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

- * Associate Fellow, Korea Development Institute (E-mail: han@kdi.re.kr)
- * Received: 2021. 4. 9
- * Referee Process Started: 2021. 4. 14
- * Referee Reports Completed: 2021. 5. 4

 $[\]dagger$ I would like to thank Professor Dongchul Cho and two anonymous referees for their helpful comments. All remaining errors are mine.

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.

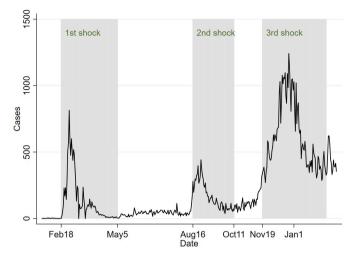


FIGURE 1. THE COVID-19 CRISIS IN KOREA

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

¹The identifiers were provided before 2004.

²Final 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.

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

⁴DD 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.

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

⁶If 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. 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.

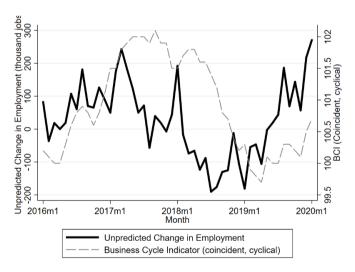


FIGURE 2. UNPREDICTED JOB CHANGES AND BUSINESS CYCLES

⁷I 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., $u_{b}^c = E_{b}^c - \hat{E}_{b}^c$) 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. 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

⁸The 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 days⁹ 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.

⁹Specifically, 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.

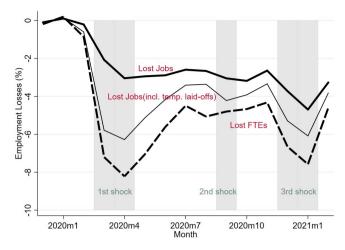


FIGURE 3. EMPLOYMENT LOSSES DURING THE COVID-19 CRISIS

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

¹⁰The 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.

¹¹The 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.

¹²The 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.

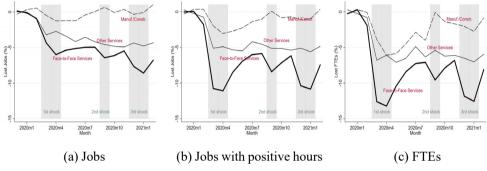


FIGURE 4. EMPLOYMENT LOSSES DURING THE COVID-19 CRISIS: BY INDUSTRY

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.

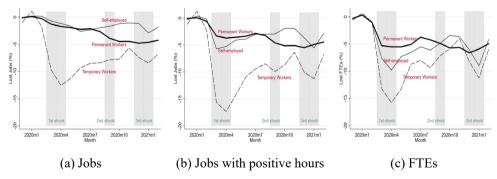


FIGURE 5. EMPLOYMENT LOSSES DURING THE COVID-19 CRISIS: BY EMPLOYMENT TYPE

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 higherorder 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.

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

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.

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

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. 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

¹³Consumption 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.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Job	Job	Job(h > 0)	Job(h > 0)	FTE	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		
$\overline{\gamma} = \alpha/(\alpha + \beta)$	0.88		0.71		0.75	

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

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

	obeb b ore			-,		,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Face-t	o-Face Se	rvices	Ot	her Servio	es	Ma	anuf./Con	str.
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
Dansistant sammamant (a)	-0.007***	-0.004**	-0.002	-0.003*	-0.001	-0.000	-0.001	-0.000	0.000
Persistent component (α)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Transitary assumes ant (0)	-0.000	-0.002**	-0.001	0.000	0.000	0.000	-0.000	-0.000	0.000*
Transitory component (β)	(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	-0.005***	-0.005***	-0.002	-0.002	-0.002*	-0.000	-0.000	-0.001	-0.000
Persistent × First shock	(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*
^ Second snock	(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
^ THIRd SHOCK	(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
Transitory ^ First shock	(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
^ Second Shock	(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
^ THIRd SHOCK	(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	•	•	•	•

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

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

¹⁵The 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 Se	rvices	Ot	her Servio	ees	Ma	anuf./Con	str.
	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
reisistent component (a)	(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
Transitory component (p)	(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	-0.006***	·-0.006***	-0.004**	-0.003**	-0.002*	-0.000	-0.001	-0.001	-0.001
Persistent × First shock	(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
^ Second shock	(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
^ I fill'd shock	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Tuomaitams y Einst also als	-0.000	-0.005***	-0.004***	0.001	-0.001	-0.000	-0.001	-0.001	0.000
Transitory × First shock	(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
^ Second snock	(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
^ 1 mru snock	(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-t	o-Face Se	ervices	Ot	her Servio	es	M	anuf./Con	str.
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
D	-0.010***	-0.005**	-0.005**	-0.005**	-0.001	-0.000	0.002	-0.002	-0.000
Persistent component (α)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
T :	-0.002**	-0.004***	-0.004***	0.000	-0.001	-0.000	0.000	-0.000	0.000
Transitory component (β)	(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	-0.009***	-0.006***	-0.005***	-0.004**	-0.001	-0.000	-0.002	-0.002	-0.001
Persistent × First shock	(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
× Second snock	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	.002)	(0.002)	(0.001)
TP1: 1 1 1	-0.011***	-0.004	-0.006**	-0.005**	-0.001	-0.001	-0.001	-0.001	0.001
× Third shock	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	.002)	(0.002)	(0.001)
T	-0.002	-0.004**	-0.006***	0.001	-0.002	-0.000	0.000	-0.001	0.000
Transitory × First shock	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
C 1.1.1	-0.000	-0.003***	-0.002**	0.000	0.000	0.000	0.002*	0.000	-0.000
× Second shock	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
v Thind -11-	-0.002**	-0.005***	-0.003***	-0.000	-0.001	0.001	-0.002*	-0.001	0.000
× Third shock	(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 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

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

¹⁷For 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

		443	(0)	(0)		(#)	
		(1)	(2)	(3)	(4)	(5)	(6)
D		Job	Job	Job(h > 0)	Job(h > 0)	FTE	FTE
Persistent compo	onent × Men × 15-29	-0.039***	-0.037***	-0.041***	-0.040***	-0.045***	-0.039***
	v M v 20 20	(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***
	× Men × 40-49	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006) -0.018**
	× Men × 40-49	-0.005	-0.003	-0.012*	-0.009	-0.024***	
	v M v 50 50	(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***
	w.M	(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
	15.00	(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 comp	onent × 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)
	\times Men \times 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)
	\times Men \times 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)
	\times Men \times 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)
	\times Men \times 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)
	\times Women \times 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)
	\times Women \times 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)
	\times Women \times 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	-	-		,142	-	
	**			033	,- ·-		

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

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

¹⁸Appendix Table A4 estimates the following equation,

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

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

²⁰The 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 Sea	rvices	Ot	her Servic	es	M	anuf./Cons	tr.
	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+	+	_	-	+	_***	-	_**	_	+
<i>FTEs</i> 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)
		to-Face Ser			ther Service			anuf./Cons	
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
$P\times M\times 15\text{-}29$	-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)
\times M \times 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)
\times M \times 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)
\times M \times 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)
\times M \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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)
$T\times M\times 15\text{-}29$	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)
\times M \times 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)
\times M \times 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)
\times M \times 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)
\times M \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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 Se	rvices	C	Other Servic	es	Manuf./Constr.			
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self	
$P \times M \times 15-29$	-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)	
\times M \times 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)	
\times M \times 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)	
\times M \times 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)	
\times M \times 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)	
\times F \times 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)	
\times F \times 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)	
\times F \times 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)	
\times F \times 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)	
\times F \times 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)	
$T \times M \times 15-29$	-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)	
\times M \times 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)	
\times M \times 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)	
\times M \times 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)	
\times M \times 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)	
\times F \times 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)	
\times F \times 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)	
\times F \times 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)	
\times F \times 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)	
\times F \times 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)
		to-Face Ser			ther Service			Ianuf./Cons	
	Perm	Temp	Self	Perm	Temp	Self	Perm	Temp	Self
$P \times M \times 15-29$	-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)
\times M \times 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)
\times M \times 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)
\times M \times 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)
\times M \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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)
$T \times M \times 15-29$	-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)
\times M \times 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)
\times M \times 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)
\times M \times 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)
\times M \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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)
\times F \times 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

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

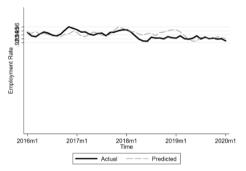
TABLE A4—Persistence of the Employment Losses: Alternative Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Job	Job	$Job(h \ge 0)$	$Job(h \ge 0)$	FTE	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)
\times Men \times 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)
\times Men \times 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)
\times Men \times 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)
\times Women \times 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)
\times Women \times 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)
\times Women \times 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)
\times Women \times 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)
\times Women \times 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)
\times 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)
\times 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

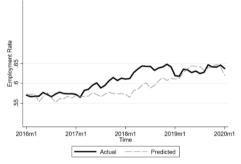
Note: 1) All that regressions are weighted by the population weights at the group level, 2) The unit of analysis is defined at the level of gender-by-age-by-education groups. The base is men in their 30s who are college graduates from a four-year program, 3) Standard errors are clustered at the demographic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

TABLE A5—THE REFERENCE WEEK OF THE EAPS

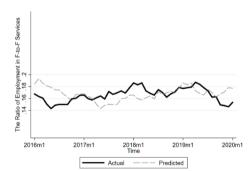
2019	Reference Week	Holidays	2020	Reference Week	Holidays	2021	Reference Week	Holidays
Jan	13-19	-	Jan	12-18	-	Jan	10-16	-
Feb	10-16	-	Feb	9-15	-	Feb	14-20	-
Mar	10-16	-	Mar	15-21	-			
Apr	14-20	-	Apr	12-18	15(Wed)			
May	12-18	-	May	10-16	-			
Jun	9-15	-	Jun	14-20	-			
Jul	14-20	-	Jul	12-18	-			
Aug	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 2	24-26	Seol	Feb 1	1-13
Chuseok	Sep 1	2-14	Chuseok	Sep 30	-Oct 2	Chuseok	ep 20)-22



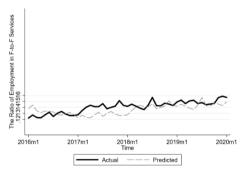
<Men, 35-39, College Graduate (4-yr)>



<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

REFERENCES

- **Albanesi, Stefania and Jiyeon Kim.** 2021. "The Gendered Impact of the COVID-19 Recession on the US Labor Market," Working Paper 28505, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w28505).
- Alon, Titan, Matthias Doepke, Jane Olmstead-Rumsey, and Michèle Tertilt. 2020. "This Time It's Different: The Role of Women's Employment in a Pandemic Recession," Working Paper 27660, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w27660).
- Alstadsæter, Annette, Bernt Bratsberg, Gaute Eielsen, Wojciech Kopczuk, Simen Markussen, Oddbjorn Raaum, and Knut Røed. 2020. "The First Weeks of the Coronavirus Crisis: Who Got Hit, When and Why? Evidence from Norway," Working Paper 27131, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w27131).
- **Amior, Michael and Alan Manning**. 2018. "The Persistence of Local Joblessness," *American Economic Review*, 108(7): 1942-1970.
- Aum, Sangmin, Sang Yoon Tim Lee, and Yongseok Shin. 2021a. "Inequality of Fear and Self-Quarantine: Is There a Trade-Off between GDP and Public Health?" *Journal of Public Economics*, 194: 1043-1054.
- **Aum, Sangmin, Sang Yoon Tim Lee, and Yongseok Shin.** 2021b. "COVID-19 doesn't need lockdowns to destroy jobs: The effect of local outbreaks in Korea," *Labour Economics*, forthcoming.
- Barth, Erling, James Davis, Richard Freeman, and Sari Pekkala Kerr. 2017. "Weathering the Great Recession: Variation in Employment Responses, by Establishments and Countries," RSF: The Russell Sage Foundation Journal of the Social Sciences, 3(3): 50-69.
- Bartik, Alexander W, Marianne Bertrand, Feng Lin, Jesse Rothstein, and Matt Unrath. 2020. "Measuring the Labor Market at the Onset of the COVID-19 crisis," Working Paper 27613, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w27613).
- **Bui, Truc Thi Mai, Patrick Button, and Elyce G Picciotti.** 2020. "Early Evidence on the Impact of Coronavirus Disease 2019 (COVID-19) and the Recession on Older Workers," *Public Policy & Aging Report*, 30(4): 154-159.
- Cajner, Tomaz, Leland D Crane, Ryan A Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, and Ahu Yildirmaz. 2020. "The U.S. Labor Market during the Beginning of the Pandemic Recession," Working Paper 27159, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w27159).
- Campello, Murillo, Gaurav Kankanhalli, and Pradeep Muthukrishnan. 2020. "Corporate Hiring Under COVID-19: Labor Market Concentration, Downskilling, and Income Inequality." Working Paper 27208, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w27208).
- **Chan, Sewin and Ann Huff Stevens.** 2001. "Job Loss and Employment Patterns of Older Workers," *Journal of Labor Economics*, 19(2): 484-521.
- Cheng, Wei, Patrick Carlin, Joanna Carroll, Sumedha Gupta, Felipe Lozano Rojas, Laura Montenovo, Thuy D Nguyen, Ian M. Schmutte, Olga Scrivner, Kosali I. Simon, Coady Wing, and Bruce Weinberg. 2020. "Back to Business and (Re)employing Workers? Labor Market Activity During State COVID-19 Reopenings," Working Paper 27419, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w27419).
- Chetty, Raj, John N Friedman, Nathaniel Hendren, Michael Stepner, and the Opportunity Insights Team. 2020. "The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data," Working Paper 27431, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w27431).
- Costa Dias, Monica, Robert Joyce, Fabien Postel-Vinay, and Xiaowei Xu. 2020. "The Challenges for Labour Market Policy during the Covid-19 Pandemic," Fiscal Studies, 41(2):

371-382.

- **Davis, Steven J. and Till von Wachter.** 2011. "Recessions and the Costs of Job Loss," *Brookings Papers on Economic Activity,* Fall 2011: 1-72.
- Gallant, Jessica, Kory Kroft, Fabian Lange, and Matthew J Notowidigdo. 2020. "Temporary Unemployment and Labor Market Dynamics during the COVID-19 Recession," Working Paper 27924, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w27924).
- Haltiwanger, John C, Henry R Hyatt, Lisa B Kahn, and Erika McEntarfer. 2018. "Cyclical Job Ladders by Firm Size and Firm Wage," *American Economic Journal: Macroeconomics*, 10(2): 52-85.
- **Han, Joseph**. 2018. "Long-Term Effects of Labour Market Entry Conditions: The Case of Korea," *Global Economic Review*, 47(4): 434-463.
- Han, Joseph. 2020. "The Employment Situation of Youth and Policy Suggestions," KDI Feature Article, 2020. 5. 6.
- **Jacobson, Louis S, Robert J LaLonde, and Daniel G Sullivan**. 1993. "Earnings Losses of Displaced Workers," *The American Economic Review*, 83(4): 685-709.
- **Jeong, Daehee and Jiwoon Kim**. 2017. "Analysis on the Recent Employment Growth and Outlook for 2018," *KDI Feature Article*, 2017. 12. 6.
- **Kahn, Lisa B.** 2010. "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy," *Labour Economics*, 17(2): 303-316.
- Kurmann, André, Etienne Lalé, and Lien Ta. 2020. The Impact of COVID-19 on Small Business Employment and Hours: Real-Time Estimates with Homebase Data, ESG UQÀM, Département des sciences économiques, École des sciences de la gestion, Université du Québec à Montréal.
- **Lee, Jongkwan and Hee-Seung Yang.** 2021. "Pandemic and Employment: Evidence from COVID-19 in South Korea," Mimeo.
- Mongey, Simon, Laura Pilossoph, and Alex Weinberg. 2020. "Which Workers Bear the Burden of Social Distancing Policies?" Working Paper 27085, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w27085).
- Montenovo, Laura, Xuan Jiang, Felipe Lozano Rojas, Ian M Schmutte, Kosali I Simon, Bruce A Weinberg, and Coady Wing. 2020. "Determinants of Disparities in COVID-19 Job Losses," Working Paper 27132, Working Paper Series, National Bureau of Economic Research (https://doi.org/10.3386/w27132).
- **Oreopoulos, Philip, Till Von Wachter, and Andrew Heisz**. 2012. "The Short- and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, 4(1): 1-29.
- **Russell, Lauren and Chuxuan Sun**. 2020. "The Effect of Mandatory Child Care Center Closures on Women's Labor Market Outcomes during the COVID-19 Pandemic," *Covid Economics*, 62(18): 124-154.
- Schwandt, Hannes and Till Von Wachter. 2019. "Unlucky Cohorts: Estimating the Long-Term Effects of Entering the Labor Market in a Recession in Large Cross-Sectional Data Sets," *Journal of Labor Economics*, 37(S1): S161-S198.
- **Sevilla, Almudena and Sarah Smith.** 2020. "Baby Steps: The Gender Division of Childcare during the Covid-19 Pandemic," *Oxford Review of Economic Policy,* 36(Supplement_1): S169-S186.
- **Stevens, Ann Huff.** 1997. "Persistent Effects of Job Displacement: The Importance of Multiple Job Losses," *Journal of Labor Economics*, 15 (1, Part 1): 165-188.