COVID-19 Doesn't Need Lockdowns to Destroy Jobs: The Effect of Local Outbreaks in Korea

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April 6, 2021

Abstract

Unlike most countries, Korea did not implement a lockdown in its battle against COVID-19, instead successfully relying on testing and contact tracing. Until the summer of 2020, only one region, Daegu-Gyeongbuk, had a significant number of infections, traced to a religious sect. This allows us to estimate the causal effect of the outbreak on the labor market using difference-in-differences. We find that a one per thousand increase in infections caused a 2 to 3 percent drop in local employment in the early spring. We also find that employment losses caused by local outbreaks in the absence of lockdowns were (i) mainly due to reduced hiring by small establishments, (ii) concentrated in the accommodation/food, education, real estate, and transportation industries, and (iii) worst for economically vulnerable workers who are less educated, young, in low-wage occupations, and on temporary contracts, even controlling for industry effects. These patterns are similar to what we observed in the US and UK: The unequal effects of COVID-19 were the same with or without lockdowns. Our findings are consistent with the lifting of lockdowns having led to only modest employment recoveries in the US and UK, absent larger drops in infection rates.

JEL Classifications: *E24,I14,J21*
Keywords: COVID-19, regional difference-in-differences, labor market, inequality

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1 Introduction

We isolate the economic effect of COVID-19 that operates through the fear of infection: The fact that people voluntarily hunker down and curtail economic activities in response to local outbreaks, even without government-mandated lockdowns. Our estimate provides a unique reference point for the economic costs of the epidemic itself, which gives a sense of how much lockdowns are to blame for the ongoing economic crisis and also how quickly the economy may recover as lockdowns are lifted.

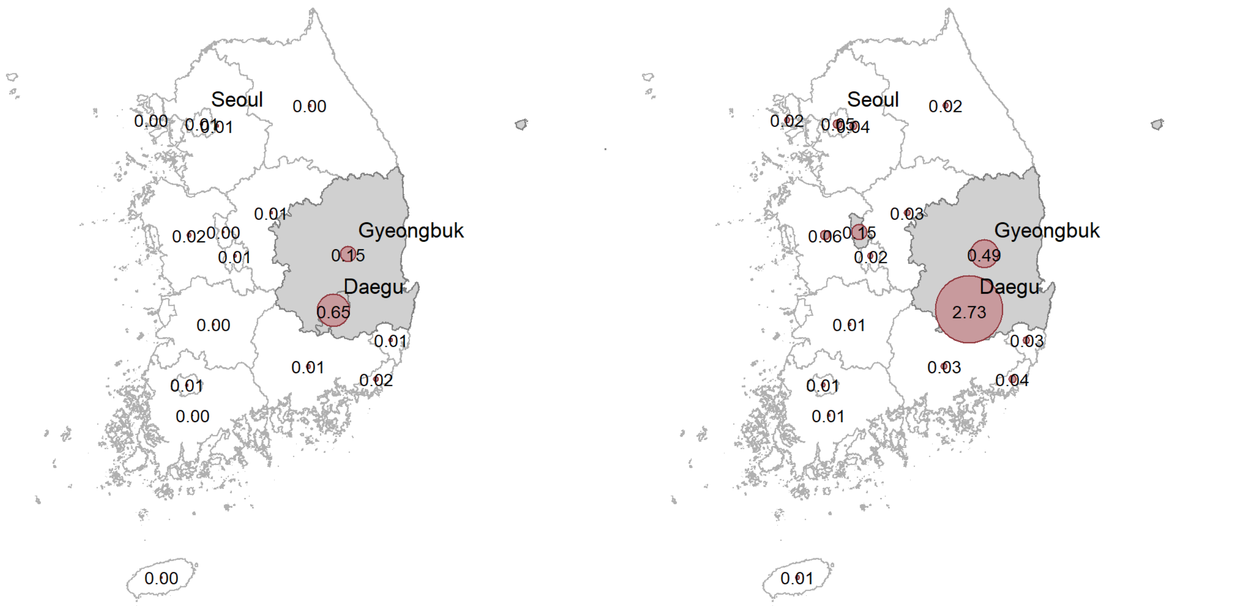
Our estimation exploits regional variation in South Korea's COVID-19 outbreak, as well as the absence of mandatory lockdowns or other social-distancing measures imposed by the government.[1] Korea had only 30 confirmed infections prior to February 18, 2020, when "Patient 31" attended a religious gathering of the "Shincheonji" sect in Daegu, a metropolitan city in Gyeongbuk province. By February 28, the number of cases in Korea had exploded to 2,337, with 1,989 cases (or 85.1 percent) in the Daegu-Gyeongbuk region (DG hereafter) alone. Of these, more than 60 percent were traced to Shincheonji. Figure 1 depicts cumulative COVID-19 infections per thousand on February 28 and March 15 by region. Importantly, it is not the case that DG is more susceptible to the Shincheonji sect, which has members and churches spread all over Korea. The regional variation in infections was uncorrelated with any other underlying socioeconomic factors as well, providing grounds for a natural experiment.[2]

The Korean government prioritized intensive testing and contact tracing over social distancing during this period, and never mandated a lockdown. This resulted in two additional advantages of our estimation strategy: (i) Economic reactions were not prescribed by the government's promulgation of what are essential or non-essential economic activities, unlike a vast majority of countries, and (ii) As of May 20, 2020, its containment strategy resulted in a very low

[1] Another celebrated example of a lockdown-free country is Sweden, and researchers have tried to infer the economic effect of lockdowns by comparing Sweden with other countries (Andersen et al., 2020; Born et al., 2020). By design, such studies cannot recover the direct, causal effect of the pandemic and can only estimate the effect of a lockdown. But their lockdown effects are still subject to omitted variable bias and endogeneity—lockdowns are a choice variable for the government, not an exogenous variation across countries. In addition, Sweden had a much higher cumulative infection rate (3.2 per thousand as of May 20, 2020) than some of the comparison countries (e.g., Denmark, 1.9 per thousand), rendering a simple comparison of economic outcomes less informative.

[2] The DG region comprises 10 percent of South Korea's total population of 52 million and 9 percent of national GDP. As we show in the appendix, DG's industry and worker composition are also fairly similar to the rest of the country.

Fig. 1: Confirmed COVID-19 infections across administrative regions



(a) February 28, 2020 (b) March 15, 2020

Notes: Circle sizes represent cumulative infection cases per thousand. 1st and 2nd largest circles are the city of Daegu and Gyeongbuk province, respectively. DG, shaded in gray, is the only region with more than 0.1 cumulative cases per thousand.
Source: KCDC

cumulative infection rate of 0.06 per thousand in Korea, excluding DG, ensuring that the direct effect was entirely confined to DG with a rate of 1.6 per thousand.

We exploit this setting using difference-in-differences (DiD) on data from an establishment survey, and separately from a household survey. The scheme captures the causal effect of the outbreak on local employment relative to the rest of the country. The establishment survey allows us to break down the effect by industry and establishment size, and the household survey allows us to estimate the effect by occupation, education, age, gender, and employment type. Our results are robust to seasonal adjustments and heterogeneous pre-trends between regions.

Results Our causal estimate implies that even in the absence of lockdowns, a one per thousand increase in confirmed infections leads to a 2 to 3 percent drop in local employment. In comparison, non-causal estimates for the United States or the United Kingdom, which implemented large-scale lockdowns, range from 5 to 6 percent. Our results suggest that a significant fraction of their job losses may be due to voluntary reductions in economic activity by private businesses and consumers, rather than a consequence of government-mandated lockdowns, with the caveat that the estimate from one country cannot be readily applied to other contexts.

Employment losses caused by local outbreaks stem mostly from reduced hiring by businesses and are mirrored by a rise in labor market non-participation rather than unemployment. Broken down by industry, losses are concentrated in the accommodation/food, education, real estate, and transportation industries, similar to (non-causal) patterns observed in the US and UK.

In addition, the causal effects of the COVID-19 shock without lockdowns are very unequally distributed: More or less all employment losses were accounted for by small establishments (fewer than 30 employees), while large establishments on average grew. Less-educated workers, the young, workers in low-wage occupations and on temporary contracts, and the self-employed lost the most jobs to the COVID-19 shock, even controlling for industry effects. In a nutshell, the most economically vulnerable groups even before the shock experienced the most dire effects. However, while the COVID-19 shock hit industries in which women are over-represented harder, the within-industry effect was positive for women and negative for men. Consequently, the total causal effect destroyed more jobs for men than for women. All these patterns of causal effects—with the exclusion of the breakdown by gender—are similar to what we observed in the US and UK: The unequal effects of COVID-19 are the same with or without lockdowns.[3]

Our finding that a rise in infections itself destroys jobs, even in the absence of lockdowns, suggests that lifting lockdowns may lead to only modest employment recoveries absent faster reductions in COVID-19 infection rates. In fact, the US unemployment rate remained in double digits and household spending continued to recover only slowly in June (https://tracktherecovery.org), despite most states reopening. The UK started to reopen all retail shops in mid-June, but year-to-year foot traffic was still down by 50 percent, from a drop exceeding 80 percent in March and April (https://www.spring-board.info/benchmarks). Almost half of UK survey respondents chose safety as the number one factor when deciding where to shop (https://www.retaileconomics.co.uk).[4]

Of course, this is not to say that lockdowns are harmless. As a blunt tool to squash infections, they may cause more economic damage than necessary. We

[3]But nationwide, the drop in women's employment was larger than men's in lockdown-free Korea as well.

[4]These data sources also show that employment and retail sales were already down before any lockdowns, in the early stages of the epidemic.

show that targeted policies can contain the epidemic more effectively at a lower economic cost in Aum et al. (2020a,b).

2 Data

We use three data sets. The first is the Labor Force Survey at Establishments (LFSE), a monthly survey of 40,000 sampled employers (out of 4.1 million in 2018) by the Ministry of Employment and Labor. It reports the number of employees and vacancies as of the last business day of the month, as well as the number of new hires and separations for the month for each of the 16 metropolitan cities and provinces in Korea.[5] The second is the Economically Active Population Survey (EAPS), a monthly survey of 35,000 households collected around the 15th of each month by Statistics Korea, which includes information on worker characteristics (education, age, gender) and their jobs (occupation and employment type).[6] The last is the number of confirmed COVID-19 cases over time published by the Korea Centers for Disease Control & Prevention (KCDC).

We present three sets of estimates using DiD, using LFSE data as of February 28 and March 31, and EAPS data as of March 15, all in 2020. Since the Korean government closed all schools on March 2 and commenced nationwide social distancing campaigns on March 22, later estimates may downward-bias the causal effect, which relies on capturing differences in regional outcomes. Nonetheless, at no point did the government even suggest the possibility of a lockdown, so all our estimates are free of potential large-scale disruptions.

3 Methodology and Estimation Results

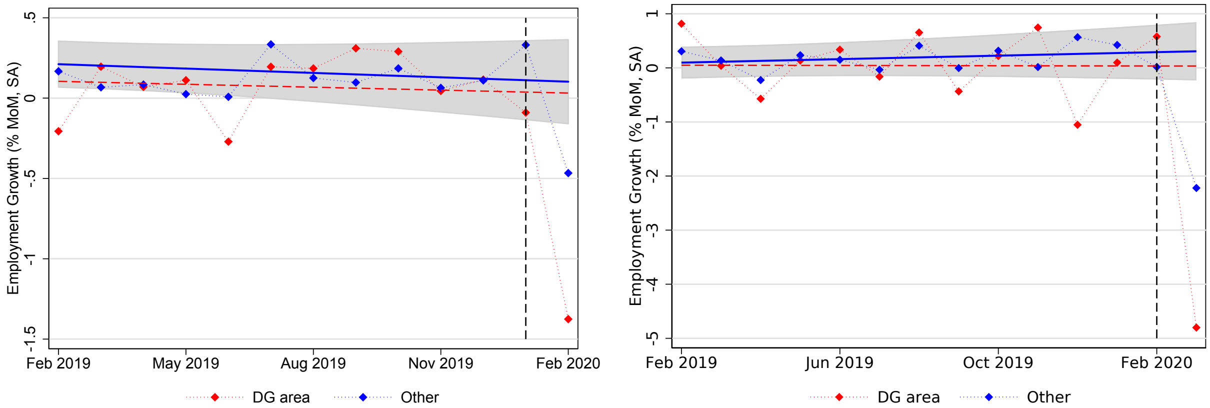
3.1 Identification of the effect of local outbreaks

For a causal interpretation, a DiD scheme requires the treatment to be exogenous to outcomes, and a parallel trends assumption to hold between comparison groups pre-treatment. Furthermore, the treatment and control groups should be similar in levels, as well as in trends (Kahn-Lang and Lang, 2020).

[5]The LFSE is comparable to the US Job Openings and Labor Turnover Survey, a monthly survey by the Bureau of Labor Statistics that collects information on the number of employees, vacancies, hires and separations from 16,000 establishments. The Vacancy Survey is a UK equivalent collected by their Office for National Statistics.

[6]The EAPS is comparable to the US Current Population Survey and the UK Labor Force Survey. Respondents' region is not available in the public-use microdata, but Statistics Korea provides detailed summary tables by region.

Fig. 2: Time trend of employment growth by region



(a) Establishment survey (LFSE) (b) Household survey (EAPS)

Note: Time trends are computed using data from January 2018 to January 2020 for LFSE and to February 2020 for EAPS. The shaded areas are the 95-percent confidence interval of the difference between the time trends, centered on the trend of the rest of the nation.

In our case, the treatment is DG having experienced a major outbreak, which was traced to local Shincheonji gatherings. Shincheonji is a secretive religious sect, but from what we know, is popular throughout the country with more than 200,000 members spread throughout Korea, regardless of local economic standings. If anything, the DG region has fewer followers per capita than other regions. So the epidemic variation can be considered exogenous.

Economically, DG's share of Korean GDP and employment has been stable for at least the last three years. Figure 2 shows that employment growth over time was also more or less similar between DG and other regions through January 2020, both in levels and in linear trends, the latter of which are statistically equivalent.[7] Tables A1 and A2 and Figure A1 in the appendix show that DG's industrial and demographic composition is similar to that of the rest of the nation, with minor exceptions.

Moreover, Korean exports and imports were higher in February and March 2020 than the monthly average throughout 2019, so it is unlikely that our results are driven by international factors, including the economic contraction of China, an important trading partner. In any case, DG's share of international trade has remained stable, and in fact grew faster than the national average in February. Consequently, the causal effect of outbreaks actually becomes larger if regional

[7]The difference in trends between the LFSE and EAPS is driven by the fact that EAPS includes single-person businesses, while LFSE excludes self-employed persons with zero employees.

export is controlled for, as we show in Appendix Tables A3 and A4.

Still, to alleviate any remaining concerns that differences in industrial or demographic composition across regions may introduce nonparallel pre-trends, our cross-regional analysis is performed not only on the entire sample for each of our data sources but also by industry and by demographic group. These serve as robustness checks in addition to disaggregating COVID-19's causal effects. All results are also robust to the inclusion of seasonal adjustments and/or heterogeneous (linear) pre-trends across regions, as reported in Appendix Tables A3 and A5.

3.2 Establishment-side employment data (LFSE)

We first focus on LFSE data as of February 28, 2020, nine days after the Shincheonji outbreak. At this point, the Korean government is yet to implement any social distancing measures, relying exclusively on testing, contact tracing, and quarantines of the confirmed infected. Given the exogenous regional variation in confirmed infections and the timing of the survey, we estimate the causal effect of the outbreak on the labor market using the following DiD specification:

$$y^i_{r,t} = \beta^i_0 + \beta^i_1 \cdot D_r(\mathrm{DG}) + \beta^i_2 \cdot D_t(\mathrm{Feb}) + \gamma^i \cdot D_r(\mathrm{DG}) \cdot D_t(\mathrm{Feb}) + \varepsilon^i_{r,t}, \quad (1)$$

where $y^i_{r,t}$ is the variable of interest in industry i, region r in month t, $D_r(\mathrm{DG})$ is a dummy variable that equals 1 if $r = \mathrm{DG}$ and 0 otherwise, and $D_t(\mathrm{Feb})$ equals 1 if t is February 2020 or later months, and 0 otherwise. The primary coefficient of interest is the DiD term γ^i, designed to capture the effect on the DG region, the lone hot spot in the spring of 2020.[8]

Table 1 reports estimation results from when the dependent variable is the percentage change in monthly employment. To be precise, $y_t = 100 \times \left(\frac{E_t}{E_{t-1}} - 1\right)$, where E_t is employment at time t.[9] The first and the second columns are the results from using monthly and bi-monthly data from January 2018 onward, respectively. Coefficients are estimated for the whole sample (that is, dropping

[8]The DiD term γ^i may well be an underestimate of the true effect of private individuals' and businesses' fear of infection. Fear effects likely spread nationwide, and industrial linkages across regions would also reduce employment outside the DG area. Therefore, even if we cannot attach a causal interpretation, our β^i_2 coefficient may still be of interest, as it is uncontaminated by a government-imposed lockdown. It can also be useful for international comparisons.

[9]An alternative dependent variable is employment over population by region (e.g. Cho et al., 2015). Results for this alternative are shown in Appendix Tables A3 and A4. The units differ, but the results are consistent with our benchmark analysis.

Table 1: COVID-19 effect on employment, total and by industry

	Monthly till Feb 2020				Bimonthly till Mar 2020			
	β_2		γ		β_2		γ	
Total	-0.89^{***}	(0.09)	-1.02^{***}	(0.17)	-2.08^{***}	(0.20)	-1.22^{***}	(0.41)
Accommodation, food svc.	-5.70^{***}	(0.14)	-9.45^{***}	(0.51)	-13.19^{***}	(0.37)	-7.30^{***}	(1.08)
Facility mgmt., support, rental	-0.98^{***}	(0.11)	-0.50^{*}	(0.27)	-2.83^{***}	(0.28)	1.36^{***}	(0.48)
Repair, other personal svc.	-1.15^{***}	(0.08)	0.43^{*}	(0.22)	-3.17^{***}	(0.19)	-2.60^{***}	(0.38)
Real estate	0.14^{*}	(0.08)	-1.25^{***}	(0.22)	-0.43^{**}	(0.19)	-2.60^{***}	(0.40)
Health, social svc.	-0.56^{***}	(0.08)	-1.03^{***}	(0.14)	-1.49^{***}	(0.17)	-3.41^{***}	(0.28)
Arts, sports, recreation	-1.99^{***}	(0.32)	0.89	(0.68)	-9.07^{***}	(0.73)	-0.33	(1.70)
Water, sewage, waste mgmt.	0.05	(0.08)	1.17^{***}	(0.20)	0.18	(0.18)	0.85^{*}	(0.44)
Wholesale, retail	-0.76^{***}	(0.06)	-0.09	(0.30)	-1.96^{***}	(0.11)	-1.81^{***}	(0.57)
Public adm., defense	1.60^{***}	(0.25)	0.55	(0.45)	3.42^{***}	(0.48)	-0.57	(0.96)
Transportation, storage	-0.31^{***}	(0.06)	-0.37^{**}	(0.16)	-2.36^{***}	(0.12)	-3.16^{***}	(0.24)
Manufacturing	-0.21^{***}	(0.03)	-0.23^{**}	(0.08)	-0.59^{***}	(0.06)	-0.00	(0.14)
Mining	0.64^{**}	(0.27)	1.12	(0.88)	1.35^{**}	(0.51)	-1.37	(1.56)
Construction	-0.55^{**}	(0.24)	-0.52	(0.60)	0.29	(0.61)	-0.49	(1.45)
Education	-2.37^{***}	(0.51)	-3.31^{***}	(0.78)	-3.05^{**}	(1.33)	-1.46	(1.87)
Professional, scientific	-0.04	(0.05)	-1.11^{***}	(0.21)	-0.07	(0.11)	-0.60	(0.46)
Information, comm.	-0.31^{***}	(0.07)	0.50^{**}	(0.17)	-0.89^{***}	(0.11)	-1.28^{***}	(0.31)
Electricity, gas	0.18	(0.18)	-0.95^{***}	(0.22)	-0.09	(0.50)	-0.91	(0.55)
Finance, insurance	0.53^{***}	(0.08)	-1.01^{***}	(0.14)	-0.24^{**}	(0.11)	0.63^{**}	(0.30)

Notes: Industries sorted in ascending order of average hourly wage in Feb 2020. Robust standard errors in parentheses. *, **, *** represent significance at 10, 5, 1 percent. Dependent variable is percentage change in monthly employment. β_2: coefficient on time dummy D_t(Feb); γ: coefficient on interaction term D_r(DG)$\cdot D_t$(Feb).

the industry superscript i in Equation 1) and also separately for the 18 different industries that span our data. In addition to revealing heterogeneous effects across industries, the industry-by-industry estimation alleviates concerns of heterogeneous pre-trends that may arise from regions having different industry compositions. In any case, the appendix shows that the results are robust to heterogeneous pre-trends across regions.

The first row shows the effect of the incipient COVID-19 epidemic on overall employment. The estimated β_2 reveals that between the end of January and the end of February (from 11 confirmed cases to 2,337 nationwide), nationwide employment fell by 0.89 percent (not annualized). To put this in perspective, employment *grew* by an average of 0.23 percent per month (not annualized) from January 2018 to January 2020. Although causality cannot be established, this suggests the effect of the incipient epidemic on the Korean economy was large.

The effect was much stronger for DG, which accounted for 85.1 percent of the 2,337 total confirmed cases (there were no cases in DG as of January 31).

The estimated value for γ translates into DG employment falling at more than double the rate of the rest of the country, by 1.91 (0.89 plus 1.02) percent in a month.[10] The γ estimate is the direct causal effect of the local epidemic on local employment, given the exogenous nature of the regional variation in confirmed infections.

Table 1 shows that the effects differed across industries, sorted in ascending order of average wage. Not surprisingly, the accommodations/food services industry was hit hardest, not only nationwide (-5.7 percent), but especially in DG (-15.2 percent), as people avoided contact-intensive services. They also happen to be the lowest-paying industry. Employment in education industries—which does not include public school teachers—also saw a large drop (2.4 percent nationwide and 5.7 percent in DG). Employment in arts/sports/recreation fell substantially nationwide (2 percent) but there was no additional effect from the local outbreak. On the other hand, real estate shows a significant negative causal effect, despite its nationwide employment rising, albeit weakly.

The right panel of Table 1 shows the cumulative employment effect from the end of January to the end of March (9,569 cases nationwide, 83.4 percent in DG) from a regression of bimonthly data. Employment fell by 2.1 percent nationwide over two months (not annualized) and by 3.3 percent in DG. The Korean government delayed the start of the school year on March 2, 2020 and launched social distancing campaigns on March 22, both at the national level. As a result, the estimated β_2 must now partly reflect the effect of government policies and the γ estimate is likely biased downward.

Still, the estimates of the causal effect γ are similar to those in the left panel, with accommodation/food services showing the largest additional employment decrease in DG. Wholesale/retail, health/social services, transportation/storage show a significant additional drop in DG in March (1.8, 3.4, and 3.2 percent, respectively) compared to February, suggesting a delayed impact. On the other hand, the differential effect on education industries in DG disappeared in March, which is not surprising given the nationwide delay of the school year.

To unpack the decline in employment, we estimate equation (1) with three alternative dependent variables: the monthly number of hires, separations, and vacancies, all in percentage of the previous month's employment. The top panel

[10] Regional LFSE data are available only from Jan 2018, implying that γ compares 25 monthly observations with one (Jan 2018 to Jan 2020 vs Feb 2020). This is a small sample, especially post COVID-19, but most of our estimates are still highly significant.

Table 2: Hiring, separations and effect on employment by establishment size

	Hires		Separations		Vacancies	
Total	−1.08***	(0.23)	−0.24	(0.19)	−0.21***	(0.05)

	Employment effect by establishment size					
	Small		Medium		Large	
Total	−2.29***	(0.26)	0.10	(0.26)	0.77***	(0.27)
Accommodation, food svc.	−10.04***	(0.63)	−3.38***	(0.93)	·	
Real estate	−1.51	(1.03)	−0.80	(1.03)	−12.71***	(3.45)
Health, social svc.	−1.13***	(0.28)	−1.49***	(0.30)	0.18	(0.28)
Wholesale, retail	−0.22	(0.36)	0.63*	(0.32)	−1.16**	(0.42)
Transportation, storage	−0.81**	(0.39)	−0.23	(0.39)	2.36***	(0.58)
Manufacturing	−0.75***	(0.11)	0.24**	(0.10)	0.02	(0.13)
Education	−10.46***	(1.22)	0.85	(1.29)	1.17	(1.20)
Professional, scientific	−1.79***	(0.37)	0.11	(0.38)	−0.94**	(0.43)
Information, comm.	0.95**	(0.38)	−0.27	(0.35)	2.42**	(1.10)

Notes: Estimates of γ, coefficient on interaction term $D_r(\text{DG})\cdot D_t(\text{Feb})$. In the top panel, dependent variables are new hires, separations, and vacancies, all in percentage of the previous month's employment. In the lower panel, dependent variable is percentage employment change. Small, medium, and large denote establishments with fewer than 30, between 30 and 299, and 300 or more employees, respectively. Selected industries are sorted in ascending order of average hourly wage in Feb 2020. Robust standard errors in parentheses. *, **, *** represent significance at 10, 5, 1 percent.

of Table 2 shows that DG's February employment drop was driven entirely by less hiring and not by more separations (layoffs and quits).

The first row in the lower panel of Table 2 shows that the causal effect of the local outbreak disproportionately affected small establishments (fewer than 30 employees) while if anything large establishments (300 or more employees) increased employment between January and February in DG. This result is partly driven by industrial composition: Most establishments in accommodation/food services, the industry hardest hit, are small. However, even within industries, small establishments lost employment by more than large establishments as shown in the lower panel of Table 2, which reports the estimation results for a subset of industries sorted in ascending order of average hourly wage. This pattern is especially stark in accommodation/food services and education, the two industries showing the largest causal impact in Table 1. And in the transportation/storage and information/communication industries, the rise in employment by large establishments is large and significant. The lone exception is the real estate industry, where the negative effect was concentrated among large establishments.

3.3 Household survey data (EAPS)

We now turn to EAPS, the household survey that provides more worker-side information. We still again estimate (1) , but now i indexes a demographic group, and the time dummy is $D_t(\text{Mar})$, because the first post-Shincheonji survey was as of March 15, 2020. This is one week before the launching of the social distancing advisory campaign, but after the decision to delay the beginning of the school year on March 2. The appendix shows that the EAPS estimation results are also robust to seasonal adjustments and heterogeneous pre-trends.

The top panel of Table 3 shows that between February 15 and March 15, employment fell by 0.6 percent nationwide and by 3.2 (0.64 plus 2.53) percent in DG (not annualized). These numbers are not directly comparable to the February LFSE estimates (0.89 and 1.91), since daily infection levels reached their peak between February 28 (the LFSE survey date) and March 15, and also because EAPS includes the self-employed, not included in the LFSE.[11] It is noteworthy that the fall in employment did not manifest as a rise in unemployment, neither nationwide nor in DG. People who left employment instead reported themselves as non-participants. One possible explanation is that they were waiting out the epidemic rather than searching for jobs in the midst of it. Alternatively, they may be expecting to return to their previous job and are thus not searching for new ones.

The lower panels of Table 3 show the nationwide change in employment, β_2, and the causal effect of DG's outbreak on local employment, γ, by occupation, by educational attainment, by gender, by age, and by employment type. We focus on the causal estimate γ. The second panel, which stratifies employed workers by one-digit occupations, shows that service, sales, and craft workers were hit the hardest by the outbreak in DG. In contrast, the number of managers actually increased by more than 7 percent. The next two panels show that by education, less educated workers lost disproportionately more jobs, while by gender, the direct causal effect was larger for men (-2.8 vs -2.2 percent).[12] By age, the causal effect is the largest for younger workers (up to 29 year-olds), followed distantly by those in their forties and those aged 60 or older. Finally, by employment type, job losses were heavily concentrated among temporary workers and unpaid family workers, and self-employment also fell by 2.4 percent. The overall pattern

[11]The EAPS definition of "self-employed" is non-employers with zero employees, who are not covered by the establishment survey of *employers*.

[12]But nationwide, the drop in women's employment was larger (-1.4 vs -0.1 percent).

Table 3: COVID-19 effect on employment by worker characteristics

	β_2		γ		Hourly wage (Aug 2019)	Share (percent)
Unemployment	0.12	(0.09)	−0.08	(0.16)		(4.1)
Non-participation	0.34***	(0.09)	1.61***	(0.16)		(37.4)
Employment						
Total	−0.64***	(0.19)	−2.53***	(0.34)	19.4	
By occupation						
Managers	−0.08	(0.53)	7.96***	(1.02)	44.9	(1.4)
Professionals	−1.92***	(0.11)	−2.40***	(0.32)	25.8	(20.8)
Clerks	−1.39***	(0.10)	−1.26***	(0.35)	23.0	(17.7)
Service workers	−4.52***	(0.20)	−5.79***	(0.45)	12.1	(11.9)
Sales workers	−1.83***	(0.16)	−6.28***	(0.50)	15.0	(11.2)
Craft and related trades	1.44***	(0.29)	−6.30***	(0.50)	17.9	(8.9)
Machine operators	−1.05***	(0.13)	0.66	(0.40)	17.1	(11.3)
Elementary workers	−0.33	(0.68)	−2.44*	(1.29)	11.5	(12.6)
By education						
Middle school	0.39	(0.45)	−5.00***	(0.71)	11.7	(13.6)
High school	−1.82***	(0.13)	−3.79***	(0.34)	15.2	(38.5)
College	−0.68***	(0.10)	−2.37***	(0.16)	24.0	(47.9)
By gender						
Male	−0.07	(0.14)	−2.82***	(0.23)	21.8	(57.2)
Female	−1.40***	(0.26)	−2.19***	(0.53)	16.1	(42.8)
By age						
15-19	−21.05***	(1.71)	−13.08***	(3.71)	9.6	(0.8)
20-29	−3.34***	(0.20)	−6.80***	(0.52)	14.5	(14.0)
30-39	−1.60***	(0.10)	−0.23	(0.26)	20.6	(20.6)
40-49	−0.27***	(0.08)	−3.62***	(0.16)	22.5	(24.1)
50-59	−0.70***	(0.16)	−1.33***	(0.26)	21.7	(23.8)
60+	2.64***	(0.87)	−3.58***	(1.26)	14.0	(16.8)
By employment type						
Regular worker	−0.46***	(0.07)	−0.59***	(0.18)	22.2	(54.4)
Temporary worker	−4.43***	(0.55)	−7.20***	(0.96)	12.6	(21.6)
Employer	−3.50***	(0.26)	−1.97**	(0.82)	·	(5.4)
Self-employed	3.01***	(0.31)	−2.43***	(0.43)	·	(15.0)
Unpaid family worker	7.79***	(0.93)	−13.87***	(1.65)	·	(3.6)

Notes: Dependent variable is percentage change in monthly employment, except the top panel, where it is percentage point change in unemployment and non-participation rates. β_2: coefficient on time dummy, D_t(Mar). γ: coefficient on interaction term $D_r(\text{DG})\cdot D_t(\text{Mar})$. Robust standard errors in parentheses. *, **, *** represent significance at 10, 5, 1 percent. Hourly wage in thousand KRW (approximately 0.82 USD). Shares of the categories are from January 2020.

that emerges from Table 3 is that workers of lower socioeconomic status were much more vulnerable to the local outbreak.

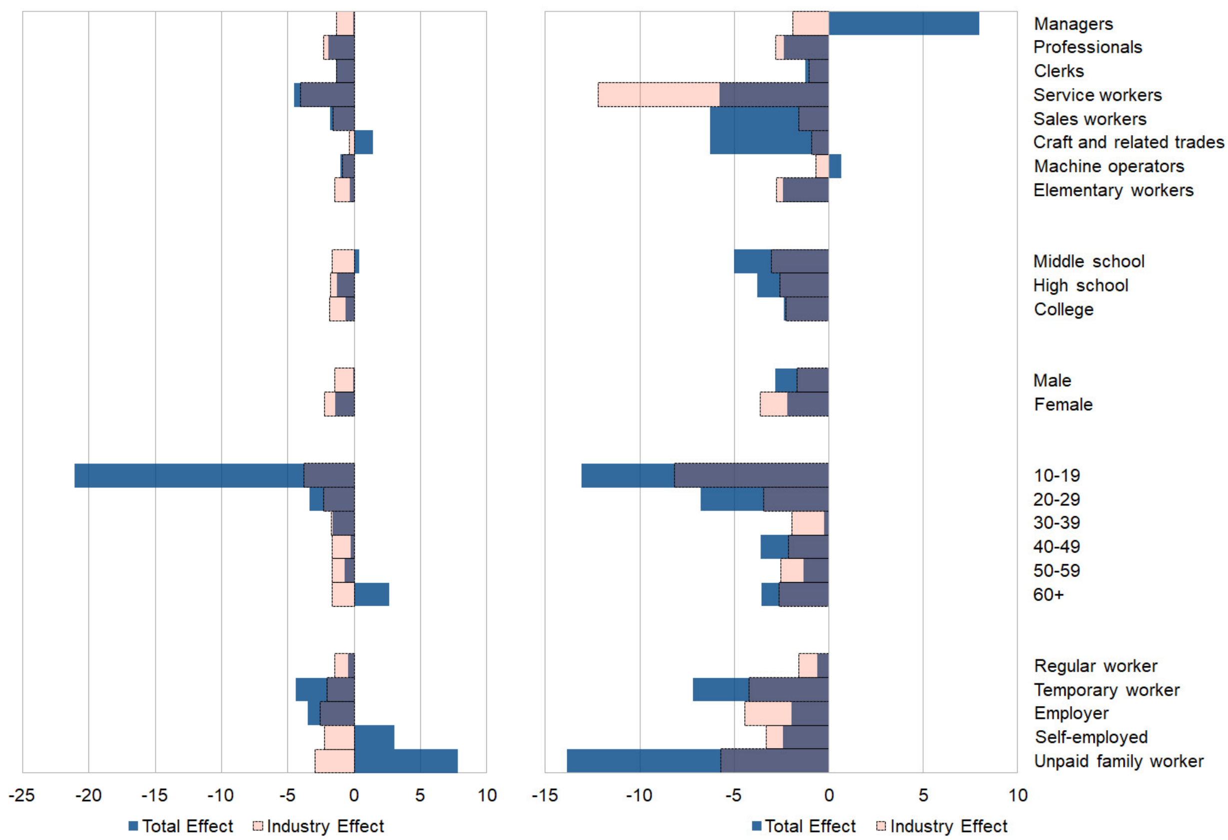
But are the unequal employment effects across different worker groups driven by industrial composition? That is, do the effects differ solely because certain types of workers are over-represented in industries more exposed to the COVID-19 shock? We answer this question by decomposing the causal employment effect of a given demographic group, γ, into an industry component (that differs only between industries) and a group-specific component (that varies within industries). A potential problem is that the EAPS only provides data by industry or by region, but not by industry-and-region. We sidestep this issue by computing what the effect on each group's employment would have been if a shock to an industry in DG, estimated off LFSE in Table 1, equally affected all demographic groups within it, which is the industry-specific effect.[13] Then for each demographic group, the between-industry effect is computed as the average of industry-specific effects using as weights each group's nationwide employment share by industry in February 2020, only available from EAPS, times employment share by industry for all workers in DG in January 2020, only available from LFSE. The difference between the actual effect in Table 3 and this between-industry effect is the within-industry or group-specific effect.[14] Figure 3 shows the total effect and the between-industry effect on the employment of each demographic group. We focus on the causal effect of local outbreaks γ in the right panel.

By occupation, the positive employment effect on managers is entirely an occupation-specific phenomenon—if anything, the hardest hit industries had more managers than other industries (i.e., a negative between-industry effect on manager employment). Similarly, the industry effect alone would have cut service worker employment by more than 10 percent, but it was partly offset by a positive occupation-specific effect on service workers. Sales workers, on the other hand, were negatively affected by both the industry effect and the occupation-specific effect. That is, industries with larger drops in employment had relatively more sales workers, and at the same time, the local outbreak disproportionately destroyed more sales jobs, even within industries. The same is true for less educated workers.

[13]The magnitude of γ for all workers is larger in EAPS than in LFSE. Thus we also re-scale LFSE's industry-specific γ^i's by the ratio between the EAPS and LFSE estimates for all workers.

[14]We do a similar exercise for the nationwide estimate β_2 as well, for which we encounter no such data availability issues since EAPS reports employment of each demographic group by industry.

Fig. 3: Effect on employment by worker characteristic: within and between industries



(a) National (β_2)

(b) DG (γ)

Notes: The dark bars represent the estimates from Table 3. The light bars represent the implied coefficients if for each demographic group, employment changes were solely due to industrial effects only, estimated in Table 1.

By gender, comparing the light bars, we see that hard-hit industries had a larger presence of women than men. However, the within-industry effect is actually positive for women while negative for men, leading to our earlier observation that the causal effect of the outbreak was such that it destroyed men's jobs more than women's.

Next, the figure shows that younger workers were not only more likely to work in industries that experienced larger employment losses, but also more exposed to the COVID-19 shock regardless of the industry in which they worked. For those 60 or older, the causal effect on their employment turns out to be almost entirely accounted for by the between-industry effect.

Finally, the large drop in the employment of temporary workers and unpaid family workers caused by the local outbreaks are nearly evenly divided into the between- and the within-industry effects. Not only did such workers tend to be employed in vulnerable industries, but they also faced similar disadvantages even within a given industry.

In summary, this decomposition exercise shows that the large employment losses experienced by the less educated, young workers and temporary workers were not only caused by their larger presence in industries hit harder by the COVID-19 shock. In contrast, while women were over-represented in more vulnerable industries, the within-industry effect was such that men were more exposed to a causal drop in employment from local outbreaks.

4 Fear of COVID-19 vs. Lockdowns

4.1 Impact on total employment

Our estimate of the causal effect parameter γ allows us to compute how many jobs were destroyed solely due to private responses to incremental COVID-19 infections, in the absence of lockdowns. The cleanest estimate of γ is -1.02, reported in Table 1 from the February 2020 LFSE, since at this point Korea is yet to implement even the weakest social distancing measures. Cumulative infection rates through February 28, 2020 were 0.39 per thousand in DG and less than 0.01 per thousand nationwide, excluding DG. Linearly extrapolating from our γ estimate, we find that a one per thousand increase in infections causes a $\frac{1.02}{0.39-0.01} \approx 2.68$ percent drop in employment.[15]

[15] Cumulative infection rates through March 31, 2020 were 1.56 per thousand in DG and 0.034 per thousand nationwide, excluding DG. Linearly extrapolating from the March 31 LFSE γ estimate, a one per thousand

Compare this causal effect, free from any contamination by government-imposed lockdowns, against the observed labor market outcomes in the US and the UK. Relative to Korea, both countries experienced much higher infection rates and country-wide outbreaks, and implemented large-scale lockdowns in response.[16] But since both the US and the UK implemented lockdowns almost at the same time as confirmed cases began to spiral upward, it is not possible to estimate a causal effect such as our γ separately from the effect of lockdowns or other time effects. So we instead simply compare nationwide employment losses against nationwide cumulative confirmed infections per thousand (the counterpart to our estimate of β_2).[17]

In the US, Cajner et al. (2020) report a 14-percent decline in active employment between February 15 and April 18, 2020, using ADP payroll data. The cumulative infection count for the US on April 18 was 738,913, or 2.3 per thousand, implying that a one per thousand increase in infections is associated with a 6.3-percent decline in employment, a little more than double our causal estimate from Korea. Another estimate for US employment losses is found in Tedeschi and Bui (2020), who report a 12-percent employment decline between March 1 and April 18 from Civis Analytics. This implies that a one per thousand increase in infections is associated with a 5.4-percent decline in employment, a number between our causal estimate and the one implied from the ADP data. For the UK, Gardiner and Slaughter (2020) estimate that employment fell by 19 percent (15 percent furloughed plus 4 percent unemployed) based on data collected between May 6 to 11, 2020. The cumulative infection count on May 11 was 3.2 per thousand, implying that a one per thousand increase in infections is associated with a 6-percent decline in employment.[18]

increase in infections causes a 0.8 percent drop in employment. Similarly, cumulative infection rates through March 15 were 1.4 per thousand in DG and 0.02 per thousand nationwide, excluding DG. According to our estimate from the March 2020 EAPS, a one per thousand increase in infections causes a 1.83 percent drop in employment. These are smaller than the calculation based on the February LFSE, possibly because the nationwide policies in March attenuated the causal effect of local outbreaks.

[16] In the US, lockdown decisions were made by local governments. Forty-two states issued stay-at-home orders of varying degrees of intensity. Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Oklahoma, Utah, and Wyoming never issued state-wide orders, but some of their cities still implemented localized lockdowns. The UK mandated a nationwide lockdown lasting several months, but each devolved country (England, Wales, Scotland and Northern Ireland) had some discretion on when to ease restrictions.

[17] One could argue that we should compare monthly employment changes against monthly—and not cumulative—flows of new infections. But since employment is persistent, it is unclear how to choose a time frame from which to count infection flows. In any case, choosing a monthly or bi-monthly time frame is all but equivalent to cumulative infection rates for Korea, the US, and the UK, since our exercise focuses only on their first waves of infections.

[18] If we were instead to compare UK's employment drop against new infections only in the last 30 days, the

The three calculations from the US and the UK yield three estimates that are strikingly close to one another, and they are roughly double the relationship between employment losses and infection rates implied by our causal estimate without lockdowns.[19] One interpretation is that, even if they had not implemented any lockdowns, the rise in COVID infections alone may have led to employment losses half as large as observed in the data. Furthermore, lockdowns are implemented to contain the epidemic. So suppose that infection counts would have reached twice the levels we observed in those countries had they not implemented any lockdowns.[20] Then our causal estimate implies that the resulting employment losses could have been just as large as what we actually observed in the US and the UK.

We caution readers that these are back-of-the-envelope calculations, under the untested assumption that the fear effect we estimate in Korea are readily applicable to the US and the UK. Nevertheless, our finding suggests that one should not attribute all, or even the majority of, job losses in the US and the UK to their lockdown policies.

4.2 Impact across industries and demographic groups

Government implementation of lockdowns specifies which activities are essential or non-essential. As a result, any differences in employment effects across industries are at least partly by design, and to the extent that the demographic composition of workers differs across industries, the effects would also be heterogeneous across demographic groups.

We compare the pattern of the causal employment effects from local outbreaks without lockdowns (Tables 1, 2, 3 and Figure 3) with the patterns with lockdowns in the US reported by Cajner et al. (2020). First, with or without lockdowns, nearly the same set of industries are hit hardest by the epidemic, including accommodation/food services, real estate, transportation/storage, and

elasticity increases to a 10.3-percent decline in employment per one per thousand increase in infection rates. This is because UK was already at peak infection on April 11, 2020. However, this does not necessarily mean that lockdown effects were large, since we do not know when the employment drop happened—that is, employment may have already fallen in April and simply persisted through May 2020.

[19] Fear and lockdown effects may not be mutually independent. Lockdowns may raise fear effects and vice versa. For certain groups, lockdowns may in fact reduce fear, as suggested by Andersen et al. (2020) who find that older people's consumption in locked-down Denmark increased compared to their counterparts in lockdown-free Sweden. The rationale is that lockdowns made the Danish elderly feel safer.

[20] By all accounts, this is a lower-bound of counterfactual infection counts had no control measures been put in place in those countries, e.g. https://covid19.healthdata.org.

education. One exception is arts/sports/recreation, which fell significantly nationwide in both Korea and the US, but the causal effect (estimated from regional differences) is insignificant. Second, in both cases, small establishments are hit hardest, controlling for industry effects. Third, nearly the same sets of workers are disproportionately affected with or without lockdowns: low-skill workers, young workers, and those on temporary contracts.[21] Finally, in both cases, the heterogeneous effects across workers are accounted for by both between- and within-industry effects.

One difference is the effect by gender. As shown in Figure 3, the between-industry causal effect is larger for women, but the within-industry effect is larger for men so that male workers lose more jobs. In the US, largely due to the between-industry effect, female employment falls by more, and also in the UK.[22]

5 Concluding Remarks

We estimate the causal effect of COVID-19 outbreaks on the labor market, exploiting exogenous regional variation in Korea. Our DiD estimate is uncontaminated by lockdowns, which were never pursued by the Korean government, capturing only the voluntary response by private businesses and consumers.

Our main result that a one per thousand increase in confirmed infections causes a 2.7-percent decline in employment is about half the magnitude of non-causal estimates from the US or the UK, which confound the direct effects of COVID-19 with lockdown effects. Moreover, the causal patterns we obtain across industries, establishment size classes, and workers' occupation, education, age, and employment type tell us that the epidemic struck high-contact industries, small establishments, and workers of lower socioeconomic status the hardest. The causal patterns are very much in line with descriptive evidence from the US and the UK.

This suggests that the primary culprit of the COVID-19 recession is COVID-19 itself, rather than lockdowns. Consistent with our results, reopenings around the world led to only modest economic recoveries, especially as observed in the US and the UK, two countries which experienced persistently high rates of infection. The best way to revive the labor market, then, is to eradicate the virus.

[21] Gardiner and Slaughter (2020) show that the same patterns hold in the UK as well .

[22] But nationwide, also in Korea, women lost more jobs than men both between- and within-industries, as shown in Table 3 and Figure 3.

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Appendix: Robustness

Tables A1 and A2 respectively show that the DG's industrial composition and worker demographics are similar to those of other regions. Figure A1 compares industrial employment by region in the LFSE, our benchmark sample, against the Regional Employment Survey (RES), Korea's official survey for regional employment by industry, conducted every April and October by Statistics Korea. The figure confirms that industrial composition by region is well-represented by the LFSE.

The remaining tables are robustness checks for our DiD estimates against heterogeneous pre-trends, seasonality, regional exports, and using an alternative dependent variable. To address potentially different pre-trends across regions, we modify equation (1) as:

$$\begin{aligned} y^i_{r,t} = \beta^i_0 + \beta^i_1 \cdot D_r(\text{DG}) + \beta^i_2 \cdot D_t(\text{Feb}) \\ + \gamma^i \cdot D_r(\text{DG}) \cdot D_t(\text{Feb}) + \delta^i_1 t + \delta^i_2 t \cdot D_r(\text{DG}) + \varepsilon^i_{r,t}. \end{aligned} \tag{2}$$

The coefficients δ^i_1 and δ^i_2 capture linear trends over the sample periods that may differ by region (nationwide vs DG).

Seasonality is more of a concern for the time dummy β_2 than for the DiD term γ that captures the causal effect of the local outbreak. Neither the establishment survey (LFSE) nor the household survey (EAPS) provides seasonally adjusted series by region. So we first adjust for seasonality by i, where i indexes industry, occupation, gender, age, or employment type, call it $E^{i,sa}_t$. Then seasonally adjusted employment of group i in region r at time t is constructed as:

$$E^{i,sa}_{r,t} = E^i_{r,t} \times \left(E^{i,sa}_t / E^i_t \right).$$

We also address the possibility of lockdowns in other countries negatively affecting Korean exports and hence employment by region. The data, however, suggests that this should not be a concern. First, Korean exports did not decline in February and March. Moreover, the DG area is less export-dependent than the national average, and in any case, experienced higher growth in exports than other areas in February and average growth in March. As a result, controlling for exports make the local impact of COVID-19 (γ) larger.

Finally, we run regression (1) with an alternative dependent variable, regional employment divided by regional population (percentage share of employment). Our dependent variable in the benchmark estimation was employment change from time $t-1$ to t, as a percentage of time $t-1$ employment.

Table A1: Employment share by industry in 2019

	DG	The rest	Mean	Std. dev
Accommodation, food svc.	0.061	0.070	0.069	(0.013)
Facility mgmt., support, rental	0.044	0.064	0.062	(0.027)
Repair, other personal svc.	0.030	0.029	0.029	(0.003)
Real estate	0.017	0.022	0.021	(0.005)
Health, social svc.	0.115	0.095	0.097	(0.017)
Arts, sports, recreation	0.017	0.018	0.018	(0.005)
Water, sewage, waste mgmt.	0.008	0.006	0.006	(0.003)
Wholesale, retail	0.117	0.125	0.125	(0.024)
Public adm., defense	0.050	0.040	0.040	(0.018)
Transportation, storage	0.032	0.040	0.040	(0.010)
Manufacturing	0.269	0.194	0.201	(0.116)
Mining	0.001	0.001	0.001	(0.002)
Construction	0.071	0.074	0.074	(0.015)
Education	0.088	0.085	0.086	(0.010)
Professional, scientific	0.030	0.058	0.056	(0.030)
Information, comm.	0.013	0.035	0.033	(0.029)
Electricity, gas	0.007	0.003	0.004	(0.003)
Finance, insurance	0.032	0.042	0.041	(0.013)

Notes: Industries sorted in ascending order of average hourly wage in Feb 2020. Industrial employment shares for DG and the rest of the country are shown in the first and second columns. The mean and standard deviation in the third and fourth columns are computed across 16 regions in Korea.

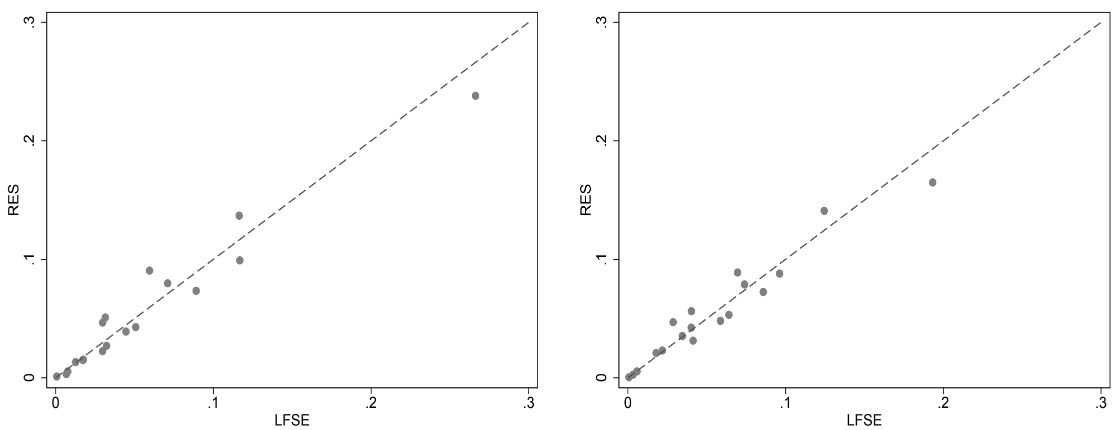
Tables A3–A5 show the results. Time trends barely change our results, and seasonal adjustments lead to the post-treatment dummy β_2 becoming more negative, especially in EAPS. For example, between February 15 and March 15, 2020, nationwide employment dropped by 2.5 percent with seasonal adjustment, compared to 0.6 percent from the baseline specification in the text. However, the DiD coefficient estimates, γ, are nearly identical to their counterparts in Tables 1 and 3. Controlling for regional exports has a minor effect on the coefficients of interest.

When using employment as a fraction of the population (in percent) as a dependent variable, note that the coefficients cannot be directly compared to our benchmark estimates since the variables are in different units (percent change in employment vs. percentage-point change in the employment over population ratio). Nonetheless, the signs and relative magnitudes by industry or demographic are consistent with our benchmark estimates.

Table A2: Composition of workers in 2019

	DG	The rest	Mean	Std. dev.
By occupation				
Managers	0.020	0.015	0.016	(0.004)
Professionals	0.179	0.219	0.215	(0.047)
Clerks	0.159	0.187	0.184	(0.026)
Service workers	0.122	0.121	0.121	(0.020)
Sales workers	0.120	0.117	0.117	(0.011)
Craft and related trades	0.111	0.090	0.092	(0.013)
Machine operators	0.156	0.113	0.117	(0.043)
Elementary workers	0.132	0.137	0.137	(0.021)
By education				
Middle school	0.103	0.080	0.082	(0.023)
High school	0.414	0.408	0.408	(0.049)
College	0.482	0.512	0.509	(0.064)
By gender				
Male	0.575	0.570	0.570	(0.017)
Female	0.425	0.430	0.430	(0.017)
By age				
15-19	0.006	0.007	0.007	(0.002)
20-29	0.120	0.140	0.138	(0.020)
30-39	0.173	0.207	0.204	(0.025)
40-49	0.234	0.240	0.240	(0.014)
50-59	0.252	0.236	0.238	(0.013)
60+	0.215	0.169	0.173	(0.044)
By employment type				
Regular worker	0.469	0.530	0.524	(0.052)
Temporary worker	0.205	0.232	0.229	(0.027)
Employer	0.060	0.056	0.057	(0.007)
Self-employed	0.198	0.145	0.150	(0.044)
Unpaid family worker	0.068	0.037	0.040	(0.023)

Notes: Shares for DG and the rest of the country are shown in the first and second columns. The mean and standard deviation in the third and fourth columns are computed across 16 regions.



(c) DG (d) Rest

Fig. A1: Comparison between LFSE and RES by region and industry

Notes: Each dot represents an industry where the horizontal axis represents an employment share of the industry in the LFSE and the vertical axis represents an employment share of the industry in the RES. The dashed line is 45 degree line.

Table A3: Robustness of effect on employment, total and by industry

	Controlling for export				Employment/Population			
	β_2		γ		β_2		γ	
Total	−0.73***	(0.09)	−1.36***	(0.21)	−0.29***	(0.07)	−1.00***	(0.12)
Accommodation, food svc.	−5.61***	(0.21)	−9.63***	(0.52)	−0.14***	(0.01)	−0.28***	(0.02)
Facility mgmt., support, rental	−0.86***	(0.15)	−0.76*	(0.38)	−0.07***	(0.01)	−0.02*	(0.01)
Repair, other personal svc.	−1.15***	(0.12)	0.42	(0.27)	−0.01***	(0.001)	−0.01***	(0.004)
Real estate	0.11	(0.12)	−1.18***	(0.26)	0.03***	(0.01)	−0.04***	(0.01)
Health, social svc.	−0.45***	(0.10)	−1.26***	(0.21)	0.13***	(0.02)	−0.17***	(0.03)
Arts, sports, recreation	−1.54***	(0.42)	−0.05	(0.71)	−0.04***	(0.004)	−0.01	(0.01)
Water, sewage, waste mgmt.	0.03	(0.11)	1.22***	(0.21)	0.004***	(0.001)	−0.003***	(0.001)
Wholesale, retail	−0.64***	(0.13)	−0.35	(0.41)	−0.03***	(0.004)	−0.14***	(0.02)
Public adm., defense	1.70***	(0.30)	0.35	(0.45)	0.05***	(0.01)	−0.01	(0.01)
Transportation, storage	−0.25***	(0.08)	−0.51**	(0.21)	−0.004***	(0.001)	−0.01***	(0.003)
Manufacturing	−0.15***	(0.04)	−0.34***	(0.12)	−0.03***	(0.002)	−0.25***	(0.04)
Mining	0.72	(0.46)	0.94	(0.97)	−0.001***	(0.000)	−0.003***	(0.001)
Construction	−0.12	(0.33)	−1.42*	(0.76)	−0.07***	(0.01)	0.01	(0.02)
Education	−1.63***	(0.46)	−4.83***	(1.11)	−0.13***	(0.02)	−0.05*	(0.03)
Professional, scientific	−0.14	(0.10)	−0.90***	(0.26)	0.04***	(0.01)	−0.03***	(0.01)
Information, comm.	−0.28***	(0.10)	0.46**	(0.22)	0.001	(0.003)	−0.000	(0.003)
Electricity, gas	0.18	(0.21)	−0.94***	(0.26)	0.01***	(0.001)	−0.01***	(0.001)
Finance, insurance	0.57***	(0.09)	−1.10***	(0.21)	−0.02***	(0.003)	0.02***	(0.003)

	Pre-trends				Pre-trends + Seasonal adj.			
	β_2		γ		β_2		γ	
Total	−0.59***	(0.15)	−0.87***	(0.26)	−0.43***	(0.05)	−0.92***	(0.10)
Accommodation, food svc.	−5.25***	(0.29)	−8.84***	(0.80)	−2.86***	(0.42)	−9.08***	(0.81)
Facility mgmt., support, rental	−0.65***	(0.21)	−0.15	(0.55)	−0.49***	(0.09)	−0.16	(0.47)
Repair, other personal svc.	−0.95***	(0.15)	0.48	(0.55)	−0.44*	(0.24)	0.48	(0.60)
Real estate	0.09	(0.14)	−0.93**	(0.43)	−0.18	(0.11)	−0.92**	(0.40)
Health, social svc.	−0.53**	(0.20)	−0.50*	(0.29)	−0.26**	(0.10)	−0.50*	(0.28)
Arts, sports, recreation	−0.47	(0.48)	1.96*	(1.10)	−1.78***	(0.23)	1.97**	(0.81)
Water, sewage, waste mgmt.	0.21	(0.17)	1.82***	(0.38)	−0.18	(0.14)	1.81***	(0.34)
Wholesale, retail	−0.46***	(0.09)	0.09	(0.54)	−0.41***	(0.10)	0.09	(0.53)
Public adm., defense	1.93***	(0.60)	0.92	(0.88)	0.13	(0.14)	0.91**	(0.45)
Transportation, storage	−0.21**	(0.10)	−0.34	(0.30)	0.15	(0.10)	−0.34	(0.29)
Manufacturing	−0.23***	(0.05)	−0.15	(0.16)	0.02	(0.03)	−0.15	(0.14)
Mining	0.83	(0.67)	2.43	(2.68)	0.76	(0.60)	2.45	(2.52)
Construction	0.16	(0.38)	−0.09	(0.98)	0.05	(0.33)	−0.09	(0.77)
Education	−1.47*	(0.81)	−3.54**	(1.35)	−1.65***	(0.44)	−3.58***	(0.74)
Professional, scientific	0.20**	(0.08)	−1.01**	(0.46)	−0.08	(0.11)	−1.01**	(0.43)
Information, comm.	−0.09	(0.18)	0.36	(0.36)	0.45***	(0.14)	0.36	(0.34)
Electricity, gas	−0.11	(0.41)	−0.69	(0.48)	0.33	(0.27)	−0.69**	(0.33)
Finance, insurance	0.88***	(0.17)	−1.80***	(0.21)	0.86***	(0.17)	−1.80***	(0.21)

Notes: Industries sorted in ascending order of average hourly wage in February 2020. Robust standard errors in parentheses. *, **, *** represent significance at 10, 5, 1 percent. Dependent variable is percentage change in monthly employment. β_2: coefficient on time dummy D_t(Feb); γ: coefficient on interaction term $D_r(\text{DG})\cdot D_t(\text{Feb})$. The coefficients in panel "Employment/Population," for which the dependent variable is the percentage share of regional employment in a region's population, are not directly comparable to those in the other panels.

Table A4: Robustness of effect on employment by worker characteristics

	Controlling for export				Employment/Population			
	β_2		γ		β_2		γ	
Unemployment	0.12	(0.09)	−0.08	(0.16)				
Non-participation	0.35***	(0.09)	1.61***	(0.16)				
Employment								
Total	−0.70***	(0.19)	−2.57***	(0.33)	−1.07***	(0.16)	−1.81***	(0.27)
By occupation								
Managers	−0.21	(0.54)	8.09***	(1.02)	−0.04***	(0.01)	0.21***	(0.02)
Professionals	−1.90***	(0.12)	−2.42***	(0.32)	−0.31***	(0.02)	0.50***	(0.11)
Clerks	−1.41***	(0.11)	−1.24***	(0.36)	−0.22***	(0.01)	−0.74***	(0.07)
Service workers	−4.53***	(0.21)	−5.79***	(0.45)	−0.01	(0.05)	−0.72***	(0.06)
Sales workers	−1.80***	(0.17)	−6.30***	(0.50)	−0.34***	(0.02)	−0.19***	(0.04)
Craft and related trades	1.46***	(0.30)	−6.32***	(0.50)	−0.08***	(0.02)	−0.10*	(0.05)
Machine operators	−1.04***	(0.14)	0.64	(0.40)	−0.20***	(0.03)	0.13**	(0.05)
Elementary workers	−0.28	(0.70)	−2.49*	(1.28)	−0.01	(0.06)	−0.67***	(0.13)
By education								
Middle school	−0.67	(0.68)	−4.92***	(0.68)	−0.23***	(0.03)	−0.36***	(0.06)
High school	−1.93***	(0.29)	−3.78***	(0.34)	−0.59***	(0.04)	−1.72***	(0.12)
College	−0.89***	(0.17)	−2.36***	(0.16)	−0.11	(0.08)	0.30*	(0.15)
By gender								
Male	−0.10	(0.15)	−2.87***	(0.22)	−1.13***	(0.13)	−0.75***	(0.18)
Female	−1.50***	(0.26)	−2.22***	(0.53)	−1.04***	(0.21)	−2.83***	(0.39)
By age								
15-19	−21.13***	(1.75)	−13.00***	(3.82)	−0.12***	(0.01)	−0.01	(0.01)
20-29	−3.34***	(0.20)	−6.80***	(0.53)	−0.49***	(0.02)	−0.25***	(0.05)
30-39	−1.57***	(0.11)	−0.26	(0.27)	−0.41***	(0.03)	−0.12**	(0.05)
40-49	−0.24***	(0.09)	−3.65***	(0.15)	−0.48***	(0.05)	−0.76***	(0.10)
50-59	−0.70***	(0.16)	−1.33***	(0.27)	−0.26***	(0.03)	−0.41***	(0.05)
60+	2.57***	(0.89)	−3.50***	(1.26)	0.69***	(0.15)	−0.26	(0.24)
By employment type								
Regular worker	−0.44***	(0.08)	−0.61***	(0.17)	0.98***	(0.11)	−0.58***	(0.17)
Temporary worker	−4.41***	(0.57)	−7.22***	(0.96)	−1.67***	(0.10)	−0.82***	(0.18)
Employer	−3.66***	(0.29)	−1.80**	(0.74)	−0.43***	(0.04)	−0.15**	(0.06)
Self-employed	3.01***	(0.32)	−2.42***	(0.44)	0.16***	(0.04)	0.28***	(0.05)
Unpaid family worker	7.67***	(0.95)	−13.75***	(1.66)	−0.11***	(0.04)	−0.53***	(0.10)

Notes: Robust standard errors in parentheses. *, **, *** represent significance at 10, 5, 1 percent. Dependent variable is percentage point change in unemployment rate, percentage point change in labor force non-participation rate, and percentage change in monthly employment. β_2: coefficient on time dummy, D_t(Mar). γ: coefficient on interaction term $D_r(\text{DG})\cdot D_t(\text{Mar})$. The coefficients in panel "Employment/Population," for which the dependent variable is the percentage share of regional employment in a region's population, are not directly comparable to those in the other panels.

Table A5: Robustness of effect on employment by worker characteristics

	Pre-trends				Pre trends + Seasonal Adj.			
	β_2		γ		β_2		γ	
Unemployment	0.09	(0.18)	−0.05	(0.34)	0.63***	(0.16)	−0.07	(0.34)
Non-participation	0.10	(0.15)	1.47***	(0.26)	1.18***	(0.13)	1.49***	(0.20)
Employment								
Total	−0.44	(0.34)	−2.46***	(0.67)	−2.50***	(0.10)	−2.42***	(0.28)
By occupation								
Managers	2.40***	(0.75)	6.02***	(1.97)	3.14***	(0.91)	6.07***	(2.04)
Professionals	−1.74***	(0.25)	−2.28***	(0.71)	−3.11***	(0.18)	−2.26***	(0.67)
Clerks	−1.26***	(0.19)	−1.10	(0.75)	−1.00***	(0.24)	−1.11	(0.78)
Service workers	−4.52***	(0.44)	−5.85***	(0.92)	−4.85***	(0.31)	−5.85***	(0.85)
Sales workers	−1.78***	(0.32)	−6.49***	(1.14)	−0.80***	(0.26)	−6.55***	(1.19)
Craft and related trades	1.91***	(0.52)	−6.75***	(0.99)	0.43	(0.42)	−6.70***	(1.00)
Machine operators	−1.47***	(0.24)	0.77	(0.80)	−1.78***	(0.22)	0.77	(0.73)
Elementary workers	0.43	(1.44)	−2.26	(2.97)	−5.95***	(0.62)	−2.03	(1.89)
By education								
Middle school	0.83	(0.80)	−4.57***	(1.21)				
High school	−1.96***	(0.26)	−3.15***	(0.71)				
College	−0.24	(0.16)	−2.80***	(0.32)				
By gender								
Male	0.08	(0.26)	−3.09***	(0.45)	−1.43***	(0.12)	−3.06***	(0.27)
Female	−1.13**	(0.48)	−1.65	(1.06)	−3.89***	(0.11)	−1.58***	(0.50)
By age								
15-19	−22.82***	(3.75)	−10.25	(8.44)	−8.52***	(3.05)	−12.24*	(6.75)
20-29	−2.95***	(0.48)	−6.20***	(0.96)	−3.03***	(0.41)	−6.21***	(0.83)
30-39	−1.65***	(0.20)	−0.22	(0.67)	−2.02***	(0.12)	−0.22	(0.61)
40-49	−0.22	(0.13)	−3.81***	(0.28)	−0.65***	(0.16)	−3.80***	(0.28)
50-59	−0.40	(0.29)	−1.06**	(0.52)	−1.85***	(0.15)	−1.04***	(0.32)
60+	4.58***	(1.66)	−3.36	(2.42)	−8.69***	(0.49)	−3.00***	(0.88)
By employment type								
Regular worker	−0.60***	(0.13)	−0.58	(0.43)	−0.93***	(0.12)	−0.58	(0.45)
Temporary worker	−3.20***	(1.05)	−6.82***	(2.11)	−6.15***	(0.47)	−6.66***	(1.47)
Employer	−3.12***	(0.63)	−1.84	(2.09)	−4.13***	(0.57)	−1.81	(1.96)
Self-employed	3.61***	(0.49)	−3.01***	(1.00)	−0.41	(0.26)	−2.96***	(1.06)
Unpaid family worker	10.29***	(1.61)	−11.26***	(2.59)	−0.26	(0.73)	−10.35***	(1.13)

Notes: Robust standard errors in parentheses. *, **, *** represent significance at 10, 5, 1 percent. Dependent variable is percentage point change in unemployment rate, percentage point change in labor force non-participation rate, and percentage change in monthly employment. β_2: coefficient on time dummy, D_t(Mar). γ: coefficient on interaction term D_r(DG)$\cdot D_t$(Mar). Statistics Korea does not provide seasonally-adjusted series by education.