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

Version 7.5 *

Deokjae(Jay) Jeong

May 22, 2022

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.

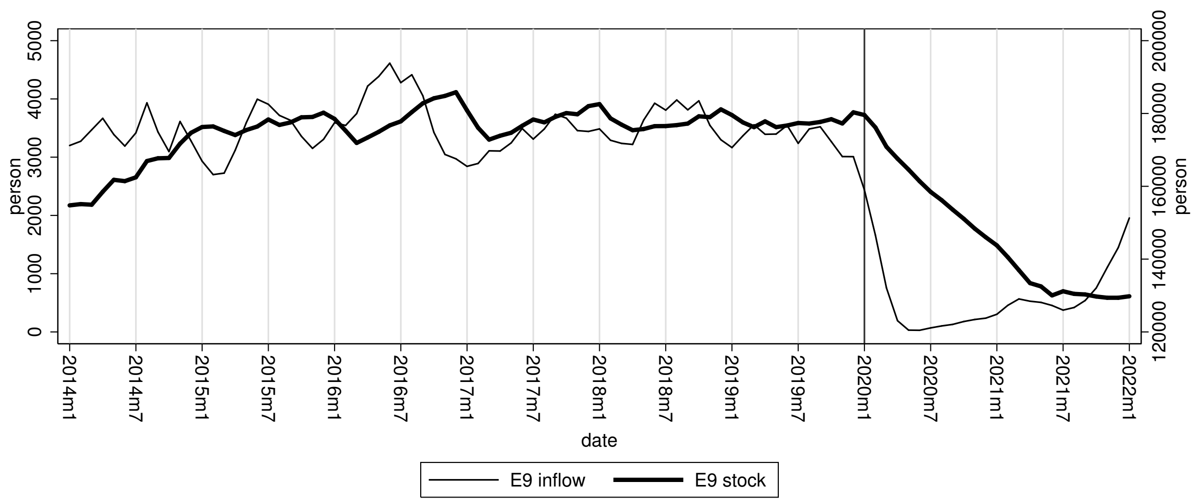
The South Korean government allows the inflow of low-skilled temporary foreign workers (TFWs) only when there is a labor shortage. This TFW policy is grounded on the notion that accepting TFWs help alleviate the employers' difficulties finding low-skilled workers. Opponents of TFW policy, however, argue 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. Vacancy in this study follows the same definition as Job openings variable in JOLTS (Job Openings and Labor Turnover Survey): positions that are open on the last business day of the reference month, and the job could start within 30 days.

[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

This paper uses the difference in difference method to find that low-skilled TFWs' reduction caused vacancy to rise in the South Korean manufacturing sectors. Identifying the causal effect 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 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 1). This event was unrelated to the vacancy measure, so it naturally provides a quasi-experiment opportunity to study the causal effect.

Figure 1: E9 Workers in Manufacturing Sector



Source: Employment Permit System (EPS)

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 and time during the post-period, the identification fails. Unfortunately, COVID-19 has had a variety of impacts on every aspect. There are lots of possible determinants that caused vacancy rise: 1)*Unemployment insurance benefits* , 2)*labor demand shock*, 3) *Termination rate*, 4) *Matching efficiency*, and 5) *Excess retirement*. The aforementioned definitions will be discussed in a separate section. These potential determinants will be properly handled to claim a reasonable causality.

DD regressions using various dependent variables show the following results. The sectors that heavily relied on TFWs have had an intensive workload: the sectors with larger reliance on TFWs, the higher average monthly working hours. Before COVID-19, 90.19% of TFWs were full-time workers (as of 2019h2)[1] . 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.

In addition to DD regression analysis, the paper explored three extra different approaches. The first is the Arellano-Bond estimation, which affirms the DD results. The second one is Impulse Response Functions (IRF) using Structural Vector Autoregression (SVAR). It predicts the vacancy pattern with an extended horizon for ten years. Again, this result is consistent with existing literature. Finally, the paper explored IRF using the Local Projection(LP) method. The results are again consistent with all of the aforementioned results.

This finding contributes to the scarce literature about the effect of immigration on vacancy. Up to my 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 3 Panel A of their paper). Mariel Boat-lift occurred in 1980 (April to October), and the influx lasted about two years until many refugees left from Miami to other cities. The figure shows that the vacancy *dropped* until 1988 and *bounced up* after. Meanwhile, Schiman (2021)'s case shows the similar pattern (Figure 5 of his paper). 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 the figure, 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,

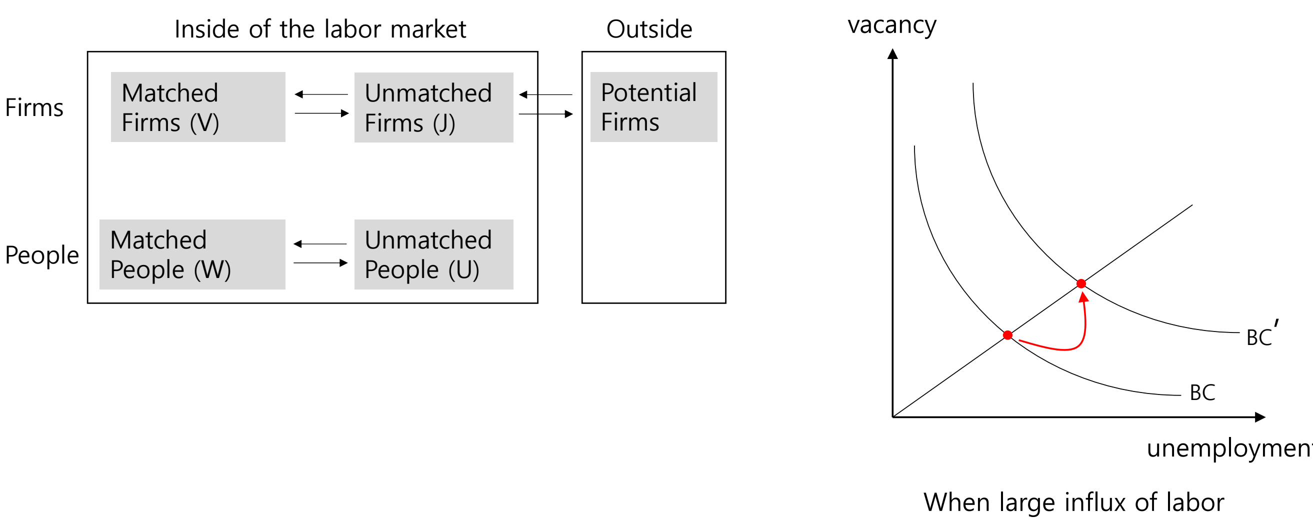
[1]Source: Survey on Immigrants' Living Conditions and Labour Force
A full-time worker has a contract longer than a year or indefinite term; a part-time worker has a contract lesser than a year.

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. 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 it 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 is consistent in the three studies (Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019)) as well as the search and matching model.

Figure 2: Search and Matching Model

(a) Model flows (b) Long run



2 Literature Review

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 more relevant for long run analysis.

As noted in the Introduction section, there are four studies about the effects of immigration on vacancy to the best of 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.

They 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, 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.

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. His'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). (3) Figure 8 of his paper is his third finding. 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.

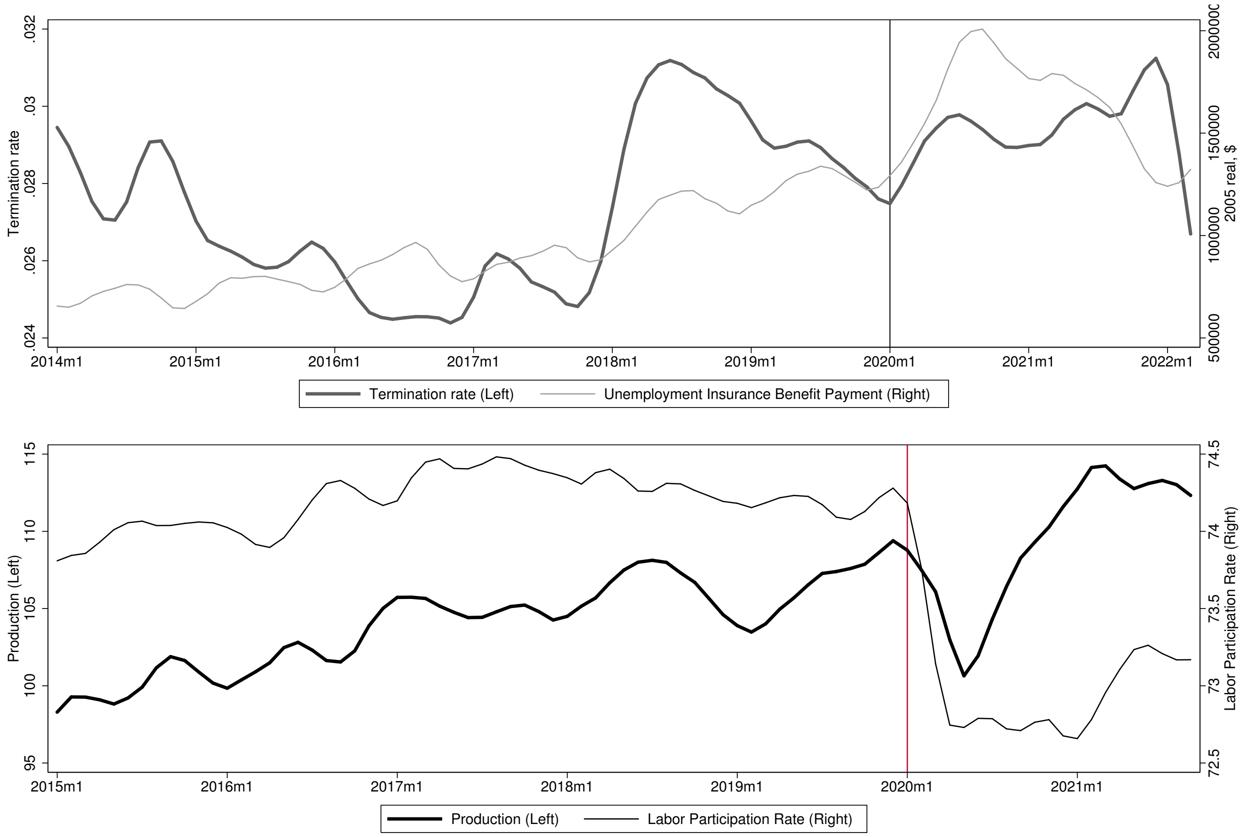
Literature about the immigration effect on vacancy using the search and matching framework is rare. One of the influential research is Chassamboulli and Palivos (2014), but they focus on the unemployment and wage outcome (not vacancy). The same applies to Liu (2010). Therefore, up to my knowledge, the closest study is Iftikhar and Zaharieva (2019). They analyze the implications of the immigrants' 25% increase in Germany during 2012-2016.

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). 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 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

Figure 3



incentives for more intense job search and helping the matching process.

3 Confounding Factors

COVID-19 has had a variety of impacts on every aspect. There are lots of possible determinants that caused vacancy rise: 1)*Unemployment insurance benefits* , 2)*labor demand shock*, 3) *Termination rate*, 4) *Matching efficiency*, and 5) *Excess retirement*. These confounding factors should be handled properly. Otherwise, the identification fails and the causal interpretation is not persuasive.

Unemployment insurance benefits: the government eased requisites for unemployment insurance benefits (UIB) right after the COVID-19 outbreak to help recipients cope with the hardship (Figure 3). Larger UIB, however, may induce people to be economically inactive (lesser desperate to search for other jobs). UIB variable is available for panel dataset, which varies by sector and time. Therefore, UIB will be added as a control variable.

Labor demand shock: the production suddenly plummeted for about 5 months since the outbreak, and then recovered to its previous level (Figure 3). There will be three control variables to handle this labor demand shock: the level of shipment to domestic, the level of shipment to abroad, and the level of operation intensity (the ratio of real production to total production ability).

Termination rate: as Figure 3 shows, participation rate dropped after COVID-19. Unfortunately, labor participation rate is not provided by sector since economically inactive status does not belong to any specific sector. Alternatively, the termination rate will capture the combined effect of the labor participation rate and the *Labor demand shock*.

The employer-employee relationships had disconnected more frequently since COVID-19 until 2021m11 (Figure 3). In Equation 1, the termination rate represents this disconnection. The paper uses 'the number of separations' as the number of employees separated from the payroll during the month, which is the same definition as JOLTS. The calibration of 'the number of people in the labor market', L_{it}, will be explained in Appendix C.

$$\begin{aligned} \text{Number of separations}_{it} =& \text{Termination rate}_{it} \times L_{it} \\ \Rightarrow \text{Termination rate}_{it} =& \frac{\text{Number of separations}_{it}}{L_{it}} \end{aligned} \tag{1}$$

Matching efficiency: after the disconnection of the employer-employee relationships, it naturally takes time to be matched again. The search and matching models by Howitt and Pissarides (2000) introduce the matching efficiency. Appendix C will explain the basic calibration method in detail. As explained there, the basic calibration method entails endogeneity issues. Borowczyk-Martins et al. (2013) summarizes this issue as follows: "the search behavior of firms and/or job seekers implies that labor market tightness and the job finding rate are simultaneously determined as functions of the unobserved efficiency of the matching process. As a consequence, the standard practice of regressing the job finding rate on a measure of labor market tightness using, e.g., OLS, is exposed to a simultaneity bias."

Therefore, estimating a matching efficiency that removed the endogeneity bias is the key to this study. This paper will use a biasedness corrected matching efficiency proposed by Borowczyk-Martins et al. (2013). Appendix Section C will explain this approach in detail. Figure 4 compares the matching efficiency between biased and unbiased. Although not shown in the paper, the time series cross-correlation between the matching efficiency and the vacancy is much lower for the unbiased case than biased one.

Figure 4: Comparison of Matching Efficiencies

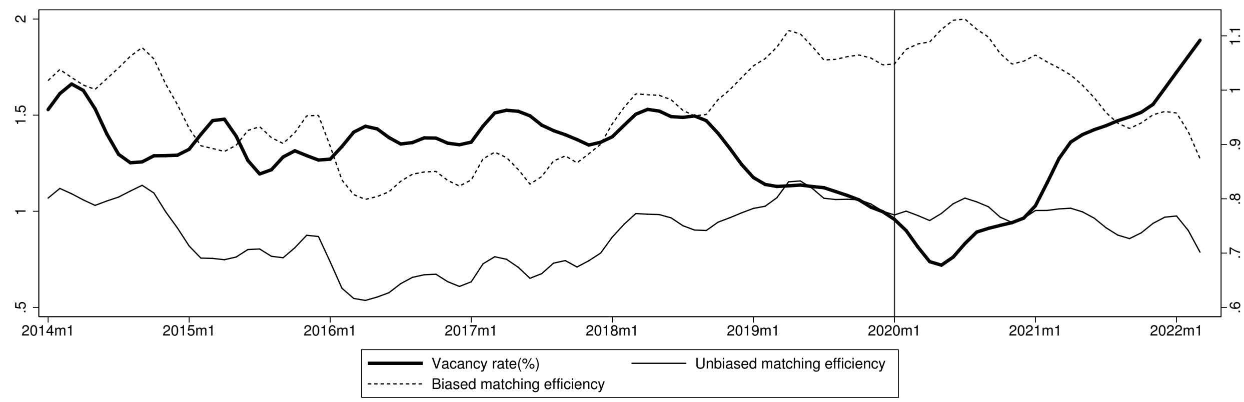
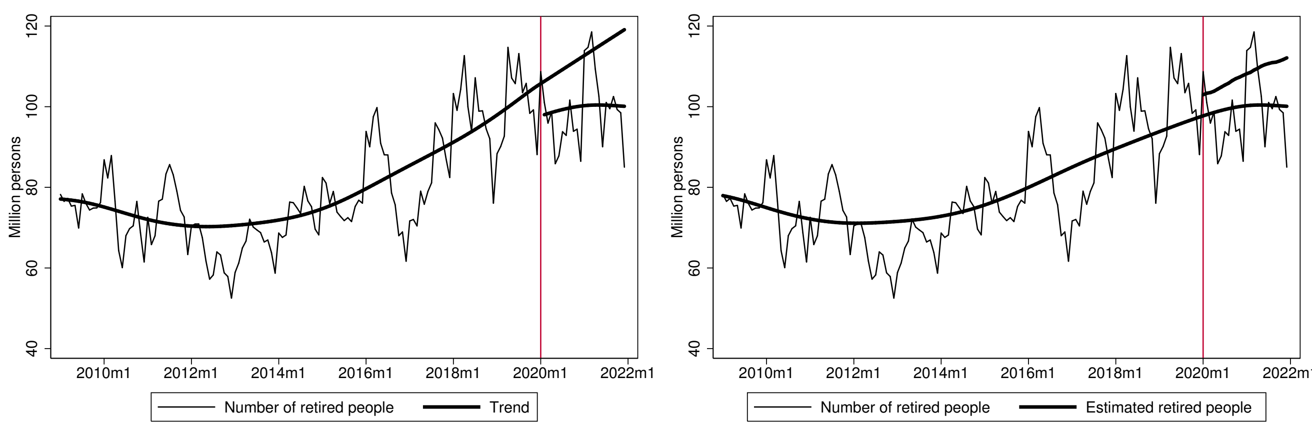


Figure 5

(a) Retirement Trend using Extrapolation

(b) Retirement Estimation using Age Cohort



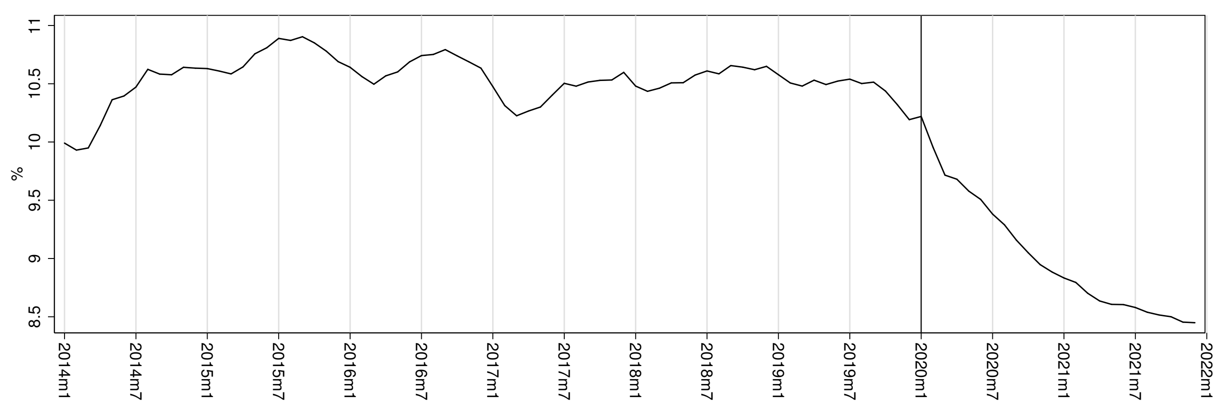
Excess retirement: The study measures *Excess retirement*, the actual number of retired people minus a trend absence of COVID-19. Figure 5(a) shows that there was a retirement drop after COVID-19 compared to the imaginary trend without COVID-19. So it shows that *Excess retirement* did not happen. Using the trend extrapolation may not be accurate. Therefore, Figure 5(b) shows an alternative estimation using five years of age cohort. In each cohort, first calculate the probability of being retired in year 2019, before COVID-19. Second, multiply the probability by the actual total population after COVID-19. The result is similar to the result using trend extrapolation.

4 Background

E9 workers as proxy for TFWs

In the manufacturing sectors in South Korea, TFWs' proportion to total workers dropped from 10.44% (2019m12) to 8.21%(2021m12) as shown in Figure 6. Table 1 shows the workers' proportion by visa types. TFWs in manufacturing sectors mainly consist of E9, F4, and H4 visa workers. Figure 7 shows the stock of visa holders staying in South Korea. 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 8(a), the manufacturing sectors that have a higher proportion of TFWs also have a higher proportion of E9 workers. Therefore, this study proxies E9 workers for TFWs.

Figure 6: TFWs' Proportion in Manufacturing Sector



Source: Korea Immigration Service Monthly Statistics & Survey on Immigrant's Living Conditions and Labour Force

Figure 8(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.

E9 workers

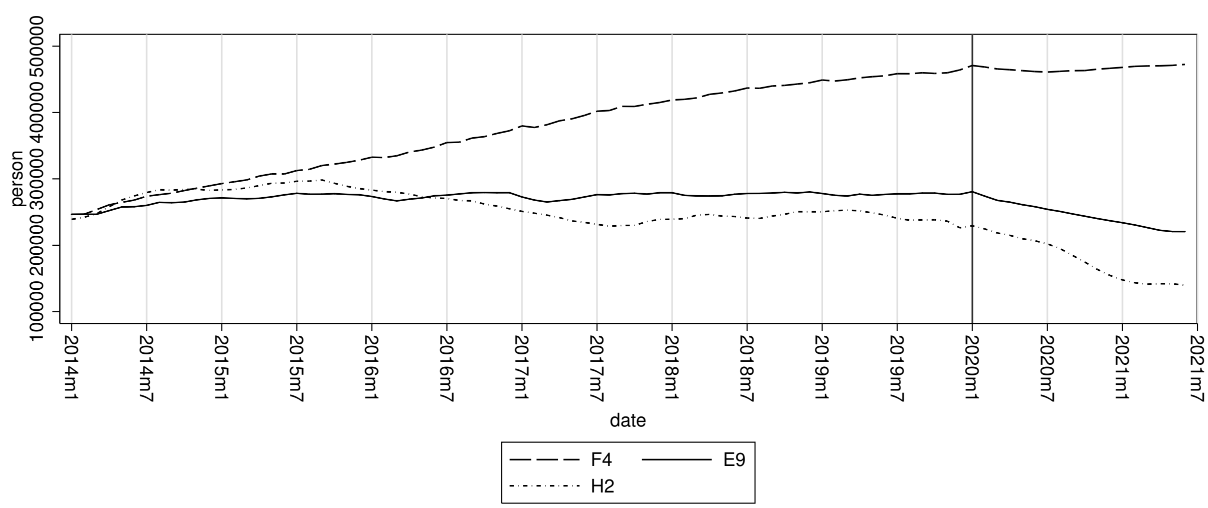
United Kingdom has Migration Advisory Committee(MAC), a group of five economists who produce a list of occupations that the government is recommended to facilitate immigration (Sumption, 2011). If an occupation turned out to be in a labor shortage, this occupation is exempted from the labor market test, which is employers' demonstration that they could not find native workers even after some period of effort to hire. Similar

Table 1: Workers' Proportion in 2019

		Manufacture	Service
Foreign Students	D2,D4	0.02	0.08
Professional Employment	E1∼E7	0.13	0.12
Other VISA		0.35	0.09
Marriage Immigrants	F2,F6	0.61	0.10
Permanent Residents	F5	0.63	0.15
Working Visit	H2	1.21	0.23
Korean Descendants	F4	2.03	0.34
Non-Professional Employment	E9	5.68	0.02
Domestic Citizens		89.35	98.87
Total		100.00	100.00

Source: Survey on Immigrants' Living Conditions and Labor Force[2]

Figure 7: Stock of Visa Holders Staying in South Korea



Source: Monthly Korea Immigration Service Statistics, Ministry of Justice.

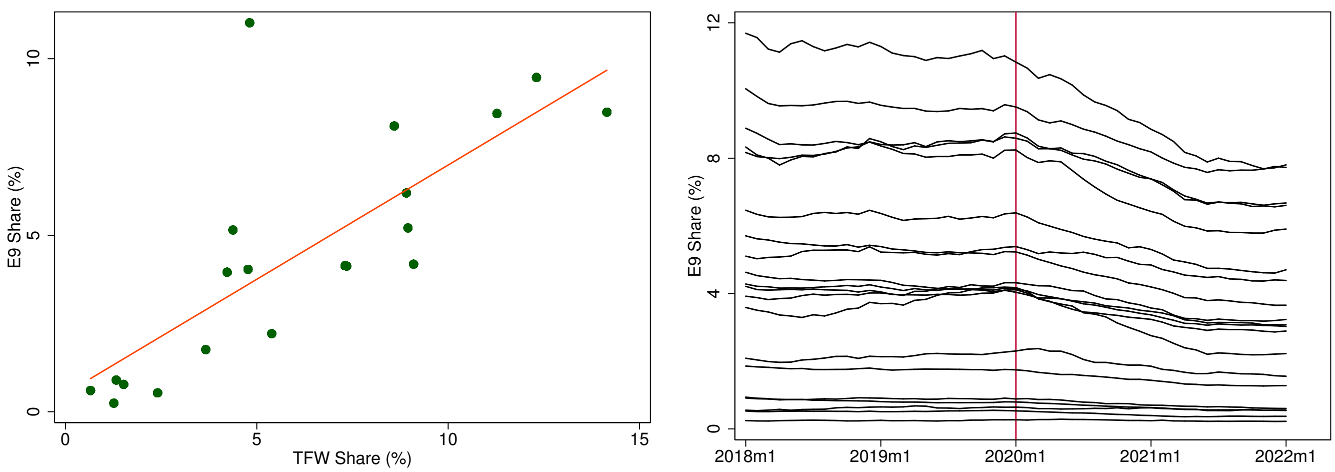
to MAC, South Korea has a committee with a group of twenty experts including vice-ministers of various government departments. The procedure of accepting E9 workers is different from the United Kingdom. Firstly, in each year and each industrial sector, the committee decides the quota of E9 visa, an employer-sponsored visa for temporary workers with low-skilled jobs. The quota decision is made based on the labor shortage. In addition to this quota, employers are required to make 14 days of announcements on Korea Employment Center to hire native workers (labor market test). Then the government arranges a connection between the employer and applicant for E9 visa.

When government agency arranges the connection, they consider the scores from each party. The higher the score, the higher the priority of arrangement. First, the gov-

Figure 8

(a) Correlation between E9 and TFW

(b) E9Share by sectors



ernment has a list of scores for the employer side. A detailed score system is provided at the webpage of the agency, and the basic criterion are as in the footnote.[3] Second, the government has a list of scores for the applicants of E9 workers. The most important criteria is the Korean language test score, because most of E9 workers can speak Korean language in elementary level.

After the government arranges the relationship between the employer and employee, each party has to accept it. Otherwise, they are not matched and will not get additional opportunities for arrangement again. Once the applicants become E9 workers, they will enter South Korea only as full-time workers. Moreover, they should leave South Korea after three years since the entrance, so that turning into permanent residents is almost impossible. Besides, they should not change the establishment location, and they should leave South Korea immediately when they are fired. Therefore, they cannot receive unemployment insurance benefit.

F4 and H2 workers

Meanwhile, F4 and H2 visa holders are Korean descendants, who are fluent in Korean language — so they are a good substitute for domestic workers in the workplace where communication is necessary, such as service sector. For Korean descendants, acquiring H2 visa is easier than F4 visa because many paperworks are exempted. However, since

[3] 1) the ratio of currently hired number of E9 workers to the number of maximum allowance for E9 workers —the lower the ratio, the higher the score, 2) the number of additionally hired natives before requesting E9 workers —the larger the number, the higher the score, 3) the number of excellent dormitory installed for the E9 workers, 4) the number of deaths from accidents due to violation of safety laws, 5) the number of violation of labor laws, and 6) the number of tax delinquency, and so on.

the year 2015, it has been a trend that the more people are getting F4 instead of H2 (Figure 7) as government promotes F4 visa application.

F4 visa holders can enter South Korea whenever they want and work almost wherever they want. Therefore, they are technically foreigners but similar to domestic citizens. Strictly speaking, F4 visa holders are illegal to work in the Elementary Occupations.[4] However, there has not been any law enforcement until now, and most of F4 holders are actually working in elementary occupations. Therefore, the study treats that F4 visa holders who work in elementary occupations as realistically legal.

While F4 visa does not expire, H2 visa expires after three years, and the extension request of 22 months is possible only once (acceptance is not guaranteed). H2 visa holders can work anywhere they want, as long as it belongs to Elementary occupations.

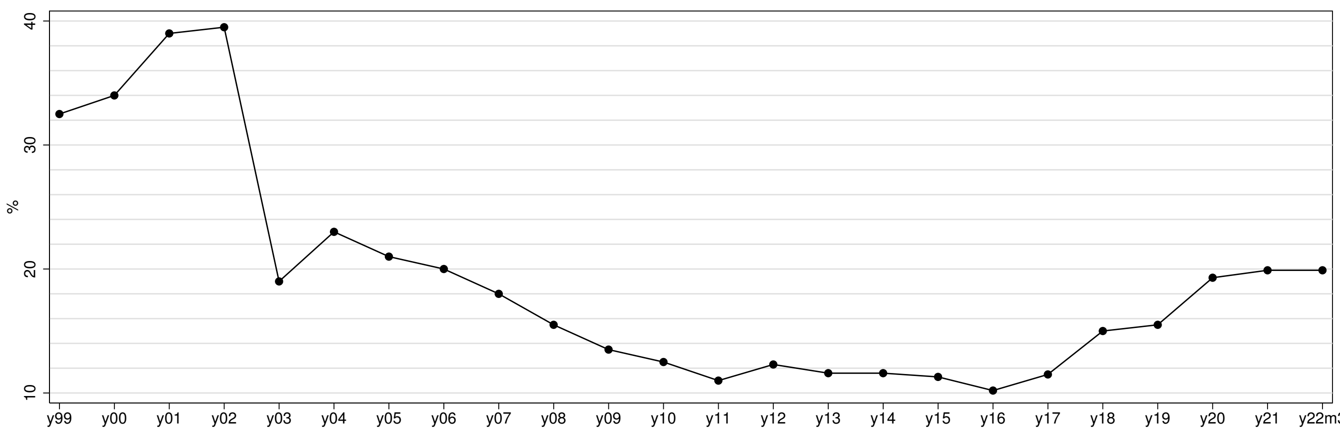
Unauthorized workers

There is the Survey on Immigrants' Living Conditions and Labor Force, starting from year 2012. However, it excludes the temporary foreigners from the sample. Moreover, it does not provide a variable that tells whether a surveyee is illegal resident or not. Therefore this survey is not appropriate for studying unauthorized workers. Since there is not a survey in South Korea that aims to study unauthorized foreign workers, one needs to rely on several indirect sources to estimate them.

Unauthorized workers in South Korea belong to either of four categories: A) people who overstay than allowed period, B) people who left the legally assigned establishments and work in other places illegally, C) people who work without permission to work, and D) people who illegally entered South Korea without visa.

First, Korea Immigration Service Statistics (KISS) from Ministry of Justice provides information about people in Category A. Figure 9 shows that the share of overstaying foreign residents to the total non-immigration residents. It plummeted in year 2003 due to a legalization policy and strong enforcement. Then it started to rise from year 2018 due to more generous issuance for Visa Exemption (B1) and Temporary Visit (C3). This policy was initiated because of Winter Olympic Games opened in South Korea in 2018. In 2020, the share is 19.3%, which is similar to the USA (21.2% in 2019)[5] . Using KISS, Lee (2020) estimates that among the unauthorized foreign residents in 2020, 43.8% is from Visa Exemption (B1), 20.1% is from Temporary Visit (C3), 12.0% is from Non-professional Employment (E9), and 0.7% is from Working Visit (H2). He also estimates that among Visa Exemption (B1, 43.8%) residents, about 72.4% people are from Thailand, many of whom work in the illegal massage service industry. B1 visa holders are not allowed to work, so these workers also belong to Category C.

Figure 9: Share of Overstaying Residents



Second, Lee (2020) studies people in Category B using data from Employment Permit System (EPS). As mentioned previously, E9 workers should not change the establishment location and should leave South Korea immediately when they are fired. He estimates that among unauthorized E9 workers, about 79.4% belong to Category A, while 20.6% belong to Category B. Therefore, the unauthorized issue stems more from Category A than B.

Finally, estimating the people in Category C and D is not possible because of lack of official data. However, there is one paper that personally surveyed foreign workers including illegal foreigners (Lim, 2021). The sample size was 8.7% of total foreign population in year 2020 in Nonsan city, one of the foreigner populous city in South Korea. He concluded that among the illegal foreign workers, 90% of them belong to Category A. Also, among the illegal foreign workers, 60% of them work in agriculture industry, while only 10% work in manufacturing industry. He surmised that illegal foreign workers are prevalent in agricultural sector because the government does not supervise this sector in practice. On the contrary, the government supervises and strictly enforces the law on the manufacturing sector.

[5]Fiscal Year 2019 Entry/Exit Overstay Report, Homeland Security, USA.
Meanwhile, among non-EU-EFTA citizenship living in the UK in 2017, 42.9% were unauthorized immigrants; Source: Pew Research Center.

[5]Category 9 of the International Standard Classification of Occupations (ISCO)

5 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 part-time workers. Since LFSE relicates JOLTS, the definitions of variables are the same as JOLTS. For instance, vacancy in LFSE corresponds to Job openings in JOLTS; matching corresponds to Hires; and separation corresponds to Separations. Similar to JOLTS, the individual level microdata is not provided to public. One difference to JOLTS is that LFSE provides the variables in a variety of categories. For example, the employment, vacancy, matching, and separation variables are provided in two-digit detailed industrial categories. This enables an analysis by detailed sectors inside the manufacturing sector. Also, it provides by full-time and part-time categories.

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.

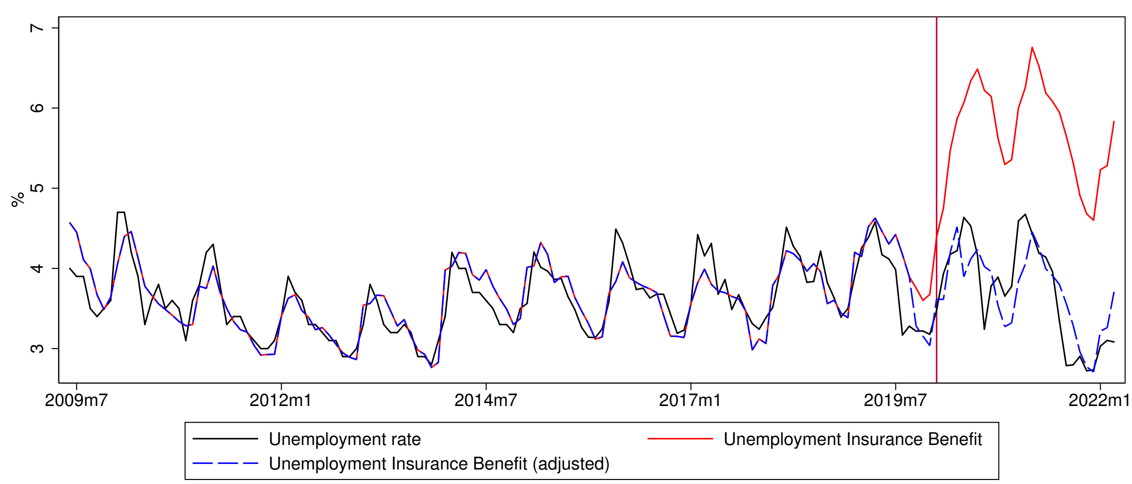
MSMM provides various production-related variables, such as the shipment level to domestic or abroad and the ratio of real production to total production ability. MSMM, conducted by Statistics Korea, is the vital data source when the Bank of Korea calculates Gross Domestic Product.

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. Therefore, the structure is the same as CPS, and definitions for the most of the variables are the same as CPS. EAPS has annual supplementary survey similar to March supplements (CPS ASEC). EAPS provides wage variable only annualy. One major difference from CPS is that the variable that can distinguish between natives and foreigners does not exist. Formally, EAPS does not exclude foreigners when it samples, but technically most of its samples are natives. Therefore, EAPS can be thought of as sampling only natives. Another big difference from CPS is that EAPS does not easily provide panel id to public. Therefore, the repeated cross sectional analysis is accessible only through a secured facility.

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.[6]

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.[7] Subscript i represents twenty subgroups of manufacturing industries as shown in Table 7 in Appendix E. Figure 10 shows that the unemployment and UI rates are serially correlated. Therefore, UI benefits rate[8] can be a good proxy for the unemployment rate. Unfortunately, there was a time break from 2019m10 because of the UI policy change. The policy has become more generous to cope with people's hardship after COVID-19. The red line is the actual UI rate, and the study adjusted it by dummy regression, where $D_t = 1$ after the UI policy change from 2019m10. To sum up, this paper will use UI benefits rate as u_i.

Figure 10: Unemployment rate and UI rate



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

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

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

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

Throughout the entire analysis, this paper uses seasonal adjustment using seasonal dummy. When showing a figure, the paper sometimes uses Hodrick-Prescott (HP) filter for readability. However, the paper never used X-13 ARIMA-SEATS Seasonal Adjustment. Seasonal differencing using ARIMA needs to be performed with care, and should be done when there is a clear indication that the seasonality is stochastic rather than deterministic. Franses (1991) warns against automatically taking seasonal differences. It is difficult to distinguish between deterministic and stochastic seasonality. If the seasonality is deterministic, seasonal differencing results in misspecification and poor forecasting ability. Ghysels and Perron (1993) found that many of the standard de-seasonalizing procedures used by statistical agencies introduce an upward bias on the estimates of the AR coefficients and their sum.

6 Results

Equation 2 is the difference in difference (DD) regression model for an instrumental variable estimation with the just-identified case. The result for this is provided in Table 4.

$$Y_{it} = S_i + T_t + \beta(\mathrm{E9CHG}_i \cdot D_t) + \gamma X_{it} + \varepsilon_{it} \tag{2}$$

Subscript i is manufacturing sectors, and t is monthly time. S_i and T_t are sector and time fixed effect, respectively. To account for the serial correlation, the model uses fixed effect assumptions with sector clustered. Therefore, the standard errors are conservatively estimated. The definitions for the dependent variables are summarized in Table 2. X_{it} is a vector of exogenous control variables (Table 2).

$\mathrm{E9CHG}_i$ is a treatment intensity that is continuous variable. It varies by sectors(i) but constant across time(t). D_t is a dummy for DD regression, where $D_t = 0$ for the period of 2017m1$\sim$2019m12 (pre-COVID), and $D_t = 1$ for the period of 2021m8$\sim$2022m04 (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).

The research interests are the coefficients of $\mathrm{E9CHG}_i \cdot D_t$, which is the interaction term for DD. It is instrumented by $\mathrm{E9SHARE}_i \cdot D_t$. Prior to showing an instrumental variable estimation with the just-identified case in Table 4, the paper briefly provides Table 3, a reduced form estimation that direclty uses instrumental variable as explanatory

Table 2

Variables	Definitions	Main source of data
E9CHG_i	$\frac{\text{(E9 in 2022m1)} - \text{(E9 in 2019m08)}}{\text{Total workers in 2019m08}} \times 100$	EPS
E9SHARE_i	$\frac{\text{E9 in 2017m01}}{\text{Total workers in 2017m01}} \times 100$	EPS, LFSE
X_{it}	UIB = UIB payment (base year=2005, $)	EPS
	Termination = Termination rate	LFSE, EAPS
	Match Eff = Matching efficiency	LFSE, EAPS
	ProdDomestic_{it} = The level of shipment to domestic	MSMM
	ProdAbroad_{it} = The level of shipment to abroad	MSMM
	$\text{ProdOperation}_{it}$ = The level of operation intensity (The ratio of real production to total production ability)	MSMM

Dependent Variables	Definitions	Main source of data
Tightness	$\frac{\text{Vacancy rate}}{\text{Unemployment rate}}$	LFSE, EAPS
Vacancy	$\frac{\text{Number of vacant spots at month t}}{\text{Number of workers at month t}} \times 100$	LFSE
Vacancy(Full)	Full-time workers' vacancy	LFSE
Vacancy(Part)	Part-time workers' vacancy	LFSE
Part/Full	$\frac{\text{Number of part-time workers}}{\text{Number of full-time workers}}$	LFSE
Wage	Hourly real wage	LFSE
Work hours	Monthly working hours	LFSE

variable. Since E9SHARE_i and E9CHG_i is highly correlated, the results are consistent with the instrumental variable estimation in Table 4.

Table 3

	(1) Tightness	(2) Vacancy	(3) Vacancy(Full)	(4) Vacancy(Part)	(5) Part/Full	(6) Wage(Full)	(7) Hour(Full)
E9SHARE × D	0.007	0.060*	0.068*	-0.025	0.311**	-0.153	-0.193
	(0.003)	(0.026)	(0.027)	(0.071)	(0.106)	(0.073)	(0.339)
UIB	-0.092**	0.104	0.211	-2.894*	0.343	1.083	-10.641*
	(0.031)	(0.209)	(0.255)	(1.227)	(1.162)	(1.324)	(3.978)
Termination	0.793*	6.504*	6.949*	19.174	-19.256*	-25.626*	59.461
	(0.342)	(2.707)	(2.965)	(11.775)	(8.655)	(11.825)	(30.590)
Match Eff	-0.046**	-0.335*	-0.317*	-1.400	-0.091	0.447	-0.300
	(0.016)	(0.130)	(0.129)	(0.680)	(0.131)	(0.645)	(0.909)
ProdDomestic	0.001*	0.005*	0.005*	0.010	0.000	-0.003	0.025
	(0.000)	(0.002)	(0.002)	(0.011)	(0.005)	(0.004)	(0.025)
ProdAbroad	0.000	0.003	0.003	-0.009	0.022	0.010	0.006
	(0.000)	(0.002)	(0.002)	(0.007)	(0.011)	(0.011)	(0.015)
ProdOperation	0.000	0.004	0.005	-0.001	0.008	-0.011	0.074
	(0.001)	(0.004)	(0.005)	(0.021)	(0.014)	(0.015)	(0.058)
Observations	820	820	820	820	820	820	820
R^2	0.378	0.342	0.362	0.099	0.397	0.504	0.932

Standard errors in parentheses

S_i and T_t included but not reported.

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

Table 4 shows an instrumental variable estimation. The dependent variables of Tightness, Vacancy, Vacancy(Full), Part/Full, and wage(Full) are statistically significant. For instance, the coefficient estimate of -0.238 in the second column means that the industrial sectors that experienced a larger decrease of E9 workers had a larger vacancy increase. Under the valid DD assumptions, one can infer that TFWs' decrease caused the vacancy increase.

Equation 3 is a reduced form DD regression model for Figure 11.

$$\begin{aligned} Y_{it} = S_i + T_t &+ \sum_{t \in \text{Pre}} \beta_t (\text{E9SHARE}_i \cdot T(\text{month} = t)) \\ &+ \sum_{t \in \text{Post}} \beta_t (\text{E9SHARE}_i \cdot T(\text{month} = t)) \\ &+ \gamma X_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

Table 4

	(1) Tightness	(2) Vacancy	(3) Vacancy(Full)	(4) Vacancy(Part)	(5) Part/Full	(6) Wage(Full)	(7) Hour(Full)
E9CHG $\times$ D	-0.027*	-0.238*	-0.267*	0.098	-1.232**	0.608*	0.766
	(0.013)	(0.103)	(0.107)	(0.281)	(0.412)	(0.294)	(1.375)
UIB	-0.085**	0.164	0.279	-2.919*	0.655	0.928	-10.836**
	(0.031)	(0.199)	(0.244)	(1.230)	(1.111)	(1.350)	(4.067)
Termination	0.809*	6.643**	7.105*	19.116	-18.537*	-25.981*	59.014
	(0.325)	(2.545)	(2.772)	(11.668)	(9.147)	(11.912)	(31.048)
Match Eff	-0.046**	-0.339**	-0.322*	-1.398*	-0.112	0.458	-0.286
	(0.016)	(0.127)	(0.127)	(0.684)	(0.154)	(0.641)	(0.895)
ProdDomestic	0.001**	0.005*	0.006**	0.010	0.002	-0.003	0.024
	(0.000)	(0.002)	(0.002)	(0.011)	(0.006)	(0.004)	(0.026)
ProdAbroad	0.000	0.003	0.003	-0.009	0.024*	0.009	0.005
	(0.000)	(0.002)	(0.003)	(0.007)	(0.012)	(0.011)	(0.016)
ProdOperation	0.000	0.004	0.005	-0.001	0.007	-0.010	0.074
	(0.001)	(0.004)	(0.005)	(0.021)	(0.015)	(0.014)	(0.058)
Observations	820	820	820	820	820	820	820
R^2	0.374	0.339	0.361	0.100	0.392	0.504	0.932
First-stage F	172.91	172.91	172.91	172.91	172.91	172.91	172.91

Standard errors in parentheses

S_i and T_t included but not reported.

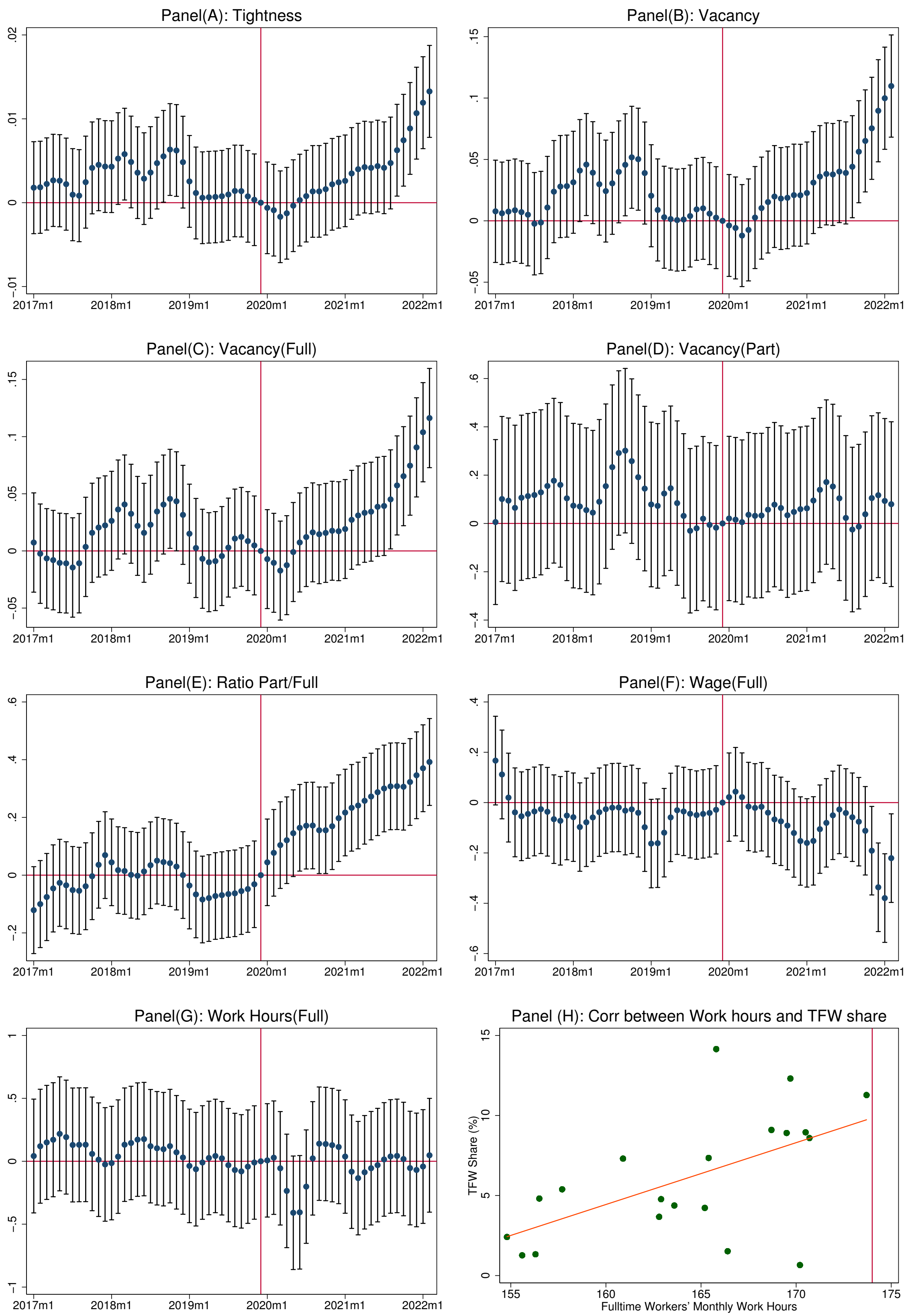
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The figures are consistent with the regression results in Table 4. The figures and tables in combination show that full-time workers' hourly wages have decreased when the foreign workers are reduced more than before. This is an unexpected result because one would imagine that the wage will increase when finding workers is tough. One possibility is that the vacancy rate does not identify the labor shortage well: the vacancy rate is defined by the number of vacant spots divided by the total number of employees. It can increase when the number of employees decreases even if the vacant spots stay the same. Then the rise in the vacancy rate does not necessarily mean the tough condition for finding the workers. Moreover, the decrease in unemployed people can also affect the toughness of finding the workers. Therefore, a more relevant variable that identifies the toughness is the market tightness, defined by $\frac{\text{Vacancy rate}}{\text{Unemployment rate}}$. In previous figures and tables, the market tightness increases when the foreign workers are reduced more than before. This implies that it is indeed challenging to find workers. This paper could not find the reason for the wage decrease.

Panel G of the figure 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. It implies these sectors have a tough working condition. While these sectors do not experience difficulties in hiring part-time workers (Panel C), they do in finding full-time workers (Panel B). Consequently, the ratio of part-time workers to full-time workers is increasing significantly in these sectors (Panel D). They are not responding to this tight situation by extending working hours (Panel F) or raising wages (Panel E). Surprisingly, their wage to the currently employed full-time workers acutally decreased (Panel E). 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.

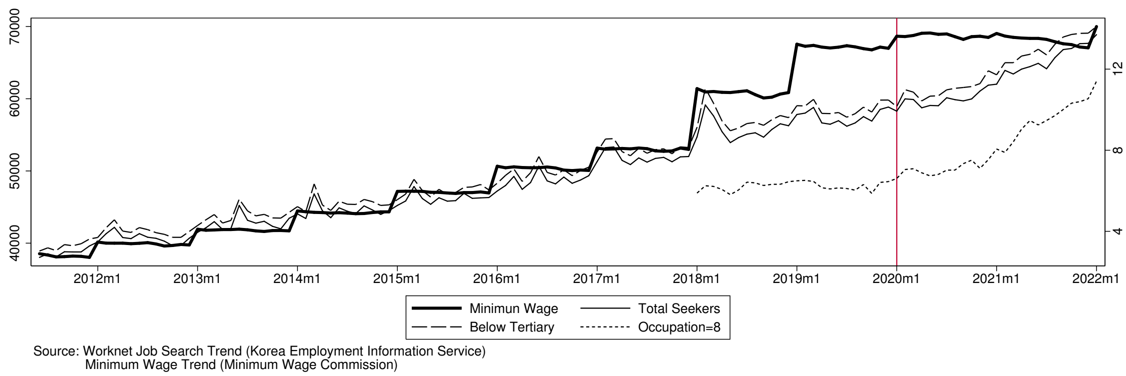
Figure 12 shows the increasing proportion of part-time job-seekers. It was around 3.0% in 2011m6 but increased to 13.7% in 2022m1. This trend may have exacerbated the difficulties of finding full-time workers. The increased minimum (real) wage may attribute to the increasing trend of part-time applicants. 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

Figure 11: DD regressions



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 8 of Appendix E.

Figure 12: The proportion of part-time job-seekers



7 Robustness Check

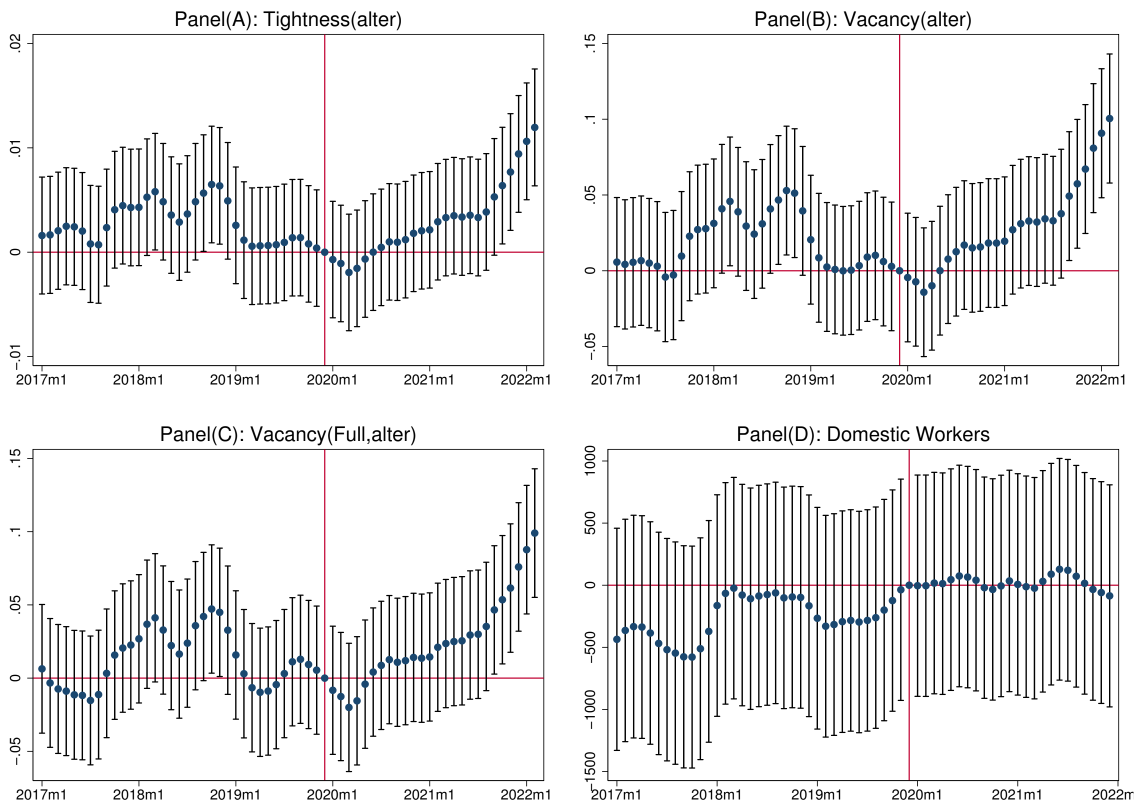
7.1 Vacancy rate

Throughout this paper, the vacancy rate has been measured by $\frac{\text{Number of vacant spots}_{it}}{\text{Number of total workers}_{it}}$. Using this variable, the the previous section showed that vacancy rate has increased more in the manufacturing sectors which relied more on E9 workers. However, this result might be spurious if the result is mainly driven by the change of 'the number of domestic workers' (a part of the denominator of the vacancy rate). To put it another way, it is fine if the number of domestic workers has decreased evenly across the sectors, because then DD will cancel out the differences. On the contrary, it is problematic if the number of domestic workers has decreased(or increased) more in the manufacturing sectors which relied more on TFWs.

One way to overcome this possibility is to fix the denominator of the vacancy rate. Let $\{\text{Number of total workers}\}_{i,t0}$ as the average of the number of total workers during 2019m6 $\sim$ 2019m12 (pre-COVID). Then define an alternative vacancy rate, valter, as follows:

$$\text{valter}_{it} = \begin{cases} \frac{\text{Number of vacant spots}_{it}}{\text{Number of total workers}_{it}} & \text{if } t < \text{2020m1} \\ \frac{\text{Number of vacant spots}_{it}}{\text{Number of total workers}_{i,t0}} & \text{if } t \geq \text{2020m1} \end{cases}$$

Figure 13: DD (Robustness Check)



Panel A, B, and C of Figure 13 show the same DD regression as Figure 11 above. The only difference is using valter_{it} instead. Comparing between Figure 11 and Figure 13, one can see that the figures are almost identical.

Another way of checking the falsity is performing the same DD regression as above using the number of domestic workers as a dependent variable. Unfortunately, the exact number of TFWs is known only for the total manufacturing sector (TFW_t). For two digit sectors level, only the number of E9 workers is known (E9_{it}). Therefore, the paper assumes for now that the proportion of TFWs across sectors is the same as that of E9 workers. Under this assumption, TFW_{it} can be estimated as follows:

$$\begin{aligned} \text{TFW}_{it} &= \text{TFW}_t \times \frac{\text{E9}_{it}}{\sum_i \text{E9}_{it}} \\ \Rightarrow \text{Domestic Workers}_{it} &= \text{Total Workers}_{it} - \text{TFW}_{it} \end{aligned} \tag{4}$$

Equation 4 shows the estimated number of domestic workers for two digit sectors level. Panel D of Figure 13 shows the DD regression using this as a dependent variable. It confirms that there is not any spurious force that the number of domestic workers drove the vacancy rate.

7.2 IRF using SVAR with Sign Restrictions

Structural VAR includes current period variables into the explanatory side (Equation 5), where Y_t is a vector of n endogenous variables. $B_0 Y_t$ is included in the explanatory side because the variables may have a contemporaneous effect on each other. One important assumption is that ε_t is a white noise with a zero covariance of $\mathbb{E}(\varepsilon_t \varepsilon_t')$.

$$
\begin{aligned}
& Y_t = B_0 Y_t + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + \varepsilon_t && (5) \\
\Leftrightarrow & (I - B_0) Y_t = B(L) Y_t + \varepsilon_t \\
\Leftrightarrow & Y_t = (I - B_0)^{-1} B(L) Y_t + (I - B_0)^{-1} \varepsilon_t \\
\Leftrightarrow & Y_t = A_1 B(L) Y_t + \epsilon_t \ \text{, where } \ \epsilon_t = (I - B_0)^{-1} \varepsilon_t && (6)
\end{aligned}
$$

Equation 5 is converted to Equation 6, a reduced form, to estimate the coefficients using OLS. However, the variance-covariance matrix of ϵ_t is not anymore diagonal (it is contemporaneously correlated). Therefore, the innovations of ϵ_t lack a structural interpretation (Breitenlechner et al., 2019). A general approach to recover the structural information in Equation 6 is using the Cholesky decomposition of the covariance matrix $\mathbb{E}(\epsilon_t \epsilon_t')$. However, this solution imposes a too strong assumption that a shock of a specific variable does not have any current effect on another variable (depends on ordering). Consequently, there are some alternative methods which relax this strong assumption. One method is using sign restrictions (Uhlig, 2005), and another is using the Local Projection (LP) method by Jordà (2005) —the results using LP method will be provided in a separate section.

Among the many variants for SVAR with sign restrictions, this paper uses Rubio-Ramirez et al. (2010)'s rejection method. Moreover, the accuracy of SVAR with sign restrictions can increase when narrative restrictions are added (Antolín-Díaz and Rubio-Ramírez, 2018a). Using this narrative restrictions method, Figure 5 of Schiman (2021)'s paper shows that when there is a foreign labor supply's *positive* shock, the vacancy drops for the first three years, rises in the next three years, and eventually converges to zero. As mentioned in the Introduction section, many existing studies and the search and matching model also predict the same pattern.

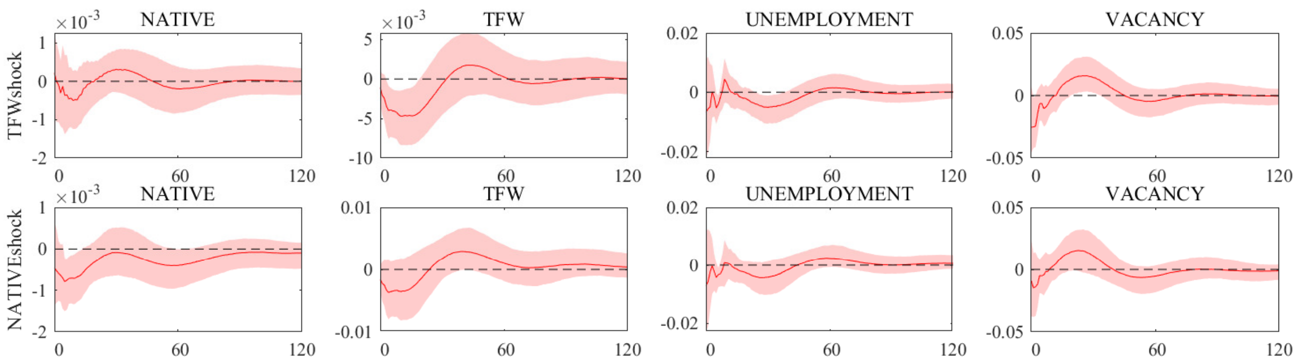
This paper provides Figure 14 using the same settings as Schiman (2021). Specifically, shocks, included variables, the sign and narrative restrictions, lag length ($l = 6$), and forecast horizon (120 months) are the same. The sign and narrative restrictions used in this paper[9] are provided in Table 5, which are the same as the Schiman (2021)'s argument

Table 5: Impact sign restrictions, 4-dimensional VAR

<table>
<tr><th>$b_{ij} \in \boldsymbol{B}^{-1\prime}$</th><th>NATIVE</th><th>TFW</th><th>UNEMPLOYMENT</th><th>VACANCY</th></tr>
<tr><td>Reallocation shock</td><td colspan="2">−</td><td>+</td><td>+</td></tr>
<tr><td>Aggregate activity shock</td><td colspan="2">−</td><td>+</td><td>−</td></tr>
<tr><td rowspan="2">TFW supply shock</td><td colspan="2">−</td><td rowspan="2">−</td><td rowspan="2">NA</td></tr>
<tr><td>$> b_{32}$</td><td>−</td></tr>
<tr><td rowspan="2">NATIVE supply shock</td><td colspan="2">−</td><td rowspan="2">−</td><td rowspan="2">NA</td></tr>
<tr><td>$> b_{41}$</td><td>−</td></tr>
</table>

Figure 14

(a) IRFs using narrative sign restrictions



(the directions are just opposite): the foreign labor's *negative* supply shock would have a positive effect on the domestic employment; a negative effect on unemployment; and undetermined effect on vacancy; TFW supply shock is the most important contributor to TFW (Type A restriction by Antolín-Díaz and Rubio-Ramírez (2018a)).

Figure 14 shows IRFs over ten years using the monthly dataset ranges from 2012m1 to 2022m3 (123 observations). The dashed lines are 68 percent error bands as in standard. When there is a *negative* foreign workers' shock, the vacancy rate surges for about three years, drops next three years (although this is insignificant), and eventually converges to zero. This result is consistent with Figure 5 of Schiman (2021)'s paper.

7.3 IRF using the Local Projection Method

As briefly mentioned in the previous section, Jordà (2005) proposed the Local Projection method (LP), an alternative method for IRF. Nowadays, LP is becoming more popular method than SVAR. One of the advantages of LP is its flexible applications to situations

[9] This paper used a program coded by Antolín-Díaz and Rubio-Ramírez (2018b)

when an exogenous shock is identified. Once an exogenous shock is identified, IRF can be directly estimated using OLS regressions (Adämmer, 2019). Another merit of LP is that it can be used to a panel dataset (Owyang et al. (2013); Jordà et al. (2015)).

$$y_{i,t+h} = S_i^h + \beta^h \text{E9Share}_{i,t} + \gamma^h X_{i,t} + \varepsilon_{i,t+h}^h, \quad h = 0, 1, ..., H-1 \tag{7}$$

Equation 7 is for LP estimation, where $\text{E9Share}_{i,t}$ is the share of E9 workers among total workers in manufacturing sector i at time t. The coefficient β^h is the response of $y_{i,t+h}$ to the exogenous shock at time t. The LP estimation is clustered by industrial sectors since it is important for LP method to account for the heteroskedasticity and serial autocorrelation. $X_{i,t}$ is a vector of control variables, which are the same as before (Table 2). S_i^h is the sector fixed effect.

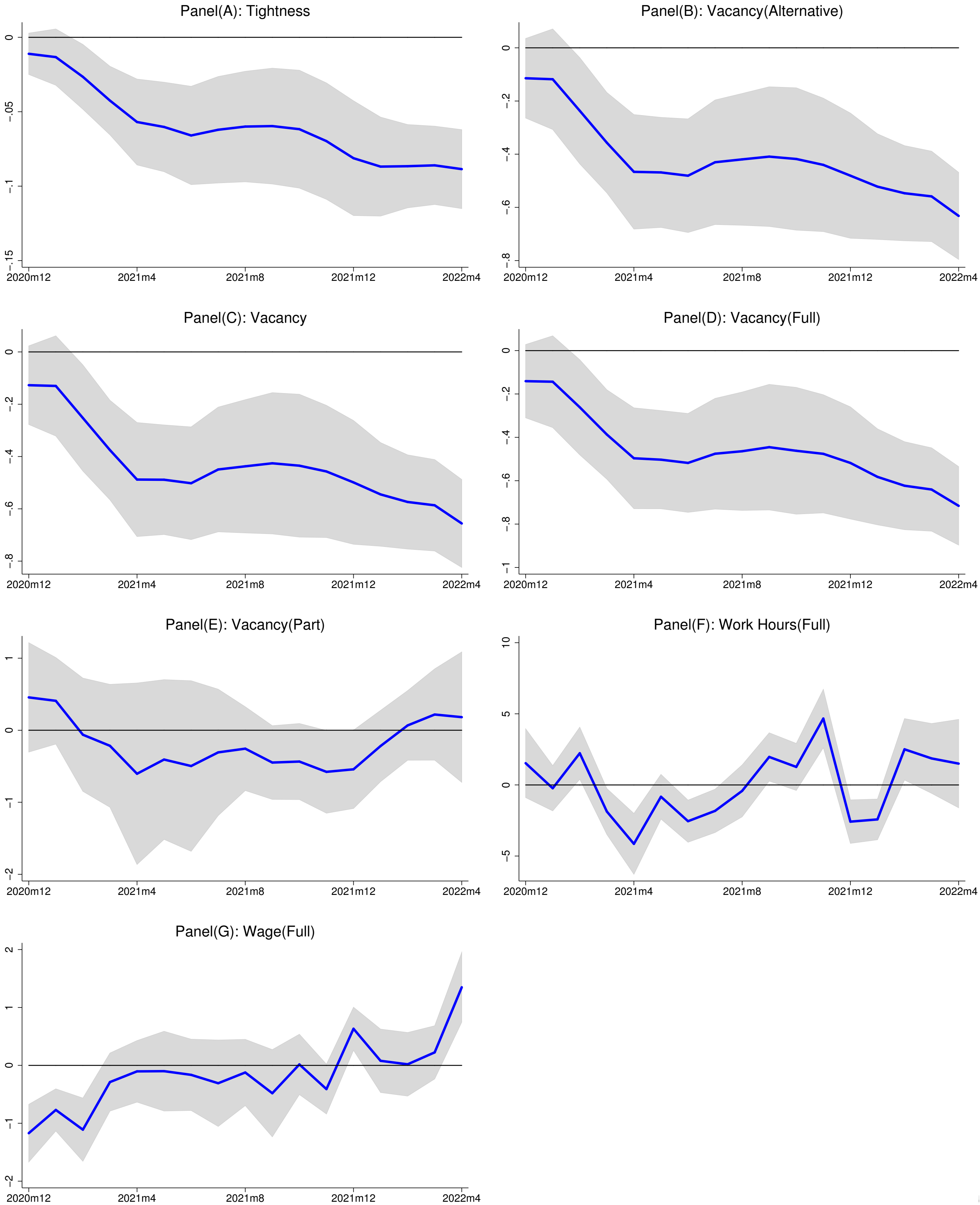
The time frame (t) spans from 2019m5 to 2020m12, and the forecast horizon (h) spans until $H-1$(2022m4), which is the most recent data available. The forecast horizon needs to be already happened at the time of the study. Therefore, the long run analysis is yet not possible. Likewise, the DD regression using LP method is not yet possible since DD uses $D_t = 1$ for the period of 2021m8$\sim$2022m04 (post-COVID). The more future data such as until 2023m4 is necessary for DD analysis.

Figures 15 show the IRFs using LP method. These are more robust than IRFs using VAR, especially when VAR is misspecified (Jordà, 2005). Therefore, LP results are more reliable than VAR, although the analysis in this paper only presents the short-run. When the share of E9 workers decreases, the the following dependent variables in the future increases: Market tightness, Vacancy(alternative), Vacancy, Vacancy(full-time), and Vacancy(part-time). These results are consistent with all of the previous analysis. Vacancy(alternative) is the one defined in Section 7.1 for the robustness check. For the full-time wage variable, it converges to zero as the time passes. This is not consistent with the DD results, where it declined when there is a negative TFW shock. Overall, the wage results seem to be not consistent throughout the analysis.

8 Conclusion

Using a quasi-experiment opportunity of TFWs' exogeneous reduction, the study found that the vacancy rose in the short run in the manufacturing sector in South Korea. Natives filled the vacant spots primarily as part-time workers, and firms have had difficulty finding full-time workers. As a consequence, the ratio of part time to full time

Figure 15: IRFs using LP



workers has surged. The analysis controlled the other potential reasons for the vacancy rise appropriately. Specifically, it controlled the unemployment insurance benefit (UIB), termination rate, and matching efficiency.

In the long run, there is a possibility that the vacancy would drop according to some existing studies as well as the search and matching model. If it happens, many firms will exit in the long run, and the industry which faces the labor shortage will decline. This implies that the labor shortage may accelerate the manufacturing deterioration. Therefore, if unskilled people outside South Korea can freely join the manufacturing sector, the sector may decline lesser dramatically. Modeling this would be interesting future research.

Based on the findings in this paper, there could be some policy implications. First, the TFW (temporary foreign workers) policy has helped alleviate the labor shortage issue in the manufacturing sector. Therefore, even if there is sentiment against foreigners among natives, the paper suggests keeping this TFW policy. Second, the government need to help match the relationship between employer-employee as the study found that the matching efficiency was one of the biggest reason for the vacancy rise. Third, unlike the USA case, where generous UIB was one of the causal reason for the recent vacancy rise (Jeong, 2022), UIB in South Korea was not the case. Therefore, a generous UIB would not harm the vacancy (and also tightness) issue in South Korea.

A Appendix: Derivation of Search and Matching Model

The notations are the same as Howitt and Pissarides (2000) and is summarized in Table 6. 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 6: 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 8, and the matching rate per one firm is Equation 9, where $\theta \equiv \frac{v}{u}$. Conventionally, $\frac{m}{u}$ is represented as q, and

$\frac{m}{v}$ is represented as θq.

$$\frac{mL}{uL} = \frac{m}{u} = a\big(\frac{v}{u}\big)^{\eta} = a\theta^{\eta} \equiv q \tag{8}$$

$$\frac{mL}{vL} = \frac{m}{v} = a\big(\frac{v}{u}\big)^{\eta-1} = a\theta^{\eta-1} \equiv \theta q \tag{9}$$

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

$$\begin{aligned}
u_{t+1}L_{t+1} - u_t L_t =& \lambda_t(1-u_t)L_t + b_t L_t - q_t u_t L_t - d_t u_t L_t \\
\Leftrightarrow u_{t+1}(1+b_t-d_t)L_t - u_t L_t =& \lambda_t(1-u_t)L_t + b_t L_t - q_t u_t L_t - d_t u_t L_t \\
\Leftrightarrow (u_{t+1}(1+b_t-d_t) - u_t) =& \lambda_t(1-u_t) + b_t - q_t u_t - d_t u_t
\end{aligned}$$

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

$$\Leftrightarrow (b_t - d_t)u_t = \lambda_t(1-u_t) + b_t - q_t u_t - d_t u_t$$

$$\Leftrightarrow u_t = \frac{\lambda_t + b_t}{\lambda_t + b_t + q_t} \tag{BC}$$

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:

$$\begin{aligned}
&\frac{F}{N} - \frac{\delta K}{N} - \frac{rK}{N} - w \\
\Leftrightarrow\ & pf(k) - \delta pk - rpk - w \\
\Leftrightarrow\ & p[\text{FDR}] - w, \text{ where FDR} \equiv f(k) - \delta k - rk
\end{aligned} \tag{10}$$

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 11. Then it can convert to an Exponential distribution as in Equation 12

$$f(x) = \frac{\lambda^x e^{-\lambda}}{x!} \tag{11}$$

$$f(t) = \lambda e^{-\lambda t} \tag{12}$$

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 13. And the probability that an event happens for the first time at time t is Equation 14.

$$f(0) = e^{-\lambda t} \tag{13}$$

$$f(t) = \lambda e^{-\lambda t} \tag{14}$$

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:

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

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

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

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.

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

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

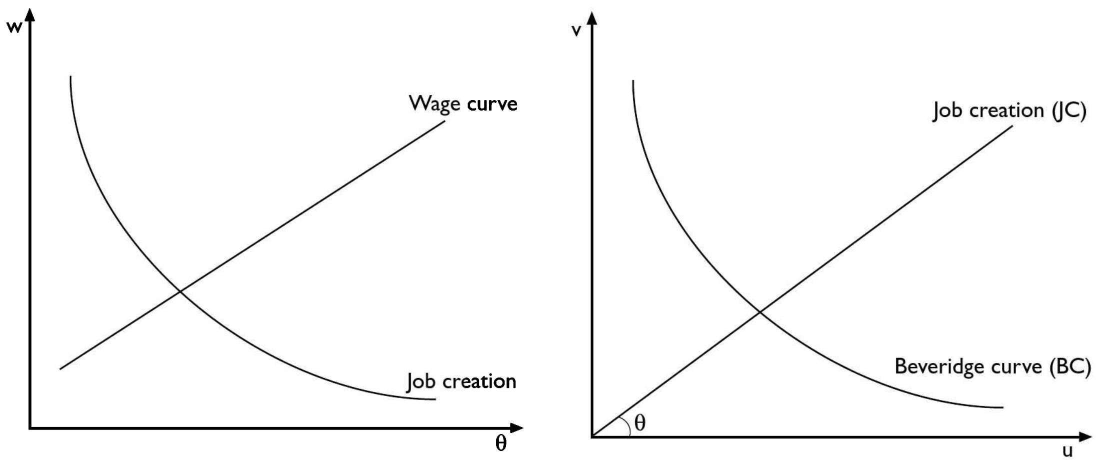
$$w = p \cdot (f(k^*) - \delta k^* - rk^*) - \frac{pc(r + \lambda + d)}{a\theta^\eta} \tag{JC}$$
$$w = z + \beta(p \cdot (f(k^*) - \delta k^* - rk^*) - z + \theta pc) \tag{WC}$$
$$v = \Big(\frac{(\lambda + b)(1-u)}{au^\eta}\Big)^{\frac{1}{\eta}} \tag{BC}$$

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 16(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 16(b).

Figure 16

(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. Let $m(u_t, v_t)$ in Equation 15 as the arrival rate of matching. This is the most frequently used one in literature.

$$m(u_t, v_t) = {u_t}^{1-\eta} {v_t}^{\eta} \tag{15}$$

Let a_t as the matching efficiency. In general, it is the inserted into Equation 15 as a form of $m(a_t u_t, a_t v_t)$.[10] The idea is that matching efficiency (a_t) is commonly shared by job seekers and employers. Therefore, the matching function becomes

$$m(a_t u_t, a_t v_t) = a_t {u_t}^{1-\eta} {v_t}^{\eta} \tag{16}$$

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 time(t) will be omitted for notational convenience throughout this section. The first step is estimating L_t, the total number of people in the labor market. Let EMP the total number of matched workers, which is available in LFSE dataset. Furthermore, EIS dataset provides u. Therefore, L can be calculated as follows:

$$\begin{aligned} \text{EMP} =& (1-u)L \\ \Leftrightarrow L =& \frac{\text{EMP}}{1-u} \end{aligned} \tag{17}$$

The second step is estimating η. Denote M as total matchings per month, which is

[10] Howitt and Pissarides (2000) has suggested dividing the matching efficiency into 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 16).

provided by LFSE dataset. From $m(au, av) = a \cdot u^{1-\eta} v^{\eta}$, it follows that

$$\begin{aligned}
M &= m(au, av)L \\
\Leftrightarrow \frac{M}{uL} &= \frac{m(au, av)}{u} \\
\Leftrightarrow \frac{M}{uL} &= a \cdot \theta^{\eta}, \text{where } \theta \equiv \frac{v}{u} \\
\Leftrightarrow \ln\left(\frac{M}{uL}\right) &= \ln(a) + \eta \ln(\theta) \\
\Leftrightarrow \ln\left(\frac{M}{uL}\right) &= \ln(a_0) + \eta \ln(\theta) + \ln(\varepsilon) \qquad (18)
\end{aligned}$$

The last equation is the regression model, where each manufacturing sector can estimate η. Then matching efficiency, a, follows by:

$$\begin{aligned}
M &= m(au, av)L \\
\Leftrightarrow M &= a \cdot u^{1-\eta} v^{\eta} L \\
\Leftrightarrow a &= \frac{M}{u^{1-\eta} v^{\eta} L}.
\end{aligned}$$

The above method is the basic calibration method. However, it has an endogeneity issue: In Equation 18, the past market tightness(θ) may affect the current number of matching(M), and vice versa. In other words, if finding workers was tighter in the past, then it may increase(or decrease) the matching. As a result, the error term is correlated with the market tightness, resulting in biased estimation of η.

To correct this biasedness, Borowczyk-Martins et al. (2013) proposed a method using an ARMA process.[11] They impose an ARMA structure on matching efficiency as in Equations 7 and 8 of their paper. Using this ARMA structure, they transform from Equation 18 in my paper to Equation 9 in their paper. Then they estimate the transformed equation by the generalized method of moments (GMM), using lags of the labor market tightness and/or the job finding rate as instrumental variables.

D Appendix: Tables and Figures

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

Table 7: 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 8: 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

References

Philipp Adämmer. Lpirfs: An R package to estimate impulse response functions by local projections. *The R Journal (2019)*, 11(2):421–438, 2019.

L Jason Anastasopoulos, George J Borjas, Gavin G Cook, and Michael Lachanski. Job Vacancies and Immigration: Evidence from the Mariel Supply Shock. *Journal of Human Capital*, 15(1):1–33, 2021. ISSN 1932-8575.

Juan Antolín-Díaz and Juan F Rubio-Ramírez. Narrative sign restrictions for SVARs. *American Economic Review*, 108(10):2802–29, 2018a. ISSN 0002-8282.

Juan Antolín-Díaz and Juan F Rubio-Ramírez. Replication data for: Narrative sign restrictions for SVARs. *American Economic Association*, 2018b. ISSN 0002-8282. doi: 10.3886/E113168V1.

Regis Barnichon and Andrew Figura. The determinants of the cycles and trends in US unemployment. *Unpublished manuscript, CREI*, 2012.

Burt S Barnow, John Trutko, and Jaclyn Schede Piatak. *Conceptual Basis for Identifying and Measuring Occupational Labor Shortages*, volume 1. 2013. ISBN 978-0-88099-413-2.

Daniel Borowczyk-Martins, Gregory Jolivet, and Fabien Postel-Vinay. Code and data files for "Accounting For Endogeneity in Matching Function Estimation", 2012.

Daniel Borowczyk-Martins, Grégory Jolivet, and Fabien Postel-Vinay. Accounting for endogeneity in matching function estimation. *Review of Economic Dynamics*, 16(3):440–451, 2013. ISSN 1094-2025.

Max Breitenlechner, Martin Geiger, and Friedrich Sindermann. ZeroSignVAR: A zero and sign restriction algorithm implemented in MATLAB. *Unpublished manuscript. Innsbruck: University of Innsbruck*, 2019.

Andri Chassamboulli and Theodore Palivos. A search-equilibrium approach to the effects of immigration on labor market outcomes. *International Economic Review*, 55(1):111–129, 2014. ISSN 0020-6598.

Amelie F Constant and Bienvenue N Tien. Germany's immigration policy and labor shortages. *IZA, DP*, 41(November), 2011.

Peter A Diamond. Wage determination and efficiency in search equilibrium. *The Review of Economic Studies*, 49(2):217–227, 1982. ISSN 1467-937X.

Michael W L Elsby, Ryan Michaels, and David Ratner. The Beveridge curve: A survey. *Journal of Economic Literature*, 53(3):571–630, 2015. ISSN 0022-0515.

Philip Hans Franses. Seasonality, non-stationarity and the forecasting of monthly time series. *International Journal of forecasting*, 7(2):199–208, 1991. ISSN 0169-2070.

Eric Ghysels and Pierre Perron. The effect of seasonal adjustment filters on tests for a unit root. *Journal of Econometrics*, 55(1-2):57–98, 1993. ISSN 0304-4076.

B. Herrendorf, R. Rogerson, and T. Valentinyi. *Growth and Structural Transformation*, volume 2. 2014. doi: 10.1016/B978-0-444-53540-5.00006-9.

Peter Howitt and Christopher A. Pissarides. *Equilibrium Unemployment Theory.* MIT press, 2000. ISBN 0-262-26406-4. doi: 10.2307/2555075.

Zainab Iftikhar and Anna Zaharieva. General equilibrium effects of immigration in Germany: Search and matching approach. *Review of Economic Dynamics*, 31:245–276, 2019. ISSN 1094-2025.

Deokjae Jeong. Causal analysis of the vacancy rise in the USA during COVID-19 (working paper). 2022.

Òscar Jordà. Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182, 2005. ISSN 0002-8282.

Òscar Jordà, Moritz Schularick, and Alan M Taylor. Betting the house. *Journal of International Economics*, 96:S2–S18, 2015. ISSN 0022-1996.

Takehiro Kiguchi and Andrew Mountford. Immigration and unemployment: A macroeconomic approach. *Macroeconomic Dynamics*, 23(4):1313–1339, 2019. ISSN 1365-1005.

Sabine Klinger and Enzo Weber. Decomposing Beveridge curve dynamics by correlated unobserved components. *Oxford Bulletin of Economics and Statistics*, 78(6):877–894, 2016. ISSN 0305-9049.

Kyu-Yong Lee. Unauthorized Foreign Residents and Employment Status (외국인 비합법 체류 및 고용실태). *Korea Labor Institute*, pages 30–49, 2020.

Mu Song Lim. The Actual Conditions of Illegal Employment and Countermeasures for Foreign Workers: Focusing on the case of Nonsan City (외국인근로자 불법취업 실태와 대응방향: 논산시 관내 실태조사 결과를 중심으로). *Korean Journal of Immigration Policy and Administration*, 4(1):79–103, 2021. ISSN 2508-5182. doi: 10.46894/kaipa.2021.4.1.4.

X. Liu. On the macroeconomic and welfare effects of illegal immigration. *Journal of Economic Dynamics and Control*, 34(12):2547–2567, 2010. doi: 10.1016/j.jedc.2010.06.030.

Martin Ruhs and Bridget Anderson. Who Needs Migrant Workers? 2019.

Dale T Mortensen and Christopher A Pissarides. Job creation and job destruction in the theory of unemployment. *The review of economic studies*, 61(3):397–415, 1994. ISSN 1467-937X.

Michael T Owyang, Valerie A Ramey, and Sarah Zubairy. Are government spending multipliers greater during periods of slack? Evidence from twentieth-century historical data. *American Economic Review*, 103(3):129–34, 2013. ISSN 0002-8282.

Juan F Rubio-Ramirez, Daniel F Waggoner, and Tao Zha. Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, 77(2):665–696, 2010. ISSN 1467-937X.

Stefan Schiman. Labor supply shocks and the Beveridge Curve — Empirical evidence from EU enlargement. *Review of Economic Dynamics*, 40:108–127, 2021. ISSN 10942025. doi: 10.1016/j.red.2020.09.005.

Madeleine Sumption. Filling Labor Shortages through Immigration : An Overview of Shortage Lists and their Implications. (February):1–9, 2011.

Harald Uhlig. What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419, 2005. ISSN 0304-3932.