Temporary Foreign Workers' reduction led to vacancy rise in the South Korean manufactures

Version 3.2 *

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1 Introduction

In economics, an ideal environment allows free movement of labor. In the real world, the labor movement across countries is regulated. Consequently, some firms cannot compete with the other firms from low-wage countries. This is not because the firms are incompetent but because the labor market is restricted.

The South Korean government allows the inflow of temporary foreign workers (TFWs) only when there is a labor shortage. This TFW policy is grounded on the notion that accepting TFWs help alleviate the employers' difficulties finding the workers. Opponents of TFW policy, however, argue that TFWs are reducing the natives' employment opportunities. They say that natives can instead fill the jobs. Therefore, it would be meaningful to study whether the opponents' argument is valid.

Defining the labor shortage is the first step of studying. The literature has actively discussed the definition (Martin Ruhs and Bridget Anderson (2019); Constant and Tien (2011); and Barnow et al. (2013)). The studies agree that there is no clear-cut definition, but vacancy is important. Therefore, this study will use vacancy to proxy the labor shortage.

This paper uses the difference in difference method to find that TFWs' reduction caused vacancy to rise in the South Korean manufacturing sectors. This finding contributes to the scarce literature about the effect of immigration on vacancy. Up to my

[0]The following link provides the most updated draft version:
https://raw.githubusercontent.com/jayjeo/public/master/LaborShortage/DissertationDraft.pdf
It is possible to replicate all of the results from a Stata code link below:
https://raw.githubusercontent.com/jayjeo/public/master/LaborShortage/LScode.do

knowledge, there are four studies until now. First, Anastasopoulos et al. (2021) found that labor inflow from Mariel Boat-lift in Miami led to vacancy *drop*. On the contrary, Schiman (2021) showed that labor inflow to Austria due to EU enlargement led to vacancy *rise*. Third, Iftikhar and Zaharieva (2019) demonstrated a vacancy *rise* when high-skilled immigrants flow into the manufacturing sector in Germany. Finally, Kiguchi and Mountford (2019) showed the vacancy results in three different scenarios, which will be explained in the next section.

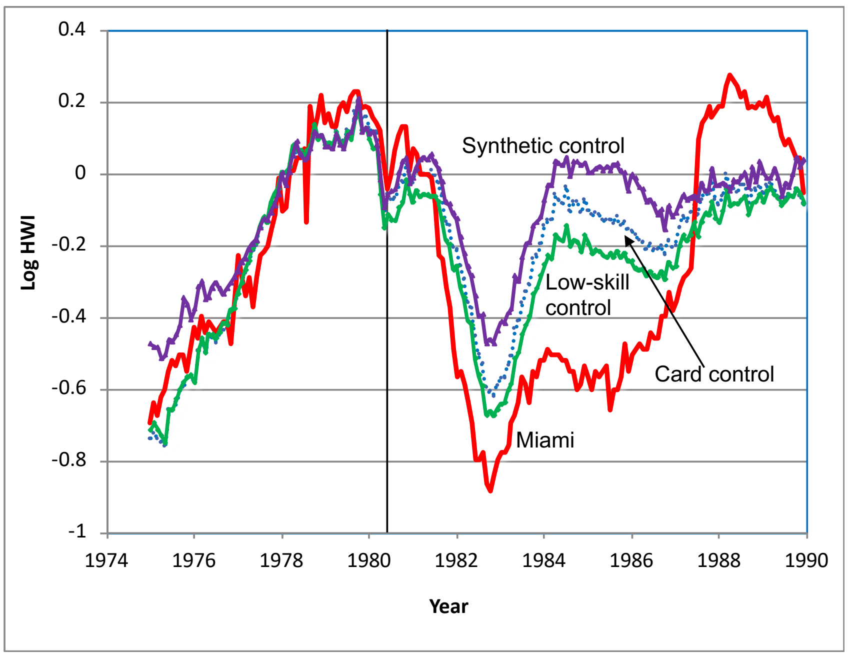
Although the findings by the first three studies (Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019)) seem contradictory, they are consistent. Starting with Anastasopoulos et al. (2021), they study the job vacancies comparing between the synthetic control and Miami treated (Figure 1(a)). Mariel Boat-lift occurred in 1980 (April to October), and the influx effect lasted about two years because many refugees had left from Miami to other cities. The figure shows that the vacancy *dropped* until 1988 and *bounced up* after 1988. Meanwhile, Schiman (2021)'s case shows the similar pattern (Figure 1(b)). Due to EU enlargement, labor influx to Austria started in 2004 and accelerated from 2011 (Figure 2 in his paper). The influx has persisted for more than a decade and is still ongoing. In Figure 1(b), where the impulse response function is shown using Structural Vector Autoregression (SVAR), the vacancy initially *drops* for about three years and then *bounces up* after. It eventually converges to zero in ten years. Finally, Iftikhar and Zaharieva (2019)'s result is also consistent with the pattern. They analyzed the effect of immigrants' 25% increase in Germany (2012–2016) and found that —in the post 2016— the average vacancy duration has almost tripled. This vacancy *rise* is a long run result since they used a typical search and matching model. In other words, they analyzed the effect of immigrants' increase during 2012-2016 (short run) on the steady-state equilibrium (long run).

The search and matching model by Howitt and Pissarides (2000) also predicts the same pattern as in Figures 1 (a) and (b). In the short run, where capital is fixed, firms cannot enter and exit from the labor market (Figure 2(a)). Therefore, potential firms outside the labor market cannot enter the labor market even though there is a large influx of unmatched people. As a result, the vacancy *drops* in the short run (This is formally explained in Appendix B). However, in the long run, potential firms outside the labor market enter the labor market since they expect increased profit by matching more people. As a consequence, the vacancy *rises* as shown in Figure 2(b). To sum up, the vacancy pattern when there is an influx of foreign labors is consistent in the three studies (Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019))

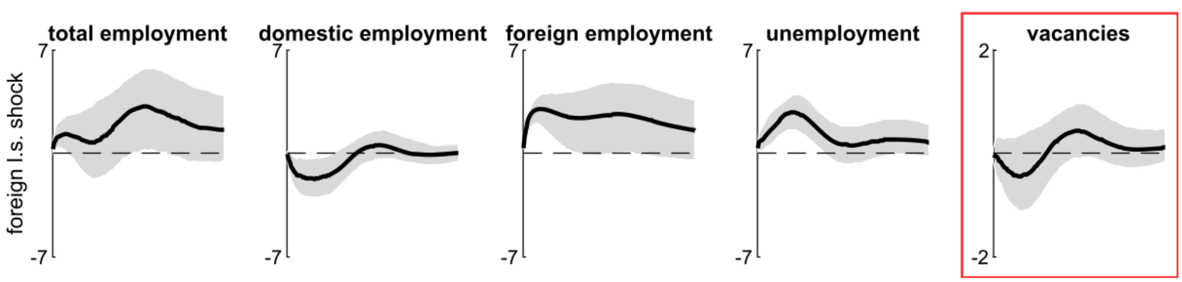
Figure 1

(a) Anastasopoulos's Figure 5

Figure 5. Job vacancies in Miami relative to control cities, 1975-1989



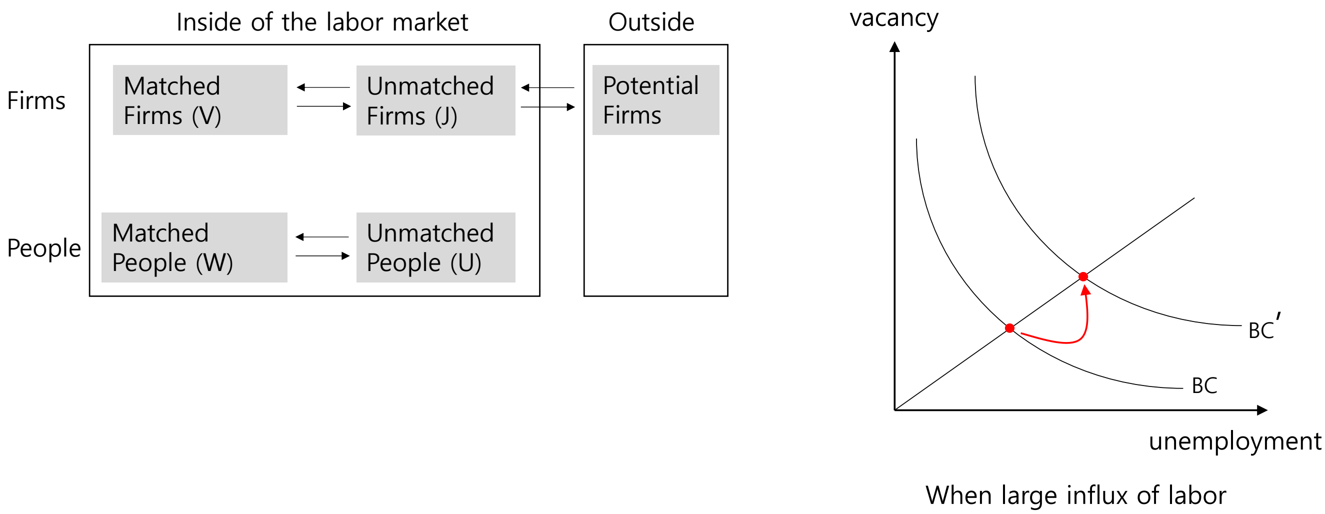
(b) Schiman's Figure 5



as well as the search and matching model.

Figure 2: Search and Matching Model

(a) Basic flows (b) Long run

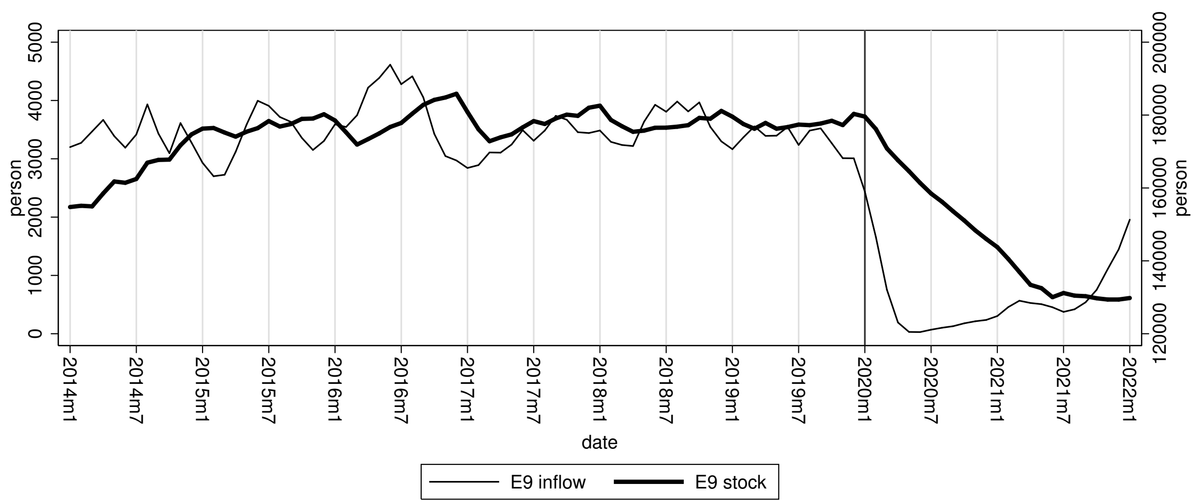


It is worth noting that any typical search and matching models eventually analyze the long run consequence (capital is extremely fluid). This is true even for the dynamic analysis (out of steady-state). The dynamic analysis studies how an out of steady-state converges with a unique path to a new steady-state equilibrium (under the extremely fluid capital). There are numerous versions of the search and matching models as in Howitt and Pissarides (2000), Elsby et al. (2015), Diamond (1982), and Mortensen and Pissarides (1994), but all of these are implicitly assuming long run. Therefore, the search and matching model is inappropriate for the short run analysis.

Anastasopoulos et al. (2021) found that Miami's Beveridge curve (BC) shifted *inward* from 1980 to 1984. They argued that this finding contrasts with the search and matching model's predictions that refugees' influx would move BC *outward*. However, in the short run, the search and matching model predicts the vacancy *drop* and BC's *inward* movement. Therefore, their empirical finding and the prediction of the search and matching model actually do not contradict. Furthermore, as asserted in the previous paragraph, using the search and matching model in the short run might not be appropriate. Considering that the Mariel event started in the mid-1980 and ended in late 1980, their analysis focuses on the three-year term, which is pretty short.

Turning to the findings of this paper, identifying the causal effect of the temporary foreign workers' (TFWs') reduction on vacancy is challenging. One of the difficulties is the reverse causality: The South Korean government accepts TFWs based on the vacancy measure. One way to overcome this issue is using lagged dependent variables as instruments (Arellano and Bond, 1991), but the result turned out to be unreliable. An alternative method is using a quasi-experimental event. Starting in January 2020, the quarantine policy was initiated due to COVID-19. As a result, TFWs who already contracted with the employers and were ready to enter South Korea suddenly were forbidden to enter (Figure 3). This event was unrelated to the vacancy measure, so it naturally provides a quasi-experiment opportunity to study the causal effect.

Figure 3: E9 Workers in Manufacturing Sector



Source: Employment Permit System (EPS)

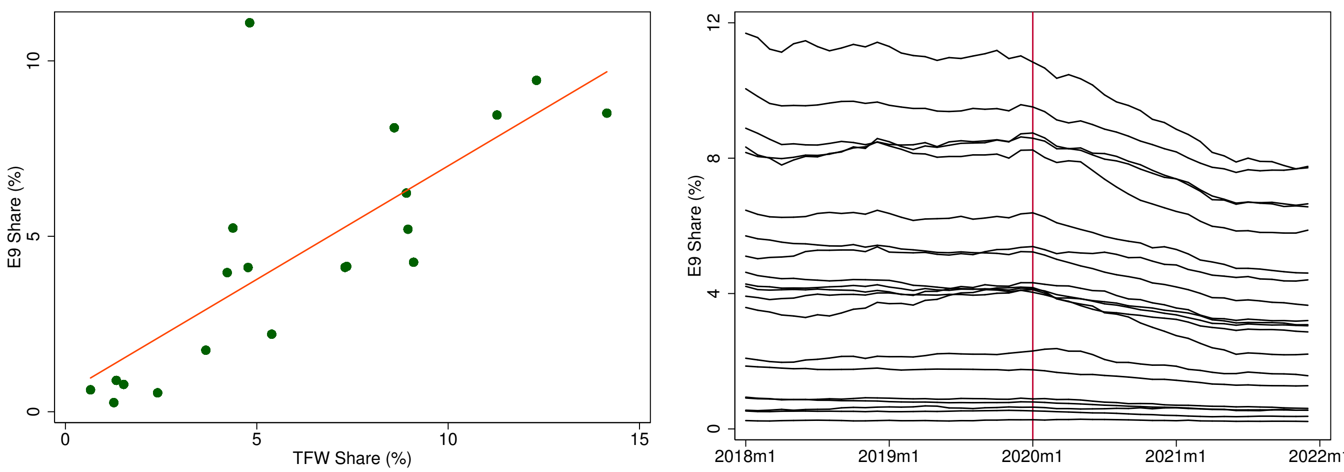
In the manufacturing sectors in South Korea, TFWs' proportion to total workers dropped approximately 9% (2019h2) to 7%(2021h2).[1] TFWs in manufacturing sectors mainly consist of E9, H2, and F4 visa workers. Among them, only E9 visa holders are closely tracked and supervised by Employment Permit System (EPS). Therefore, the monthly flow and stock data of H2 and F4 visa holders are unavailable (only half-yearly rough estimates are available). However, their compositions are not much heterogeneous compared to E9 visa holders. For example, in Figure 4(a), the manufacturing sectors that have a higher proportion of TFWs also have a higher proportion of E9 workers.

Figure 4(b) plots E9 workers' proportion to the total workers in each manufacturing sector. Sectors that heavily relied on E9 workers have experienced a large decline of E9 workers while other sectors have not. This observation provides continuous treatment intensity for the difference in difference (DD) framework. Using DD, this paper finds

[1] Source: Occupational Labor Force Survey at Establishments (OLFSE)

Figure 4

(a) Correlation between E9 and TFW (b) E9Share by sectors

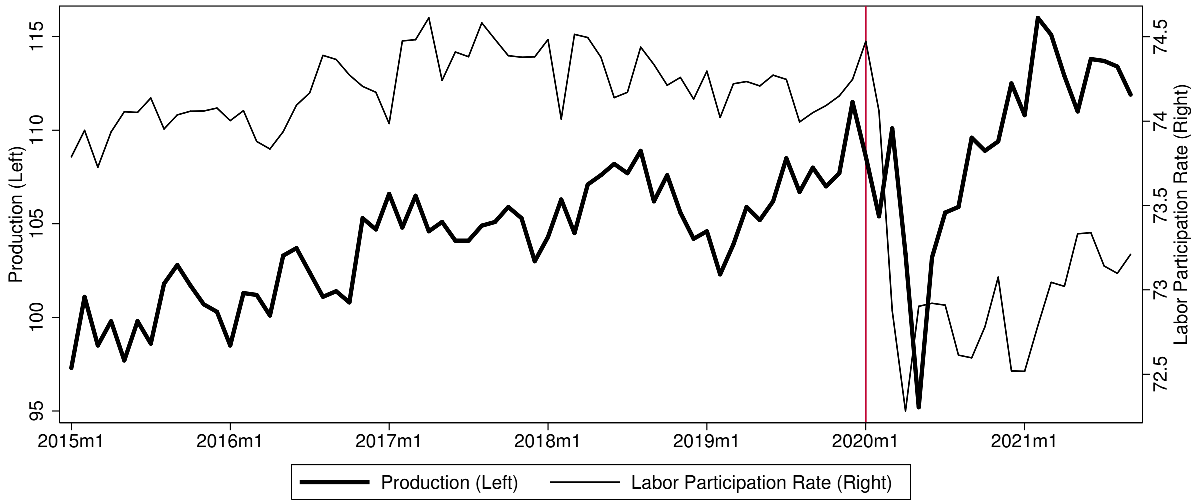


that TFWs' reduction caused vacancy to rise in the short term in the South Korean manufacturing sectors.

The identification of DD crucially depends on the assumption that a single event is the only difference between the control and treated. If otherwise, any other events differ by sectors during the post-period, the identification fails. Unfortunately, COVID-19 has had a variety of impacts on every aspect. Therefore, at least two major events should be regarded seriously. As shown in Figure 5, one is a labor demand shock (production drop), and another is a labor supply shock (participation rate drop). The labor demand shock will be handled by a control function method. The labor supply shock will be discussed in the Robustness Check section. To sum up, the paper will appropriately manage the two shocks to reasonably claim causality.

DD regressions using various dependent variables show the following results. The sectors that heavily relied on TFWs have had an intensive workload: average monthly work time is more than 170 hours, which exceeds legally maximum hours without overtime wage. Before COVID-19, 90.19% of TFWs were full-time workers (as of 2019h2)[2] . After COVID-19, firms that heavily relied on TFWs had difficulties finding full-time workers, while finding part-time workers was easy. Consequently, the ratio of part-time to full-time workers is significantly increasing in these sectors. Also, the termination rate is increasing since part-time workers are easily quitting their job. These sectors are not responding to the shortage of full-time workers by increasing the wage or working

Figure 5



hours. This is because the working hour already has reached their legal maximum.

2 Literature Review

As noted previously, there are only four studies about the effects of immigration on vacancy up to my knowledge. First, Anastasopoulos et al. (2021) used DD regression as Equation 1 in their paper. The regression used monthly data from January 1975 through December 1989. Its observation unit is city and month (not individual). The treated group is Miami, and there are several versions of control groups: the Card group, the low-skill group, and the synthetic group. Table 1 in their paper reports the regression results. The synthetic control column shows a vacancy decline by over 20% in 1981-1982 and over 40% in 1985.

There are two comments on the above regression. First, it uses monthly data of 14 years, which potentially has a serial correlation. The paper seems to use the Eicker-White estimator to estimate standard errors, which does not account for the serial correlation. Using a fixed effect assumption with city clustered might improve the validity, which would conservatively yield the standard error estimation. Meanwhile, the Mariel event coincided with the onset of a recession. As a result, vacancies of both control and treated plummet during 1980-1983 (Figure 1(a)). Therefore, there is a possibility that

[2]Source: Survey on Immigrants' Living Conditions and Labour Force
A full-time worker has a contract longer than a year or indefinite term; a part-time worker has a contract lesser than a year.

the intensities of the recession differed in control and treated. However, their regression does not include any of the recession-related control variables.

Turning to their Beveridge curve (BC) analysis, they found that Miami's BC shifted *inward* during 1980-1984 while synthetic control's BC shifted *outward* (Figure 10 of their paper). They argued that the search and matching model would predict the BC's moving *outward* in Miami, and they argued that the empirical result is the opposite. Based on this contradiction, they surmised that increased matching efficiency could be the reason for this BC's *inward* shift.[3] However, my opinion is as follows. As explained in the introduction section, 1981-1984 is a short term such that even the search and matching predicts the vacancy *drop* (Miami's BC shifted *inward*). Therefore, there is no need to use matching efficiency to explain the BC's shifting inward. My last comment is that the matching efficiency is not the only factor influencing the BC's movement. Termination rate (the arrival rate of moving from a matched to unmatched status) also determines the BC's locus. Both the increase of matching efficiency and the decrease of termination rate move BC *inward*. Therefore, it might be hasty to conclude that an increase of matching efficiency would have been only the reason for the BC's inward shift.

Meanwhile, Schiman (2021) studied the impact of foreign labor inflow from the Eastern European countries to Austria due to EU enlargement starting from 2011. Unlike the Mariel event, the mass migration to Austria persisted for over a decade and is still ongoing. He used Structural Vector Autoregression (SVAR) with sign restrictions for the study. Section 3 of Schiman (2021) explained in detail the reasoning of these structural and sign assumptions. His reasoning is mainly based on Blanchard et al. (1989) that (1) *aggregate activity shocks* move vacancies and unemployment in opposite directions, and (2) *reallocation shocks* creates vacancies, and at the same time raising unemployment. The last assumption about *labor supply shock* is based on Schiman's own logic: employment and unemployment move in the same direction on impact, while the response of vacancies is undetermined. All of these sign restrictions are summarized in Table 1 of his paper.

The key identification to his study is the validity of the structural modeling and sign restrictions since the results will largely depend on these assumptions. Sims (1980) first introduced Vector Autoregression (VAR) in order to not rely on structural assumptions. However, SVAR, a departure from VAR, started to rely much on the structural assumptions on macro theories. Moreover, the sign-restricted SVAR is reliant on the

[3] They present a model by Barnichon and Figura (2015) as in Equation 7 through 10 in their paper to explain the matching efficiency. Unfortunately, they did not show the empirical result may be due to data unavailability.

sign assumptions.

Schiman (2021)'s findings are threefold. The first finding is Figure 5 of his paper. When there is a foreign inflow shock, (1) the unemployment increases both in the short and long run for ten years; (2) vacancy drops in the first three years and then bounces up for another three years and then converges to zero eventually. The second finding is Figure 6 of his paper. The actual Beveridge curve (BC) coincides with the counterfactual draw of a foreign labor supply shock. This implies that the BC movement since 2011 was indeed due to foreign workers' labor supply shock (not due to reallocation, aggregate activity, or domestic labor supply shocks). The third finding is Figure 8 of his paper. Since the Eastern part of Austria is closer to Eastern countries, the reasonable prediction is that Austria's Eastern region would have more impact from foreign labor inflow. The figure confirms this prediction: The Eastern region had a significant increase in vacancies (in the long run) due to foreign labor supply shocks.

Literature about the immigration effect on vacancy using the search and matching framework is rare. One of the influential research is Chassamboulli and Palivos (2014), but they focus on the unemployment and wage outcome (not vacancy). The same applies to Liu (2010). Therefore, up to my knowledge, the closest study is Iftikhar and Zaharieva (2019). They analyze the implications of the immigrants' 25% increase in Germany during 2012-2016. Their model setting is as follows. Every worker is either native or immigrant, either high or low-skilled, and either in manufacturing or service sectors (or unemployed). Therefore, there are eight heterogeneous worker groups. Unemployed high-skill workers simultaneously apply for both high and low-skilled jobs. Furthermore, high-skilled workers matched to low-skilled jobs continue to search and apply for high-skilled jobs while working.

Table 9 of their paper summarizes analysis results. After immigrants' 25% increase, low-skilled immigrants suffered more unemployment than low-skilled natives, especially in the manufacturing sector. Meanwhile, the manufacturing firms expected higher profits due to increased high-skilled immigrants, so firms increased the job posting (vacancy). Consequently, the mismatch rate of high-skilled workers fell in the manufacturing sector, and there was also a spill-over effect on the low-skilled workers, which mitigated the unemployment rate surge. On the contrary, the service sector did not experience job posting increases or unemployment decreases. It is noticeable that their result shows the vacancy *rise*. The reason is that their model is under the long run assumption (fluid capital movement), as emphasized in the introduction section. They calculated the effect on the post-2016 steady-state equilibrium of the immigrant's inflow during 2012-2016.

Meanwhile, Kiguchi and Mountford (2019) studied the impact of immigration on economic outcomes, especially unemployment and vacancy, with the USA annual data from 1950 to 2005. Their analysis starts with a dynamic stochastic general equilibrium (DSGE) framework using households', firms' (intermediate and retail), and a government's optimization conditions. Based on this optimization model, they incorporate migrants' entering conditions into the labor market. Then, they find the Nash bargaining result by calculating the firm's value of filling a vacancy (V_t^F) and the household's value of being employed (V_t^E). Therefore, their model is basically the search and matching model. Next, they get the simulation results by solving optimization problems from everything mentioned above. Based on this simulation, they use SVAR with sign restriction and show the impulse response functions.

Their simulation consists of three scenarios. The baseline scenario assumes immigrants' entering the market with unemployed status with a low job-finding probability (Figure 4 of their paper). The second scenario assumes they enter the market with employed status (Figure B.1 of their paper). This can be interpreted as employment-based immigration where employers sponsor immigrant workers for green cards. Finally, the third scenario assumes they enter the market with unemployed status with a high job-finding probability (Figure B.2 of their paper). In terms of vacancy simulation, neither of their three scenarios are consistent with the pattern discussed in the introduction section. For instance, vacancy of the second scenario *drops* in the short run and converges to zero, but never *bounces up* in the long run.

There are some studies about the Beveridge curve (BC) and matching efficiency, although they do not use the search and matching model in detail. For example, Barnichon and Figura (2012) showed that lower labor supply led to BC's inward shift in the USA from 1976 to 2010 (CPS and Help-Wanted-Index). They also showed that matching efficiency was not a factor for this BC movement. Meanwhile, Klinger and Weber (2016) studied BC in Germany from 1980 to 2013. The BC shifted inwards during 2005-2011 for the first time in decades. They showed that improvement of matching efficiency accounts for half of the substantial decline in unemployment (which moves BC inwards). They claimed that matching efficiency was improved by Hartz reforms, which aimed at raising incentives for more intense job search and helping the matching process.

No study relates vacancy and job termination rate together to my knowledge. However, literature is active in decomposing the unemployment rate into two components: job-finding rate (JF) and job-leave rate (JL), where JL and job termination rate are closely related ideas. Initially, influential papers by Shimer (2012) and Hall (2005) claimed that JF (but not JL) plays a significant role on the unemployment rate. Later, this idea was opposed by some follow-up studies: (Petrongolo and Pissarides, 2008); (Elsby et al., 2009); and (Fujita and Ramey, 2009). For instance, Smith (2011) argued that "The separation rate (JL) accounts for just under half of unemployment variance and leads to cyclical changes in unemployment".

3 Data

This paper uses mainly five datasets: The Labor Force Survey at Establishments (LFSE), Employment Permit System (EPS), Monthly Survey of Mining And Manufacturing (MSMM), Economically Active Population Survey (EAPS), and Employment Information System (EIS).

LFSE provides data for the employment, vacancy, matching, and separation variables. LFSE is a South Korean version of the Job Openings and Labor Turnover Survey (JOLTS). LFSE replicates the list of variables and definitions from JOLTS. It is a monthly survey and has a 50,000 sample size on establishments with more than one any-type of worker — either full-time or temporary workers.

EPS, managed by Korea Employment Information Service (KEIS), provides the number of E9 and H2 visa workers. This paper will use only the number of E9 workers since KEIS supervises every flow of E9 visa holders. Although EPS also provides the data for H2 visa holders, it is unreliable. This is because only about 10% of H2 workers voluntarily report to the EPS system.

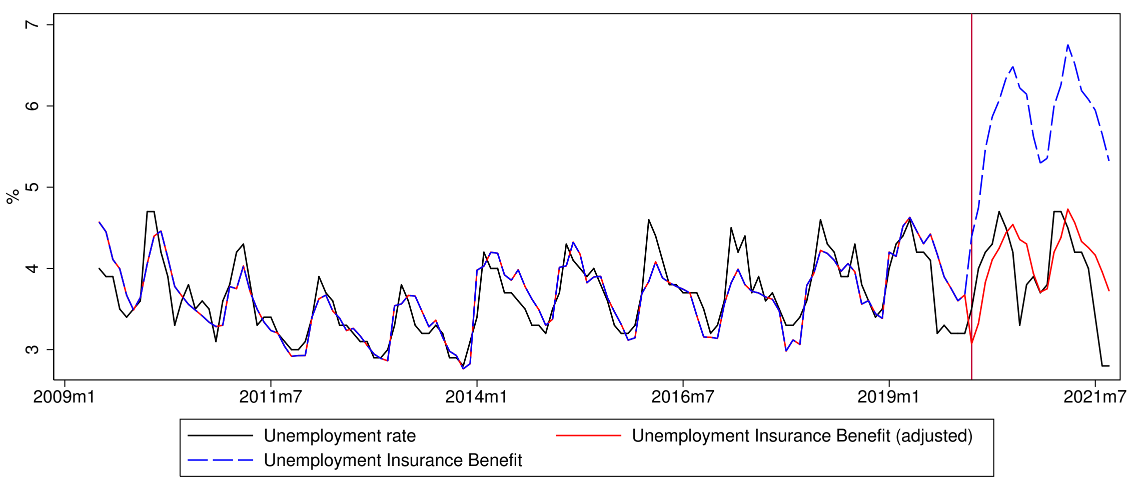
MSMM provides various production-related variables, such as the shipment level to domestic or abroad and the ratio of real production to total production ability. MSMM, conducted by Statistics Korea, is the vital data source when the Bank of Korea calculates Gross Domestic Product.

EAPS provides the unemployment rate. It is a South Korean version of the Current Population Survey (CPS) in the USA. It replicates the list of variables and definitions from CPS. EAPS asks the unemployed or inactive surveyee about the previous job information, including the type of industrial sectors. Assuming that most people are looking for jobs in the same industrial sectors they previously worked in, it is possible to calculate the unemployment rate by industrial sectors. Similar to EAPS, the USA and Canada also provide the unemployment rate by industrial sectors.[4]

[4] https://www.bls.gov/news.release/empsit.t14.htm

The shortcoming of EAPS is that it only provides unemployment rates by large categories of industries, such as agriculture, manufacturing, and service sector. On the contrary, EIS provides unemployment insurance (UI) recipients by detailed category of industries.[5] Subscript i represents twenty subgroups of manufacturing industries as shown in Table 6 in Appendix E. Figure 6 shows that the unemployment and UI rates are serially correlated. Therefore, UI benefits rate[6] can be a good proxy for the unemployment rate. Unfortunately, there was a time break from 2019m12 because of the UI policy change. The policy has become more generous to cope with people's hardship after COVID-19. The dashed blue line is the actual UI rate, and the study adjusted it by multiplying 0.7 after the UI policy change from 2019m12. To sum up, this paper will use UI benefits rate as u_i.

Figure 6: Unemployment rate and UI rate



Using UI Benefit rate as a proxy for detailed manufacturing subsectors might be a too strong assumption. This is because people may move from one sector to another sector quickly. Therefore, this paper will also use an alternative unemployment rate for a robustness check. In other words, this paper will use an alternative unemployment rate $u_i = u$ for all i, where u is the unemployment for the entire manufacturing sector.

[6]Up to two digits of International Standard Industrial Classification (ISIC Rev.4), United Nation.

[6]Unemployment rate $= \frac{\text{Unemployed}}{\text{Employed+Unemployed}}$

UI rate $= \frac{\text{UI recipients}}{\text{Employed+UI recipients}}$

4 Results

Equation 1 is the difference in difference (DD) regression model for Table 2 and 3. Subscript i is manufacturing sectors, and t is monthly time. S_i and T_t are sector and time fixed effect, respectively. X_{it} is a vector of control variables (Table 1). E9CHG_i is a treatment intensity that is continuous variable. It varies by sectors(i) but constant across time(t).

$$Y_{it} = S_i + T_t + \beta(\text{E9CHG}_i \cdot D_t) + \gamma X_{it} + \varepsilon_{it} \quad (1)$$

D_t is a dummy for DD regression, where $D_t = 0$ for the period of 2017m1∼2019m12 (pre-COVID), and $D_t = 1$ for the period of 2021m8∼2022m01 (post-COVID). The period between 2019m12 and 2021m8 is omitted for the two reasons: 1) there was a large production shock right after the onset of the outbreak, and it is necessary to avoid this shock, and 2) the vacancy rise needed some time to activate (there was some lag).

$\text{E9CHG}_i \cdot D_t$ is the interaction term for DD. It is instrumented by $\text{E9SHARE}_i \cdot D_t$. Meanwhile, to account for the serial correlation, the model uses fixed effect assumptions with sector clustered. Therefore, the standard errors are conservatively estimated.

Table 1

Variables	Definitions
E9CHG_i	$\frac{\text{(E9 in 2022m1)}-\text{(E9 in 2019m08)}}{\text{Total workers in 2019m08}} \times 100$
E9SHARE_i	$\frac{\text{E9 in 2019m08}}{\text{Total workers in 2019m08}} \times 100$
X_{it}	ProdDomestic_{it} = The level of shipment to domestic
	ProdAbroad_{it} = The level of shipment to abroad
	$\text{ProdOperation}_{it}$ = The level of operation intensity (The ratio of real production to total production ability)

The regression results are presented in Table 2 and 3. The definitions for the dependent variables are summarized in Table 4. The research interests are the coefficients of $\text{E9CHG}_i \cdot D_t$. The tables show that dependent variables with Vacancy, Vacancy(Full), Part/Full, and Termination are only statistically significant. For instance, the coefficient estimate of -0.217 in the first column of Table 2 means that the industrial sectors that experienced a larger decrease of E9 workers have a larger vacancy increase. With the valid DD assumptions, this result can infer causality. In other words, TFW's decrease caused the vacancy increase.

Table 2

	(1) Vacancy	(2) Wage	(3) Work Hours	(4) Non-emloyment rate
E9CHG × D	-0.217*	412.527	1.225	-0.024
	(0.108)	(275.175)	(1.177)	(0.150)
ProdDomestic	0.005*	13.278	-0.009	-0.012
	(0.002)	(9.899)	(0.026)	(0.007)
ProdAbroad	0.003	-21.765	0.001	0.006
	(0.002)	(14.981)	(0.019)	(0.005)
ProdOperation	0.003	-39.231	0.155	-0.052
	(0.003)	(31.015)	(0.095)	(0.042)
Observations	840	760	820	840
R^2	0.283	0.443	0.913	0.372

Standard errors in parentheses

S_i and T_t included but not reported.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3

	(1) Part/Full	(2) Vacancy(Full)	(3) Vacancy(Part)	(4) Match Eff	(5) Termination
E9CHG × D	-1.136**	-0.246*	0.139	-0.118	-0.004*
	(0.436)	(0.110)	(0.298)	(0.132)	(0.002)
ProdDomestic	0.003	0.005*	0.010	0.006	0.000
	(0.007)	(0.002)	(0.013)	(0.003)	(0.000)
ProdAbroad	0.024*	0.004	-0.011	0.002	0.000
	(0.012)	(0.002)	(0.008)	(0.002)	(0.000)
ProdOperation	0.008	0.003	0.006	0.002	-0.000**
	(0.011)	(0.004)	(0.024)	(0.010)	(0.000)
Observations	840	840	840	820	840
R^2	0.369	0.302	0.085	0.294	0.211

Standard errors in parentheses

S_i and T_t included but not reported.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4

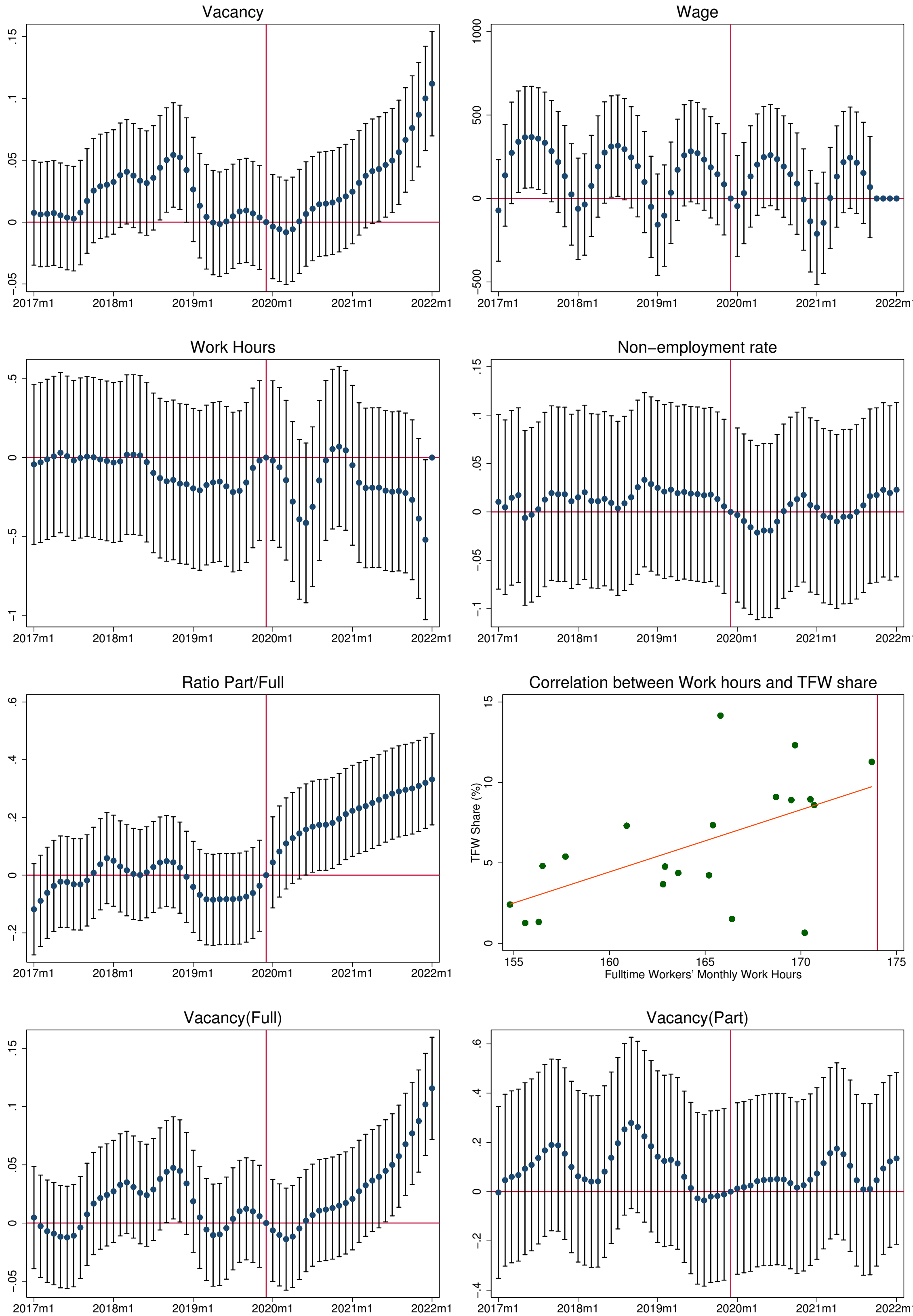
Variables	Definitions
Vacancy	$\frac{\text{Number of vacant spots at month t}}{\text{Number of workers at month t}} \times 100$
Vacancy(Full)	Full-time workers' vacancy
Vacancy(Part)	Part-time workers' vacancy
Wage	Hourly real wage
Work hours	Monthly working hours
Non-employment rate	$\frac{\text{Unemployed+Inactive}}{\text{Employed+Unemployed+Inactive}}$
Part/Full	$\frac{\text{Number of part-time workers}}{\text{Number of full-time workers}}$
Match Eff	Matching efficiency (Derived in Appendix C)
Termination	Termination rate (Derived in Appendix D)

$$
\begin{aligned}
Y_{it} = S_i + T_t &+ \sum_{t \in \text{Pre}} \beta_t (\text{E9SHARE}_i \cdot T(\text{month} = t)) \\
&+ \sum_{t \in \text{Post}} \beta_t (\text{E9SHARE}_i \cdot T(\text{month} = t)) \\
&+ \gamma X_{it} + \varepsilon_{it} \qquad (2)
\end{aligned}
$$

Equation 2 is a DD regression model for Figure 7. The figures are consistent with the regression results in the previous tables. The figure, 'Correlation between Work hours and TFW share', shows that the sectors with higher TFW workers have higher work hours. In 2021, the legal maximum monthly work hours are 174. With the overtime payment, the legal maximum is 226 hours. The figure shows that sectors with higher dependence on TFWs have work hours close to the legal maximum hours. These sectors do not experience difficulties in hiring part-time workers. On the contrary, they have a hard time finding full-time workers than those with lower dependence on TFWs. Consequently, the ratio of part-time workers to full-time workers is increasing significantly. They are not responding to this tight situation by extending working hours or raising wages. The possible reason could be that they have already reached the maximum working hours, and they do not have room to offer higher wages due to competition with the lower-wage countries.

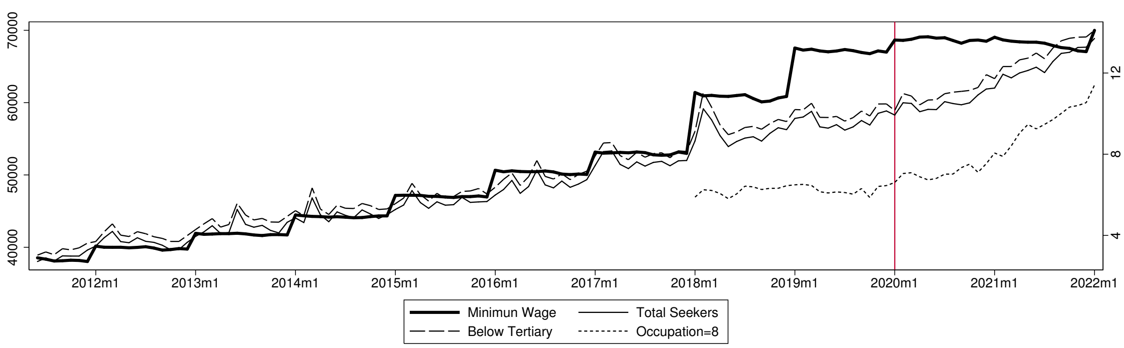
Figure 8 shows the increasing proportion of part-time job-seekers. It was around 3.0% in 2011m6 but increased to 13.7% in 2022m1. This trend may have exacerbated

Figure 7: DD regressions



the harsh condition of finding full-time workers. The increased minimum (real) wage may attribute to the increasing trend of part-time applicants. The minimum wage in the figure includes an extra allowance by law that any workers (including daily-worker) who work more than 15 hours per week should get paid. This allowance is not negligible, and the law is strictly enforced. For instance, in 2021, the minimum hourly wage was \$7.3 if they worked less than 15 hours a week, but it is \$8.8 if they worked more than 15 hours. In the figure, the total seekers and the below tertiary seekers do not differ much. Occupation=8 seekers are the one who belongs to 'Installation, maintenance, and manufacturing works' in Korean Employment Classification of Occupations (KECO). The full classification of KECO is provided in Table 7 of Appendix E.

Figure 8: The proportion of part-time job-seekers



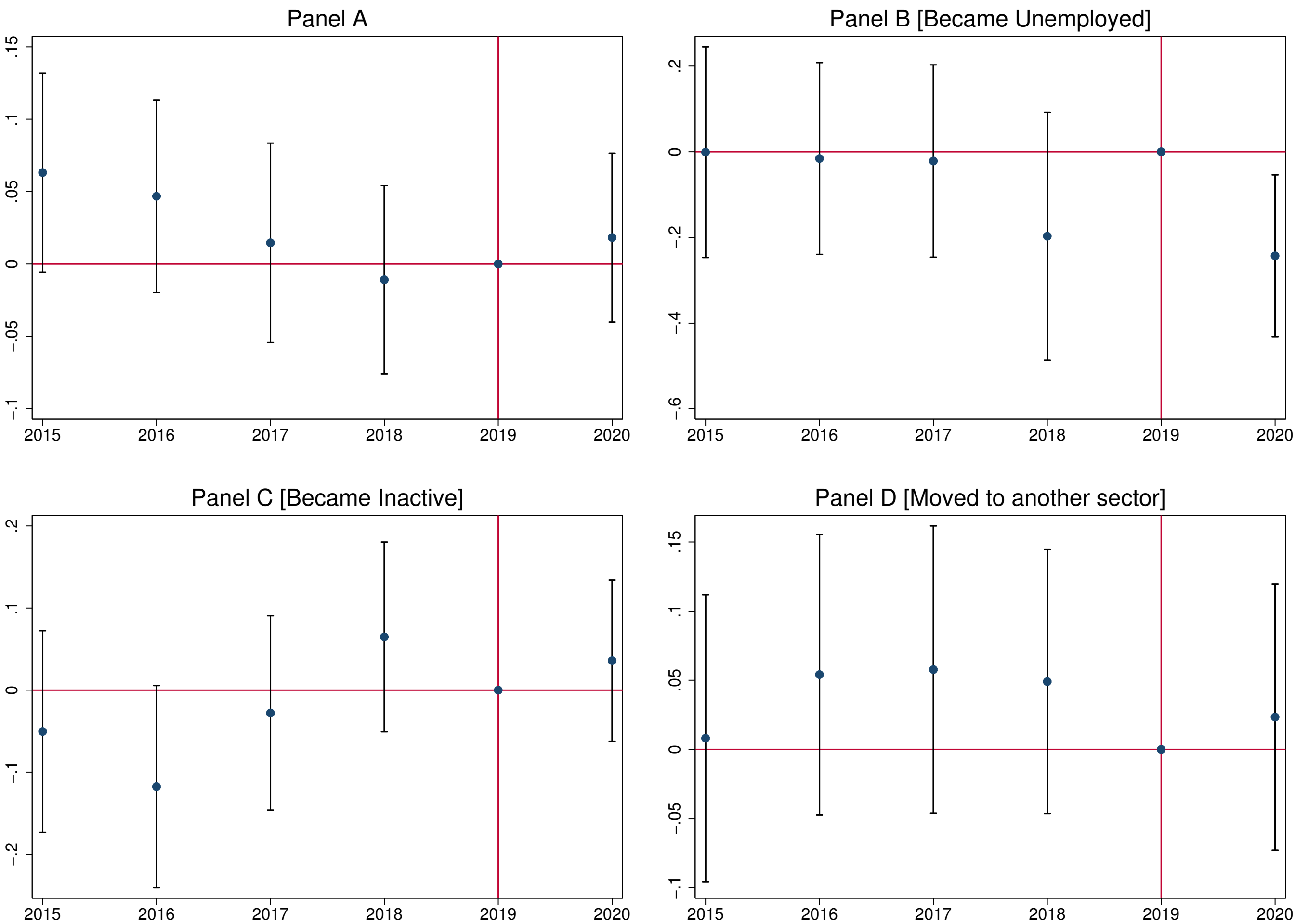
Source: Worknet Job Search Trend (Korea Employment Information Service)
Minimum Wage Trend (Minimum Wage Commission)

5 Robustness Check

The labor participation rate plummeted at the COVID-19 outbreak (Figure 5). There is a possibility that the drop was larger in the sectors that heavily relied on TFWs. If this is true, then the crucial assumption for DD regression for causality is violated. Using Korean Labor and Income Panel Study (KLIPS), this section checks the probability of remaining employed in the same sector. KLIPS is the only dataset in South Korea that satisfies the following conditions: 1) individual leveled panel, 2) identifies economic status (employed, unemployed, and inactive), and 3) provides information on two-digit industrial sectors.

From this data, construct a dummy variable, $D_{it} = \mathbb{1}\{\text{A person remains the same sector } i \text{ from time } t-1 \text{ to } t\}$. Therefore, $D_{it} = 0$ if a person moved to other sectors (including agriculture, service, and so on), became unemployed, or became inactive. Define $T_{it} = \mathbb{1}\{t = 2020\}$, where $t = 2019$ is a reference dummy. Equation 3 is a

Figure 9: Logit Regressions



logit regression. Panel A of Figure 9 is the result, which shows insignificance.

$$
\begin{aligned}
D_{it} = S_i + T_t &+ \sum_{t \in \text{Pre}} \beta_t (\text{E9SHARE}_i \cdot T(\text{year} = t)) \\
&+ \sum_{t \in \text{Post}} \beta_t (\text{E9SHARE}_i \cdot T(\text{year} = t)) \\
&+ \gamma \text{X}_{it} + \varepsilon_{it} \qquad (3)
\end{aligned}
$$

Panel B, C, and D of Figure 9 are the results when D_{it} is set into four categories and performed multinomial logit regressions. From each person who is employed in a sector, track the following year status and categorize as follows: remain employed in the same sector ($D_{it} = 0$), became unemployed ($D_{it} = 1$), became inactive ($D_{it} = 2$), or moved to another sector ($D_{it} = 3$). Only Panel B is significant, where it means that the probability that a person becomes unemployed is smaller in sectors with a larger proportion of TFWs.

6 Conclusion

A Appendix: Derivation of Search and Matching Model

The notations are the same as Howitt and Pissarides (2000) and is summarized in Table 5. The people and firms' flow is depicted in Figure 2(a). Each firm hires only one worker. The firms outside the market can freely enter the market, and the firms inside the market can also freely exit the market. Therefore, when firms expect a large profit increase or decrease, numerous firms can enter or exit the market immediately (long run environment).

Table 5: Definitions

a	Matching efficiency
b	Birth rate (enter the labor market)
β	Worker's bargaining power
c	Search cost
d	Death rate (exit the labor market)
δ	Depreciation rate
λ	Job termination rate
K	Representative firm's capital
N	Representative firm's employees
FDR	$f(k) - \delta k - rk$
p	Labor augmented productivity
r	Interest rate
z	Unemployment benefit

The total number of people is L_t, and evolves by birth rate (b_t) and death rate (d_t). So $L_{t+1} = L_t(1 + b_t - d_t)$. This means that firms' entrance is unlimited, but the number of people is strictly projected by the birth and death rate. The total number of employed workers is $(1 - u_t)L_t$, the total number of unemployed people is u_tL_t, and the total number of vacant firms is v_tL_t. This is because v_t is defined as the number of vacant firms per one mass of the population.

$m(u_t, v_t)$ is the arrival rate of matching. Therefore, $m(u_t, v_t)L_t$ is the total number of matching at time t. There are many versions of matching functions, but this paper will use the most common and simplest Cobb-Douglas version, $m = au^{1-\eta}v^{\eta}$. a is matching efficiency. Therefore, the matching rate per one person is Equation 4, and the matching rate per one firm is Equation 5, where $\theta \equiv \frac{v}{u}$. Conventionally, $\frac{m}{u}$ is represented as q, and

$\frac{m}{v}$ is represented as θq.

$$\frac{mL}{uL} = \frac{m}{u} = a\big(\frac{v}{u}\big)^{\eta} = a\theta^{\eta} \equiv q \tag{4}$$
$$\frac{mL}{vL} = \frac{m}{v} = a\big(\frac{v}{u}\big)^{\eta-1} = a\theta^{\eta-1} \equiv \theta q \tag{5}$$

The inflow to unemployed status is $\lambda_t(1-u_t)L_t + b_tL_t$. The first term is job termination. The second term is birth. The outflow from unemployed status is $q_tu_tL_t + d_tu_tL_t$. The first term is job matching. The second term is death. Therefore, the total flow of unemployed people is:

$$\begin{aligned}
u_{t+1}L_{t+1} - u_tL_t =& \lambda_t(1-u_t)L_t + b_tL_t - q_tu_tL_t - d_tu_tL_t \\
\Leftrightarrow u_{t+1}(1+b_t-d_t)L_t - u_tL_t =& \lambda_t(1-u_t)L_t + b_tL_t - q_tu_tL_t - d_tu_tL_t \\
\Leftrightarrow (u_{t+1}(1+b_t-d_t) - u_t) =& \lambda_t(1-u_t) + b_t - q_tu_t - d_tu_t
\end{aligned}$$

In steady state $u_{t+1} = u_t$,

$$\begin{aligned}
\Leftrightarrow (b_t - d_t)u_t =& \lambda_t(1-u_t) + b_t - q_tu_t - d_tu_t \\
\Leftrightarrow u_t =& \frac{\lambda_t + b_t}{\lambda_t + b_t + q_t}
\end{aligned} \tag{BC}$$

A representative firm's production function has labor augmented productivity, and pN is normalized to one.

$$\begin{aligned}
F &\equiv F(K, pN) \\
&= F(\frac{K}{pN}, 1) \times pN \\
&= f(k) \times pN, \text{ where } k \equiv \frac{K}{pN}
\end{aligned}$$

A matched job at time t has a value worth as:

$$\begin{aligned}
&\frac{F}{N} - \frac{\delta K}{N} - \frac{rK}{N} - w \\
\Leftrightarrow\ & pf(k) - \delta pk - rpk - w \\
\Leftrightarrow\ & p[\text{FDR}] - w, \text{ where FDR} \equiv f(k) - \delta k - rk
\end{aligned} \tag{6}$$

V, J, W, and U represent the Bellman functions (the value of infinite horizon). V is the value of a firm's vacant status, J is the value of a firm's matched status, W is the value of a person's matched status, and U is the value of a person's unemployed status.

In order to calculate these values, a Poisson and an Exponential distributions are used. Suppose a random variable x follows a Poisson distribution with the arrival rate of λ, then the distribution is Equation 7. Then it can convert to an Exponential distribution as in Equation 8

$$f(x) = \frac{\lambda^x e^{-\lambda}}{x!} \tag{7}$$

$$f(t) = \lambda e^{-\lambda t} \tag{8}$$

Using these distribution functions with an arrival rate of λ, the probability that an event never happens until time t equals as $x = 0$, which is Equation 9. And the probability that an event happens for the first time at time t is Equation 10.

$$f(0) = e^{-\lambda t} \tag{9}$$

$$f(t) = \lambda e^{-\lambda t} \tag{10}$$

The value function of V can be calculated as below. For each t from zero to infinity, the probability that matching never happens until time t is e^{-qt}, and its value is $-pc$; the probability that the matching eventually happens for the first time at time t is qe^{-qt}, and its value is J. Under the assumption of firms' free entry and exit, the value function of V will eventually be zero.

$$\begin{aligned} V &= \int_0^\infty e^{-rt}[e^{-qt}(-pc) + qe^{-qt}J]\,dt \\ \Rightarrow rV &= -pc + q(J - V) \end{aligned} \tag{V}$$

Similarly, the value function of J can be calculated as below.

$$\begin{aligned} J &= \int_0^\infty e^{-rt}[e^{-(\lambda+d)t}(p \cdot \text{FDR} - w) + \lambda e^{-\lambda t}e^{-dt}V + de^{-dt}e^{-\lambda t}V]\,dt \\ \Rightarrow rJ &= p \cdot \text{FDR} - w + (\lambda + d)(V - J) \end{aligned} \tag{J}$$

The value function of W can be calculated as below.

$$\begin{aligned} W &= \int_0^\infty e^{-rt}[e^{-(\lambda+d)t}w + \lambda e^{-\lambda t}e^{-dt}U + de^{-dt}e^{-\lambda t}0]\,dt \\ \Rightarrow rW &= w + \lambda(U - W) - dW \end{aligned} \tag{W}$$

The value function of U can be calculated as below.

$$\begin{aligned} U &= \int_0^\infty e^{-rt}[e^{(\theta q+d)t}z + \theta qe^{-\theta qt}e^{-dt}W + de^{-dt}e^{-\theta qt}0]\,dt \\ \Rightarrow rU &= z + \theta q(W - U) - dU \end{aligned} \tag{U}$$

The model assumes the identical firms and people, and when they are matched they negotiate the wage condition. This negotiation is calculated by Nash bargaining problem as follows:

$$
\begin{aligned}
&w = \arg\max_{w} (W-U)^{\beta}(J-V)^{1-\beta} \text{ , where } \beta \text{ is the bargaining power.} \\
&\Rightarrow (1-\beta)(W-U) = \beta J \text{ , since } V = 0 && \text{(Nash)}
\end{aligned}
$$

Lastly, a representative firm maximizes the value function of J to determine optimal capital, K. Rearranging Equation J yields:

$$
\begin{aligned}
J &= \frac{pf(k) - \delta pk - rpk - w + (\lambda + d)U}{r + \lambda + d} \\
\Rightarrow k^* &= \arg\max_{k} J \\
\Rightarrow k^* &\text{ satisfies } f'(k) = \delta + r \text{, where } k \equiv \frac{K}{pN} && \text{(k)}
\end{aligned}
$$

It is worth to note that k^* is determined implies that K^* is determined, where $k \equiv \frac{K}{pN}$. Therefore, optimal capital is decided in the long run.

Based on this k^*, a combination of all Equations V, J, W, U, Nash, and BC yields the optimal wage, unemployment, and vacancy. In detail, a combination of Equation V and J yields Equation JC as below. A combination of Equations V, J, W, U, and Nash yields Equation WC.

$$
\begin{aligned}
w &= p \cdot \text{FDR} - \frac{pc(r + \lambda + d)}{q} && \text{(JC)} \\
w &= z + \beta(p \cdot \text{FDR} - z + \theta pc) && \text{(WC)} \\
u &= \frac{\lambda + b}{\lambda + b + q} && \text{(BC)}
\end{aligned}
$$

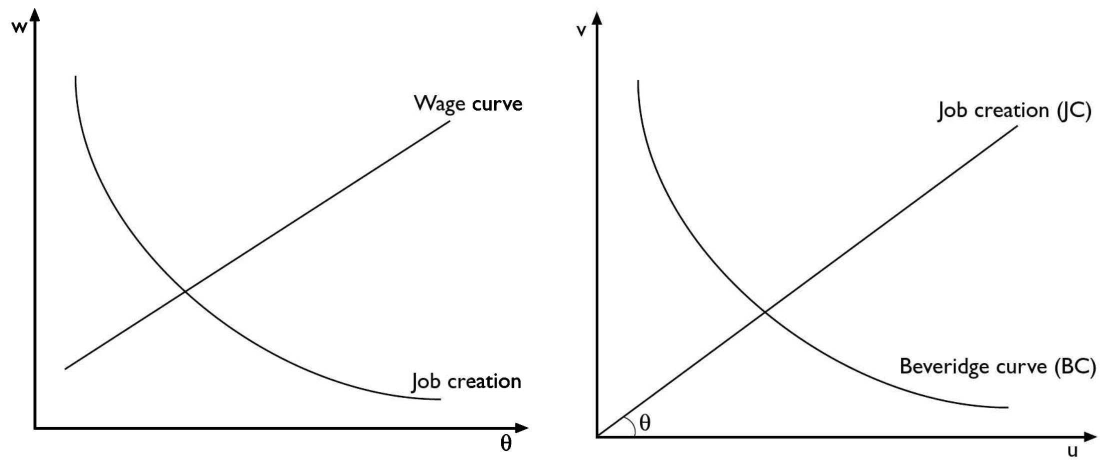
Rewriting the above equations to simplify the notations, using the fact that $q = a\theta^{\eta}$, and $\theta = \frac{v}{u}$.

$$
\begin{aligned}
w &= p \cdot (f(k^*) - \delta k^* - rk^*) - \frac{pc(r + \lambda + d)}{a\theta^{\eta}} && \text{(JC)} \\
w &= z + \beta(p \cdot (f(k^*) - \delta k^* - rk^*) - z + \theta pc) && \text{(WC)} \\
v &= \left(\frac{(\lambda + b)(1-u)}{au^{\eta}}\right)^{\frac{1}{\eta}} && \text{(BC)}
\end{aligned}
$$

The above three equations are the final result. Equation JC and WC are both the function of w and θ. θ is typically called as the market tightness. The tighter θ implies firms' difficulty of finding workers. The intersection of Equation JC and WC yields an equilibrium (steady-state) wage(w) and market tightness(θ), as shown in Figure 10(a). After optimal θ is determined, the intersection of a tangent line of θ and Equation BC yields an equilibrium (steady-state) unemployment(u) and vacancy(v) as in Figure 10(b).

Figure 10

(a) Wage and Job Curve (b) Beveridge Curve



B Appendix: Comparison between long and short run

It is important to note that results in Appendix A are steady-state equilibrium, which assumes the extremely fluid capital adjustment (long run). The long and short run results are distinct. Suppose there is an influx of immigrants so that the birth rate (b) increases. Then the long run model predicts as Figure 2(b). The Beveridge curve (BC) moves *outward* when the birth rate(b) increases. Firms anticipate the increased availability of people, so many enter into the labor market. As a consequence the vacancy *rises*.

However, firms cannot enter the labor market in the short run. Furthermore, many people are searching for jobs. So the vacancy *drops*. Formally speaking, k^* from Equation k does not change unless $f(\cdot),\ r,$ or δ change. K^* is also fixed in the short run. Assume that there is no production shock, p. In the short run, when there is a labor supply shock such that N changes, the only way to achieve k^* is to recover to the initial N^*. For instance, if there is an influx of labor so that N increases, the vacancy should *drop*.

C Appendix: Calibration of Matching Efficiency

Matching efficiency represents the matching speed per job seeker and employer. It can go down for many reasons: the job matching system becomes inefficient, or job seekers and employers become pickier or less desperate when finding matches.

$m(u_t, v_t)$ is the arrival rate of matching. This paper will use it as Equation 11, which is most frequently used one in literature. There is other types of matching function such as $m(u_t, v_t) = \frac{u_t v_t}{u_t + v_t}$. The overall results in this paper does not change by which functions are used.

$$m(u_t, v_t) = {u_t}^{1-\eta} {v_t}^{\eta} \tag{11}$$

Secondly, the type of matching efficiency needs to be selected. The widely used one is a general efficiency, $m(a_t u_t, a_t v_t)$. The idea is that matching efficiency (a_t) is commonly shared by job seekers and employers. The paper will use this one. Therefore, the matching function now becomes

$$m(a_t u_t, a_t v_t) = a_t {u_t}^{1-\eta} {v_t}^{\eta} \tag{12}$$

Howitt and Pissarides (2000) has suggested differentiating between job seekers' side and employers' side (Chapter 5). Specifically, $m(s_t u_t, a_t v_t)$, where s_t is suppliers' job search intensity, and a_t is demanders' job advertising intensity. By firm's free entry assumption, a_t becomes invariant to other shocks. There is also a version that only considers firms' side: $m(u_t, a_t v_t)$ (Chapter 6.2 of Elsby et al. (2015)). This becomes meaningful in the presence of inelastic entry, such as the model with entry cost. Anyway, the paper will use the most widely used version (Equation 12).

Calibration of matching efficiency (a_t) has been actively discussed in literature since it is the core of any studies with the search and matching model. The commonly used method is as follows. The first step is estimating L_t. Time(t) will be omitted for notational convenience throughout this and the next sections. Denote M as total matchings per month, which is provided by LFSE dataset. Let EMP the total number of workers, which is also available in LFSE dataset. Furthermore, EIS provides u. Therefore, L can be calculated as follows:

$$\begin{aligned} \text{EMP} =& (1-u)L \\ \Leftrightarrow L =& \frac{\text{EMP}}{1-u} \end{aligned} \tag{13}$$

The second step is estimating η. Denote M as total matchings per month, which is provided by LFSE dataset. From $m(au, av) = a \cdot u^{1-\eta} v^{\eta}$, it follows that

$$\begin{aligned}
M &= m(au, av)L \\
\Leftrightarrow \frac{M}{uL} &= \frac{m(au, av)}{u} \\
\Leftrightarrow \frac{M}{uL} &= a \cdot \theta^{\eta}, \text{where } \theta \equiv \frac{v}{u} \\
\Leftrightarrow \ln\left(\frac{M}{uL}\right) &= \ln(a) + \eta \ln(\theta) \\
\Leftrightarrow \ln\left(\frac{M}{uL}\right) &= \ln(a_0) + \eta \ln(\theta) + \ln(\varepsilon)
\end{aligned}$$

The last equation is the regression model, where η can be estimated (it does not vary by time or industry). Then matching efficiency for each subsector of the manufacturing industry is as follows:

$$\begin{aligned}
M_i &= m(a_i u_i, a_i v_i)L_i \\
\Leftrightarrow M_i &= a_i \cdot u_i^{1-\eta} v_i^{\eta} L_i \\
\Leftrightarrow a_i &= \frac{M_i}{u_i^{1-\eta} v_i^{\eta} L_i}.
\end{aligned}$$

The above method is the basic calibration method. However, it has an endogeneity issue. As a result, the matching efficiency becomes serially correlated with the market tightness. To correct this biasedness, Borowczyk-Martins et al. (2013) proposed a method using an ARMA process.[7] Sedláček (2014) and Dixon et al. (2014) proposed another alternative method using the unobserved components (UCs) model. This paper will use the basic calibration method, which is a limitation of this paper.

D Appendix: Calibration of Termination Rate

The job termination rate, λ_i, represents the termination of the matching status either by workers' or by employers' reason: workers may leave the job voluntarily, or employers may fire the employee. The termination rate is distinct from the death rate. Both job termination and death result in job separation. However, job terminated workers are still economically active (remain in the labor market) while dead workers become economically inactive (leave the labor market). The study assumed that the death rate is relatively stable compared to the termination rate. Calibration of the termination rate

[7] The complete replication is provided by Borowczyk-Martins et al. (2012).

is simple. Let EXIT_i, available from LFSE dataset, be the number of separations in each subsector. Then it follows that

$$\text{EXIT}_i = \lambda_i L_i$$
$$\Leftrightarrow \lambda_i = \frac{\text{EXIT}_i}{L_i}$$

E Appendix: Tables and Figures

Table 6: Share of TFW Workers on Total Workers in 2019h2

ISIC	Industry Names	TFW Shares (%)
19†	Coke, hard-coal and lignite fuel briquettes and Refined Petroleum Products	0.01
12†	Tobacco products	0.59
11	Beverages	0.66
21	Pharmaceuticals, Medicinal Chemicals and Botanical Products	1.27
14	Wearing apparel, Clothing Accessories and Fur Articles	1.33
26	Electronic Components, Computer, Radio, Television and Communication Equipment and Apparatuses	1.52
27	Medical, Precision and Optical Instruments, Watches and Clocks	2.41
28	Electrical equipment	3.67
20	Chemicals and chemical products except pharmaceuticals, medicinal chemicals	4.23
18	Printing and Reproduction of Recorded Media	4.38
31	Other Transport Equipment	4.77
33	Other Manufacturing	4.81
15	Tanning and Dressing of Leather, Luggage and Footwear	5.39
30	Motor Vehicles, Trailers and Semitrailers	7.31
29	Other Machinery and Equipment	7.35
13	Textiles, Except Apparel	8.59
23	Other Non-metallic Mineral Products	8.91
24	Basic Metal Products	8.95
10	Food Products	9.10
17	Pulp, Paper and Paper Products	11.28
22	Rubber and Plastic Products	12.31
25	Fabricated Metal Products, Except Machinery and Furniture	14.15
32‡	Furniture	17.15
16‡	Wood Products of Wood and Cork; Except Furniture	18.22
C	Total Manufactures	7.24

†: industries are removed because of scarce observations.
‡: industries are removed because of vacancy's too much fluctuations in pre-period.

Table 7: Korean Employment Classification of Occupations (KECO)

KECO 1-digit	2-digits
0 Managerial, clerical, financial, insurance works	Management (executive and director)
	Administrative and clerical works
	Financial and insurance works
1 Research and engineering works	Humanities and social sciences researchers
	Natural and bioscience researchers
	Information and Communications researchers
	Construction and mining researchers
	Manufacturing researchers
2 Education, law, social welfare, police, firefighting, and military	Education
	Law
	Social welfare and religious works
	Police, firefighting, prison officers
	Military serviceman
3 Health and medical works	Health and medical works
4 Art, design, broadcasting, and sports works	Art, design, and broadcasting works
	Sports and recreation works
5 Beauty, tour, accommodation, food, security, and cleaning works	Beauty works
	Tour, accomodation works
	Food service works
	Guard and security works
	Nursing and parenting works
	Cleaning and other service works
6 Sales, drive, and transportation works	Sales works
	Drive and transportation works
7 Construction and mining works	Construction and mining works
8 Installation, maintenance, and manufacturing works	Machine installation, maintenance, and manufacturing works
	Metal and material installation, maintenance, and manufacturing works (Metal plate, forge, foundry, welding, painting, etc)
	Electricity and electronics installation, maintenance, and manufacturing works
	Information and Communications installation, maintenance, and manufacturing works
	Chemistry installation, maintenance, and manufacturing works
	Textile and apparel manufacturing works
	Food manufacturing works
	Printing, wood, and craft manufacturing works
	Routine manufacturing works
9 Agriculture, forestry, and fisheries	Agriculture, forestry, and fisheries

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