	5. 13.
Gyeonggi-do	Namyangju-si	100,000	5. 1.

TABLE 2—SHARES OF TRANSACTION TYPES IN KOREA (TRANSACTION AMOUNT)

(UNIT: %)

Type	2017	2019
Cash	20.3	17.4
Credit Card	32.8	53.8
Debit Card	10.1	15.3
Account Transfer	16.7	8.0
Mobile Card	2.0	3.8
Prepaid magnetic Card / Electronic Currency	0.0	0.5

Source: Bank of Korea (2020).

with four members. The distribution timing varied from March 28 to June 3, with this being utilized as an identification strategy. The earliest payments were in Busanjin-gu in Busan starting on April 8, and the last payments were in Donghae-si of Gangwon-do from June 3.

We use the difference-in-difference method to identify the effect of the regional relief funding on businesses' sales, along with the corresponding heterogeneity of the number of confirmed COVID-19 cases. Here, we compare the treated groups who receive an additional cash subsidy from the local government to those who did not receive any additional subsidy in Chungcheongnam-do, Ulsan, and Incheon.

Local governments transferred cash into the checking accounts of the heads of household. Therefore, individuals may have used a certain percentage of their increased income in the form of credit or debit cards. Table 2 shows the portion of each payment type in Korea. As of 2019, 53.8% of credit cards and 15.3% of debit cards were used. Compared to 2017, the proportion of cash payments decreased further in 2019, and the proportion of credit and debit cards increased further. The decreasing trend in cash use is expected to have intensified in 2020, when COVID-19 spread. Therefore, it can be assumed that households with increased cash incomes may consume by credit cards or debit cards at least 70% of their total consumption.

III. Data and Empirical Strategy

A. *Data*

The card sales data used in this paper consist of credit and debit card consumption data from eight credit card companies (BC, Shinhan, Kookmin, Nonghyup, Lotte, Samsung, Hyundai, Hana). For each credit card company, weekly card sales of thirty different industries are summed at the district level (Si/Gun/Gu) from the first week of January of 2019 to the second week of August 2020. We construct card sales growth as a dependent variable compared to the sales amount of the previous year. The thirty industries are divided into sectors that accept the national EDRF vouchers and sectors that do not take them. We grouped the EDRF-accepting sectors into seven categories, as some districts do not have a particular business, out of the finely divided thirty industries. Those are face-to-face services, (semi)-durable goods, drugstores/hospitals, restaurants, essential goods, education/fitness, and others.

Face-to-face services include leisure, hairdressing, and public bathhouses. Restaurants include all types of dining establishments, coffee shops and bakeries, and fast food outlets. (Semi)-durable goods combine the sales of books, apparel/accessories, stationery, glasses, and furniture. Essential goods are sales by convenience stores and grocery shops.

IBK Industrial Bank, Citibank Korea, SC Bank Korea, Korea Development Bank, Suhyup Bank, K Bank, and local banks, including Daegu Bank, Busan Bank, and Kyeongnam Bank, all use the BC Card Network, while Kakao Bank uses the Kookmin Card Network. In addition, we only use sales put on personal cards, which are suitable for this type of analysis, excluding sales put on corporate cards. Transactions with pre-paid cards or cash are excluded from the actual sales of local businesses.

In order to control for regional characteristics, we use the ratio of the elderly (65+) population rate and the year-on-year population growth rate as control variables. These are monthly variables available through the Korean Statistical Information Service.

Because the spread of COVID-19 by region can also significantly affect local business sales, we also use the ratio of the number of confirmed COVID-19 cases relative to the regional population. We constructed a weekly ratio of confirmed cases relative to the population both at the district (Si/Gun/Gu) and province (Si/Do) level. The weekly variation of confirmed COVID-19 cases at the city level is confidential data obtained through the Korea Disease Control and Prevention Agency. Its exclusive use was pledged by the authors in this case.

B. *Empirical Strategy*

We use the difference-in-difference method to identify the effects of the regional relief funds in the form of cash on local business sales. Here, we focus on treated groups in two cities in Gangwon-do, Namyangju-si in Gyeonggi-do, and nine districts of Busan that granted cash to all residents as well as the national EDRF subsidy. The control group is the sales growth of businesses in Chungcheongnam-do, Ulsan, and Incheon province, which only provided the EDRF without any additional universal subsidies to households. Ulju-gun in Ulsan and districts that are not included in the treated groups in Busan/Gyeonggi-do/Gangwon-do are excluded from our sample as they distributed prepaid cards or paper gift cards as subsidies.

The method, amount, and timing of the payment of the regional relief funds solely depend on the local government's decision. Therefore, a cash payment represents an exogenous shock to the local economy, and this is a reliable setting in which to apply the difference-in-difference method for a policy evaluation.

In the treated groups, the regional relief fund is paid between April of 2020 and June of 2020. Therefore, the first difference in the difference-in-difference method is the period before and after the payment. Additionally, the second difference comes from whether or not a district belongs to a region where the regional relief fund is paid as cash. Because there is a difference in the timing of additional subsidies paid, a unique treated point is defined and used for each region when implementing the difference-in-difference method.

The most crucial point when identifying the effect of the regional relief funds on

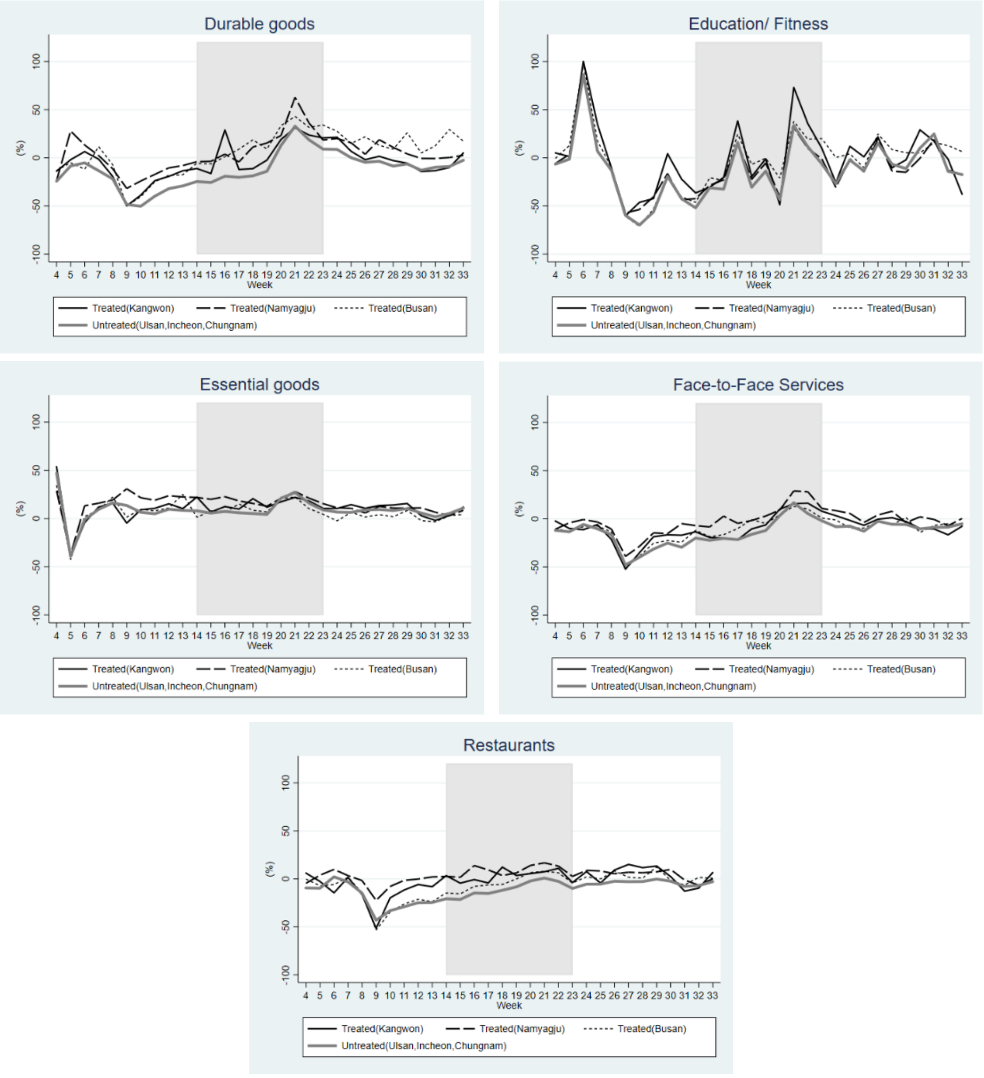

FIGURE 1. YEAR-ON-YEAR SALES GROWTH BY SECTOR

business sales using the difference-in-difference method is whether the parallel trend assumption is valid or not. Moreover, we need to assume a homogeneous treatment effect given that the national EDRF was paid to all districts as the regional relief funding was additionally paid with the EDRF subsidy.

Figure 1 shows the year-on-year change in sales for the treated group with additional cash subsidies from local governments and the control group that did not have additional subsidies. For each industry, the year-on-year sales show parallel movement before the national EDRF and regional relief funds in the form of cash.

In most industries, except for essential goods, year-on-year sales were lowest in the ninth week, when the number of confirmed COVID-19 patients surged in Korea. Later, as the number of confirmed cases decreased gradually, year-on-year sales even rose back to the level before the EDRF distribution. After 19-20th weeks, the EDRF payment period, year-on-year sales increased notably. Through an empirical analysis, we estimate whether year-on-year sales increased significantly in regions where local governments provided additional subsidies in cash as compared to regions without additional subsidies.

C. *Econometric Model*

The econometric model used in the empirical analysis is as follows. We apply difference-in-difference OLS regression with covariates and several fixed effects. We use control variables with the number of confirmed COVID-19 cases both at the province (Si/Do) and the district (Gun/Gu) level, the population growth rate compared to the same period in the previous year, and the ratio of the elderly population at the district level. We also include regional fixed effects (district level), time fixed effects (week level), and industry fixed effects to control for unobserved factors that may affect business sales.

Equation 1 is the basic model with covariates and regional/time/industry fixed effects, whereas in equation 2, AF1, AF2, and AF3 correspondingly capture the diff-in-diff effects for the first, second and third months. Finally, equation 3 includes the DD* Case in order to capture the heterogeneous treatment effect of the number of confirmed COVID-19 cases.

$$y_{i,j,t} = \alpha + \beta_{DD} DD_{i,t} + \beta_R R_i + X_{i,j,t}\gamma + \varepsilon_{i,j,t} \tag{1}$$

$$y_{i,j,t} = \alpha + \beta_1 AF1_{i,t} + \beta_2 AF2_{i,t} + \beta_3 AF3_{i,t} + \beta_R R_i + X_{i,j,t}\gamma + \varepsilon_{i,j,t} \tag{2}$$

$$y_{i,j,t} = \alpha + \beta_{DDD} DD * Case_{i,t} + \beta_{DD} DD_{i,t} + \beta_{R\_cf} R_i * Case_{i,t} + X_{i,j,t}\gamma + \varepsilon_{i,j,t} \tag{3}$$

IV. Empirical Results

A. *Descriptive Statistics*

Table 3 presents summary statistics of sales growth overall and in the regional characteristic variables. We compare these variables of the treatment group with additional subsidies in cash and the control group with only the national EDRF subsidy within the data period. On average, the sales growth rate in regions where other cash subsidies are paid is higher than in regions without additional local subsidies. This may be the effect of additional subsidies by the local governments but may also be due to basic differences between regions. Accordingly, additional subsidies by the local governments are estimated through the difference-in-difference method. The average corresponding population growth rates year-on-year is similarly less than zero at -0.41 and -0.49.

The ratios of the elderly population in both regions are nearly identical (19.13%).

TABLE 3—SUMMARY STATISTICS: CONTROL VARIABLES

Variable	Cash Support			Non Cash Support		
	Obs.	Mean	SD	Obs.	Mean	SD
Sales (YoY%)	3,240	0.23	24.28	7,290	-5.10	22.99
Population growth rate (YoY%)	3,240	-0.41	2.23	7,290	-0.49	2.42
Elderly population ratio (%)	3,240	19.13	4.52	7,290	19.13	8.51
Confirmed cases by District (per 0.1M population)	3,240	0.19	0.65	7,290	0.32	0.94
Confirmed cases by City (per 0.1M population)	3,240	0.22	0.36	7,290	0.35	0.57

In contrast, the number of confirmed COVID-19 cases (per 0.1M population) is lower in regions with cash subsidies than in regions without cash subsidies both by district and by city.

Table 4 and Table 5 compare card sales growth outcomes according to eight industry categories before and after the subsidy between regions with and without additional cash support. Table 4 shows the summary statistics in the region with regional relief funds by each industry category, comparing before and after the cash support in each group. Remarkably, the year-on-year growth rate of card sales increases after the cash subsidies. This may be due to the regional cash subsidies, but it can also be attributed to the decrease in the number of confirmed COVID-19 cases before and after the subsidy payments. Accordingly, we also use the number of confirmed COVID-19 cases as a control variable to estimate the effect of additional cash subsidies on the card sales of local businesses. Year-on-year sales of durable goods increased the most after the subsidies were paid, and year-on-year sales of restaurants, face-to-face services, and education and fitness services also increased. In areas with the regional relief fund, year-on-year sales of durable goods increased by approximately 29.9%p after the cash provision.

Table 5 shows the average sales growth at each industry before and after the national EDRF subsidy, which was distributed from the 19th week. In contrast, in areas without regional relief funding in cash, the year-on-year sales of durable goods increased by about 23.3%p after the national EDRF. As we estimate the increase in the growth rate of business sales from the additional cash subsidies using the difference-in-difference method, a simple comparison of the summary statistics shows that additional cash subsidies increase the sale growth rate (semi)-durable goods by about 6.6%p. As we can control for other factors such as the number of COVID-19 patients and regional characteristics, we estimate the effect of the cash subsidy via a difference-in-difference regression analysis in the following subsection. Similarly, for face-to-face services and essential goods, the effect of increasing sales due to the additional local government subsidies is not notable, while the effect is large in the education/fitness service industry.

TABLE 4—SALES GROWTH RATE (YOY%) BY INDUSTRY BEFORE AND AFTER AN ADDITIONAL CASH SUPPORT FOR THE TREATED GROUP

Business Sectors	Before Cash			After Cash			Difference
	Obs.	Mean (a)	SD	Obs.	Mean (b)	SD	(b) – (a)
Accepting Voucher Sectors	171	-4.86	14.07	189	3.78	9.71	8.64
(Semi)-durable goods	171	-12.42	27.87	189	17.50	38.13	29.92
Face-to-Face Services	171	-16.78	14.94	189	0.09	12.08	16.87
Non-Accepting Voucher sectors	171	-7.66	27.70	189	-1.98	21.69	5.69
Drugstores / Hospitals	171	9.77	26.58	189	12.32	10.46	2.54
Restaurants	171	-11.97	17.40	189	3.36	10.54	15.33
Essential goods	171	9.31	20.36	189	12.50	11.38	3.19
Education / Fitness	171	-10.19	44.89	189	8.28	26.05	18.47
Others	171	-5.89	18.97	189	-6.06	10.24	-0.18

TABLE 5—SALES GROWTH RATE (YOY%) BY INDUSTRY BEFORE AND AFTER THE NATIONAL EDRF PAYMENT FOR THE CONTROL GROUP

Business Sectors	Before EDRF			After EDRF			Difference
	Obs.	Mean (a)	SD	Obs.	Mean (b)	SD	(b) – (a)
Accepting Voucher Sectors	432	-7.12	12.90	378	0.41	9.83	7.53
(Semi)-durable goods	432	-20.66	17.97	378	2.65	19.37	23.31
Face-to-Face Services	432	-21.11	15.31	378	-4.63	14.11	16.47
Non-Accepting Voucher sectors	432	-15.17	19.90	378	-8.07	29.58	7.10
Drugstores / Hospitals	432	2.87	23.75	378	10.16	13.81	7.30
Restaurants	432	-13.83	13.61	378	-1.48	11.24	12.35
Essential goods	432	7.29	22.50	378	9.45	11.20	2.16
Education / Fitness	432	-13.15	43.20	378	-0.55	34.24	12.60
Others	432	-6.73	17.04	378	-6.10	13.75	0.63

B. *Regression Results*

Through descriptive statistics, we outlined the effect of an increase in sales growth due to additional subsidies by local governments. In this section, we control for other factors that can affect local business sales with a regression analysis. Control variables are the number of confirmed COVID-19 cases, the growth rate of the population, the ratio of the elderly population, industry fixed effects and district fixed effects, and time (weekly) fixed effects. These control variables are constructed as panel data for each district and sector.

Table 6 shows the estimation results of the effects of the additional cash support on local business sales in all sectors. The estimate of the DID variable in the third column is positive and significant at the 10% significance level, meaning that the year-on-year sales growth rate increased by about 1.58%p for three months on average due to the additional cash subsidies by local governments. Thus, we can confirm that a cash payment can boost the sales of local businesses. From the results presented in the fourth column, we can divide the effect of the cash subsidy by the time period. The consumption-boosting effect of the additional cash subsidy is concentrated one month after the reception of the subsidy, and the impact is large and significant at the 1% significance level. The year-on-year sales growth rate increases by approximately 3.34%p within the first month of the payment, while during the following month, the effect is not statistically significant.

From the negative estimate of the number of COVID-19 cases, the growth rate of local business sales decreases as the number of confirmed cases at the district level

TABLE 6—DIFF-IN-DIFF ESTIMATION RESULTS: IN TOTAL

VARIABLES	(1) YOY Sales	(2) YOY Sales	(3) YOY Sales	(4) YOY Sales
DID	2.17**	2.00**	1.58*	
(After Cash subsidy)	(0.91)	(0.91)	(0.91)	
DID_1 month				3.34***
(1^{st} month effect)				(1.11)
DID_2 month				0.31
(2^{nd} month effect)				(1.27)
DID_3 month				-0.51
(3^{rd} month effect)				(1.21)
Population Growth Rate			0.94	1.07
			(0.68)	(0.68)
Elderly Population Rate			-13.0***	-13.4***
			(3.39)	(3.38)
# COVID-19 (Si/Gun/Gu level)		-1.07***	-0.97***	-0.95***
		(0.26)	(0.27)	(0.27)
# COVID-19 (Si/Do level)		-0.69	-0.90	-0.89
		(0.54)	(0.55)	(0.55)
Constant	5.57***	5.26***	255***	263***
	(1.77)	(1.77)	(65.3)	(65.2)
Weekly Fixed Effect	o	o	o	o
Regional Fixed Effect	o	o	o	o
Business Sector Fixed Effect	o	o	o	o
Observations	9,152	9,152	9,152	9,152
R-squared	0.343	0.344	0.346	0.347

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

increases. When the number of confirmed cases per 100 thousand people within the same district increases by one unit, the year-on-year sales growth rate decreases by approximately 0.97%p. Card sales by local businesses are more sensitive to the number of patients in nearby neighborhoods. Despite the fact that the estimate of the number of confirmed cases at the city level is negative, this outcome is not statistically significant. Moreover, as the ratio of the elderly population in the region increases, the year-on-year sales growth rate decreases significantly. This occurs because in situations where the spread of an infectious disease continues, older people are at a greater risk of infection due to outdoor activities and are more likely to reduce their consumption.

In Table 7, the heterogeneous effect of the cash subsidy according to confirmed COVID-19 cases is investigated through the variable DDD. The estimate is insignificant, and we cannot find a heterogeneous effect of the cash subsidies. This is different from prior expectations. However, as shown in Figure A1 and Figure A2 in the appendix, there were few confirmed cases in the sample period. Thus, it is difficult to generalize this result to other situations and different types of relief funds.

TABLE 7—HETEROGENEOUS EFFECT ON CONFIRMED COVID-19 CASES

	(1)	(2)
VARIABLES	YOY Sales	YOY Sales
DID	1.45	
(After Cash subsidy)	(0.95)	
DID_1 month		3.19***
(1st month effect)		(1.14)
DID_2 month		0.17
(2nd month effect)		(1.30)
DID_3 month		-0.89
(3rd month effect)		(1.28)
DDD	0.73	1.14
	(1.31)	(1.32)
Treated * # COVID-19	-0.076	-0.18
	(1.21)	(1.21)
Population Growth Rate	0.92	1.06
	(0.68)	(0.68)
Elderly Population Rate	-13.0***	-13.5***
	(3.39)	(3.38)
# COVID-19 (Si/Gun/Gu level)	-1.03***	-1.03***
	(0.29)	(0.29)
# COVID-19 (Si/Do level)	-0.89	-0.88
	(0.55)	(0.55)
Constant	256***	265***
	(65.3)	(65.2)
Weekly Fixed Effect	o	o
Regional Fixed Effect	o	o
Business Sector Fixed Effect	o	o
Observations	9,152	9,152
R-squared	0.346	0.347

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Tables 8~11 show the effects of the regional cash subsidies for specific sectors. Table 8 shows the estimation results of the effects of additional cash on local business card sales growth among (semi)-durable goods. (Semi)-durable goods include furniture, glasses, fashion, books, stationery, and toys, and similar items. The regression results show that the year-on-year growth rate of the consumption of (semi)-durable goods increases by about 5.8%p, a considerable increase. This result is consistent with earlier works (Kim *et al.*, 2020; Kim and Oh, 2020; Chetty *et al.*, 2020) that found consumption boosting as highest in durable goods. The reason for the prominent increase in the consumption of (semi)-durable goods would be related to the risk of infection under the pandemic. The consumption of (semi)-durable goods does not require close and extended face-to-face interactions between customers and sellers. In the second column, the sales boost effect is divided into three periods, and the effect in the third month is large and significant while the effect in the second month is insignificant. These findings stand in contrast to results in other sectors, which show that the cash subsidy effect gradually fades over time. Most districts started to distribute cash subsidies from April, as shown in Table 1. The third month

TABLE 8—DIFF-IN-DIFF ESTIMATION: (SEMI)-DURABLE GOODS

VARIABLES	(1) YOY Sales	(2) YOY Sales	(3) YOY Sales
DID	5.80***		5.62***
(After Cash subsidy)	(1.54)		(1.63)
DID_1 month		8.26***	
(1st month effect)		(1.99)	
DID_2 month		0.24	
(2nd month effect)		(2.12)	
DID_3 month		6.62***	
(3rd month effect)		(2.15)	
DDD			0.91
			(2.53)
Treated * # COVID-19			0.12
			(2.45)
Population Growth Rate	0.60	0.64	0.58
	(1.55)	(1.52)	(1.56)
Elderly Population Rate	-14.6*	-15.1*	-14.7*
	(8.26)	(8.26)	(8.27)
# COVID-19 (Si/Gun/Gu level)	-0.95*	-1.00**	-1.05*
	(0.49)	(0.50)	(0.54)
# COVID-19 (Si/Do level)	-1.74	-1.84*	-1.71
	(1.06)	(1.06)	(1.06)
Constant	266*	276*	268*
	(159)	(159)	(159)
Weekly Fixed Effect	o	o	o
Regional Fixed Effect	o	o	o
Business Sector Fixed Effect	o	o	o
Observations	1,144	1,144	1,144
R-squared	0.794	0.796	0.794

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

becomes June, when households purchase clothes and shoes due to the seasonal change. As clothes and shoes are included in this (semi)-durable sector, the time heterogeneous effect of the cash subsidy can differ from those in other sectors.

On the other hand, the consumption of face-to-face services does not increase much. Table 9 shows estimates from the regression analysis of the face-to-face service sector. The year-on-year sales growth rate of the face-to-face service sector increases by about 1.98%p due to the subsidy payment. Like the changes in sales of other industries, the increase in sales growth due to cash payments is mainly concentrated in the first month of the payment. In the first month, the year-on-year growth rate of the face-to-face service sector increased by approximately 3.89%p and did not show a significant effect in the following months. In the face-to-face industry, the effect of the increase in sales is small because consumers do not pursue consumption with a high risk of infection as a pandemic spreads. The estimate of the population growth is negative, and it is significant in the first and the third columns. This result appears to go counter to prior expectations. However, the negative estimate indicates that consumption in this service does not strongly

TABLE 9—DIFF-IN-DIFF ESTIMATION: FACE-TO-FACE SERVICES

VARIABLES	(1) YOY Sales	(2) YOY Sales	(3) YOY Sales
DID	1.98**		1.79*
(After Cash subsidy)	(0.97)		(1.02)
DID_1 month		3.89***	
(1st month effect)		(1.13)	
DID_2 month		-0.71	
(2nd month effect)		(1.47)	
DID_3 month		1.01	
(3rd month effect)		(1.28)	
DDD			1.00
			(1.39)
Treated * # COVID-19			-0.13
			(1.32)
Population Growth Rate	-1.44*	-1.34	-1.46*
	(0.83)	(0.83)	(0.83)
Elderly Population Rate	-15.1***	-15.5***	-15.1***
	(3.73)	(3.75)	(3.74)
# COVID-19 (Si/Gun/Gu level)	-0.82	-0.83	-0.90
	(0.51)	(0.52)	(0.58)
# COVID-19 (Si/Do level)	-1.42*	-1.46*	-1.41*
	(0.76)	(0.76)	(0.77)
Constant	281***	289***	283***
	(71.6)	(72.0)	(71.8)
Weekly Fixed Effect	o	o	o
Regional Fixed Effect	o	o	o
Business Sector Fixed Effect	o	o	o
Observations	1,144	1,144	1,144
R-squared	0.709	0.711	0.709

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

correlate with the residential population. In this study, the face-to-face service sector includes leisure, hairdressing, and public bathhouses, and consumers can often drive outside of their residential areas to consume these services, especially with regard to leisure. The estimate of COVID-19 is significant only at the broader province level, while it is more significant at the narrow district level in other sectors. This result can also show that consumption of face-to-face services, like leisure, is executed in the broader market compared to other sectors.

Table 10 shows estimation results of restaurants, which represent the food and beverage service sector. The year-on-year sales growth rate of this sector increases by approximately 2.42%p due to the cash subsidy payment. The effect on local business sales by the cash subsidy is also weaker in the food and beverage sector than in (semi)-durable goods. This may stem from the fact that consumers are worried about the risk of contagion in these businesses. This result is consistent with Kim and Oh (2020), who found that a policy impact or universal payment policy is weaker in the service industry, which experienced a larger shock from the pandemic. The estimate of population growth is significant and positive only in this sector. This

TABLE 10—DIFF-IN-DIFF ESTIMATION: FOOD AND BEVERAGE

VARIABLES	(1) YOY Sales	(2) YOY Sales	(3) YOY Sales
DID	2.42**		2.33**
(After Cash subsidy)	(0.96)		(1.02)
DID_1 month		2.95***	
(1st month effect)		(0.97)	
DID_2 month		2.49*	
(2nd month effect)		(1.28)	
DID_3 month		1.33	
(3rd month effect)		(1.54)	
DDD			0.54
			(1.47)
Treated * # COVID-19			-0.31
			(1.20)
Population Growth Rate	1.87**	1.92**	1.86**
	(0.76)	(0.77)	(0.77)
Elderly Population Rate	-3.38	-3.52	-3.41
	(3.36)	(3.37)	(3.36)
# COVID-19 (Si/Gun/Gu level)	-1.67***	-1.66***	-1.68***
	(0.30)	(0.29)	(0.32)
# COVID-19 (Si/Do level)	-1.19*	-1.18*	-1.19*
	(0.71)	(0.71)	(0.72)
Constant	70.7	73.2	71.3
	(65.0)	(65.2)	(65.1)
Weekly Fixed Effect	o	o	o
Regional Fixed Effect	o	o	o
Business Sector Fixed Effect	o	o	o
Observations	1,144	1,144	1,144
R-squared	0.753	0.754	0.753

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

result suggests that the consumption of food and beverages is mostly done within residential districts.

Table 11 shows the regression results from the effect of the regional relief fund in cash on card sales growth in the education and fitness sector. The year-on-year growth rate increases by about 6.72%p due to the cash subsidy payment. Like the changes in the sales of other sectors, the increase in sales due to the subsidy payments is mainly concentrated in the first and second months of the payment. In the first month, the year-on-year growth rate in the education and fitness service sector increased by about 8.23%p and 5.89%p in the following month. Considering that education and fitness services require personal interaction for a certain number of hours, this strong impact of the cash subsidy is somewhat perplexing. However, the consumption of these services can be performed with a face mask, which is the most crucial factor related to the prevention of infection. Thus, we find that some service industries also had considerable advantages from the government's stimulus payment policy when consumers believe that the risk of infection is not high. This point was not indicated in previous studies.

TABLE 11—DIFF-IN-DIFF ESTIMATION: EDUCATION AND FITNESS

VARIABLES	(1) YOY Sales	(2) YOY Sales	(3) YOY Sales
DID	6.72***		6.50***
(After Cash subsidy)	(2.33)		(2.45)
DID_1 month		8.23***	
(1st month effect)		(2.99)	
DID_2 month		5.89**	
(2nd month effect)		(2.79)	
DID_3 month		4.69	
(3rd month effect)		(3.21)	
DDD			1.38
			(2.89)
Treated * # COVID-19			-0.91
			(2.14)
Population Growth Rate	-1.23	-1.11	-1.25
	(1.34)	(1.35)	(1.34)
Elderly Population Rate	-38.6***	-39.0***	-38.7***
	(11.4)	(11.5)	(11.4)
# COVID-19 (Si/Gun/Gu level)	-2.54***	-2.52***	-2.54***
	(0.75)	(0.75)	(0.82)
# COVID-19 (Si/Do level)	-1.31	-1.30	-1.32
	(1.46)	(1.46)	(1.46)
Constant	749***	756***	750***
	(220)	(220)	(220)
Weekly Fixed Effect	o	o	o
Regional Fixed Effect	o	o	o
Business Sector Fixed Effect	o	o	o
Observations	1,144	1,144	1,144
R-squared	0.761	0.762	0.761

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

In the appendix, we supplement the result of the robustness checks. Table A1 shows the regression results with more control variables, adding the employment rate of the previous month, and Table A2 shows the regression results with a smaller sample, in this case without Incheon. Certain estimates become somewhat smaller in some cases. However, the patterns in the magnitude of the estimates by sectors are identical, and the effect of the cash subsidy is still largest and firm in (semi)-durable goods.

V. Concluding Remarks

We investigate the impact of regional cash subsidies which were granted in some districts in addition to the national EDRF payment in South Korea. Analyzing the combined weekly debit and credit card sales of eight card companies with the difference-in-difference method, we find that the cash subsidy bolstered the sales of local businesses that experienced a large collapse after the outbreak of COVID-19. We also find that the consumption boosting impact was clear and strong within a month, immediately after the payment.

We find also that a simple cash subsidy effectively boosted the sales of local businesses without complicated and costly policy design efforts. However, further analysis is required to compare the costs and benefits of choosing the vouchers to boost local businesses, with extensive data on prepaid cards and paper gift card sales, which were not available in this study.

The consumption-boosting effect of the cash subsidy is extensive among (semi)-durable goods, which do not require close interaction between customers and retailers. On the other hand, the consumption boosting effect was modest in the face-to-face service sector or in restaurants, which were more directly damaged by the COVID-19 pandemic. These results suggest that the effect of the stimulus payment may have been concentrated in industries that suffered less damage from COVID-19 or that even benefited from COVID-19. On the other hand, some service sectors such as education and fitness experienced a substantial sales boost due to the cash subsidy. This result suggests that the effects of the consumption-boosting policy can be effective in some service industries in which consumption is available with a face mask when the pandemic disease is not active.

We cannot find evidence of the heterogeneous effect of subsidies varying according to how COVID-19 spreads. However, this may be due to the relatively few patients in the sample period.

Our study has several limitations in that we analyzed only combined card sales at the district level. It would be desirable to study more of a heterogeneous effect among households with different incomes or consumption patterns with more detailed and individual household-level data.

APPENDIX

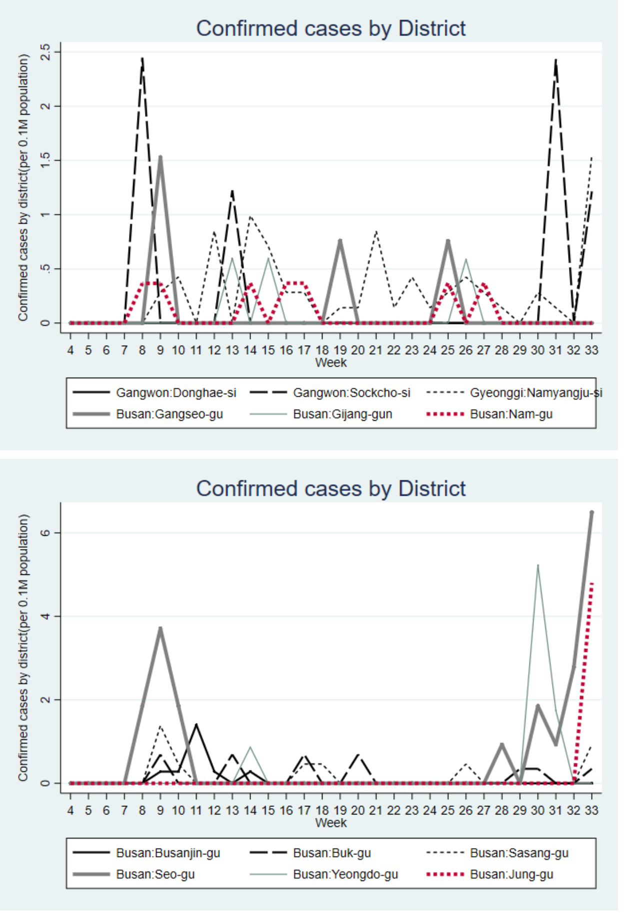

FIGURE A1. COVID-19 CONFIRMED CASES BY DISTRICT WITHIN THE TREATED GROUP

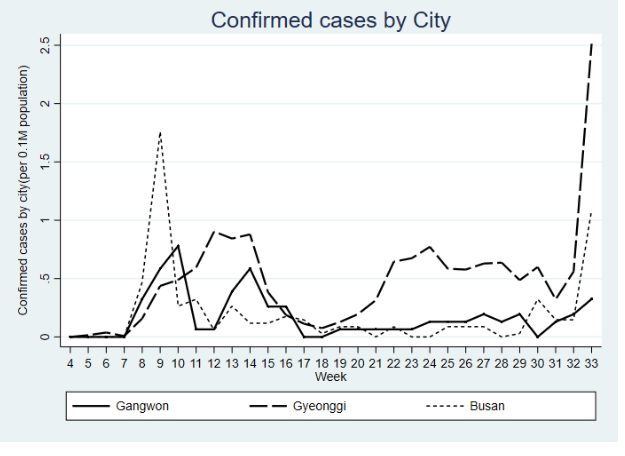

FIGURE A2. CONFIRMED COVID-19 CASES BY CITY WITHIN THE TREATED GROUP

TABLE A1—ROBUSTNESS: ADDITIONAL CONTROL VARIABLE (EMPLOYMENT RATES)

VARIABLES	(1) (Semi)-durable YOY Sales	(2) Face-to-face service YOY Sales	(3) Food and beverage YOY Sales	(4) Education and fitness YOY Sales
DID (After Cash subsidy)	5.02***	1.77*	1.70	3.57
	(1.61)	(1.01)	(1.20)	(2.46)
Population Growth Rate	0.74	-1.40*	2.00***	-0.66
	(1.58)	(0.82)	(0.76)	(1.37)
Elderly Population Rate	-14.1*	-14.9***	-2.86	-36.3***
	(8.20)	(3.67)	(3.34)	(11.2)
# COVID-19 (Gun/Gu level)	-0.93*	-0.82	-1.65***	-2.46***
	(0.49)	(0.51)	(0.29)	(0.76)
# COVID-19 (City/DO level)	-1.92*	-1.47*	-1.36*	-2.05
	(1.08)	(0.77)	(0.74)	(1.50)
Employment Rate (1 month before)	-0.45	-0.12	-0.41	-1.82***
	(0.36)	(0.26)	(0.28)	(0.58)
Constant	283*	285***	86.0	817***
	(161)	(74.5)	(66.1)	(224)
Weekly Fixed Effect	o	o	o	o
Regional Fixed Effect	o	o	o	o
Business Sector Fixed Effect	o	o	o	o
Observations	1,144	1,144	1,144	1,144
R-squared	0.795	0.709	0.754	0.764

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

TABLE A2—ROBUSTNESS: SMALLER SAMPLE (WITHOUT INCHEON)

VARIABLES	(1) (Semi)-durable YOY Sales	(2) Face-to-face service YOY Sales	(3) Food and beverage YOY Sales	(4) Education and fitness YOY Sales
DID (After Cash subsidy)	3.85**	0.97	1.88**	6.00**
	(1.58)	(1.06)	(0.92)	(2.48)
Population Growth Rate	2.63	-2.93***	1.60*	1.73
	(2.14)	(0.79)	(0.88)	(1.64)
Elderly Population Rate	-9.62	-16.0***	-1.86	-25.2**
	(8.69)	(3.85)	(3.42)	(12.3)
# COVID-19 (Gun/Gu level)	-0.87*	-0.71	-1.84***	-1.87*
	(0.52)	(0.76)	(0.37)	(0.97)
# COVID-19 (City/DO level)	7.11***	4.44***	5.38***	4.61*
	(1.77)	(1.19)	(1.51)	(2.52)
Constant	173	299***	43.3	495**
	(168)	(74.1)	(66.3)	(236)
Weekly Fixed Effect	o	o	o	o
Regional Fixed Effect	o	o	o	o
Business Sector Fixed Effect	o	o	o	o
Observations	874	874	874	874
R-squared	0.806	0.718	0.802	0.792

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

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