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Pandemic Work Mode and Automation: Evidence from South Korea

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Abstract

Does the COVID-19 crisis accelerate automation? We investigate this question by analyzing employment trends based on occupational COVID-19 exposure and automation potential, key factors influencing post-pandemic automation. Using micro-level data from South Korea (2016–2022), we find a persistent decline in employment for occupations with high exposure and high automatability since the pandemic outbreak. In contrast, other occupations have largely recovered to pre-pandemic employment levels after an initial decline. These findings suggest that the pandemic has incentivized firms to adopt labor-replacing technologies to mitigate the business risks associated with viral transmission.

Keywords: Automation, COVID-19, Employment, Technology adoption, South Korea

JEL Classification: E24, I15, J21, O33.

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I. INTRODUCTION

It is widely recognized that efforts to enhance productivity–such as the adoption of new technology, reorganization, and job training–often intensify during economic recessions (Hall, 1991; Caballero and Hammour, 1994; Aghion and Saint-Paul, 1998; Hall, 2000; Koenders and Rogerson, 2005; and Kopytov et al., 2018). Recent empirical evidence further suggests that the adoption of labor-replacing technologies tends to accelerate during economic downturns (Hershbein and Kahn, 2018; Zhang, 2019; and Jaimovich and Siu, 2020).[1] Unlike previous pandemics such as SARS, MERS, Ebola, and Zika, COVID-19 triggered a profound global economic recession beginning in 2020.[2] Consequently, it is reasonable to anticipate significant advancements in automation as a key component of productivity-enhancing measures during the COVID-19 crisis.

Moreover, firms facing disruptions in production or sales due to the spread of contagious diseases may respond by reducing labor inputs at workplaces (Autor and Reynolds, 2020; Blit, 2020; and Chernoff and Warman, 2023). In other words, the business risks of widespread viral transmission create pandemic-specific automation incentives for organizations. For instance, Sedik and Yoo (2021) find that robot integration increased following epidemic outbreaks, particularly when accompanied by severe health and economic consequences.

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[1] Hershbein and Kahn (2018) find that in U.S. regions more severely affected by the Great Recession, there were greater increases in skill requirements accompanied by increases in capital investments. Zhang (2019) shows that in response to negative aggregate shocks, firms where routine workers make up a greater share tend to decrease the use of routine-task labor while increasing their investments in machinery. Jaimovich and Siu (2020) demonstrate that employment in routine occupations that are easily replaceable by machines significantly decreased during each of the last three U.S. recessions and did not recover, leading to the widely referred-to "jobless recoveries."

[2] In 2020, as the coronavirus escalated into a pandemic, major economies experienced unrivaled negative economic growth due to severe supply disruptions and plummeting demand (Figure A1).

This paper examines whether the COVID-19 pandemic, a significant episode that could potentially promote the adoption of labor-saving technologies, has indeed accelerated automation.[3] We hypothesize that job-related sensitivity to viral transmission and the intrinsic automation potential of tasks are pivotal factors influencing labor demand in the context of post-pandemic automation. During a large-scale pandemic, the degree of susceptibility to infection by occupation may have a differential impact on a firm's incentives to adopt automation. Meanwhile, the feasibility of automating tasks limits the extent to which machines can replace labor in each occupation. To explore these dynamics, we analyze occupational employment trends in South Korea before and after the pandemic along two dimensions: exposure to COVID-19 and automation potential.

Occupational COVID-19 exposure is measured by physical proximity and teleworkability indices for Korean occupations. Each index is based on U.S. Occupational Information Network (O*NET) surveys of the degree of face-to-face contact required for job performance and the adaptability of tasks to remote work for each occupation. An occupation is considered highly exposed to COVID-19 if it requires frequent close contact (i.e., a high physical proximity score) and offers limited telecommuting options (i.e., a low teleworkability score). Based on these criteria, individual occupations are categorized into two groups: high-exposure and low-exposure. Additionally, the automation probability for each occupation, serving as a proxy for its automation potential, is calculated using the methodology proposed by Frey and Osborne (2017).

[3] Given the variations in substitutability and complementarity between labor and capital across different job tasks, automation has different implications across worker's skill levels. For related discussions, see Autor et al. (2003); Acemoglu and Autor (2011); Autor and Dorn (2013); Acemoglu and Restrepo (2018); and Acemoglu and Restrepo (2019).

Employing these metrics, we examine how employment trends have changed since the COVID-19 outbreak for each occupational group, categorized by their degree of COVID-19 exposure and automation potential. We use data from the Local Area Labor Force Survey (LALFS), a semi-annual survey on detailed local employment situations administered by the Statistics Korea. The data cover the period from October 2016 to October 2022.

Our findings reveal significant employment reductions in occupations characterized by both high exposure to COVID-19 and high automation potential since the onset of the pandemic. Although the overall economy has largely recovered from the initial pandemic shock,[4] severe job losses in these occupations have persisted, indicating a phenomenon of "jobless recovery." Furthermore, within the high-exposure group, employment in occupations with greater automation potential has declined more sharply, with this trend becoming increasingly pronounced over time. In contrast, the low-exposure group did not experience additional job losses attributable to automatability during the pandemic. Taken together, these findings suggest that automation potential alone was insufficient to drive structural shifts in employment in the post-pandemic period; rather, it required the interplay of automatability with heightened infection risks. This underscores the possibility that the COVID-19 crisis incentivized firms to adopt labor-replacing technologies as a strategic response to the business risks associated with viral transmission.

This paper contributes to the growing literature on pandemic-induced automation in several dimensions. Firstly, this study explores heterogeneity in employment trends across occupations based on two job characteristics: pandemic exposure and automation potential. It highlights how the interaction between these two factors shapes automation dynamics during the pandemic.

[4] The global economy experienced a significant decline during the first year of the pandemic, but recovered with rapid growth in subsequent years (Figure A1).

Previous studies have evaluated the pandemic's impact on automation, focusing on variations in the likelihood of automation across occupations (e.g., Ding and Molina, 2020; Bonilla et al., 2022; and Egana-delSol et al., 2022).[5] An exception is Song et al. (2023), who analyze shifts in occupational demand across different levels of disease risk and job automation capacity using U.S. job postings. Different from Song et al. (2023), we examine detailed occupational employment trends while accounting for various confounding factors and pre-existing employment patterns related to automation, providing a rigorous analysis to ascertain the relationship between the pandemic and advancements in automation.

Additionally, by encompassing both the initial and recovery phases of the pandemic, we offer a comprehensive examination of enduring changes in employment related to pandemic-induced automation. Previous studies suggest preliminary indications of the connection between the pandemic and automation, focusing on the early stages of the COVID-19 crisis. However, as automation involves the irreversible displacement of workers in certain jobs, tracking employment trends over an extended period is essential to fully understand the evolution of automation.

II. DATA AND MEASUREMENT

II.1. Data

We utilize the Local Area Labor Force Survey (LALFS) administered by the Statistics Korea, encompassing approximately 234,000 households and detailing local employment situations. The survey is conducted biannually, in April and October. For our analysis, we restrict the sample to salaried employees and exclude individuals working in non-profit organizations,

[5] While Blit (2020) and Chernoff and Warman (2023) specify occupations vulnerable to viral transmission and automation in the U.S. and Canada, respectively, they do not analyze how the risk affects employment.

including those in “Public Administration and Defense.” The dataset spans from October 2016 to October 2022, covering approximately three years before and after the onset of the pandemic.

II.2. Exposure to COVID-19

To measure the level of COVID-19 exposure by occupation, we develop two metrics for each occupation: (1) physical proximity and (2) teleworkability, utilizing information from the U.S. O*NET survey items.[6] O*NET assesses the degree of physical proximity to customers or co-workers required to perform the job on a scale of 1 to 5 for detailed U.S. occupations (O*NET SOC 6-digit).[7] We map these ONET ratings for U.S. occupations to their Korean counterparts.[8] Physical proximity scores are calculated at the 4-digit Korean Standard Classification of Occupations (KSCO) using crosswalks that links a country’s occupational classification system to the International Standard Classification of Occupations (ISCO).[9]

Dingel and Neiman (2020) assess the ability to work from home for each U.S. occupation using a scale from 0 to 1, based on 17 items from the O*NET survey. Dingel and Neiman (2020) consider an occupation that requires significant physical activity or intensive use of specialized equipment or direct interaction with the public as one that cannot be done at home. We apply the teleworkability scores for U.S. occupations (SOC 6-digit) from Dingel and Neiman (2020) to

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[6] Similarly, Mongey et al. (2020) measure physical proximity and teleworkability for each occupation based on the O*NET survey in order to predict the potential impact of social distancing on occupation-specific labor demand using the U.S data.

[7] The rating categories are defined as follows: 1 = “I don’t work near other people (beyond 100 feet),” 2 = “I work with others but not closely (e.g., private office),” 3 = “Slightly close (e.g., shared office),” 4 = “Moderately close (at arm’s length),” and 5 = “Very close (near touching).”

[8] We use release 24.2 of the database administered by O*NET (https://www.O*NETcenter.org/dictionary/24.2). Given that the O*NET variable is presented at a highly granular level, we first calculate the average O*NET scores at the SOC 6-digit level.

[9] We employ crosswalks between SOC 2010 6-digit and ISCO 08 4-digit, as well as crosswalks between ISCO 08 4-digit and KSCO 07 4-digit.

Korean occupations (KSCO 4-digit), following a similar approach used for evaluating physical proximity.[10]

Both indices are then aggregated at the KSCO 3-digit level using a simple average.[11] A job is classified as having high COVID-19 exposure if it scores above the employment-weighted median for physical proximity and below the median for teleworkability. Occupations not meeting these criteria are categorized as part of the low-exposure group.

II.3. Automation Probability

Frey and Osborne (2017) argued that occupations requiring advanced perceptual and manipulative skills, as well as high levels of creative and social intelligence, are unlikely to be fully replaced by computer capital in the near future. Building on this premise, they estimated the automation probability for 702 U.S. occupations using a combination of expert surveys and machine learning techniques.[12] Kim (2015) extended their work by mapping these U.S. occupations, whose automation probabilities were determined by Frey and Osborne (2017), to Korean occupations (KSCO 4-digit) through cross-referencing the Korean and American occupational dictionaries.

For this study, we aggregate the automation probabilities provided by Kim (2015) to the KSCO 3-digit level using a simple average. Out of a total of 153 occupations, 12 occupations are

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[10] We draw Dingel and Neiman (2020)'s remote work index from https://github.com/jdingel/DingelNeiman-workathome.

[11] The original score of physical proximity with a range of [0, 5] is rescaled to [0, 1].

[12] Frey and Osborne (2017) classified 70 occupations as either automatable or not. They identified nine O*NET variables that describe job characteristics thought to strongly correlate with automation feasibility, such as the levels of perceptual and manipulative abilities, creative thinking, and social aptitude required for job performance. Using these variables, they predicted the automation probability for 702 U.S. occupations. A Gaussian process classifier was employed to estimate the likelihood of each occupation falling into the automatable category by leveraging patterns observed in the selected O*NET variables across 70 subjectively hand-labeled occupations in the training data.

excluded from our analysis because their automation probabilities are not calculated. The proportion of occupations omitted is minimal, accounting for only 2.89% of total employment as of October 2019.[13] Occupations are categorized as easily automatable if their automation probability is greater than or equal to 0.7 and as less automatable if their probability falls below this threshold.

II.4. Occupational Exposure to COVID-19 and Automation Probability

Figure 1 presents the scores by occupation for three key metrics—physical proximity, teleworkability, and automation probability—aggregated at the KSCO 2-digit level.[14] Physical proximity scores (x-axis) and teleworkability scores (y-axis) for each occupation are displayed on a two-dimensional plane. The two dashed lines represent the employment-weighted medians for each metric. Occupations are classified as having high COVID-19 exposure if their physical proximity score exceeds the employment-weighted median, while their teleworkability score falls below the employment-weighted median. Therefore, occupations located in the 4th quadrant delineated by the two dashed lines in Figure 1 (to the right of the red dashed line and below the blue dashed line) have high COVID-19 exposure. All occupations that do not fall into the high-exposure group are classified as the low-exposure group.

[Figure 1]

The automation potential for each occupation is visualized using the colors and shapes of the markers in Figure 1. Frey and Osborne (2017) distinguish between high-risk, medium-risk, and

[13] This is because the specific occupations (KSCO 4-digit) included in these 12 occupations do not correspond to any of the 702 U.S. occupations according to the matching results of Kim (2015).

[14] We apply an employment-weighted average for each of the three metrics at the KSCO 2-digit level, using the number of employees in 2019 as the weight. Detailed scores by occupation for the three metrics are presented in Table A1.

low-risk occupations based on their automation probability (threshold at probabilities of 0.7 and 0.3). In Figure 1, a blue circle indicates that the automation probability for that occupation falls within the range of [0, 0.3). Similarly, a yellow triangle and a red square indicate that the automation probability for those occupations falls within the ranges [0.3, 0.7) and [0.7, 1], respectively.

We begin by briefly discussing the distribution of occupations based on indicators related to the degree of COVID-19 exposure. Occupations such as “Sales,” “Cooking and Food Service,” “Health and Social Welfare,” and “Personal Service” are characterized by limited teleworkability and high physical proximity to others (located in the 4th quadrant of Figure 1). These occupations are classified as having high COVID-19 exposure, making them particularly vulnerable to viral transmission. In contrast, occupations such as “Professionals,” “Technicians,” and “Clerical Workers” involve minimal face-to-face interaction and are more adaptable to telework (2nd quadrant). Meanwhile, “Equipment and Machine Operators” are less suited to telework but require relatively low physical contact (3rd quadrant), whereas occupations in “Educational Services” exhibit high telecommuting potential despite requiring intensive interpersonal interaction (1st quadrant).

Among high-exposure occupations, roles such as “Sales,” “Cooking and Food Service,” “Food Processing,” and “Elementary Workers” (e.g., in sales, construction, and transportation) exhibit high automation potential. Conversely, occupations like “Health and Social Welfare” and “Personal Service” are relatively resistant to automation.[15] In the low-exposure group, occupations such as “Clerical Workers” and “Equipment and Machine Operators” are more likely to face

[15] The employment share of jobs with high exposure and high automation potential at the KSCO 3-digit level in 2019 is 23.5% (Figure A2).

automation, whereas roles like "Professionals," "Technicians," and "Managers" are less prone to replacement by machines.[16]

III. NAVIGATING OCCUPATIONAL EMPLOYMENT TRENDS BY COVID-19 EXPOSURE AND AUTOMATION POTENTIAL

This section investigates whether there are discernible employment patterns linked to job characteristics. Specifically, we compare the employment trends across various occupational groups categorized by their levels of COVID-19 exposure and automation potential.

Figure 2 illustrates employment trends before and after COVID-19 for easily and less automatable jobs within both high- and low-exposure groups. Prior to the pandemic,[17] employment growth in easily automatable jobs lagged behind that of less automatable jobs across both exposure groups. Post-pandemic trends reveal differing recovery patterns. In the low-exposure group, both easily and less automatable jobs returned to their pre-pandemic trajectories following an initial decline (panel (a)).

[Figure 2]

In contrast, the high-exposure group exhibits a more pronounced divergence in employment growth between jobs with high and low automation potential after the onset of the pandemic (panel (b)). While less automatable jobs in the high-exposure group experienced an initial decline in employment following the outbreak, they eventually resumed pre-pandemic growth patterns, resembling trends observed in the low-exposure group. Conversely, employment in easily automatable jobs within the high-exposure group has remained consistently below pre-

[16] The employment share of easily automatable jobs in the high-exposure group is 66.7%, which is higher than the 40.4% observed in the low-exposure group.

[17] The first case of coronavirus in South Korea occurred in January 2020.

pandemic levels since the onset of the COVID-19 crisis. Consequently, the pandemic has exacerbated the disparity in employment growth between easily automatable and less automatable jobs within the high-exposure group, widening this gap more sharply than before the pandemic.[18]

We further examine the relationship between employment growth and automatability before and after the pandemic. In the low-exposure group, the correlation between employment growth and automatability is not significant either before or after the outbreak (Figure A4, panel (a)). On the contrary, the inverse relationship between employment growth and automatability by occupation in the high-exposure group has strengthened considerably after COVID-19 (panel (b)). These results suggest that there are likely to be marked differences in automation dynamics among occupations with varying degrees of COVID-19 exposure.

IV. Empirical Evaluation of the Impact of Pandemic-Induced Automation Force

IV.1. Empirical Strategy

Building on the substantial difference in employment paths as a function of automation potential between two occupational groups with different levels of COVID exposure, we estimate the following event-study model.

[18] This observation is preserved when we use both physical-proximity and teleworkability distinctively to measure COVID exposure. In all subgroups with low exposure, the gap in employment growth between easily automatable and less automatable jobs shows little change before and after COVID-19 (panels (a), (b), and (c) of Figure A3).

$$
\begin{aligned}
lnemp_{i,o,t} = & \sum_{t=2016.10, t \neq 2019.10}^{2022.10} \gamma_t \left(D_{high} \times D_t\right) \\
& + \sum_{t=2016.10, t \neq 2019.10}^{2022.10} \delta_t (Auto_o \times D_t) \\
& + \sum_{t=2016.10, t \neq 2019.10}^{2022.10} \beta_t \left(D_{high} \times Auto_o \times D_t\right) \\
& + \alpha_{i,o} + \lambda_t + \theta X_{i,t} + \varepsilon_{i,o,t},
\end{aligned} \tag{1}
$$

where $lnemp_{i,o,t}$ is the log employment of occupation o in industry i at time t, D_{high} is a dummy variable indicating whether an occupation is highly exposed to COVID-19 or not, and $Auto_o$ is the standardized transformation of automation probabilities by occupation to mean zero and standard deviation one. D_t is a calendar time dummy variable with a semi-annual frequency that spans from October 2016 to October 2022, using October 2019 as the reference period. $\alpha_{i,o}$ is the unit fixed effect, λ_t is the time fixed effect, and $X_{i,t}$ is the control vector to account for industrial activity including an industrial production index and its lags ($t-1$ and $t-2$).[19]

This model allows us to capture the dynamic effects of occupational automation potential on employment for each group. We set up a combination of each 2-digit industry and each 3-digit occupation as a sample unit. Our regression analysis relies on a balanced panel dataset that includes only units with complete observations throughout the sample period.

We estimate Eq. (1) using different criteria to define the high-exposure group. As the baseline, we assign a value of one to the dummy variable D_{high} for each occupation if its physical proximity score exceeds the employment-weighted 50th percentile (i.e., employment-weighted

[19] We obtain the industrial production index (KSIC 2-digit) from the Statistics Korea.

median) and its teleworkability score falls at or below the employment-weighted 50th percentile. We then refine the definition of the high-exposure group by incrementally adjusting the cutoff thresholds for either the physical proximity score or the teleworkability score.

In our specification, we interpret the automation potential variable ($Auto_o$) as representing treatment intensity imposed by COVID-19 in the context of difference-in-differences (DID) design and COVID exposure (D_{high}) as moderating the treatment effects. Our primary interest is thus the coefficient on the three-way interaction term ($D_{high} \times Auto_o \times D_t$), β_t, which captures the additional employment change attributable to the occupation-specific automation potential in the high-exposure group compared to the low-exposure group. We expect it to have statistically significant negative values after April 2020 ($t \geq 2020.4$) if the spread of the pandemic led to a greater reduction in employment for occupations more susceptible to automation, particularly in the high-exposure group.

The analyses in Section III suggest that there were observable patterns in occupational employment by concerning automation potential prior to the pandemic outbreak. To alleviate potential bias arising from pre-existing trends in development of automation, we partial out pre-pandemic employment trends related to occupation-specific automation potential following Bhuller et al. (2013) and Goodman-Bacon (2021b). Specifically, we estimate linear time trends interacted with automation potential for each group on data up to just before the outbreak (October 2019). We then extrapolate the estimated pre-trends to the post pandemic period, and subtract the fitted trend from all observations.[20]

[20] Many DID (or event study) analyses control for unit-specific trends over the sample period. However, several studies indicate that this approach may introduce significant bias in the estimated coefficients if treatment effects themselves exhibit trends (see Wolfers, 2006; Meer and West, 2016; Goodman-Bacon, 2021a; and Miller, 2023). Recent research

IV.2. Main Results

We first present the results of estimating Eq. (1) by replacing the calendar time variable with a single dummy variable indicating the post-COVID-19 period. The corresponding coefficients, where the scope of the high-exposure group is gradually reduced, are presented in columns (1)–(4) of Table 1.[21] The coefficients on $D_{high} \times D_{post-COVID}$, indicating the average employment change in the high-exposure group after the pandemic, are negative, although they are statistically significant only in column (4). The coefficients on $Auto_o \times D_{post-COVID}$ are close to zero and statistically insignificant in all cases, suggesting that occupational automation potential does not contribute to post-pandemic employment changes in the low-exposure groups. In contrast, the coefficients on the three-way interaction, $D_{high} \times Auto_o \times D_{post-COVID}$, exhibit statistically significant negative values across all specifications. These results indicate that, in the high-exposure group, occupation-specific automation potential depresses employment during the pandemic.

[Table 1]

suggests focusing solely on controlling for prior trends when the intervention's effect follows a monotonic pattern over time (Bhuller et al., 2013; Goodman-Bacon, 2021b; and Miller, 2023). The results in Section III and IV.2 clearly indicate that the employment gap due to the occupational automation margin has continuously increased beyond the pre-pandemic trend, especially in the high-exposure group.

[21] For example, in column (1), the dummy variable D_{high} is set to one if the job's physical proximity score exceeds the employment-weighted 50th percentile and its teleworkability score is below or equal to that percentile, which serves as a benchmark. In column (4), D_{high} equals one if the physical proximity score is above the employment-weighted 60th percentile and the teleworkability score is at or below the employment-weighted 40th percentile (see note in Table 1).

Next, we present the results from the event-study estimation.[22] Figure 3 displays coefficients on the three-way interaction, $D_{high} \times Auto_o \times D_t$, implying the differential effect of occupation-specific automation potential on employment in the high-exposure group. Details of the estimates are reported in Table A2. The absence of pre-trends in occupational employment related to automation potential is depicted in Figure 3. In the high-exposure group, occupations with higher automation potential experienced a greater decline in employment in the immediate aftermath of the pandemic outbreak. Notably, the detrimental impact of automation potential on employment in this group has gradually intensified. In the baseline scenario, the estimated additional employment change due to one standard deviation in automation potential in the high-exposure group is –6.2% in April 2020, just after the outbreak (column (1) in Table 2). This negative impact continuously increases, with the estimate reaching –8.4% in October 2022, the last period in our sample. The main results hold even when the scope of the high-exposure group is marginally adjusted.

[Figure 3]

In summary, there was no sustained change in employment due to coronavirus exposure alone. Additionally, in the low-exposure group, we find no evidence of a change in the relationship between automation potential and employment after the pandemic. However, in the high-exposure group, occupations with greater susceptibility to automation experienced more pronounced declines in employment since the onset of COVID-19. The adverse impact of occupation-specific

[22] Consistent with earlier findings, no average change in employment is observed in the high exposure group and the effect of occupational automation potential on employment in the low-exposure group remains unchanged following the pandemic. The coefficient on $D_{high} \times \mathrm{D_t}$ decreases shortly after the outbreak (April 2020), but close to zero thereafter. The coefficients on $Auto_o \times \mathrm{D_t}$ are not different from zero across all periods. Detailed results are available upon request.

automation potential on employment has become increasingly apparent during the pandemic era. These findings are consistent with the employment trends across occupational groups categorized by their levels of COVID-19 exposure and automation potential, as described in Section III.[23]

IV.3. Possible Mechanisms

In this section, we propose a potential mechanism to refine the insights derived from the main findings. One potential explanation for the main result is that the stagnant employment in occupations characterized by high exposure and high automation potential may be driven by demand-side factors specific to their dominant industries. However, empirical evidence challenges this explanation, indicating that the persistent post-pandemic job losses cannot be solely attributed to a sluggish recovery in industrial production activity. In industries dominated by highly exposed and easily automatable jobs,[24] production levels have returned to pre-pandemic norms, comparable to other industries (Figure A5, panel (a)). Despite this recovery, employment in highly exposed and easily automatable jobs within these industries has stagnated significantly below pre-pandemic levels, while employment in other occupations has experienced rapid growth following an initial decline after the outbreak.[25] These results suggest that the substantial job losses in occupations

[23] Several experiments confirm the robustness of the main findings. First, we estimate the main model (Eq. (1)) using annual data to assess the impact of seasonal effects in our analysis. Furthermore, we replicate the main analysis using a more aggregated sample unit (combining each 2-digit industry and each 2-digit occupation) to mitigate potential measurement errors in our key metrics. All estimates align with those from the main analysis (Figures A6 and A7).

[24] Industries dominated by highly exposed and easily automatable jobs are defined as those where at least 60% of employment is concentrated in such roles (e.g., "Food and beverage service activities," "Retail trade," "Land transport and transport via pipelines," "General construction").

[25] In industries dominated by jobs with high exposure and high automation potential, production activity has grown faster than total employment post-pandemic, indicating a potential improvement in labor productivity (Figure A5, panel B).

with high exposure and high automation potential after the pandemic are not solely driven by sluggish demand in the industries where these occupations are prevalent.

Next, as noted in the introduction, we hypothesize that COVID-19 exposure in job performance and the inherent automatability of job tasks jointly influence labor demand associated with automation during the pandemic. Based on this hypothesis, we interpret the continued decline in employment in highly automatable jobs within the high-exposure group as evidence of accelerated automation in these occupations following the pandemic. However, concerns may arise that the post-pandemic employment decline in certain sectors is instead driven by reduced labor supply caused by the pandemic. To address these concerns, we re-estimate the main model (Eq. (1)) using wages as the dependent variable.[26]

The estimation results based on two periods (pre-COVID-19 and post-COVID-19) indicate that, in the high-exposure group, there is no increase in hourly wages due to occupational automation potential. Rather, occupations with higher automation potential in this group appear to have experienced an additional decline in hourly wages following the pandemic (row 3 in Table A3).[27] The findings from the event-study estimation are consistent: in the high-exposure group, hourly wages in occupations with higher automatability have consistently declined since the onset of the pandemic (Figure A8). Therefore, our key result does not seem to be driven by labor supply.

Finally, acknowledging that post-pandemic changes in employment trends likely reflect shifts in labor demand driven by automation, we aim to elucidate the mechanisms underpinning post-pandemic automation. We propose that two key drivers of this automation are recession-

[26] The data (LALFS) include three-month average monthly wages and weekly hours worked at the time of the survey. We converted the weekly hours to monthly hours (weekly hours × 4) and calculated hourly wages by dividing the monthly salary by the monthly hours.

[27] The significance of the coefficients ($D_{high} \times Auto_o \times D_t$) varied depending on the high exposure grouping criterion, but the signs of the regression coefficients are consistently negative.

induced productivity-enhancement motives and pandemic-specific incentives related to mitigating viral transmission. The empirical finding that sustained post-pandemic job losses were exclusively confined to the high-exposure group appears to support the latter scenario. However, our results may also reflect a broader process of eliminating cost-inefficient inputs, consistent with productivity improvements typically observed during recessionary periods.[28]

To determine whether pre-determined labor costs are involved in our findings, we examine whether pre-pandemic labor cost pressures at the industry or occupation level are linked to post-pandemic changes in employment trends. We estimate industry and occupation-specific wage premiums using the Mincer earnings equation as a proxy for labor cost pressures at the industry and occupation levels, respectively. Specifically, we estimate the following model using pre-pandemic data from April 2016 to October 2019:

$$lnwage_{\hbar,i,o,t} = X_{\hbar,t}\beta + \tau_t + \phi_i + \psi_o + \varepsilon_{\hbar,i,o,t} \tag{2}$$

where $wage_{\hbar}$ is the wage rate of worker h; i and o denote industry and occupation, respectively; X is the vector of individual characteristics;[29] τ_t is the time fixed effect; ϕ_i is the industry fixed effect; and ψ_o is the occupation fixed effect. Each industry and occupation fixed effect measures the industry and occupation-specific wage premium, respectively.

[28] We can consider two specific scenarios in which our main result might reflect the process of eliminating pre-existing labor cost inefficiencies. First, jobs that experienced significant employment declines after the pandemic may overlap with those that incurred high extra costs prior to the pandemic. In such cases, firms might have simply shed cost-inefficient positions during the pandemic-induced recession. Second, industries with high wage premiums may have actively reduced their workforces by targeting specific occupations, taking advantage of the favorable conditions for layoffs created by the pandemic.

[29] It includes worker's gender, age (eleven groups: 15–19, 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, and older than 65), educational attainment (five groups: less than high school graduate, high school graduate, 2-year college graduate, 4-year college graduate, and higher than graduate degree), work type (three groups: permanent employee, temporary employee, and daily worker), years of service and its quadratic term, and various interaction terms (gender × education, gender × age, gender × work type).

In jobs with high exposure and high automation potential, occupation-specific wage premiums are relatively low compared to other groups as shown in Figure 4. Furthermore, the post-pandemic employment decline in these jobs is more pronounced in sectors with low industry wage premiums (Figure A9). Consequently, these results suggest that changes in employment trends during the pandemic were unrelated to pre-pandemic labor costs, supporting the argument that the pandemic-specific incentives for automation might have played a key role in shaping post-pandemic employment dynamics.

[Figure 4]

V. CONCLUSION

Does COVID-19 boost automation? Analyzing data from South Korea, we find that significant employment contractions in occupations with high COVID-19 exposure and high automation potential have persisted until recently. However, in the low-exposure group, there is no additional job loss attributable to automatability during the pandemic. Moreover, in the high-exposure group, employment in occupations more prone to automation has fallen more significantly since the pandemic outbreak. The consistent decline in employment in more automatable occupations within the high-exposure group does not appear to be driven by either industry demand or labor supply factors. In sum, our results suggest that the COVID-19 crisis may have incentivized firms to integrate labor-replacing technologies in response to the business risks posed by viral spread.

Finally, we note that our empirical analysis provides only partial evidence of post-pandemic automation progress. Due to data limitations, we were unable to illustrate patterns of capital adoption, leaving a gap in understanding the full scope of advancements in automation prompted by COVID-19.[30] Exploring the direct link between the pandemic and automation remains an area for future research.

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[30] Based on our analysis, we anticipate a significant rise in the adoption of automated machinery in the post-COVID-19 period, particularly within the service industry, where face-to-face service jobs are predominant. The International Federation of Robotics (IFR) is a reliable source for tracking trends in automation-related capital investment. However, unlike the manufacturing sector, detailed robotics statistics for the service industry are currently unavailable in the IFR database.

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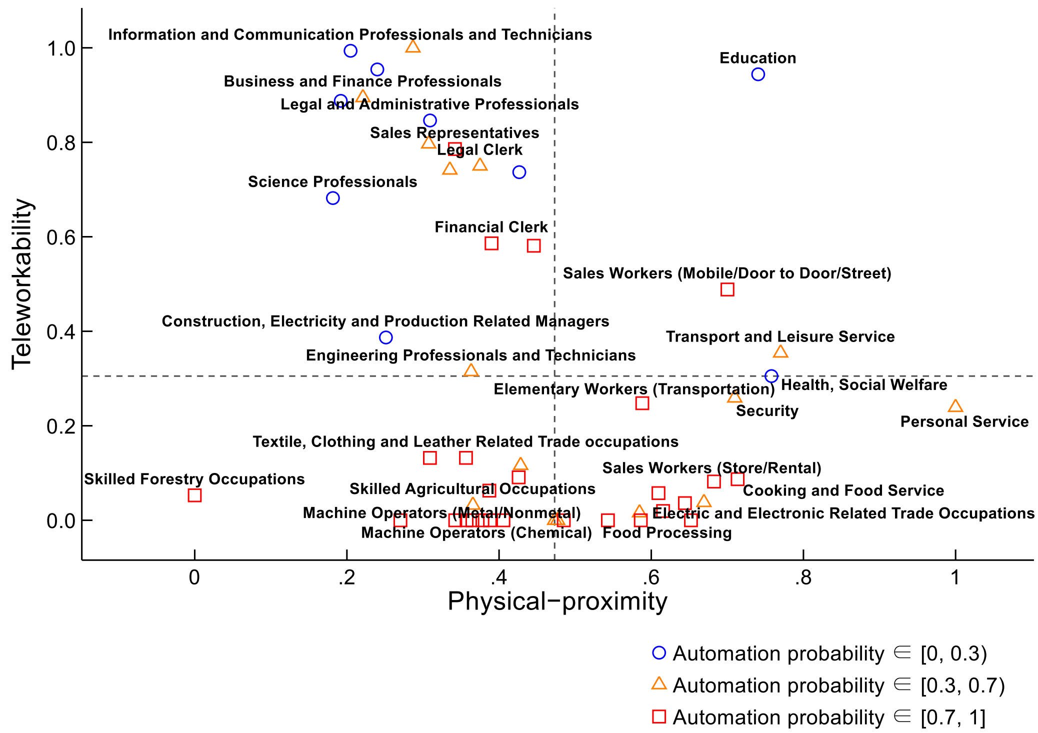
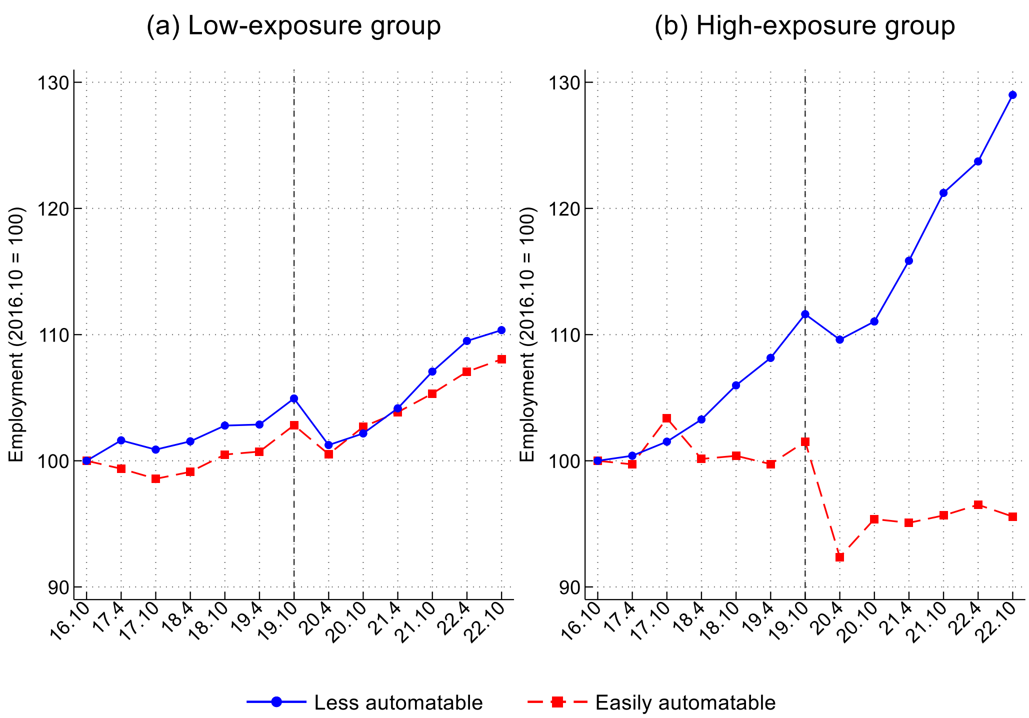
Figure 1. Physical proximity, Teleworkability, and Automation Probability by Occupation



Source: Authors' calculation.

Note: The figure summarizes the scores by occupation for the three metrics—physical proximity, teleworkability, and automation probability—at the KSCO 2-digit level. The x-axis plots the physical proximity score of each occupation based on the U.S. O*NET survey. The y-axis plots the teleworkability score based on the remote work index developed by Dingel and Neiman (2020). For graphical representation, we rescale the scores of physical proximity and teleworkability to the interval [0, 1] by subtracting the minimum value and dividing by the range (maximum minus minimum values). The farther to the right, the higher the physical proximity, and the farther up, the higher the teleworkability. The two dashed lines refer to the employment-weighted median along each dimension. Occupations with a physical proximity score above the employment-weighted median and a teleworkability score less than or equal to the employment-weighted median (4th quadrant) are classified as the high-exposure group. All occupations that do not fall into the high-exposure group (outside the 4th quadrant) are classified as the low-exposure group. The colors and shapes of the markers indicate the level of automation potential for each occupation based on its automation probability. The automation probability by occupation is based on Kim (2015) and Frey and Osborne (2017).

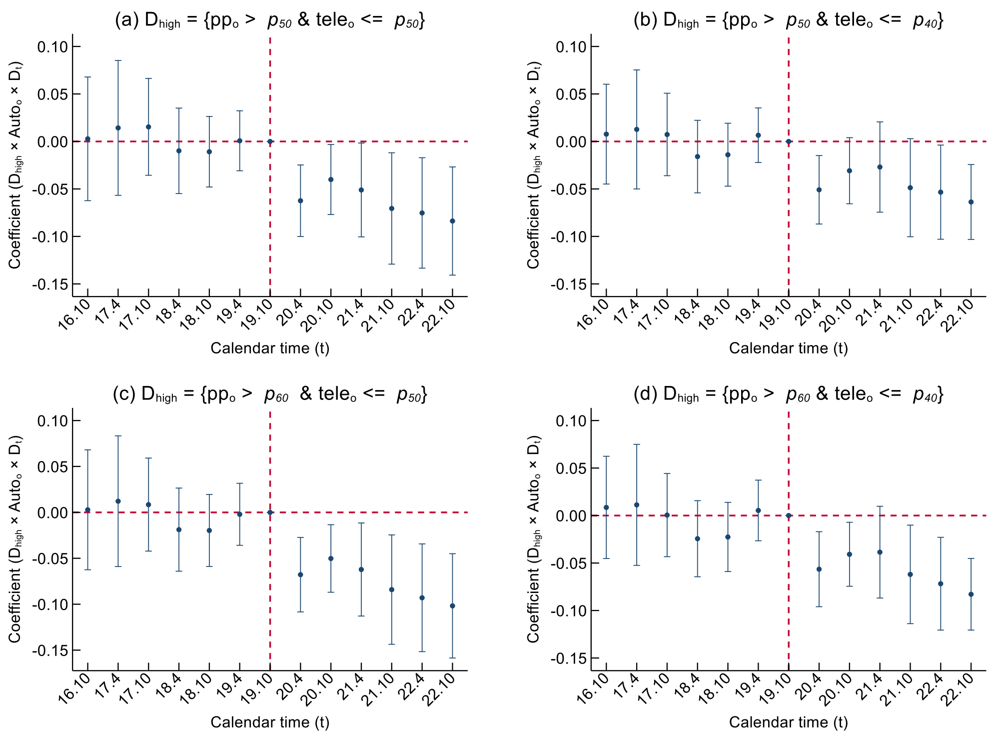
Figure 2. Employment Trends of Easily Automatable and Less Automatable Jobs
(Low-exposure group vs. High-exposure group)



Source: Local Area Labor Force Survey (LALFS).

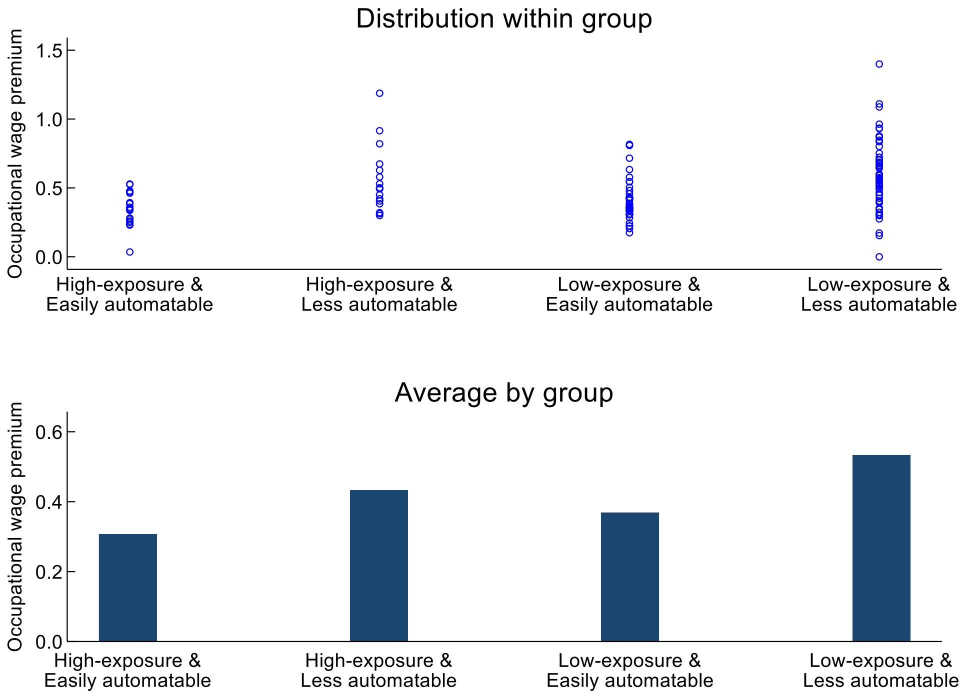
Note: The figure shows the employment levels of easily automatable jobs and less automatable jobs for each occupational group, categorized by the level of COVID exposure at the KSCO 3-digit level from October 2016 to October 2022. The number of employees is standardized to a value of 100 for October 2016. Occupations are classified as having high COVID exposure if the physical proximity score is higher than the employment-weighted median, and the teleworkability score is equal to or lower than the employment-weighted median. All occupations that do not fall into the high-exposure group are classified as the low-exposure group. Occupations are considered to be easily (less) automatable if the automation probability is higher than or equal to (less than) 0.7.

Figure 3. Event-Study Estimates of the Effect of Automation Potential Interacted with the High-Exposure Group on Employment: Coefficients on $D_{high} \times Auto_o \times D_t$



Note: The figure plots the estimated coefficients on three-way interaction between high-exposure group, automation potential, and each calendar time dummy, $D_{high} \times Auto_o \times D_t$, via Eq. (1). The estimates are adjusted for a linear trend interacted with automation potential for each group categorized by their COVID exposure during the pre-pandemic period. The regressions are weighted by employment in 2019. All models include a unit (i.e., the combination of industry-occupation) fixed effect, time fixed effect, and industrial production index. N=21,411 (1,647 units × 13 time periods). Base period is October 2019. Standard errors are clustered at the industry-occupation level and the confidence intervals are at 95% level. We apply different criteria for defining the high-exposure group indicator, D_{high}, across panels (a) to (d). In panel (a), we assign the value of the dummy variable D_{high} as one for each unit if its physical proximity score is above the 50% weighted percentile (i.e., employment-weighted median), and its teleworkability score is less than or equal to the 50% weighted percentile (i.e., employment-weighted median), serving as the baseline. In panel (b), we assign the value of dummy variable D_{high} as one for each unit if its physical proximity score is above the 50% weighted percentile and its teleworkability score is less than or equal to the 40% weighted percentile. In panel (c), we assign the value of dummy variable D_{high} as one for each unit if its physical proximity score is above the 60% weighted percentile and its teleworkability score is less than or equal to the 50% weighted percentile. In panel (d), we assign the value of dummy variable D_{high} as one for each unit if its physical proximity score is above the 60% weighted percentile and its teleworkability score is less than or equal to the 40% weighted percentile.

Figure 4. Occupation-Specific Wage Premium by Occupational Group



Source: Local Area Labor Force Survey (LALFS).

Note: The figure shows the pre-pandemic occupation-specific wage premium by occupational group, categorized by the level of COVID exposure and automation potential at the KSCO 3-digit level. The average wage premium for each group is weighted by each occupation's 2019 employment level within that group.

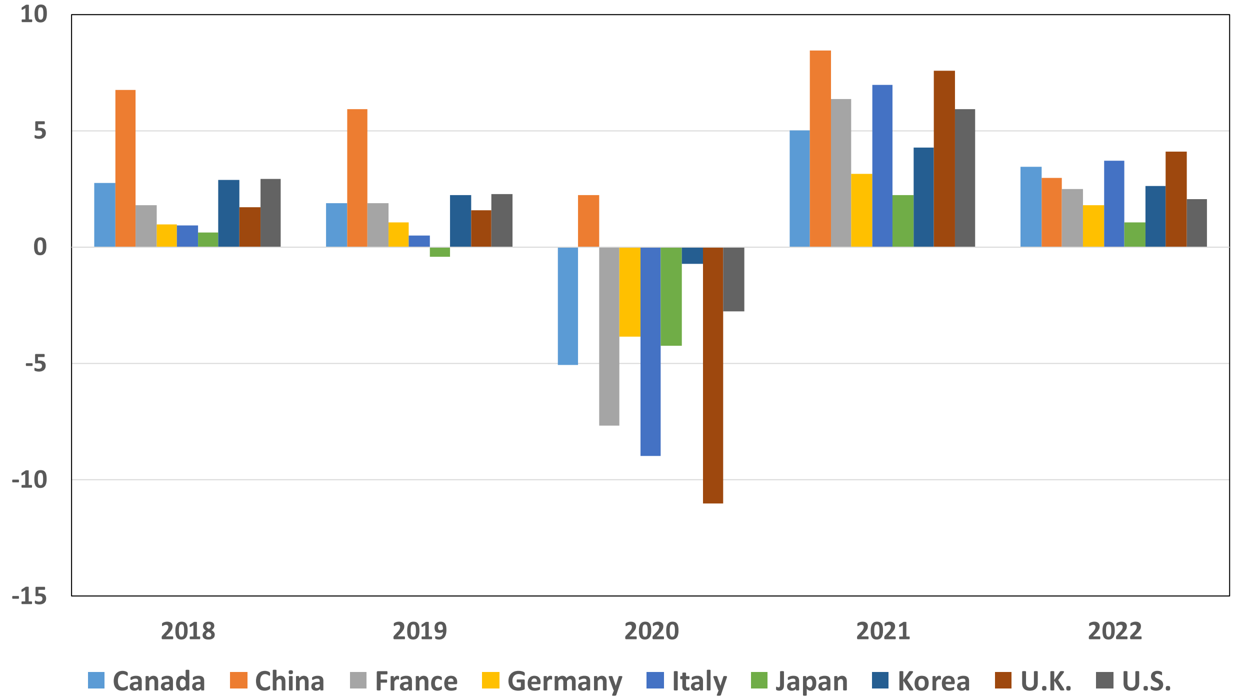
Table 1. Estimation Results of Eq. (1)
(Imposing only two periods: pre and post-COVID-19)

grouping criteria for D_{high}:	(1) $pp_o > p_{50}$ & $tele_o \leq p_{50}$	(2) $pp_o > p_{50}$ & $tele_o \leq p_{40}$	(3) $pp_o > p_{60}$ & $tele_o \leq p_{50}$	(4) $pp_o > p_{60}$ & $tele_o \leq p_{40}$
$D_{high} \times D_{post\text{-}COVID}$	-0.003	-0.030	-0.013	-0.043*
	(0.037)	(0.025)	(0.039)	(0.025)
$Auto_o \times D_{post\text{-}COVID}$	0.014	0.010	0.015	0.011
	(0.015)	(0.015)	(0.014)	(0.015)
$D_{high} \times Auto_o \times D_{post\text{-}COVID}$	-0.066*	-0.046*	-0.074**	-0.056**
	(0.037)	(0.025)	(0.037)	(0.025)
Control variables				
Industrial production	√	√	√	√
Unit fixed effect	√	√	√	√
Time fixed effect	√	√	√	√
Observations	21,411	21,411	21,411	21,411
R^2	0.235	0.235	0.236	0.237

Note: The table reports the estimation results of Eq. (1), replacing the calendar time variable with only one dummy variable indicating post-COVID-19 period. The estimates are adjusted for a linear trend interacted with automation potential for each group categorized by their COVID exposure during the pre-pandemic period. The regressions are weighted by employment in 2019. All models include a unit (i.e., the combination of industry-occupation) fixed effect, time fixed effect, and industrial production index. N=21,411 (1,647 units × 13 time periods). Base period is October 2019. Standard errors are clustered at industry-occupation level. ***p< 0.01, **p< 0.05, *p< 0.1. We apply different criteria for defining the high-exposure group indicator, D_{high}, across columns (1) to (4). In column (1), we assign the value of the dummy variable D_{high} as one for each unit if its physical proximity score is above the 50% weighted percentile (i.e., employment-weighted median), and its teleworkability score is less than or equal to the 50% weighted percentile (i.e., employment-weighted median), serving as the baseline. In column (2), we assign the value of dummy variable D_{high} as one for each unit if its physical proximity score is above the 50% weighted percentile and its teleworkability score is less than or equal to the 40% weighted percentile. In column (3), we assign the value of dummy variable D_{high} as one for each unit if its physical proximity score is above the 60% weighted percentile and its teleworkability score is less than or equal to the 50% weighted percentile. In column (4), we assign the value of dummy variable D_{high} as one for each unit if its physical proximity score is above the 60% weighted percentile and its teleworkability score is less than or equal to the 40% weighted percentile.

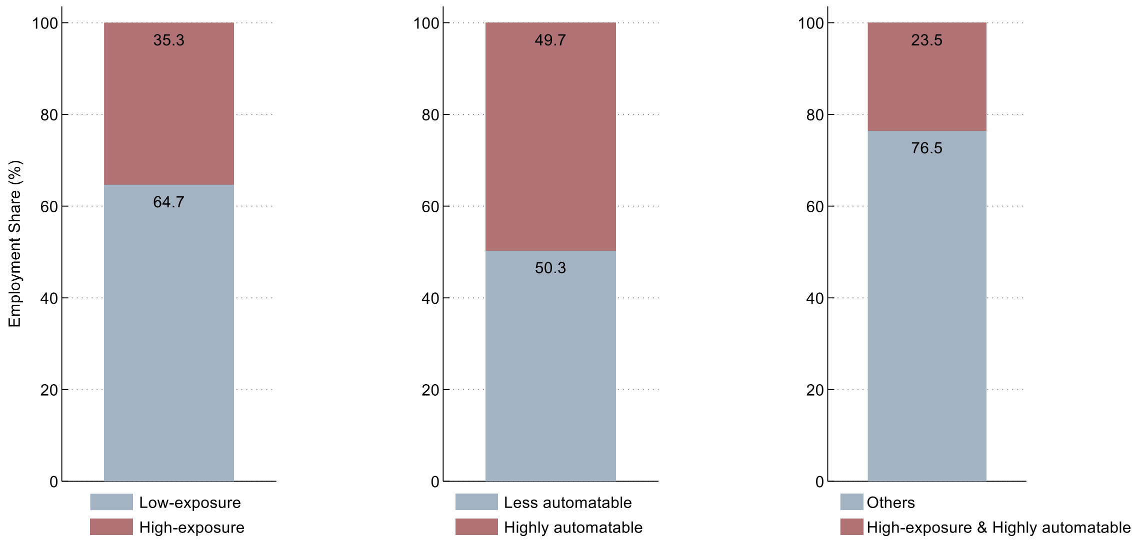
Online Appendix

Figure A1. Growth Rates of Real GDP in Major Economies



Source: IMF World Economic Outlook Database.
Note: The figure shows the annual growth rate of real GDP in major economies from 2018 to 2022.

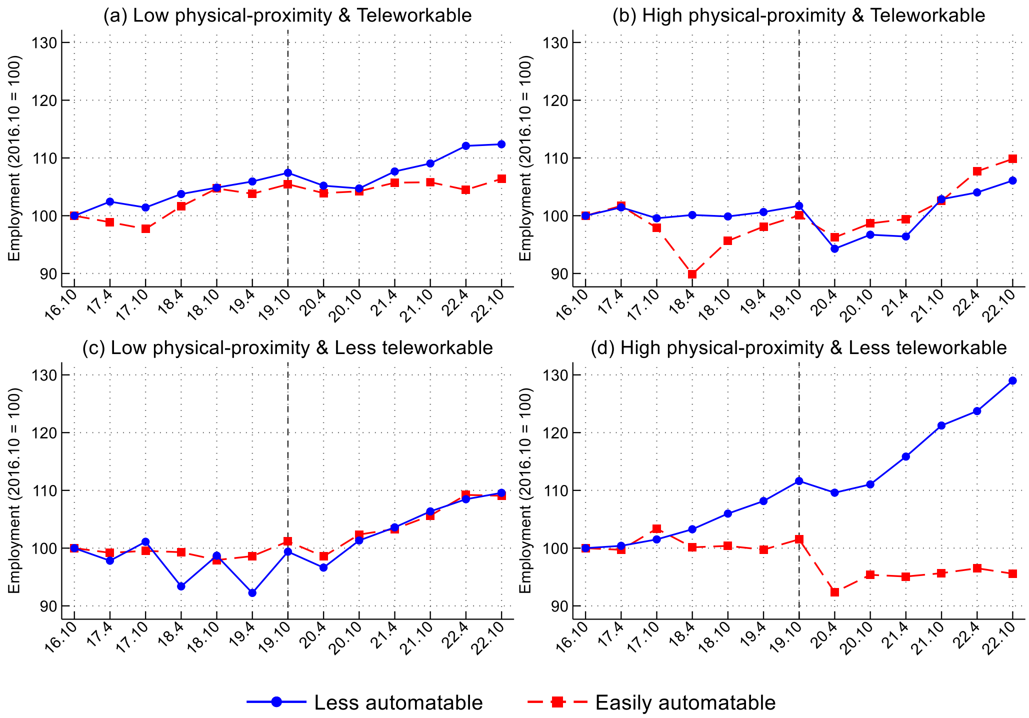
Figure A2. Employment Share by Occupational Group



Source: Local Area Labor Force Survey (LALFS).

Note: The figure shows the employment share by occupational group based on the level of COVID exposure and automation potential in 2019. Occupations are classified as having high COVID exposure if the physical proximity score is above the employment-weighted median, and the teleworkability score is less than or equal to the employment-weighted median. All occupations that do not fall into the high-exposure group are classified as the low-exposure group. Occupations are considered to be easily (less) automatable if the automation probability is higher than or equal to (less than) 0.7.

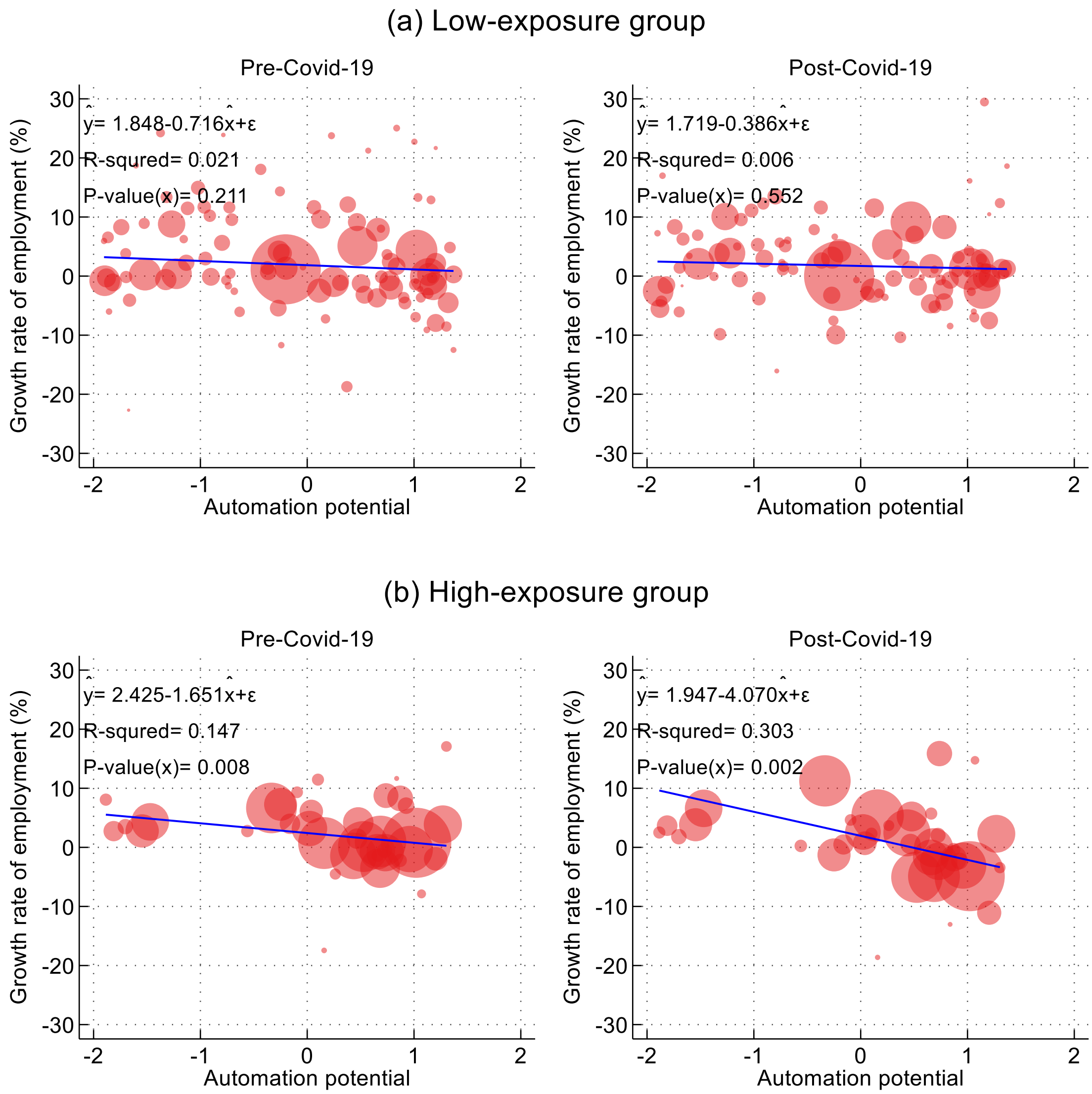
Figure A3. Employment Trends of Easily Automatable and Less Automatable Jobs by Detailed Occupational Group



Source: Local Area Labor Force Survey (LALFS).

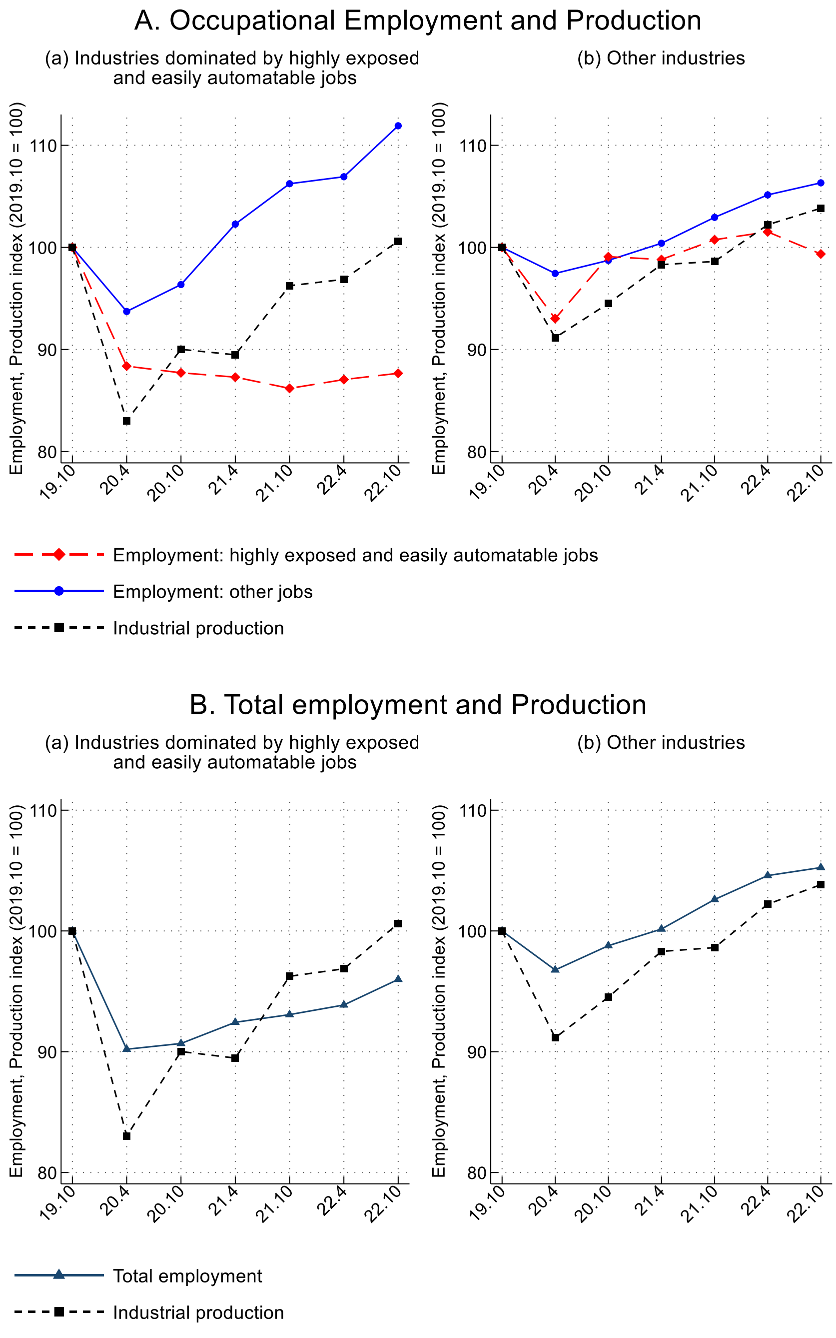
Note: The figure shows the employment levels of easily automatable jobs and less automatable jobs for each detailed occupational group, categorized by the level of each of the two metrics used to measure COVID exposure at the KSCO 3-digit level from October 2016 to October 2022. The number of employees is standardized to a value of 100 for October 2016. We define occupations as those with a "high (low) physical proximity" if the physical proximity score is above (less than or equal to) the employment-weighted median. Similarly, occupations are defined as "(less) teleworkable" if the teleworkability score is above (less than or equal to) the employment-weighted median. Occupations are considered to be easily (less) automatable if the automation probability is higher than or equal to (less than) 0.7.

Figure A4. Employment Growth and Automation Potential by Occupation before and after COVID-19 (Low-exposure group vs. High-exposure group)



Note: The figure shows the approximated annualized growth rate of employment and automation potential by occupation before and after COVID-19 for each occupational group, categorized by the level of COVID exposure at the KSCO 3-digit level. The index of automation potential is a standardized transformation of automation probabilities by occupation to have a mean of zero and a standard deviation of one. The corresponding estimation results, where employment growth is regressed on automation potential by occupation, are displayed in the upper left corner of each chart. The regressions are weighted by employment in 2019. Standard errors are robust against heteroscedasticity. For graphical representation, we exclude outliers whose annual employment grew by more than 30%. The pre-COVID-19 period spans from October 2016 to October 2019, and the post-COVID-19 period spans from October 2019 to October 2022. The circle's size denotes the employment level of each occupation in October 2019.

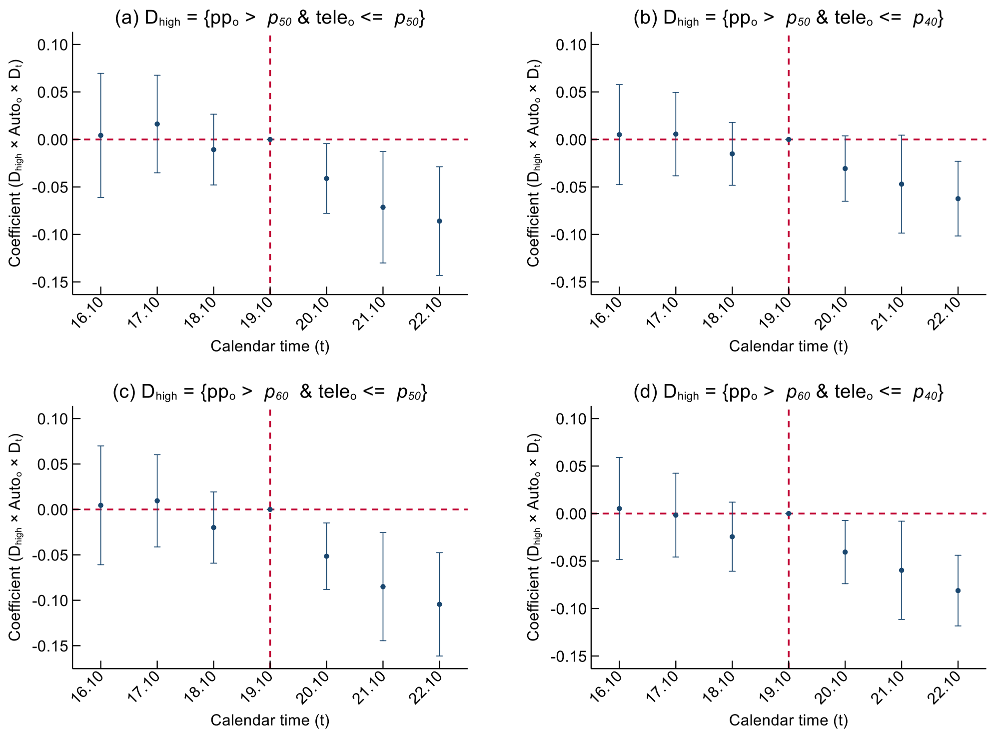
Figure A5. Occupational Employment and Industrial Production



Source: Local Area Labor Force Survey (LALFS).

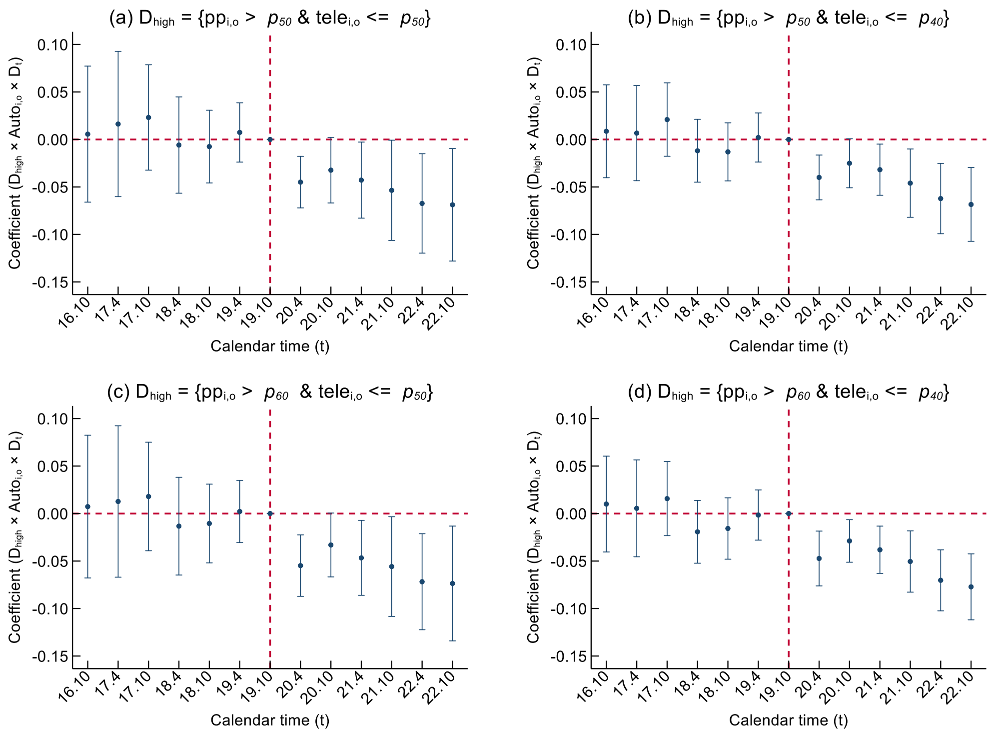
Note: The figure shows industrial production and employment by occupation group for each industrial sector, based on the employment share of highly exposed and easily automatable jobs. Industrial production for each sector is weighted by the employment level of each industry within that sector. Both industrial production and the number of employees are standardized to a value of 100 as of October 2019. We define industries dominated by highly exposed and easily automatable jobs as those where such jobs account for at least 60% of total employment.

Figure A6. Event-Study Estimates of the Effect of Automation Potential Interacted with High-Exposure Group on Employment: Coefficients on $D_{high} \times Auto_o \times D_t$ (yearly basis)



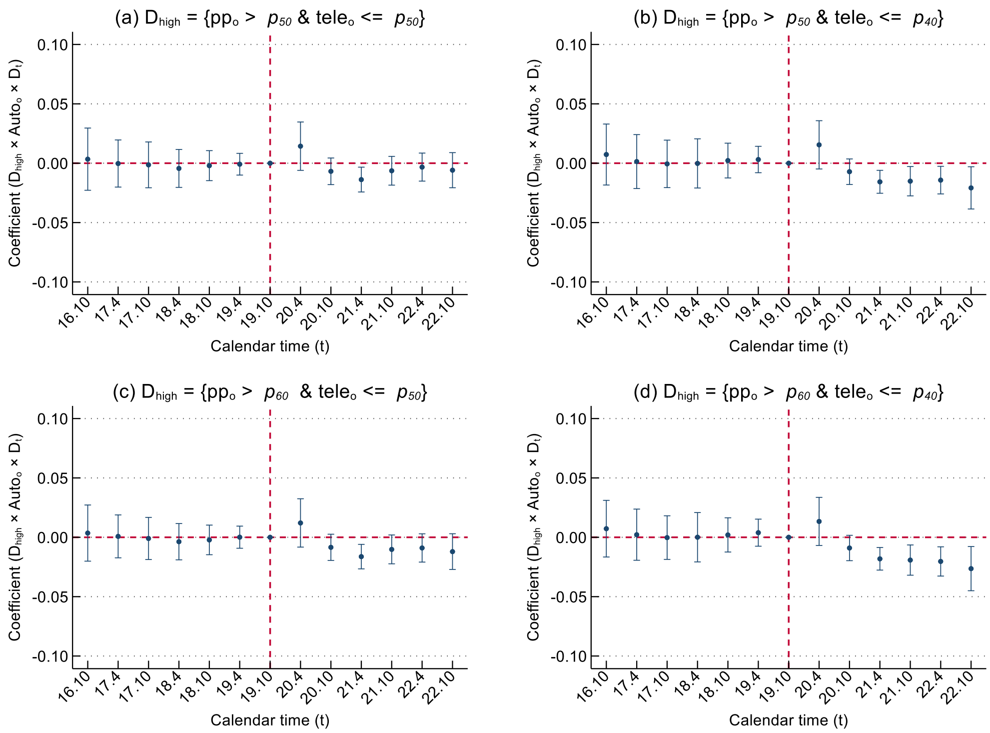
Note: The figure plots the estimated coefficients on three-way interaction between high-exposure group, automation potential, and each calendar time dummy, $D_{high} \times Auto_o \times D_t$, via Eq. (1), using only October data for each year. The estimates are adjusted for a linear trend interacted with automation potential for each group categorized by their COVID exposure during the pre-pandemic period. The regressions are weighted by employment in 2019. All models include a unit (i.e., the combination of industry-occupation) fixed effect, time fixed effect, and industrial production index. N=11,529 (1,647 units × 7 time periods). Base period is October 2019. Standard errors are clustered at the industry-occupation level and the confidence intervals are at 95% level. We apply different criteria for defining the high-exposure group indicator, D_{high}, across panels (a) to (d) (see the note in Figure 3).

Figure A7. Event-Study Estimates of the Effect of Automation Potential Interacted with High-Exposure Group on Employment: Coefficients on $D_{high} \times Auto_{i,o} \times D_t$ (aggregate level)



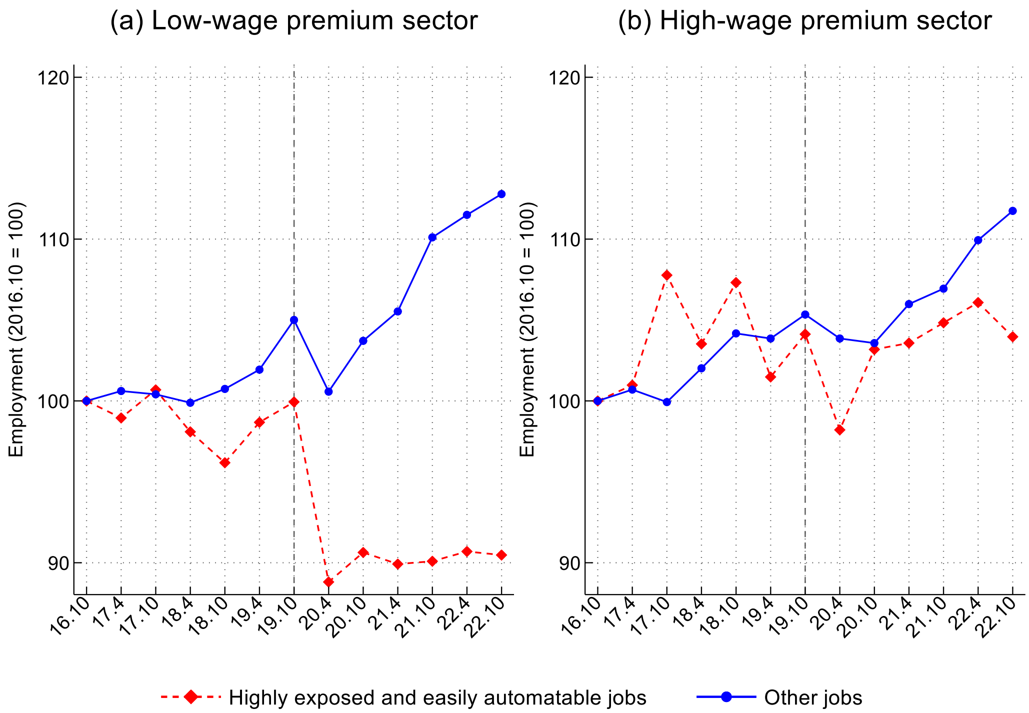
Note: The figure plots the estimated coefficients on three-way interaction between high-exposure group, automation potential, and each calendar time dummy, $D_{high} \times Auto_o \times D_t$, via Eq. (1), based on sample units at a more aggregated level – combinations of each 2-digit industry an each 2-digit occupation. The estimates are adjusted for a linear trend interacted with automation potential for each group categorized by their COVID exposure during the pre-pandemic period. The regressions are weighted by employment in 2019. All models include a unit (i.e., the combination of industry-occupation) fixed effect, time fixed effect, and industrial production index. N=14,378 (1,106 units × 13 time periods). Base period is October 2019. Standard errors are clustered at the industry-occupation level and the confidence intervals are at 95% level. We apply different criteria for defining the high-exposure group indicator, D_{high}, across panels (a) to (d) (see the note in Figure 3).

Figure A8. Event-Study Estimates of the Effect of Automation Potential Interacted with High-Exposure Group on Hourly Wages: Coefficients on $D_{high} \times Auto_o \times D_t$



Note: The figure plots the estimated coefficients on three-way interaction between high-exposure group, automation potential, and each calendar time dummy, $D_{high} \times Auto_o \times D_t$, via Eq. (1) with hourly wages as the dependent variable. The estimates are adjusted for a linear trend interacted with automation potential for each group categorized by their COVID exposure during the pre-pandemic period. The regressions are weighted by employment in 2019. All models include a unit (i.e., the combination of industry-occupation) fixed effect, time fixed effect, and industrial production index. N=21,281 (1,637 units × 13 time periods). Base period is October 2019. Standard errors are clustered at the industry-occupation level and the confidence intervals are at 95% level. We apply different criteria for defining the high-exposure group indicator, D_{high}, across panels (a) to (d) (see the note in Figure 3).

Figure A9. Employment Trends in Highly Exposed and Easily Automatable Jobs
(Low industry wage premium sector vs High industry wage premium sector)



Source: Local Area Labor Force Survey (LALFS).

Note: The figure shows the employment levels of highly exposed and easily automatable jobs compared to other jobs in each industrial sector, categorized by the level of the pre-pandemic industry wage premium. The number of employees is standardized to a value of 100 as of October 2016.

Table A1. COVID-19 Exposure and Automation Probability by Occupation (KSCO 2-digit)

Occupation Title	Physical Proximity	Teleworkability	Automation Probability	COVID Exposure	Automation Feasibility
Construction, Electricity and Production Related Managers	0.251	0.387	0.062	Low	Low
Legal and Administrative Professionals	0.309	0.846	0.186	Low	Low
Information and Communication Professionals and Technicians	0.205	0.994	0.219	Low	Low
Professional Services Management	0.240	0.954	0.222	Low	Low
Administration, Marketing Management	0.192	0.888	0.242	Low	Low
Culture, Arts and Sports Professionals	0.427	0.737	0.259	Low	Low
Science Professionals	0.182	0.682	0.289	Low	Low
Sales and Customer Service Managers	0.308	0.797	0.332	Low	Low
Engineering Professionals and Technicians	0.363	0.315	0.458	Low	Low
Senior Officials	0.287	1	0.487	Low	Low
Business and Finance Professionals	0.221	0.895	0.498	Low	Low
Legal Clerk	0.375	0.750	0.597	Low	Low
Administration and Accounting	0.335	0.741	0.631	Low	Low
Customer Service	0.446	0.581	0.769	Low	High
Sales Representatives	0.342	0.786	0.920	Low	High
Financial Clerk	0.390	0.586	0.933	Low	High
Education	0.741	0.944	0.070	Low	Low
Transport and Leisure Service	0.770	0.354	0.695	Low	Low
Sales Workers (Mobile/Door to Door/Street)	0.700	0.489	0.968	Low	High
Skilled Agricultural Occupations	0.366	0.032	0.596	Low	Low
Elementary Workers (Agriculture/Forestry/Fishery/Other Services)	0.428	0.116	0.621	Low	Low
Elementary Workers (Production)	0.473	0	0.653	Low	Low
Skilled Forestry Occupations	0	0.053	0.740	Low	High
Machine Operators (Textile/Shoe)	0.378	0	0.772	Low	High
Elementary Workers (Cleaning/Guard)	0.387	0.063	0.788	Low	High
Metal Coremakers Related Trade Occupations	0.270	0	0.794	Low	High
Skilled Fishery Occupations	0.309	0.132	0.830	Low	High
Machine Operators (Metal/Nonmetal)	0.342	0	0.852	Low	High
Machine Operators (Electrical/Electronic)	0.357	0	0.856	Low	High
Machine Operators (Food processing)	0.388	0	0.880	Low	High

Occupation Title	Physical Proximity	Teleworkability	Automation Probability	COVID Exposure	Automation Feasibility
Wood and Furniture and Related Trade Occupations	0.426	0.091	0.883	Low	High
Machine Operators (Chemical)	0.406	0	0.915	Low	High
Textile, Clothing and Leather Related Trade occupations	0.357	0.132	0.937	Low	High
Machine Operators (Wood/Printing/Others)	0.365	0	0.940	Low	High
Health, Social Welfare	0.758	0.305	0.210	High	Low
Personal Service	1	0.239	0.480	High	Low
Electric and Electronic Related Trade Occupations	0.585	0.016	0.560	High	Low
Information and Communications Technology Related Occupations	0.477	0	0.590	High	Low
Other Technical Occupations	0.669	0.038	0.642	High	Low
Security	0.710	0.259	0.685	High	Low
Cooking and Food Service	0.714	0.087	0.705	High	High
Driving and Transportation	0.610	0.057	0.706	High	High
Elementary Workers (Construction/Mining)	0.652	0	0.709	High	High
Transport and Machine Related Trade Occupations	0.543	0	0.763	High	High
Construction and Mining Related Trade Occupations	0.616	0.020	0.783	High	High
Machine Operators (Machine Production)	0.485	0	0.794	High	High
Elementary Workers (Transportation)	0.588	0.248	0.810	High	High
Food Processing	0.586	0	0.840	High	High
Elementary Workers (Household Helpers/Sales)	0.644	0.036	0.851	High	High
Sales Workers (Store/Rental)	0.682	0.082	0.886	High	High

Source: Authors' calculation.

Note: The table reports the scores by occupation for the three metrics—physical proximity, teleworkability, and automation probability—at the KSCO 2-digit level. Physical proximity score is based on U.S. O*NET survey. Teleworkability score is based on the remote work index developed by Dingel and Neiman (2020). The original score of physical proximity and teleworkability is rescaled to [0, 1]. Automation probability by occupation is based on Kim (2015) and Frey and Osborne (2017). See Section II for details of each index. Occupations are classified as having high COVID exposure if the physical proximity score is above the employment-weighted median, and the teleworkability score is less than or equal to the employment-weighted median. All occupations that do not fall into the high-exposure group are classified as the low-exposure group. Occupations are considered as those with high (low) automation feasibility if the automation probability is higher than or equal to (less than) 0.7.

Table A2. Event-Study Estimates of the Effect of Automation Potential Interacted with the High-Exposure Group on Employment: Coefficients on $D_{high} \times Auto_o \times D_t$ (for selected periods)

grouping criteria for D_{high}:	(1) $pp_o > p_{50}$ & $tele_o \leq p_{50}$	(2) $pp_o > p_{50}$ & $tele_o \leq p_{40}$	(3) $pp_o > p_{60}$ & $tele_o \leq p_{50}$	(4) $pp_o > p_{60}$ & $tele_o \leq p_{40}$
$D_{high} \times Auto_o \times D_{2018.10}$	-0.011	-0.014	-0.020	-0.023
	(0.019)	(0.017)	(0.020)	(0.019)
$D_{high} \times Auto_o \times D_{2019.4}$	0.001	0.007	-0.002	0.005
	(0.016)	(0.015)	(0.017)	(0.016)
$D_{high} \times Auto_o \times D_{2020.4}$	-0.062***	-0.051***	-0.068***	-0.056***
	(0.019)	(0.018)	(0.021)	(0.020)
$D_{high} \times Auto_o \times D_{2020.10}$	-0.040**	-0.031*	-0.050***	-0.041**
	(0.019)	(0.018)	(0.019)	(0.017)
$D_{high} \times Auto_o \times D_{2021.4}$	-0.051**	-0.027	-0.062**	-0.039
	(0.025)	(0.024)	(0.026)	(0.025)
$D_{high} \times Auto_o \times D_{2021.10}$	-0.071**	-0.049*	-0.084***	-0.062**
	(0.030)	(0.026)	(0.030)	(0.026)
$D_{high} \times Auto_o \times D_{2022.4}$	-0.075**	-0.053**	-0.093***	-0.072***
	(0.030)	(0.025)	(0.030)	(0.025)
$D_{high} \times Auto_o \times D_{2022.10}$	-0.084***	-0.064***	-0.102***	-0.083***
	(0.029)	(0.020)	(0.029)	(0.019)
Control variables				
Industrial production	√	√	√	√
Unit fixed effect	√	√	√	√
Time fixed effect	√	√	√	√
Observations	21,411	21,411	21,411	21,411
R^2	0.236	0.236	0.238	0.238

Note: The table reports the estimated coefficients on three-way interaction between high-exposure group, automation potential, and each calendar time dummy, $D_{high} \times Auto_o \times D_t$, for a selected period from the event study model (Eq. (1)). The estimates are adjusted for a linear trend interacted with automation potential for each group categorized by their COVID exposure during the pre-pandemic period. The regressions are weighted by employment in 2019. All models include a unit (i.e., the combination of industry-occupation) fixed effect, time fixed effect, and industrial production index. N=21,411 (1,647 units × 13 time periods). Base period is October 2019. Standard errors are clustered at industry-occupation level. ***p< 0.01, **p< 0.05, *p< 0.1. We apply different criteria for defining the high-exposure group indicator, D_{high}, across columns (1) to (4) (see the note in Table 1).

Table A3. Estimation Results of Eq. (1) with Hourly Wages
(Imposing only two periods: pre and post-COVID-19)

	(1)	(2)	(3)	(4)
grouping criteria for D_{high} :	$pp_o > p_{50}$ & $tele_o \leq p_{50}$	$pp_o > p_{50}$ & $tele_o \leq p_{40}$	$pp_o > p_{60}$ & $tele_o \leq p_{50}$	$pp_o > p_{60}$ & $tele_o \leq p_{40}$
$D_{high} \times D_{post\text{-}COVID}$	0.000	-0.003	0.003	0.001
	(0.006)	(0.006)	(0.006)	(0.005)
$Auto_o \times D_{post\text{-}COVID}$	-0.022***	-0.022***	-0.022***	-0.021***
	(0.004)	(0.004)	(0.004)	(0.004)
$D_{high} \times Auto_o \times D_{post\text{-}COVID}$	-0.003	-0.011*	-0.007	-0.015***
	(0.007)	(0.006)	(0.006)	(0.005)
Control variables				
Industrial production	√	√	√	√
Unit fixed effect	√	√	√	√
Time fixed effect	√	√	√	√
Observations	21,281	21, 281	21, 281	21, 281
R^2	0.366	0.366	0.366	0.365

Note: The table reports the estimation results of Eq. (1) with hourly wages as the dependent variable, replacing the calendar time variable with only one dummy variable indicating post-COVID-19 period. The estimates are adjusted for a linear trend interacted with automation potential for each group categorized by their COVID exposure during the pre-pandemic period. The regressions are weighted by employment in 2019. All models include a unit (i.e., the combination of industry-occupation) fixed effect, time fixed effect, and industrial production index. N=21,281 (1,637 units × 13 time periods). Base period is October 2019. Standard errors are clustered at industry-occupation level. ***p< 0.01, **p< 0.05, *p< 0.1. We apply different criteria for defining the high-exposure group indicator, D_{high}, across columns (1) to (4) (see the note in Table 1).