How the reduction of Temporary Foreign Workers led to a rise in vacancy rates in the South Korea*

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1 Introduction

The South Korean government allows for an inflow of low-skilled temporary foreign workers (TFWs) only when there is a labor shortage. This TFW policy is grounded in the notion that accepting TFWs helps to alleviate employers' difficulties in finding low-skilled workers. Opponents of the TFW policy, however, argue that TFWs are reducing the employment opportunities for natives. It is therefore important to study whether the opponents' arguments are valid. If a labor shortage arises when there is a reduction in TFWs, it would imply that natives are not able to fill the jobs appropriately.

The first step of this study is to define a labor shortage. The literature has actively discussed this 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 that the issue of unfilled vacancies is an important component. Unfilled vacancy (vacancies, in short)

[0]It is possible to replicate all of the results using a Stata code below: https://raw.githubusercontent.com/jayjeo/public/master/LaborShortage/LScode.do

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measure the degree of how difficulty it is for employers to find workers. Vacancies in this study follow the same definition of 'job openings' used in the JOLTS (Job Openings and Labor Turnover Survey). This definition refers to: "positions that are open on the last business day of the reference month, and the job could start within 30 days." In sum, this study will use vacancies as a proxy to measure the labor shortage. Furthermore, this study defines 'vacancy rate' as $\frac{\text{Number of unfilled vacancies}}{\text{Number of employees}} \times 100$.

This paper studies the impact of a drop in low-skilled TFWs on vacancies of manufacturing sectors in South Korea in the short run (two years). One of the difficulties in the study is reverse causality. The South Korean government accepts TFWs based on the vacancy measure. Therefore, vacancies also affect the number of TFWs. One way to overcome this issue is by using a quasi-experimental event. Starting in January 2020, the government initiated a quarantine policy in response to the COVID-19 pandemic. As a result, TFWs who were already contracted by employers, and were ready to enter South Korea were suddenly forbidden from entering (Figure 1(a)). This event was unrelated to the vacancy measure, so it naturally provides a quasi-experimental opportunity to study the causal effect.

The proportion of TFWs to total workers dropped from 10.44% (2019m12) to 8.21% (2021m12), as shown in Figure 1(b). TFWs in the South Korean manufacturing sectors mainly consist of E9, F4, and H2 visa holders, as shown and defined in Table 1. Among foreign workers, E9 workers make up 53%. As only E9 workers are closely administered at a two-digit manufacturing sector level, this study will use E9 workers as a proxy for TFWs.

The make-up of H2 and F4 visa holders is similar to that of E9 visa holders. In Figure 2(a), the manufacturing sectors that have a higher proportion of TFWs also have a higher proportion of E9 workers. Therefore, it is appropriate to use E9 workers as a proxy for TFWs. Figure 2(b) plots the proportion of E9 workers against the total workers in each two-digit manufacturing sector. Sectors that have heavily relied on E9 workers have recently experienced a significant decline in E9 workers, while other sectors have not. This observation provides continuous treatment intensity for the difference in difference (DD) framework.

The aforementioned treatment intensity is in line with the shift-share instrument (Bartik, 1991). The pre-COVID share of E9 workers is equivalent to 'share', and the reduction of aggregate E9 workers after pandemic corresponds to 'shift'. Therefore, the treatment intensity of E9 workers serves as the shift-share, which is uncorrelated with unobserved sector-specific effects during the pandemic. Goldsmith-Pinkham et al. (2020) discuss how the identification of the shift-share instrument comes from the 'share' part: using the shift-share instrument is equivalent to using local 'shares' as the instrument. Therefore, it is valid for this paper to use the 'share' part, which corresponds to the share of E9 workers before the onset of COVID. Furthermore, Jaeger et al. (2018) against using the shift-share instrument when the country origin of the inflow of foreign workers is so similar over time. Since this paper uses a sudden shock —the COVID-19 pandemic— at the national level, it meets the validity condition that Jaeger et al. (2018) posed.

Meanwhile, the identification of DD crucially depends on the assumption that a single event is the only difference between the control and treated. If this is not the case —that is, if any other events differ by sectors and time during the period after this single event— the identification of DD will fail. Unfortunately, COVID-19 has had a variety of impacts on the South Korean economy. There are some possible factors that could have caused the vacancy rate rise in South Korea: 1) *unemployment insurance benefits*, 2) *labor demand shock*, and 3) *excess retirement*. These potential factors will be properly handled throughout the remainder of this paper to claim a reasonable causality. The aforementioned factors are discussed in Section 4 in detail.

DD regressions show the following results. The sectors that heavily relied on TFWs encountered a large increase in vacancies a year after the onset of the COVID-19 pandemic (Figure 2(c)). These sectors have historically featured an intense workload; the sectors with a heavy reliance on TFWs include a higher monthly average of working hours. Therefore, when the vacancy issues arose, these firms could not increase the number of working hours, as they were already at a maximum. Furthermore, 90.19% of TFWs were full-time workers before COVID-19 (as of 2019h2).[1] After COVID-19, firms that heavily relied on TFWs have faced difficulties in finding full-time workers, while finding part-time workers was easier. Consequently, the ratio of part-time to full-time workers has significantly increased. A full-time worker is defined as having a contract lasting longer than a year or indefinite term; a part-time worker has a contract that for less than a year. Their characteristics are distinct, especially in separation rate. As of 2019m8, the monthly separation rate of full-time workers is 1.9%, while that of part-time workers is 43.6%. This implies that part-time workers quit their jobs more frequently than full-time workers, resulting in a shorter period of continuous services and lesser proficiency on jobs. Reading these results together, this paper concludes that natives could not replace E9 workers after the COVID-19 pandemic, especially as a form of full-time workers.

In addition to DD regression analysis, the paper explores Impulse Response Function (IRF) using Structural Vector Autoregression (SVAR) and the Local Projection (LP) method. The results are consistent with all of the aforementioned results. The reason for adding the LP approach is that there is a growing literature on this method as a replacement for the SVAR. Moreover, the LP approach has many advantages that the SVAR approach does not. For instance, the LP approach can incorporate the DD approach as well as panel settings. The identification assumption for the LP method

[1]Source: Survey on Immigrants' Living Conditions and Labour Force

is the exogeneity of $\text{E9SHARE}_i \cdot D_t$ in Equation 5. Since E9SHARE_i is the 'share' part, which is exogenous, it meets the identification criteria.

The search and matching model outlined by Howitt and Pissarides (2000) explains the trajectory of vacancies when there is an influx of foreign workers. In the short-run, firms cannot enter and exit the labor market (Figure 3(a)). As a result, the vacancy rate *drops* in the short run. However, in the long-run, potential firms outside the labor market enter, as they expect increased profit by matching more people to jobs. As a result, the vacancy rate *rises*, as shown in Figure 3(b).

Through a careful review of existing literature, it is possible to identify four relevant empirical studies. First, Anastasopoulos et al. (2021) found that labor inflow from Mariel Boatlift in Miami led to a vacancy *drop*. On the contrary, Schiman (2021) showed that labor inflow to Austria due to EU enlargement led to a 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 Section 3.

Although the findings of the search and matching model (Howitt and Pissarides (2000)) as well as the first three empirical studies (Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019)) may initially seem contradictory, they are actually consistent: when there is a positive shock of foreign workers, the vacancy rate *drops* in the short-run, *bounces up* in the long-run, and finally converges to *zero*. Therefore, finding and identifying this consistency is one more contribution to the literature made by this paper. This paper will further contribute to the existing literature by providing analysis results using DD, SVAR, and LP approaches: when there is a negative shock of foreign workers, the vacancy rate *surges* in the short-run, *drops* in the long-run, and finally converges to *zero*.

The structure of the paper proceeds as follows: Section 2 goes deeper into the search and matching model. It explains the short- and long-run theories when there is an influx of foreign workers. Section 3 provides detailed explanations for the empirical literature discussed in Introduction. Section 4 discusses other possible factors —aside from the reduction in TFWs— that caused a rise in vacancies. Section 5 identifies two distinct phases during the COVID-19 pandemic: the first is a Shock Phase (2020m1-2020m4) and the second is a Recovery Phase (2020m5-2022m1). This paper will focus on the Recovery Phase. Section 6 explains background information about TFWs in South Korea, as it helps to detail the underlying implications of the analysis. Section 7 presents various datasets that the paper will use. Section 8 sets out the empirical model (DD, SVAR, and LP) and identification assumptions. Then it provides the results. Section 9 checks the robustness of the main results, and Section 10 offers concluding thoughts.

2 The Search and Matching Model

Following Howitt and Pissarides (2000), Appendix B carefully derives the steady-state equilibrium of the search and matching model. This steady-state equilibrium assumes an extremely fluid capital adjustment (long-run), as is usual for any standard search and matching models. There are numerous versions of the search and matching models, including in Howitt and Pissarides (2000), Elsby et al. (2015), Diamond (1982), and Mortensen and Pissarides (1994), but all these versions implicitly assume extremely fluid capital. Therefore, the search and matching model is more relevant for long-run analysis. This is true even in instances of dynamic analysis (out of steady-state). Dynamic analysis studies how an out of steady-state converges with a unique path to create a new steady-state equilibrium under conditions of extremely fluid capital. The curved arrow line in Figure 3(b) depicts this unique path.

The model explained in Appendix B can predict the trajectory of vacancies when there is an influx of foreign workers (Table 8 summarizes notations). The influx of immigrants leads to the birth rate (b) increase. In the long-run, the model predicts as in Figure 3(b). Many firms enter the labor market as they anticipate the increased availability of people. Consequently, the Beveridge curve (BC) moves *outward*, and the vacancy rate *rises* (Figure 3(b)).

Although the search and matching model is more suitable for long-run analysis, it can also analyze short-run consequences. In the short-run, firms cannot enter the labor market. Furthermore, many people are searching for jobs. Therefore, the vacancy rate *drops* according to the search and matching model. Formally speaking, k^* from Equation k does not change unless $f(\cdot),\ r,$ or δ change (see Appendix B for notations). K^* is also fixed in the short run. In the short run, when there is a labor supply shock such that N changes, the only way to achieve k^* is to recover the initial N^*. For instance, if there is an influx of labor so that N increases, the vacancy rate should *drop*.

This section has introduced a theoretical model that describes a trajectory of vacancy rates when there is an influx (or outflow) of foreign workers. The next section explores the existing relevant empirical literature.

3 Literature Review

As noted in the Introduction, I have identified four empirical studies that outline the effects of immigration on vacancies: (Anastasopoulos et al. (2021), Schiman (2021), Iftikhar and Zaharieva (2019), and Kiguchi and Mountford (2019)). To begin, Anastasopoulos et al. (2021) study job vacancies related to the Mariel Boatlift event. The Mariel Boatlift occurred between April and October, 1980, and the influx of refugees lasted about two years until many left Miami to go to other cities. The authors used DD regression, as seen in Equation 1 in their paper. Table 1 in their paper reports the regression results. Comparing the synthetic control and Miami treated (Figure 3 Panel A of their paper), vacancies in Miami declined by over 20% in 1981-1982, and over 40% in 1985. The figure shows that —when there was an influx of refugees— the vacancy rate *dropped* until 1988, then *bounced up* from 1988, and converged to *zero* from 1990 onwards.

Meanwhile, Schiman (2021) studied the impact of foreign labor inflow from Eastern European countries into Austria due to EU enlargement. The labor influx began in 2004 and accelerated from 2011 onwards (Figure 2 in his paper). Unlike the Mariel event, the mass migration to Austria persisted for over a decade, and is ongoing. He used Structural Vector Autoregression (SVAR) with sign restrictions for the study. His findings are presented in Figure 5 of his paper. When there is a foreign inflow shock, (1) unemployment increases both in the short- and long-run for ten years; (2) vacancy rate *drops* in the first three years, then *bounce up* for another three years, and then eventually converges to *zero*. His study has two more findings that are provided in the footnotes.[2]

Literature about the effect of immigration on vacancies using the search and matching framework is rare. However, one exception can be found in the work of Chassamboulli and Palivos (2014), although they focus on unemployment and wage outcomes rather than the vacancy rate. The same applies to Liu (2010). Therefore, the most relevant study to focus on vacancies is the work of Iftikhar and Zaharieva (2019). They analyze the impli-

[2]His 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 a labor supply shock of foreign workers (not due to reallocation, aggregate activity, or domestic labor supply shocks). His third finding is included in 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.

cations of a 25% increase in immigrants in Germany from 2012-2016. Table 9 of their paper summarizes the analysis results. After the 25% increase in immigration, they identify that low-skilled immigrants suffered more unemployment than low-skilled natives, especially in the manufacturing sector. Meanwhile, the manufacturing firms expected higher profits due to an increased number of high-skilled immigrants, so firms increased their job posting (vacancies) — then, the average duration of vacancies almost tripled. It is of interest that their results show the vacancy rates *rise*. The reason for this rise is that their model relies on a long-run assumption (with fluid capital movement). They calculated the effect of the post-2016 steady-state equilibrium due to the immigrant inflow during 2012-2016. In other words, they analyzed the effect of an increase in immigrants during 2012-2016 on the steady-state equilibrium (in the long run) using the search and matching model.

Meanwhile, Kiguchi and Mountford (2019) studied the impact of immigration on economic outcomes, particularly on unemployment and vacancy rates, using annual data from the United States from 1950 to 2005. Their simulation consists of three scenarios.[3] In terms of vacancy rate simulation, none of their three scenarios is consistent with the pattern discussed in the Introduction. For instance, the vacancy rate in the second scenario *drops* in the short run and converges to zero, but never *bounces up* in the long-run.

To summarize this section, the three studies that have been discussed identify a consistent vacancy pattern (Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019)). The same can be said of the search and matching model (Howitt and Pissarides (2000)) (although

[3]The baseline scenario assumes that 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).

one exception is the study by Kiguchi and Mountford (2019)). When there is a positive shock in the foreign workers, the vacancy rate *drops* in the short-run, *bounces up* in the long-run, and finally converges to *zero*.

4 Confounding Factors

COVID-19 has had a variety of impacts on the South Korean economy. There are some possible factors that could have caused the vacancy rate rise in South Korea: 1)*unemployment insurance benefits*, 2)*labor demand shock*, and 3) *excess retirement*. Throughout the paper, these confounding factors are appropriately added as control variables.

Unemployment insurance benefits: the government increased unemployment insurance benefits (UIB) to help recipients cope with the pandemic (Figure 6). Larger UIB, however, may encourage people to be economically inactive (that is, less desperate to search for other jobs). Since UIB is available as a panel dataset, it could be added as a control variable.

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

Excess retirement: The paper measures *excess retirement*, the actual trend of retired people minus a trend of the absence of COVID-19. Figure 4(a) shows that *Excess retirement* did not happen in this period, and rather, that fewer people have retired. Meanwhile. the trend extrapolation may not be accurate. Therefore, Figure 4(b) shows the following alternative estimation: first, in each five years (age) cohort, calculate the probability of retirement in the year 2019 (before COVID-19). Second, multiply this probability by the actual population after COVID-19. The result is similar to that of the trend extrapolation. Therefore, it confirms that *Excess retirement* did that happen. Throughout this paper *Excess retirement* is not included as a control variable.

5 Time Frame

It is possible to identify two distinct phases during the COVID-19 pandemic (Figure 5). The first is a Shock Phase (2020m1-2020m4) and the second is a Recovery Phase (2020m5-present). In the United States, these two phases are even starker (Figure 5(b)). Most of the existing studies about the COVID-19 pandemic focus on the Shock Phase (Borjas and Cassidy (2020); Mongey et al. (2020); Cajner et al. (2020); Coibion et al. (2020); Forsythe et al. (2020)). Studies that focus on the Recovery Phase are relatively rare (Bishop and Rumrill (2021); Alvarez and Pizzinelli (2021); Handwerker et al. (2020)). To date, few studies distinguish the two phases and analyze them separately (Rothstein and Unrath (2020); Goda et al. (2021)). This paper focuses on the Recovery Phase.

6 Background Information about TFWs

It is important to explain who the foreign workers in South Korea are. While a detailed explanation is included in Appendix A, this section briefly summarizes their principle characteristics.

The most important criteria for E9 visa applicants is the Korean language test score: most E9 workers can speak Korean at the elementary level. When admitted, E9 workers will enter South Korea only as full-time workers. Moreover, they are required to leave the country after three years, which means that gaining permanent residency is almost impossible for them. They are not allowed to change the establishment location (their workplace), and they are supposed to leave South Korea immediately if they are fired. This rule means that they cannot receive unemployment insurance benefits.

Meanwhile, F4 and H2 visa holders are Korean descendants, who are fluent in the Korean language. They are often a good substitute for domestic workers in workplaces where communication is necessary, for example in the service sector. This is the reason why many H2 and F4 visa holders work in the service sectors.

The issue of unauthorized workers would impact the validity of this paper. Lee (2020) estimates the number of unauthorized foreign residents in 2020. According to his findings, the number of unauthorized E9, H2, and F4 visa holders is small. Among the unauthorized foreign residents in 2020, 43.8% fall within the Visa Exemption category (B1), 20.1% have Temporary Visit visas (C3), 12.0% are from the Non-professional Employment category (E9), and 0.7% are from the Working Visit category (H2). For instance, while people from the Visa Exemption category (B1) can easily enter South Korea without acquiring visas, they should not work and cannot stay long. However, many of them illegally work and reside in the country longer than allowed. Another example is that people in the Non-professional Employment category (E9) are allowed to work only for three years, but some of them stay longer than allowed.

Furthermore, Lim (2021) uses their own survey in one city in South Korea and estimates the number of illegal foreign workers. They found that illegal foreign workers are prevalent in the agricultural sector because the government does not supervise this sector. On the contrary, the government supervises and strictly enforces the law in the manufacturing sector. Therefore, the question of unauthorized workers is less relevant to the manufacturing sector, which leads me to believe that the validity of this paper is not at risk.

7 Data

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

The LFSE provides data about employment, vacancy, matching, and separation variables. The LFSE is a South Korean version of the Job Openings and Labor Turnover Survey (JOLTS), and replicates the list of variables and definitions from the latter survey. It is a monthly survey and includes a sample size of 50,000 establishments with more than one worker (including full-time and part-time workers). As the LFSE replicates the JOLTS, the definitions of variables are the same. For instance, vacancies in the LFSE correspond to job openings in the JOLTS, matching corresponds to hires, and separation corresponds to separations. As with the JOLTS, the individual-level microdata in the LFSE is not made available to the public. One difference between the two surveys, however, is that the LFSE provides the variables in a variety of categories. For example, the employment, vacancies, matching, and separation variables are provided in two-digit detailed industrial categories. This enables analysis by detailed sectors inside the manufacturing sector. Also, it offers both full-time and part-time categories.

The 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, as the KEIS strictly supervises the monthly flow of E9 visa holders. In other words, the supervision allows to track the detailed number of monthly E9 workers in two-digit industrial categories. Although the EPS also provides the data for H2 visa holders, it is unreliable, because only about 10% of H2 workers voluntarily report to the EPS system.

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

The EAPS provides the unemployment rate. It is a South Korean version of the United States' Current Population Survey (CPS). It replicates the list of variables and definitions from the CPS. Therefore, the structure is the same as the CPS, and definitions for most of the variables are the same as those used in the CPS. The EAPS has an annual supplementary survey which is similar to March supplements (CPS ASEC). The EAPS only provides wage variables annually. One major difference between the CPS and the EAPS is that the latter does not include any variables that can distinguish between natives and foreigners. Formally, the EAPS does not exclude foreigners when it samples, but in practice, most of its samples are natives. Therefore, the EAPS can be thought of as a survey that offers data about natives. Another big difference from the CPS is that the EAPS does not easily offer panel id to the public; the repeated cross-sectional analysis is only accessible through a secured facility.

The EAPS asks the unemployed or inactive respondents about their previous job information, including the type of industrial sectors in which they worked. Assuming that most people are looking for jobs in the same industrial sectors in which they previously worked, it is possible to calculate the unemployment rate by industrial sectors. Like the EAPS, the USA and Canada also provide the unemployment rate through this method of surveying.[4]

The shortcoming of the EAPS is that it only provides unemployment rates for large industries, including agriculture, manufacturing, and the

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

service sector. In contrast, the EIS provides information about the recipients of unemployment insurance (UI) within a broader and more detailed category of industries.[5] Subscript i represents twenty subgroups of manufacturing industries, as shown in Table 6. Figure 6 shows that the unemployment and UI rates are serially correlated. Therefore, the rate of UI benefits[6] is a good proxy for the unemployment rate. Unfortunately for my research, there was a time break from 2019m10 because of changes in the UI policy in South Korea. During this time, the policy became more generous in order to help people overcome hardships in the context of the COVID-19 pandemic. The red line is the actual UI rate, and the study adjusted it by a dummy regression, where $D_t = 1$ after the UI policy change from 2019m10. In conclusion, this paper will use adjusted UI benefits rate as a proxy for u_i (unemployment rate for the two-digit manufacturing sectors).

Throughout its analysis, this paper uses seasonal adjustment using seasonal dummies. When showing a figure, the paper sometimes uses a Hodrick-Prescott (HP) filter for readability. However, the paper never uses X-13 ARIMA-SEATS Seasonal Adjustment. Seasonal differencing using ARIMA needs to be performed with care, and it should be done when there is a clear indication that the seasonality is stochastic rather than deterministic. Franses (1991) warns against automatically using the seasonal differences method, as 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]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 $= \frac{\text{UI recipients}}{\text{Employed+UI recipients}}$

8 Results

8.1 DD Results

Equation 1 shows the difference in difference (DD) regression model for an instrumental variable estimation with the just-identified case.

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

Subscript i is manufacturing sectors, and t is monthly time. S_i and T_t are sector and time fixed effects, respectively. To account for the serial correlation, the model uses fixed effect assumption with the sector clustered. Accordingly, 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 for a continuous variable. It varies by sectors (i) but is constant across time (t). D_t is a dummy for a DD regression, where $D_t = 0$ for the period of 2018m4∼2019m12 (pre-COVID), and $D_t = 1$ for the period of 2021m1 $\sim$ 2022m09 (post-COVID). The period between 2020m1 and 2020m12, the Shock Phase, is omitted for two reasons: firstly, there was a large production shock right after the onset of the pandemic, and it was necessary to avoid this shock, and secondly, the rise in vacancies needed some time to become effective (due to a time lag).

Prior to showing the instrumental variable estimation in Table **??**, the paper includes Table **??**, a reduced form estimation that directly uses the instrumental variable as an explanatory variable.

In Table **??**, the research interests are the coefficients of $\mathrm{E9CHG}_i \cdot D_t$, which represents the interaction term for DD. It is instrumented by $\mathrm{E9SHARE}_i \cdot D_t$. The dependent variables for Tightness, Vacancy, Vacancy(Full), Part/Full, and wage(Full) are statistically significant. For instance, the coefficient of -0.341 in the second column means that the industrial sectors that experienced one unit decrease of E9 workers had 0.341 increase in vacancies. TFWs did not decrease by one unit, but actually decreased by 0.02. Therefore, two percent exogenous decrease of workers led to 0.682%p increase in vacancies ($0.341 \times 0.02 = 0.00682$).

Equation 2 is a reduced form of DD regression model for Figure 7. X_{it} are the same control variables as in the previous equation.

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

The figures are consistent with the regression results in Table **??**. In concert, the figures and tables imply that it was challenging to find workers after the pandemic. One potential issue 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. In this case, the rise in the vacancy rate does not necessarily reflect that conditions are more difficult for finding workers. Indeed, the decrease in unemployed people can also affect the difficulty of finding workers. Therefore, a more relevant variable —one that identifies this difficulty— is that related to market tightness, defined by $\frac{\text{Vacancy rate}}{\text{Unemployment rate}}$. In the figures and tables, market tightness increases when the foreign workers are reduced more than before. Accordingly, we can interpret that it was indeed challenging to find workers.

Panel F of the figure shows that the sectors with a higher number of TFW workers also feature higher work hours. In 2021, the legal maximum number of work hours was 174 per month. If these include overtime payments, the legal maximum is 226 hours. The figure shows that sectors with higher dependence on TFWs also require a number of work hours that is closer to the legal maximum. It implies that these sectors have tough working conditions. While these sectors do not experience difficulties in hiring part-time workers (Panel D), they do have troubles when it comes to finding full-time workers (Panel C). Consequently, the ratio of part-time workers to full-time workers increases significantly in these sectors (Panel E). Manufacturers do not respond to this difficult situation by raising wages (Panel G) or extending working hours (Panel H). A possible explanation here could be that they have already reached the maximum number of working hours, and that they do not have the ability to offer higher wages due to competition with the lower-wage countries. Another explanation could be the sticky wage.

Figure 8 shows the increasing proportion of part-time jobseekers. 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 be attributed to the increasing trend of part-time applicants. In the figure, the total number of jobseekers and the number of below-tertiary seekers does not differ much. Occupation=8 seekers are those who belongs to 'Installation, maintenance, and manufacturing works' in the Korean Employment Classification of Occupations (KECO). The full classification of KECO is provided in Table 7.

8.2 IRF using SVAR with Sign Restrictions

Structural VAR includes current period variables in the explanatory side (Equation 3), where Y_t is a vector of n endogenous variables. B_0Y_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 $\mathbb{E}(\varepsilon_t\varepsilon_t')$.

$$
\begin{aligned}
& Y_t = B_0 Y_t + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + \varepsilon_t && (3) \\
\Leftrightarrow & (I - B_0) Y_t = B(L) Y_t + \varepsilon_t \\
\Leftrightarrow & Y_t = (I - B_0)^{-1} B(L) Y_t + (I - B_0)^{-1} \varepsilon_t \\
\Leftrightarrow & Y_t = A_1 B(L) Y_t + \epsilon_t \ \text{, where } \ \epsilon_t = (I - B_0)^{-1} \varepsilon_t && (4)
\end{aligned}
$$

Equation 3 is converted to Equation 4, a reduced form, in order to estimate the coefficients using OLS. However, the variance-covariance matrix of ϵ_t is no more diagonal, but rather, is contemporaneously correlated. Therefore, the innovations of ϵ_t lack a structural interpretation (Breitenlechner et al., 2019). A general approach to recovering the structural information in Equation 4 would be to use the Cholesky decomposition of the covariance matrix $\mathbb{E}(\epsilon_t \epsilon_t')$. However, this solution imposes too strong of an assumption that a specific variable shock does not have a current effect on another variable (and rather, depends on ordering). Consequently, there are some alternative methods that rely less strongly on this assumption. One method would be to use sign restrictions by Uhlig (2005), and another would be to use the Local Projection (LP) method suggested by Jordà (2005). The results using the LP method will be discussed in a separate section.

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

The purpose of this subsection is to provide a comparison figure to Figure 5 in Schiman (2021)'s paper. Therefore, Figure 9 uses exactly the same settings as Schiman (2021). Specifically, shocks, included variables, the sign and narrative restrictions, and the lag length ($l = 6$) are the same. Figure 9 uses 120 months (10 years) as a forecast horizon. The sign and narrative restrictions used in this paper[7] are provided in Table 5. Also, the TFW supply shock is the most important contributor to TFW (Type A restriction by Antolín-Díaz and Rubio-Ramírez (2018a)). In short, every setting is the same as Schiman (2021).

Figure 9 shows IRFs over ten years, using the monthly dataset that ranges from 2012m1 to 2022m3 (123 observations). The wide area is 68% error band, as is considered standard. The figure shows that when there is a *negative* TFW shock, vacancy rate *rises* in the short run (three years), *drops* in the long run (although it is not significant in this case), and converges to *zero* eventually. This is consistent with the results in existing literature.

8.3 IRF using the Local Projection Method

Jordà (2005) proposed the Local Projection method (LP), which is an alternative method for SVAR. Indeed recently, LP has become a more popular method than SVAR. One of the advantages of LP is its flexible applications to situations 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)). Furthermore, LP can be applied to the difference in difference (DD) settings. Moreover, LP is more robust than VAR, especially when VAR is misspecified (Jordà, 2005). In sum, LP results are more reliable than VAR because this paper has DD

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

settings with panel dataset.

Equation 5 is for the LP estimation, and uses effectively the same setting as the DD regression (Equation 1). The identification assumption for LP method is the exogeneity of $\text{E9SHARE}_i \cdot D_t$ in Equation 5. Since E9SHARE_i is the 'share' part, which is exogenous, it meets the identification criteria. 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, as accounting for the heteroskedasticity and serial autocorrelation is important for the LP method. $X_{i,t}$ is a vector of the control variables, which is the same as before (Table 2). S_i^h is the sector fixed effect.

$$y_{i,t+h} = S_i^h + \beta^h(\text{E9SHARE}_i \cdot D_t) + \gamma^h X_{i,t} + \varepsilon_{i,t+h}^h, \quad h = 0, 1, ..., H-1 \tag{5}$$

The time frame (t) spans as follows: $D_t = 0$ for 2019m3 to 2019m12, and $D_t = 1$ for 2020m1 to 2020m10. The forecast horizon (h) spans until $H-1$(2022m9), which is the most recent data available. The number of h is 24 (including $h = 0$). The forecast horizon needs to have already taken place at the time of the study. Therefore, any further long-run analysis is yet not possible due to data unavailability.

Figure 10 shows the IRFs using the LP method. Panels A through D initially start from negative, reflecting the Shock Phase described in Section 5 (Figure 5). Then they bounce up, reflecting the Recovery Phase. These are consistent with the findings from the previous section. Meanwhile, Vacancy rate (part-time), Work hours (full-time), and Wages (full-time) oscillate around zero.

9 Robustness Check

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, Section 8 showed that the vacancy rate has increased more in those manufacturing sectors that relied more heavily on E9 workers. However, this result might be spurious if the result is mainly driven by the change in the number of domestic workers, which is part of the denominator of the vacancy rate. To put it another way, it is acceptable if the number of domestic workers has decreased evenly across the sectors, because in this case, the 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 that 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:

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

Panels A, B, and C of Figure 11 show the same DD regression as Figure 7. The only difference is that Figure 11 is using valter_{it} instead of the vacancy rate. Comparing Figure 7 and Figure 11, one can see that the figures are almost identical.

Another way to check the robustness is by performing the same DD regression as Equation 2, but instead to use 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:

$$\text{TFW}_{it} = \text{TFW}_t \times \frac{\text{E9}_{it}}{\sum_i \text{E9}_{it}}$$
$$\Rightarrow \text{Domestic Workers}_{it} = \text{Total Workers}_{it} - \text{TFW}_{it} \tag{6}$$

Equation 6 shows the estimated number of domestic workers for two-digit sectors level. Panel D of Figure 11 shows the DD regression using the domestic workers as a dependent variable. It confirms that there is not any spurious force which would have led to the number of domestic workers driving the vacancy rate.

10 Conclusion

The paper identified that the vacancy pattern is consistent across the three studies (Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019)) as well as within the search and matching model (Howitt and Pissarides (2000)): when there is a shock in foreign workers' decrease, vacancy rate *rises* in the short-run, *drops* in the long-run, and finally converges to *zero*. This paper contributes to the existing literature by providing analysis results using DD, SVAR, and LP approaches. In the short-run, all results are consistent with the vacancy pattern found in the literature. In the long-run, the vacancy rate *dropped* although it is not significant. It eventually converged to *zero* according to the result from SVAR.

The empirical findings in this paper are as follows. Natives filled the vacancies primarily as part-time workers, and firms have had difficulty finding full-time workers. Consequently, the ratio of part-time to full-time workers has surged. Manufacturers do not respond to this challenging situation by raising wages or extending working hours. A possible explanation here could be that they have already reached the maximum number of working hours, and that they could not offer higher wages.

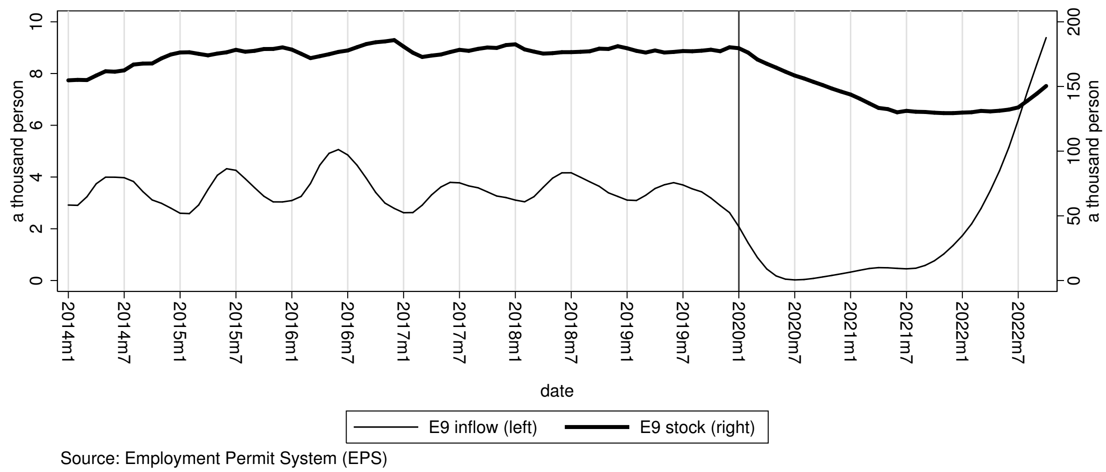
The TFW policy has helped alleviate the labor shortage issue in the manufacturing sector in South Korea. Therefore, even if there is sentiment against foreigners among natives, this paper provides findings that encourage this TFW policy. Specifically, many manufacturing sectors need full-time rather than part-time workers; the study has highlighted that domestic workers cannot fulfill the full-time demand. Therefore, accepting TFWs as full-time workers would alleviate the tight situation of finding workers.

Existing studies that use the search and matching model predict that in the long-run, there is a possibility that vacancies would drop. It implies that there is an adjustment process, which involves firms' shutting down or investing in labor-saving machines. Abramitzky et al. (2019) found that the USA's loss of immigrant workers due to a quota policy in the 1920s encouraged farmers to shift toward capital-intensive agriculture. They also found that the loss of immigrant workers pushed the mining sector to shut down. Meanwhile, Clemens et al. (2018) found that after the termination of Bracero, natives' wages actually declined. A more interesting finding is that states that relied on Braceros adopted more technical advancements. Overall, Acemoglu (2010) studied whether labor scarcity encourages technology adoption. He urged further research that explores other natural experiments testing causal links between labor scarcity and technical adoptions. In line with this idea, interesting future research would be on whether the reduction of TFWs after the pandemic pushes the manufacturing sector to adopt machines that can substitute workers.

11 Tables and Figures

Figure 1

(a) E9 Workers in Manufacturing Sector



(b) TFWs' Proportion in Manufacturing Sector

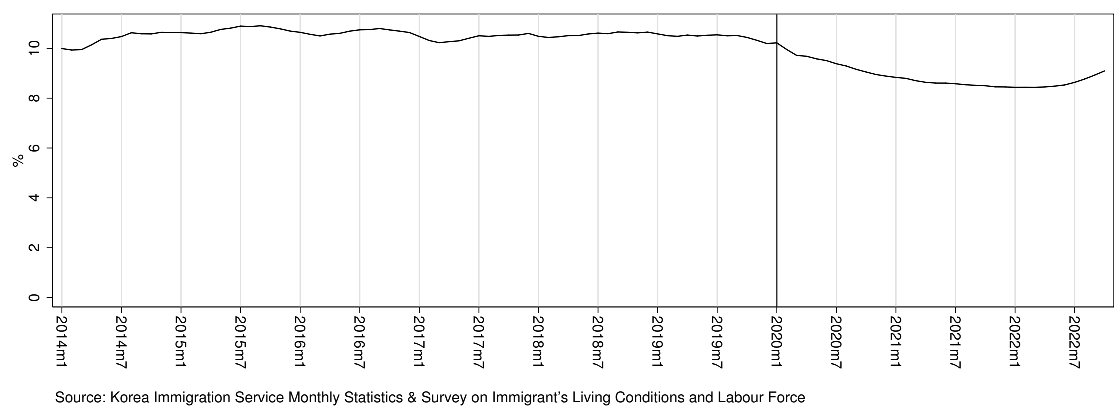
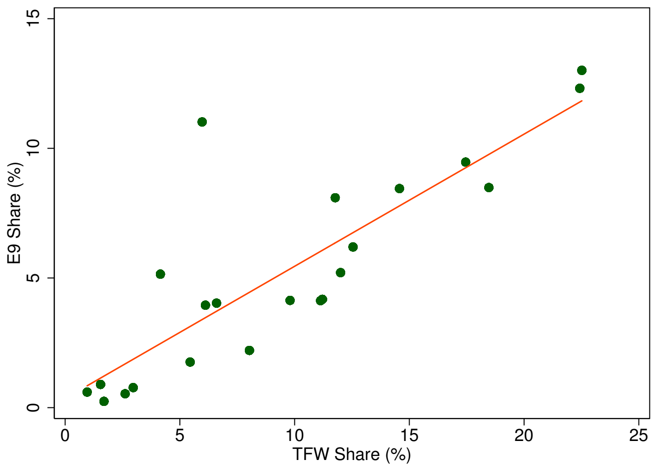
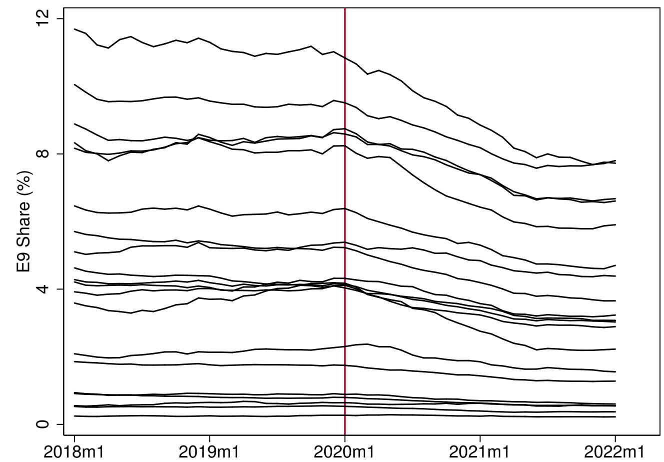


Figure 2

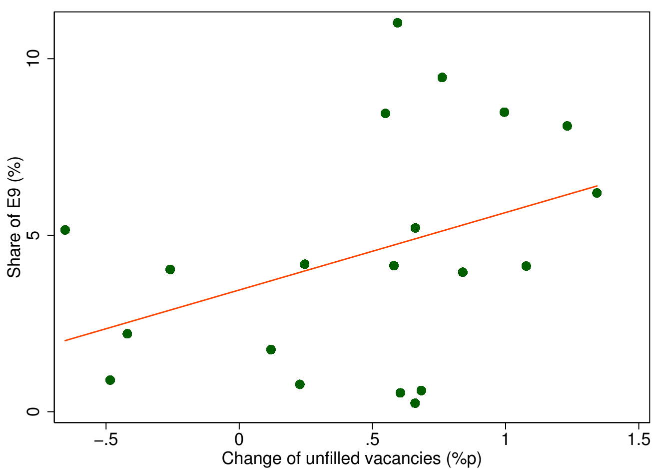
(a) E9 and TFW



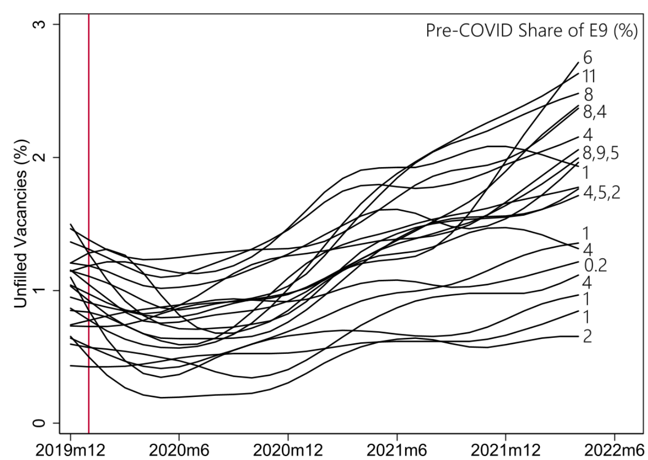
(b) Share of E9 by sectors



(c) Share of E9 and Change of Vacancies



(d) Unfilled Vacancies by sectors



Panel (c) and (d): Share of E9 $= \frac{\text{Number of E9 workers in 2019m8}}{\text{Number of total workers in 2019m8}} \times 100$

Panel (c): Change of unfilled vacancies $= \frac{\text{Number of vacancies in 2022m1} - \text{Number of vacancies in 2019m8}}{\text{Number of total workers in 2019m8}} \times 100$

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[8]

Figure 3: Search and Matching Model

(a) Model flows

(b) Long run

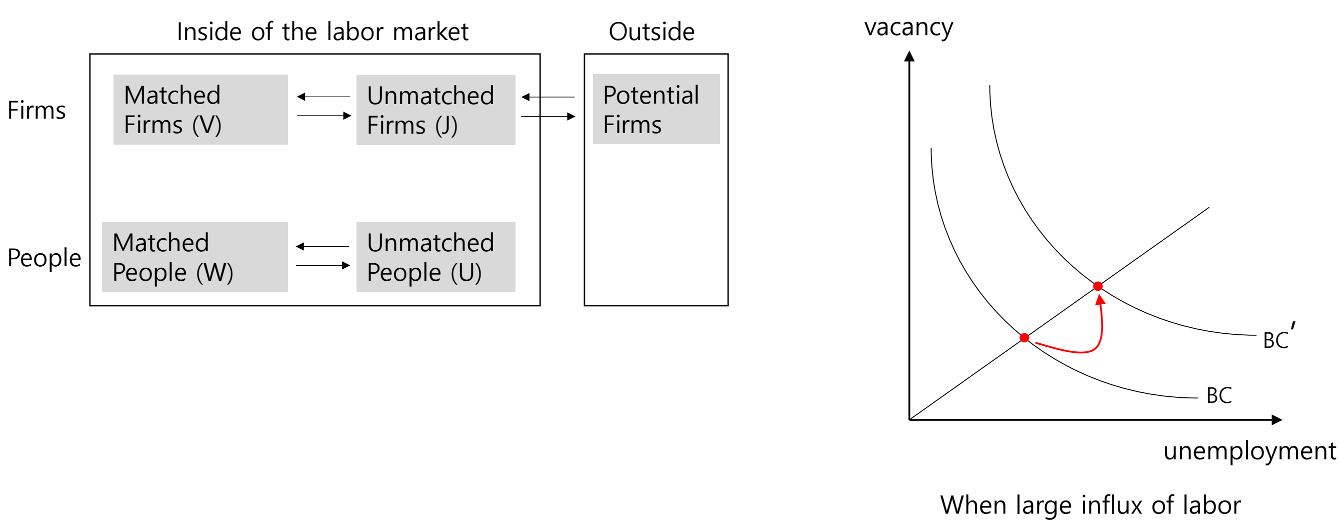
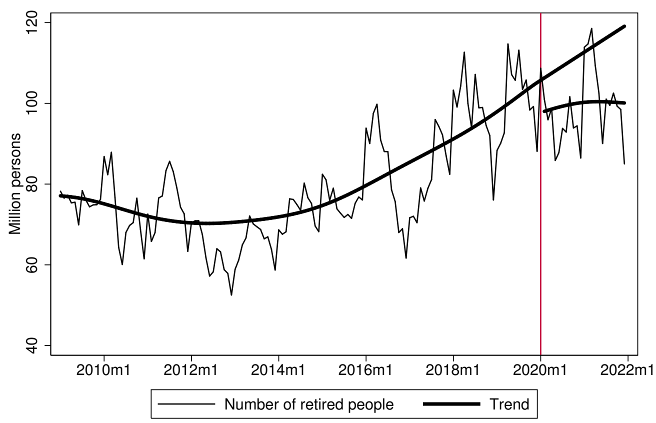


Figure 4

(a) Retirement Trend using Extrapolation



(b) Retirement Estimation using Age Cohort

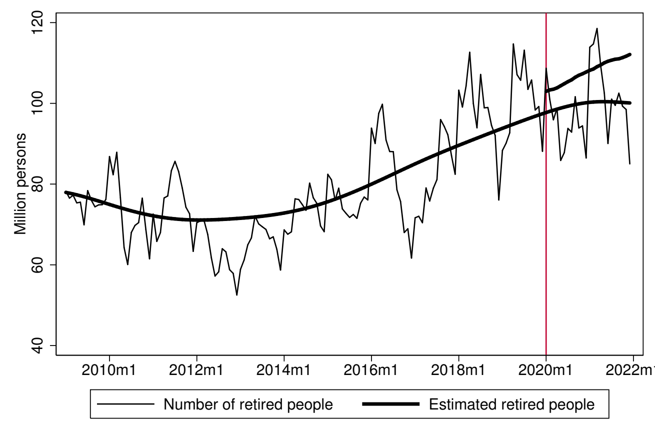
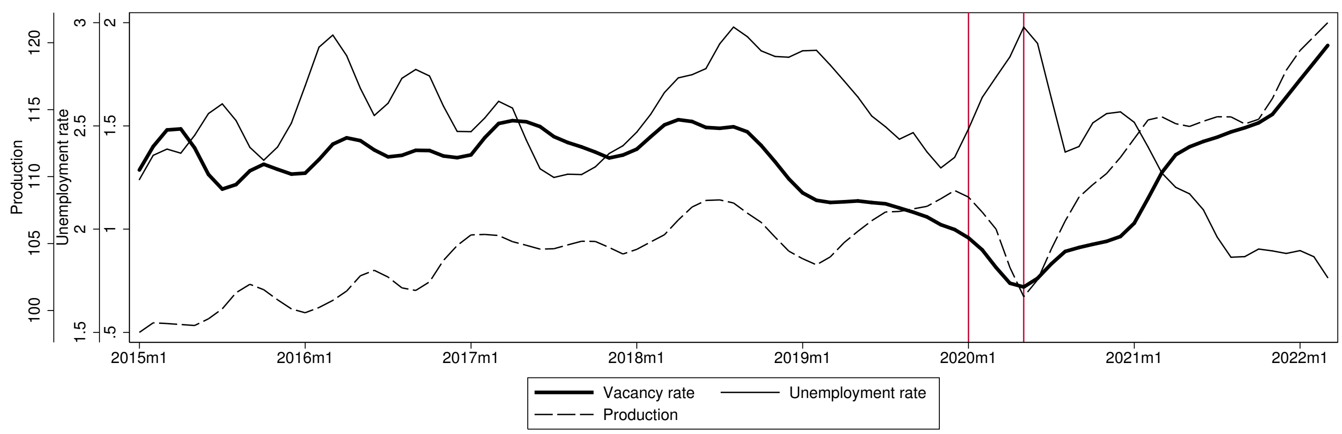


Figure 5: Two Phases since COVID-19

(a) South Korean manufacturing case



(b) The USA case

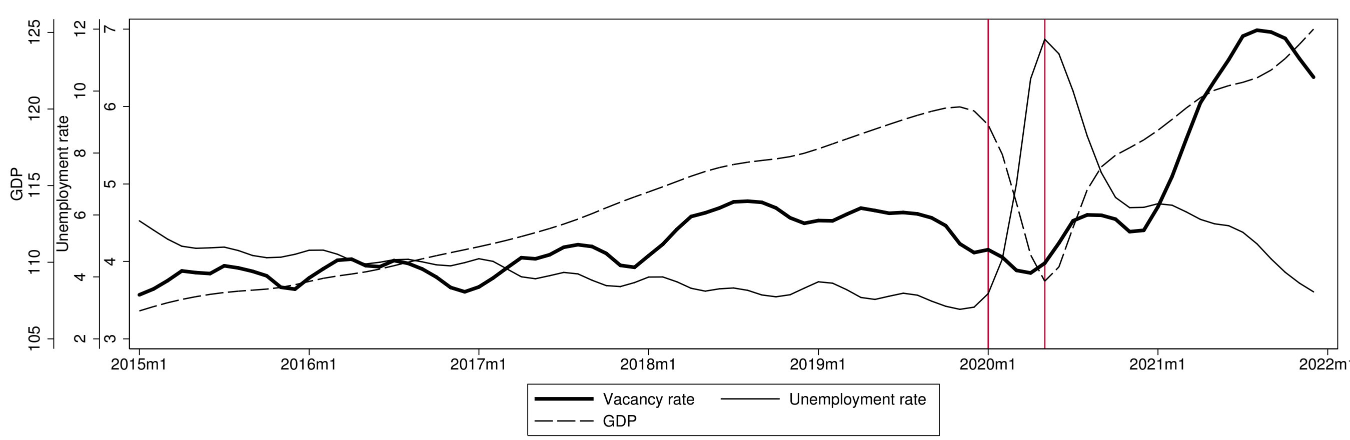


Figure 6: Unemployment rate and UI rate

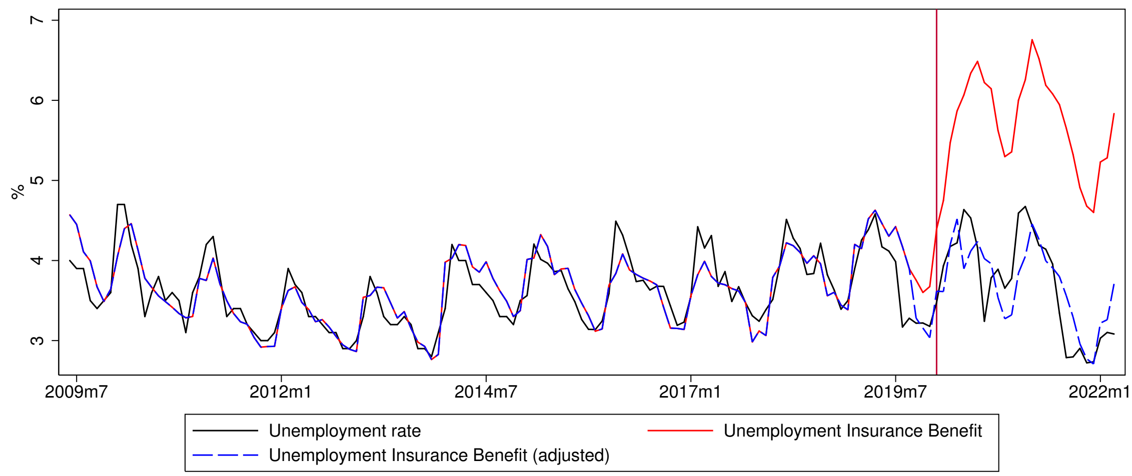


Table 2

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
	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

Table 3

	(1) Tightness	(2) Vacancy	(3) Vacancy(Full)	(4) Vacancy(Part)	(5) Part/Full	(6) Wage(Full)	(7) Hour(Full)
E9SHARE $\times$ D	0.006*	0.050*	0.055**	-0.058	0.184**	-45.032	-0.080
	(0.002)	(0.018)	(0.018)	(0.053)	(0.057)	(33.271)	(0.098)
UIB	-0.000	0.001	0.001*	-0.001	0.002	-0.661	-0.008**
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(1.166)	(0.002)
ProdDomestic	0.000	0.001	0.001	-0.001	0.009	-7.557	0.044*
	(0.000)	(0.003)	(0.003)	(0.017)	(0.010)	(6.454)	(0.020)
ProdAbroad	0.000*	0.003*	0.003*	0.005	0.013	10.977	0.002
	(0.000)	(0.001)	(0.001)	(0.011)	(0.010)	(7.773)	(0.012)
ProdOperation	0.001	0.012*	0.013*	0.039	0.002	2.276	0.009
	(0.001)	(0.005)	(0.005)	(0.030)	(0.022)	(12.773)	(0.040)
Observations	924	924	924	924	924	924	924
R^2	0.557	0.543	0.587	0.148	0.610	0.405	0.894
Pseudo R^2							

Standard errors in parentheses

S_i and T_t included but not reported.

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

Table 4

	(1) Tightness	(2) Vacancy	(3) Vacancy(Full)	(4) Vacancy(Part)	(5) Part/Full	(6) Wage(Full)	(7) Hour(Full)
E9CHG $\times$ D	-0.041**	-0.341**	-0.373**	0.399	-1.263**	308.445	0.549
	(0.016)	(0.118)	(0.117)	(0.359)	(0.408)	(232.537)	(0.724)
UIB	-0.000	0.001**	0.001**	-0.001	0.002	-0.706	-0.008***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(1.146)	(0.002)
ProdDomestic	0.000	0.001	0.001	-0.001	0.009	-7.532	0.044*
	(0.000)	(0.003)	(0.003)	(0.017)	(0.009)	(6.365)	(0.021)
ProdAbroad	0.000*	0.004**	0.004**	0.004	0.016	10.174	0.001
	(0.000)	(0.001)	(0.001)	(0.011)	(0.011)	(7.697)	(0.012)
ProdOperation	0.001	0.013**	0.014**	0.038	0.007	1.080	0.007
	(0.001)	(0.005)	(0.005)	(0.030)	(0.021)	(12.875)	(0.043)
Observations	924	924	924	924	924	924	924
R^2	0.503	0.489	0.538	0.150	0.607	0.406	0.891
First-stage F	45.77	45.77	45.77	45.77	45.77	45.77	45.77

Standard errors in parentheses

S_i and T_t included but not reported.

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

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 7: DD regressions

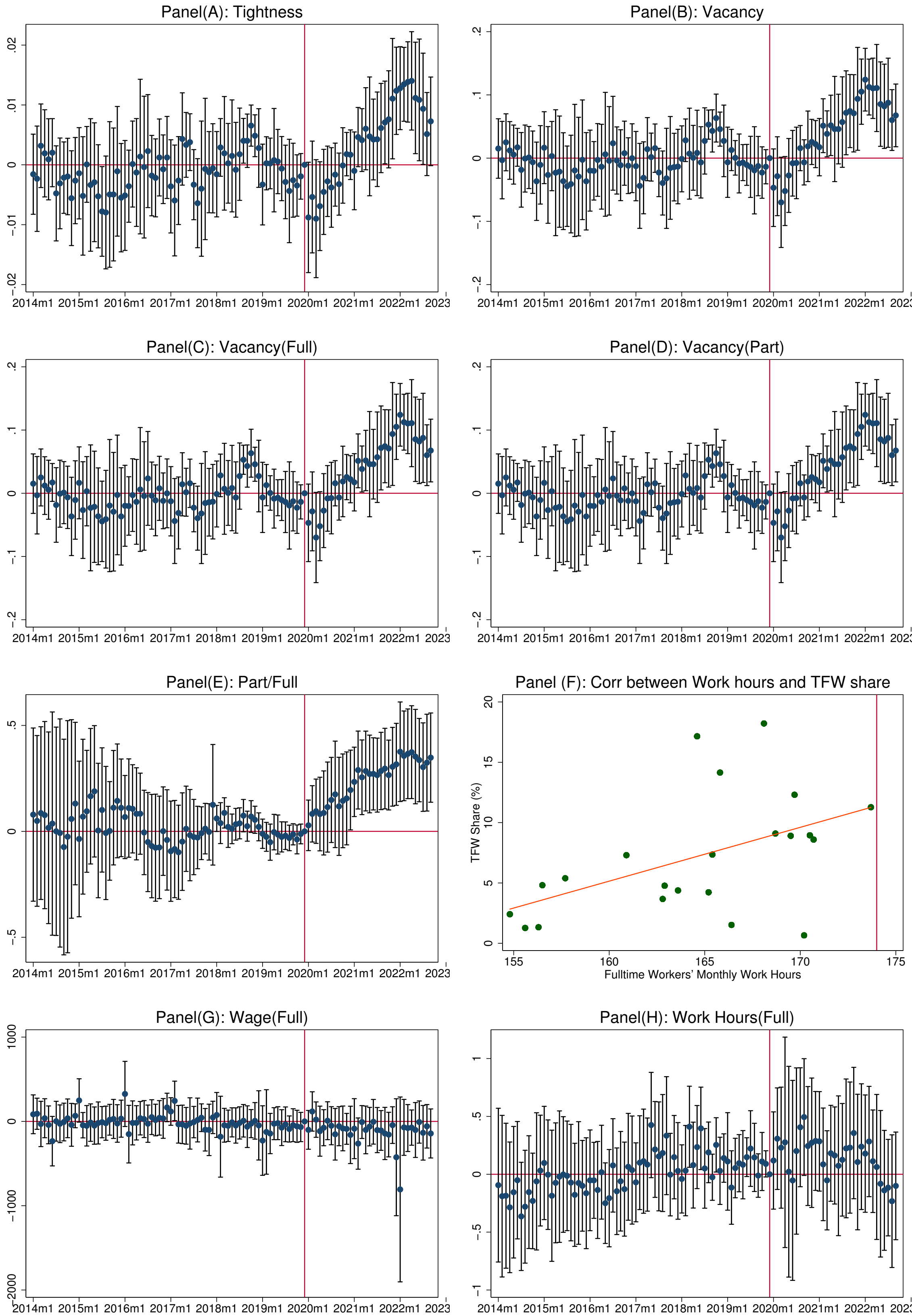


Figure 8: The proportion of part-time job-seekers

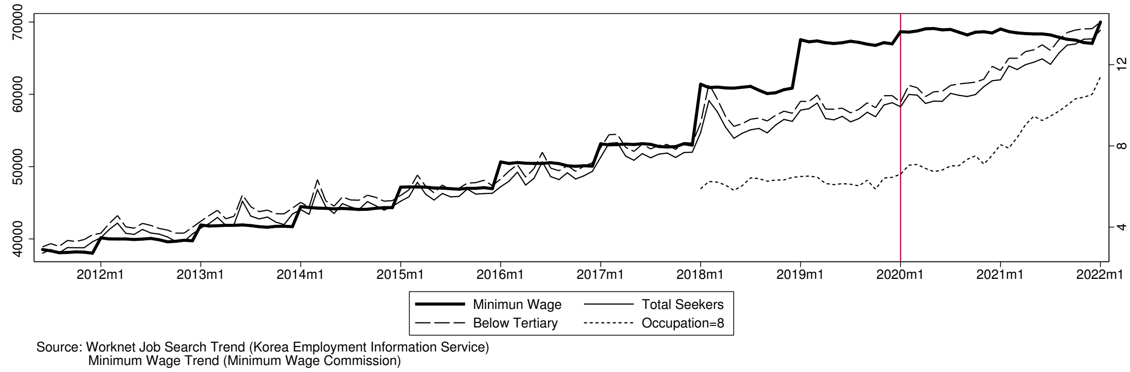


Figure 9

(a) IRFs using narrative sign restrictions

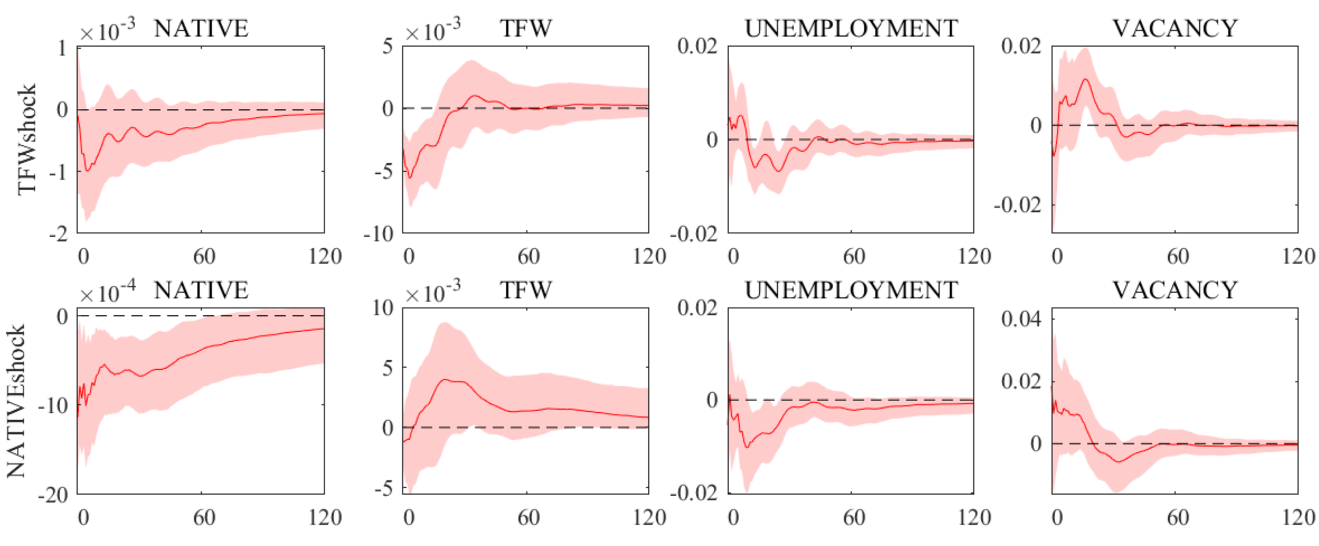


Figure 10: IRFs using LP

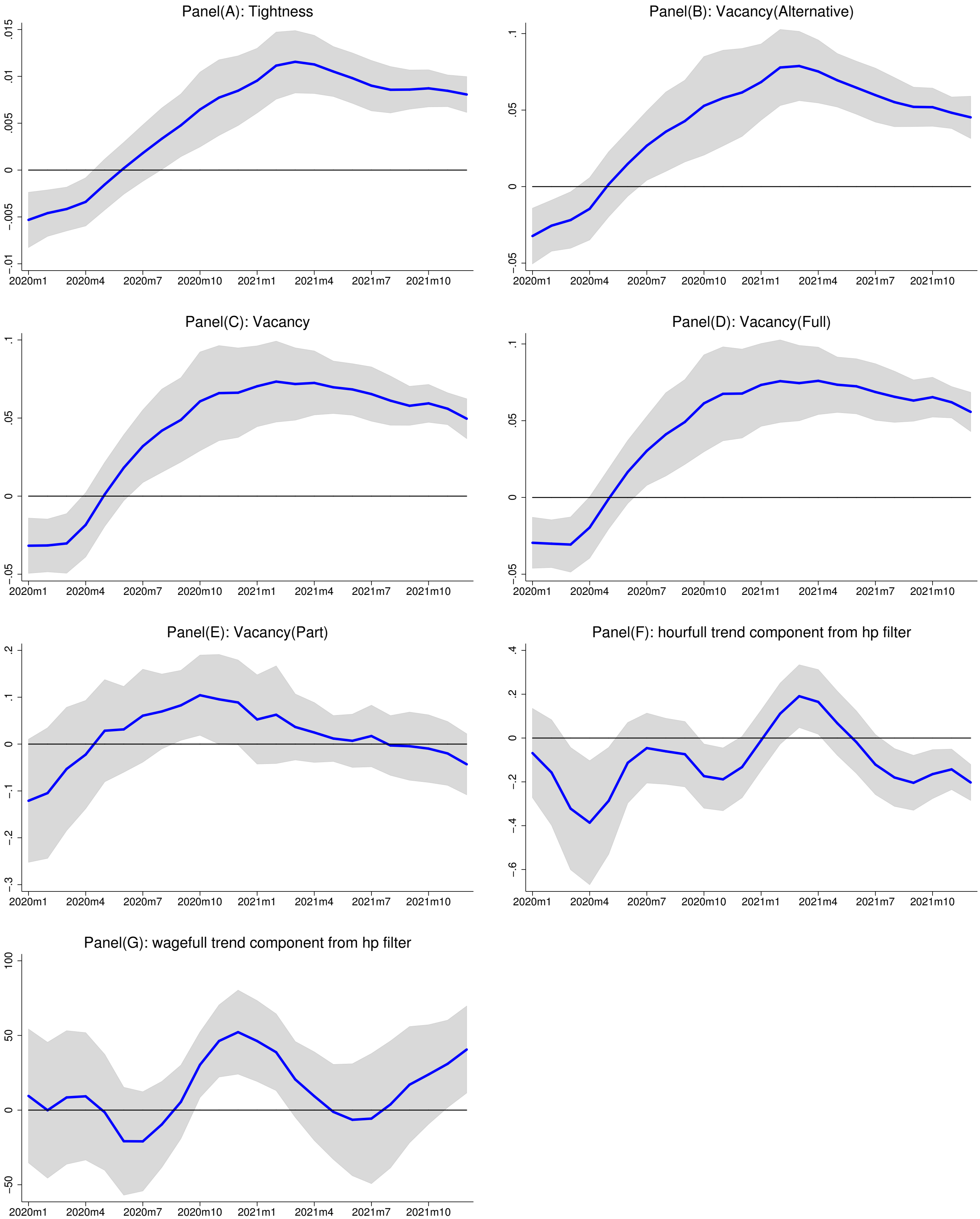


Figure 11: DD (Robustness Check)

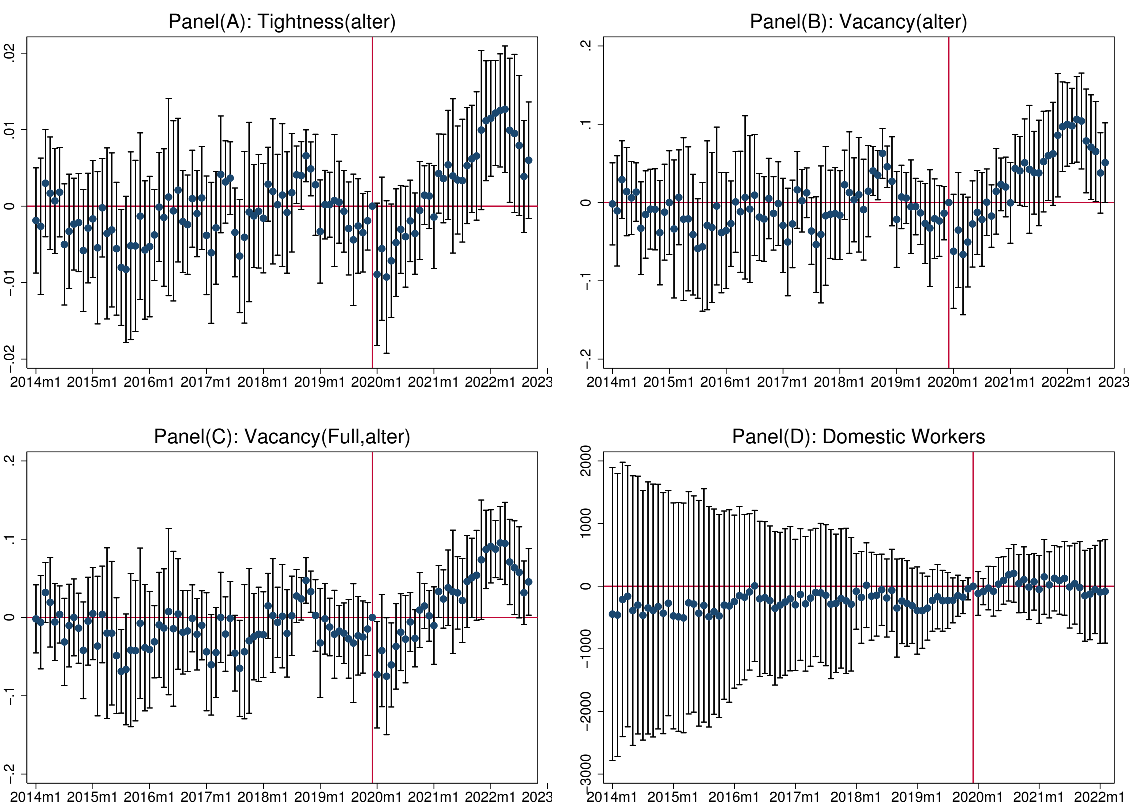


Table 6: Share of TFW Workers on Total Workers in 2019h2

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.

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

A Appendix: Background

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 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 government 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.[9] 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.

[9] 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

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 the year 2015, it has been a trend that the more people are getting F4 instead of H2 (Figure **??**) 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.[10] 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.

number of violation of labor laws, and 6) the number of tax delinquency, and so on.

Unauthorized workers

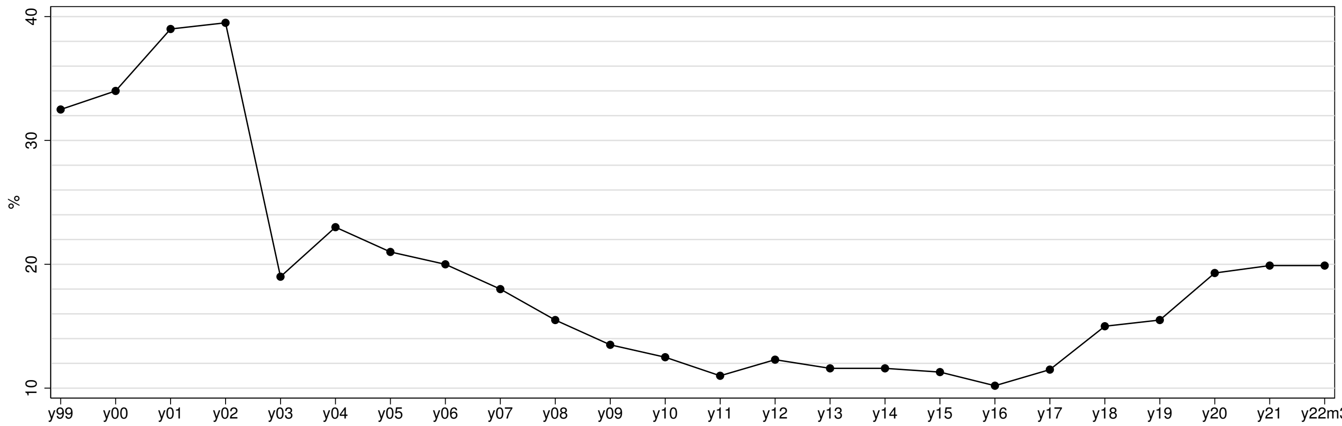
There is the Survey on Immigrants' Living Conditions and Labor Force, starting from year 2012. However, it excludes the temporary foreigners from the sample. Moreover, it does not provide a variable that tells whether a surveyee is illegal resident or not. Therefore this survey is not appropriate for 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 12 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)[11] . 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.

[11]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 immi-

Figure 12: 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

grants; Source: Pew Research Center.

manufacturing sector.

B Appendix: Derivation of Search and Matching Model

Notations are the same as Howitt and Pissarides (2000) and is summarized in Table 8. The people and firms' flow is depicted in Figure 3(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 8: 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

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

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 7, and the matching rate per one firm is Equation 8, where $\theta \equiv \frac{v}{u}$. Conventionally, $\frac{m}{u}$ is represented as q, and $\frac{m}{v}$ is represented as θq.

$$\frac{mL}{uL} = \frac{m}{u} = a\left(\frac{v}{u}\right)^{\eta} = a\theta^{\eta} \equiv q \tag{7}$$

$$\frac{mL}{vL} = \frac{m}{v} = a\left(\frac{v}{u}\right)^{\eta-1} = a\theta^{\eta-1} \equiv \theta q \tag{8}$$

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:

$$\begin{aligned} &\frac{F}{N} - \frac{\delta K}{N} - \frac{rK}{N} - w \\ \Leftrightarrow\ & pf(k) - \delta pk - rpk - w \\ \Leftrightarrow\ & p[\text{FDR}] - w, \text{ where FDR} \equiv f(k) - \delta k - rk \end{aligned} \tag{9}$$

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

$$f(x) = \frac{\lambda^x e^{-\lambda}}{x!} \tag{10}$$

$$f(t) = \lambda e^{-\lambda t} \tag{11}$$

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

$$f(0) = e^{-\lambda t} \tag{12}$$

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

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.

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

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

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

The value function of W can be calculated as below.

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

The value function of U can be calculated as below.

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

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:

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

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

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

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 $\theta = \frac{v}{u}$.

$$
w = p \cdot (f(k^*) - \delta k^* - rk^*) - \frac{pc(r + \lambda + d)}{a\theta^\eta} \tag{JC}
$$

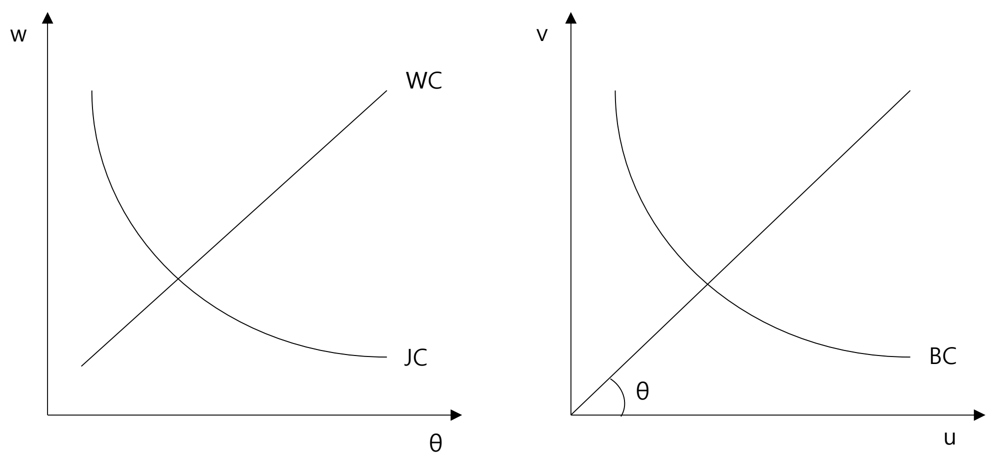
$$
w = z + \beta(p \cdot (f(k^*) - \delta k^* - rk^*) - z + \theta pc) \tag{WC}
$$

$$
v = \Big(\frac{(\lambda + b)(1 - u)}{au^\eta}\Big)^{\frac{1}{\eta}} \tag{BC}
$$

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 13(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 13(b).

Figure 13

(a) Wage, Job Curve, and Beveridge Curve



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