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

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Abstract

This paper investigates the causal impact of reducing low-skilled temporary foreign workers (TFWs) on job vacancies in South Korean manufacturing, using the COVID-19 quarantine policy as a natural experiment. The research applies Difference-in-Difference analysis with a shift-share instrument based on the quarantine 'shock' and the distribution of TFWs before the pandemic. The findings indicate that sectors heavily dependent on TFWs, especially for full-time positions, experienced higher vacancies for two years following the pandemic. Domestic workers struggled to fill these full-time vacancies. Local Projection methods also confirm these findings.

JEL J18, J21, J22, J23, J61, J63.

1 Introduction

The South Korean government allows the inflow of low-skilled temporary foreign workers (TFWs) only when a labor shortage exists. This TFW policy is based on the idea that admitting TFWs eases the challenges employers face in finding low-skilled workers. However, critics of the TFW policy argue that it diminishes employment opportunities for native workers. Therefore, it is crucial to examine the validity of the critics' arguments. If a labor shortage occurs due to a reduction in TFWs, this would suggest that native workers are not adequately filling the available jobs.

The first stage of this study involves defining what constitutes a labor shortage. Existing literature provides multiple perspectives on this subject, but converges on the importance of unfilled vacancies as a key metric (Martin Ruhs and Bridget Anderson,

*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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2019; Constant and Tien, 2011; Barnow et al., 2013). Here, the term 'vacancies' captures the extent to which employers struggle to find suitable employees. This study adopts the JOLTS (Job Openings and Labor Turnover Survey) definition of 'job openings,' which refers to "positions that are open on the last business day of the reference month, and the job could start within 30 days." Accordingly, this study will use 'vacancies' as a proxy for measuring labor shortages. The study further defines 'vacancy rate' as $\frac{\text{Number of unfilled vacancies}}{\text{Number of employees}} \times 100$.

This paper examines the impact of a decrease in TFWs on manufacturing sector vacancies in South Korea over a four-year period. A complicating factor is reverse causality: the government's TFW policy is informed by vacancy rates, which in turn impact the number of TFWs. A quasi-experimental event provides a way to address this: the COVID-19 pandemic led to stringent quarantine measures beginning in January 2020, preventing TFWs who had already secured contracts from entering the country (Figure 1(a)). This event was exogenous to vacancy rates, thus enabling a quasi-experimental assessment of causal relationships.

The proportion of TFWs to total workers declined from 10.44% in December 2019 to 8.21% in December 2021, as indicated in Figure 1(b). TFWs in South Korea's manufacturing sectors are primarily E9, F4, and H2 visa holders, as detailed in Table 1. Among these, E9 workers constitute 53%. Given that only E9 workers are closely monitored at the two-digit manufacturing sector level, this study employs E9 workers as a proxy for TFWs.

Table 1: Workers' Proportion in 2019

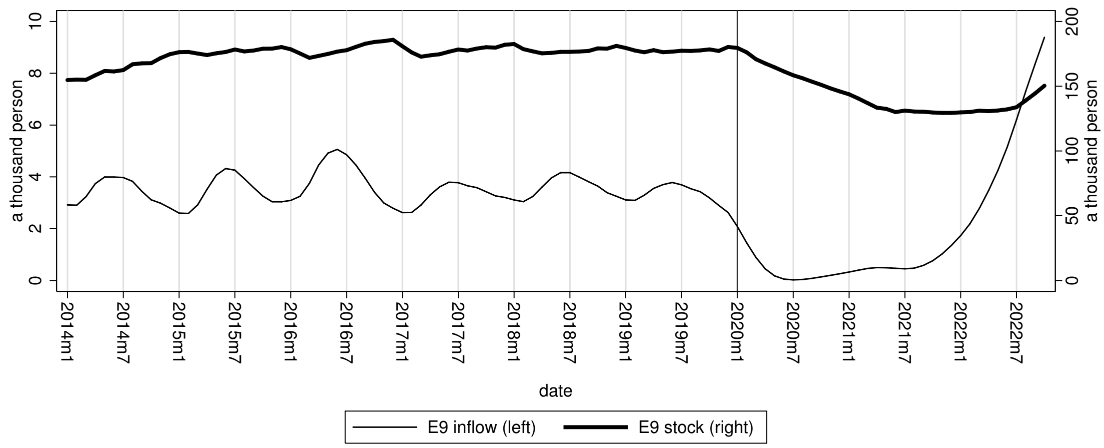
		Manufacture	Service
Foreign Students	D2,D4	0.02	0.08
Professional Employment	E1∼E7	0.13	0.12
Other VISA		0.35	0.09
Marriage Immigrants	F2,F6	0.61	0.10
Permanent Residents	F5	0.63	0.15
Working Visit	H2	1.21	0.23
Korean Descendants	F4	2.03	0.34
Non-Professional Employment	E9	5.68	0.02
Domestic Citizens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

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

Figure 2 plots the proportion of E9 workers against the total workers in each two-digit manufacturing sector. Sectors that have traditionally relied on E9 workers have recently witnessed a notable decline in their numbers, while others have not. This variation serves as a continuous treatment variable within a Difference-in-Differences (DD)

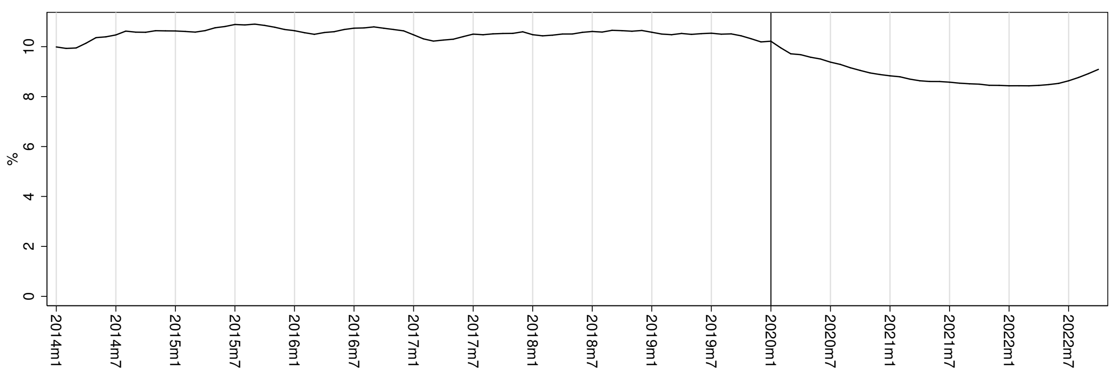
Figure 1

(a) E9 Workers in Manufacturing Sector



Source: Employment Permit System (EPS)

(b) TFWs' Proportion in Manufacturing Sector

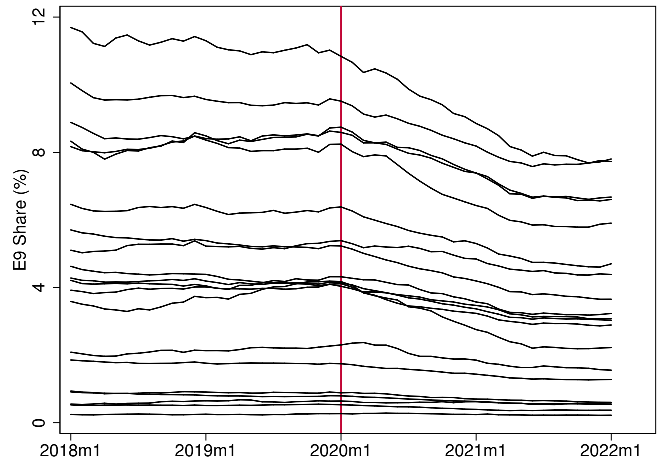


Source: Korea Immigration Service Monthly Statistics & Survey on Immigrant's Living Conditions and Labour Force

framework. This aligns with the shift-share instrument proposed by Bartik (1991). The pre-COVID share of E9 workers equates to the 'share,' and the post-pandemic decline corresponds to the 'shift.' Therefore, the treatment variable is effectively uncorrelated with any unobserved sector-specific effects during the pandemic, validating its use in this context (Goldsmith-Pinkham et al., 2020; Jaeger et al., 2018).

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

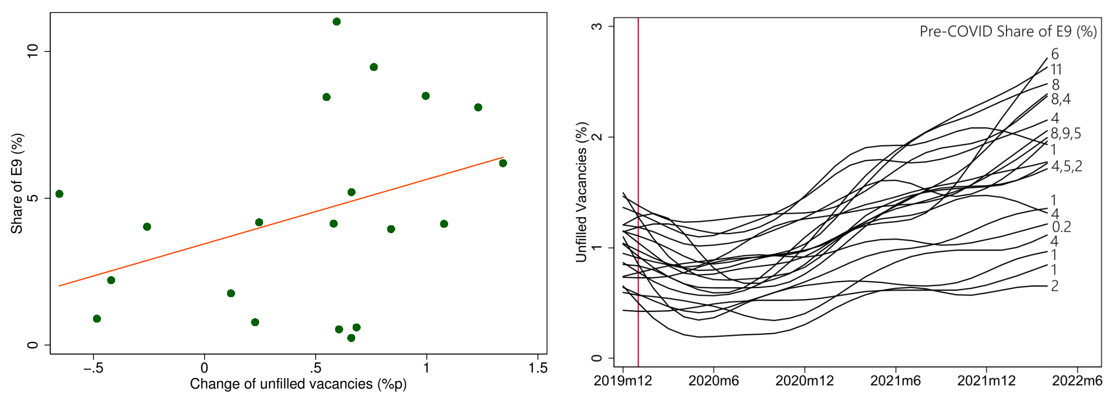
Figure 2: Share of E9 by sectors



$$\text{Share of E9} = \frac{\text{Number of E9 workers}}{\text{Number of total workers}} \times 100$$

Figure 3

(a) Share of E9 and Change of Vacancies (b) Unfilled Vacancies by sectors



$$\text{Share of E9} = \frac{\text{Number of E9 workers in 2019m8}}{\text{Number of total workers in 2019m8}} \times 100$$
$$\text{Change of unfilled vacancies} = \frac{\text{Number of vacancies in 2022m1} - \text{Number of vacancies in 2019m8}}{\text{Number of total workers in 2019m8}} \times 100$$

condition that Jaeger et al. (2018) posed.

Meanwhile, the validity of DD depends on the assumption that the post-pandemic decline of E9 workers due to stringent quarantine measures is the only event differentiating the control and treatment groups. If other factors differ across sectors and time, the identification of the DD effect will be compromised. COVID-19 has introduced multiple confounding factors, such as unemployment insurance benefits and labor demand shocks, which will be rigorously addressed in the remainder of this paper (Section 5.1).

The DD regressions offer key insights into the labor market dynamics following the onset of the COVID-19 pandemic. Specifically, sectors that have been traditionally reliant on TFWs saw a marked increase in vacancies one year after the pandemic began (Figure 3). These sectors are characterized by intense workloads, with a notably higher average of monthly working hours. Consequently, when faced with an increase in vacancies, these firms were unable to augment the work hours for existing employees, given that they were already operating at maximum capacity.

Moreover, the data reveals that 90.19% of TFWs were employed in full-time positions prior to the pandemic (as of 2019h2).[2] In post-pandemic, these firms encountered considerable challenges in recruiting full-time workers, even as they found it relatively easier to hire part-time workers. The study defines a full-time worker as one with a contract extending for more than a year or for an indefinite term, while a part-time worker is defined as having a contract lasting less than one year. The separation rates between these two categories of workers are starkly different. As of August 2019, the monthly separation rate for full-time workers stood at 1.9%, whereas it was 43.6% for part-time workers. This high turnover rate among part-time workers implies shorter tenures and reduced job proficiency, as these workers leave their jobs more frequently.

Synthesizing these findings, the study concludes that native workers were unable to fill the gap left by E9 workers in the aftermath of the COVID-19 pandemic. This substitution failure was especially pronounced for full-time positions, further exacerbating the challenges faced by firms in sectors that heavily relied on TFWs.

In addition to DD regression analysis, the paper explores Impulse Response Function using the Local Projection (LP) method. The reason for adding the LP approach is that there is a growing literature on this method as a replacement for the SVAR. For instance, the LP approach can incorporate the DD approach as well as panel settings. The identification assumption for the LP method is the exogeneity of $\text{E9SHARE}_i \cdot D_t$ in Equation 3. Since E9SHARE_i is the 'share' part, which is exogenous, it meets the identification criteria. The LP outcomes, derived from four years of data, are consistent with the observations in the Literature Review section. Following a negative shock in foreign labor, the vacancy rate initially increases, then decreases, and ultimately stabilizes at zero.

The structure of this chapter proceeds as follows: Section 2 provides detailed explanations for the empirical literature. Section 3 explains background information about TFWs in South Korea, as it helps to detail the underlying implications of the analysis. Section 4 presents various datasets that the paper will use. Section 5 sets out the empirical methods and their identification assumptions. Then it provides the results. Section 6

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

checks the robustness of the main results, and Section 7 offers concluding thoughts.

2 Literature Review

Through a careful review of the existing literature, three relevant empirical studies can be identified. First, Anastasopoulos et al. (2021) found that the labor inflow from the Mariel Boatlift in Miami led to a vacancy *drop*. In contrast, Schiman (2021) demonstrated that labor inflow to Austria due to EU enlargement resulted in a vacancy *rise*. Third, Iftikhar and Zaharieva (2019) showed a vacancy *rise* associated with the influx of high-skilled immigrants into Germany's manufacturing sector.

To begin, Anastasopoulos et al. (2021) studied job vacancies in relation to the Mariel Boatlift event. Occurring between April and October 1980, the impact of refugee influx lasted until many of the refugees left Miami for other cities. The authors employed Difference-in-Differences (DD) regression, as presented in Equation 1 of their paper. Table 1 of their paper reports the regression results. By comparing the synthetic control with the treated Miami area (as shown in Figure 3, Panel A of their paper), they found that vacancies in Miami declined by over 20% in 1981-1982 and by over 40% in 1985. Their data indicates that the vacancy rate *dropped* until 1988, then *bounced up* starting in 1988, and converged to *zero* from 1990 onwards.

Meanwhile, Schiman (2021) investigated the impact of foreign labor inflow from Eastern European countries into Austria due to EU enlargement. This labor influx began in 2004 and accelerated from 2011 onwards, as indicated in Figure 2 of his paper. Unlike the Mariel Boatlift, the mass migration to Austria has persisted for over a decade and is still ongoing. He employed Structural Vector Autoregression (SVAR) with sign restrictions for his analysis. The findings are presented in Figure 5 of his paper. In the event of a foreign labor inflow shock, (1) unemployment increased both in the short- and long-term for ten years; (2) the vacancy rate *dropped* in the first three years, then *bounced up* for another three years before eventually converging to *zero*. Additional findings from his study are provided in the footnotes.[3]

Research concerning the effects of immigration on job vacancies within the Search

[3]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.

and Matching framework is scant. The most pertinent study focusing on vacancies is that of Iftikhar and Zaharieva (2019). They examined the ramifications of a 25% increase in high-skilled immigrants in Germany from 2012 to 2016. The analysis results are summarized in Table 9 of their paper. Following the 25% surge in immigration, low-skilled immigrants faced higher levels of unemployment than low-skilled natives, particularly in the manufacturing sector. Meanwhile, manufacturing firms anticipated higher profits due to the increase in high-skilled immigrants, prompting them to increase their job postings (vacancies). As a result, the average duration of vacancies nearly tripled. Interestingly, their results indicate that the vacancy rates *rose*. This rise can be attributed to their model's long-run assumptions, which include fluid capital movements.[4]

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. 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*. Appendix B provides a detailed discussion of the Search and Matching model in this context.

To summarize this section, the three studies are discussed (Anastasopoulos et al., 2021; Schiman, 2021; Iftikhar and Zaharieva, 2019), along with the Search and Matching model by Howitt and Pissarides (2000), and they show a consistent vacancy pattern. In the event of a positive shock in foreign labor, the vacancy rate *drops* in the short term, *bounces up* in the long term, and eventually converges to *zero*. To extend the current literature, this paper employs the Local Projection (LP) approach to analyze the impact of labor inflows on vacancy rates. The findings corroborate the consistent vacancy patterns identified in previous studies, revealing that in the event of a positive shock in foreign labor, the vacancy rate *drops* in the short-run, *bounces up* in the long-run, and eventually converges to *zero*.

3 Temporary Foreign Workers in South Korea

The proportion of Temporary Foreign Workers (TFWs) in the total workforce has decreased from 10.44% in December 2019 to 8.21% by December 2021, as depicted in Figure 1(b). In South Korea's manufacturing sector, TFWs primarily hold E9, F4, and H2 visas,

[4] They calculated the effects of post-2016 steady-state equilibrium resulting from the immigrant inflow during 2012-2016. In essence, their analysis probed the long-run impact of the increase in immigrants during 2012-2016 using the Search and Matching model.

as detailed in Table 1. E9 visa holders account for 53% of these. Given that E9 workers are monitored specifically at the two-digit manufacturing sector level, this study utilizes E9 workers as a representative proxy for TFWs. It is crucial to delineate who these foreign workers in South Korea are.

3.1 E9 Workers

In the United Kingdom, the Migration Advisory Committee (MAC), comprising five economists, compiles a list of occupations for which the government should facilitate immigration to address labor shortages, exempting these from labor market tests (Sumption, 2011). This test requires employers to demonstrate extensive efforts to hire native workers unsuccessfully.

Similarly, South Korea's committee, consisting of twenty experts including vice-ministers, adopts a different approach for E9 workers. Annually, this committee sets sector-specific E9 visa quotas based on labor shortages. Employers must advertise these jobs for 14 days at the Korea Employment Center before foreign hiring can proceed, ensuring native workers have the opportunity to apply.

The government then facilitates connections between employers and E9 visa applicants based on a scoring system, which considers several factors. For employers, the criteria include the ratio of current to maximum allowable E9 workers, the hiring of additional native workers prior to seeking E9 workers, the quality of dormitories provided, adherence to safety and labor laws, and tax compliance history. For E9 applicants, the primary criterion is their score on the Korean language test, reflecting their language proficiency.

After initiating the employer-employee connection, both parties must consent to the match. Rejections from either side prevent further matching opportunities. Once approved, E9 workers enter South Korea as full-time employees but must leave after three years, with no option for permanent residency or changing employers without special permission. If terminated, they should leave the country.

3.2 F4 and H2 Workers

Conversely, F4 and H2 visa holders are Korean descendants, fluent in the Korean language —making them excellent substitutes for domestic workers in sectors where communication is crucial, such as the service industry. For Korean descendants, acquiring an H2 visa is typically easier than obtaining an F4 visa because many paperwork requirements are waived. However, since 2015, there has been a trend toward more individuals opting for the F4 visa instead of the H2, as the government promotes F4 visa applications.

F4 visa holders can enter South Korea at will and are permitted to work in almost any sector. As such, although they are technically foreigners, their status closely resembles that of domestic citizens. However, strictly speaking, it is illegal for F4 visa holders to work in Elementary Occupations. Despite this restriction, there has been no law enforcement to date, and most F4 holders are actually employed in these elementary occupations. Consequently, this study treats F4 visa holders working in elementary occupations as de facto legally employed.

While the F4 visa does not expire, the H2 visa expires after three years, and an extension of 22 months can be requested only once, with acceptance not guaranteed. H2 visa holders are permitted to work in any sector, provided it falls within the category of Elementary Occupations.

3.3 Unauthorized Workers

The prevalence of unauthorized workers could compromise this study's integrity. A detailed discussion is provided in Appendix D. Lee (2020) estimate a small number of unauthorized E9, H2, and F4 visa holders in 2020. A significant portion of unauthorized residents were under the Visa Exemption category (B1), with 43.8% of these residents overstaying or working illegally. Similarly, Lim (2021) found a high incidence of illegal workers in the agricultural sector, which is less regulated compared to the manufacturing sector where stricter enforcement minimizes the relevance of unauthorized workers to this study.

4 Data and Time frame

4.1 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 this. 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 LFSE replicates 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 are 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 subsectors within a 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 the 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 collects 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 in South Korea.[5]

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

[5]Another big difference from the CPS is that the EAPS does not easily offer panel ID to the public. Therefore, the repeated cross-sectional analysis is only accessible through a secured facility.

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.[6]

The shortcoming of the EAPS is that it only provides unemployment rates for large industries, including agriculture, manufacturing, and the service sector. In contrast, the EIS offers detailed data on recipients of unemployment insurance (UI) across more specific industry categories. [7] Subscript i represents twenty subgroups of manufacturing industries, as shown in Appendix Table 5. Figure 5 shows that the unemployment and UI rates are serially correlated. Therefore, the rate of UI benefits[8] is a good proxy for the unemployment rate. Regrettably for my research, there was a discontinuity starting in October 2019 due to changes in South Korea's unemployment insurance (UI) policy. During this period, the policy was made more generous to assist individuals facing hardships amid the COVID-19 pandemic. The red line is the actual UI rate, and the study adjusted it by a dummy regression, with $D_t = 1$ after the UI policy change from 2019m10. In conclusion, this paper will use the 'adjusted UI benefits rate' as a proxy for u_i (unemployment rate for the two-digit manufacturing sectors).

Throughout the analysis, this paper applies seasonal adjustments using seasonal dummies. For enhanced readability in graphical representations, a Hodrick-Prescott (HP) filter is occasionally employed. However, the X-13 ARIMA-SEATS method for seasonal adjustment is not utilized, with the rationale provided in the corresponding footnote. [9]

4.2 Time Frame

It is possible to identify two distinct phases during the COVID-19 pandemic (Figure 4(a)). The first is the Shock Phase (2020m1-2020m4) and the second is the Recovery Phase (2020m5-2022m2). In the United States, these two phases are even starker (Figure 4(b)). Many 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 include Bishop and

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

[7] 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 $= \frac{\text{UI recipients}}{\text{Employed+UI recipients}}$

[9] 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.

Rumrill (2021), Alvarez and Pizzinelli (2021), and Handwerker et al. (2020)). Some studies distinguish the two phases and analyze them separately (Rothstein and Unrath (2020); Goda et al. (2021)).

It is important to note that only the inflow of E9 workers was restricted after the pandemic began in January 2020. Conversely, the government did not interfere with the outflow and did not force them to leave. As a result, the number of E9 workers gradually decreased, as shown in Figure 1(a). Consequently, the effects of the decline in Temporary Foreign Workers on research interests were minimal during the Shock Phase.

This paper concentrates on the Recovery Phase, and the rationale is as follows: The primary objective is to compare vacancy rates before and after the COVID-19 pandemic, primarily utilizing the Difference-in-Differences (DD) technique, which is also applicable to the Local Projection (LP) method. The DD approach facilitates clear differentiation between two time periods; however, it becomes challenging to apply to three distinct periods. Furthermore, this study primarily focuses on the Recovery Phase, covering the period from May 2020 to September 2022, and extending to February 2024 for the LP analysis. This phase is emphasized due to its extended duration and substantial implications, unlike the Shock Phase, which was brief, spanning only from January to April 2020.

5 Estimations

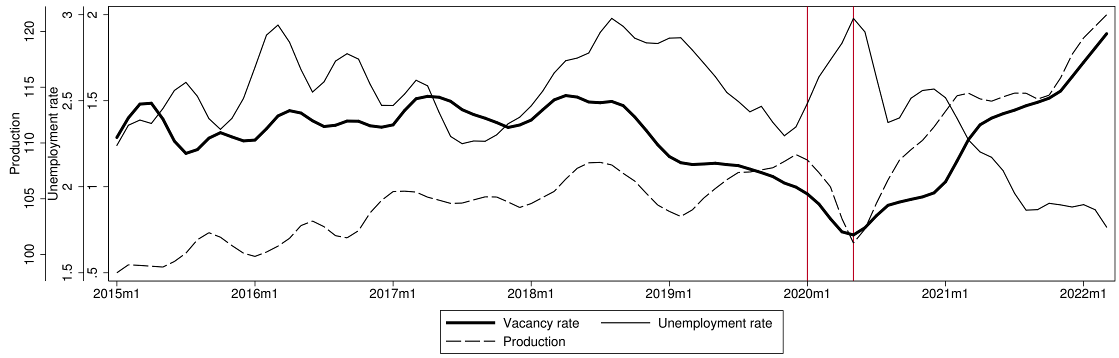
5.1 Control Variables

The effectiveness of the Difference-in-Differences (DD) approach largely depends on the assumption that the decline in the number of E9 workers in the post-pandemic period, resulting from strict quarantine measures, serves as the sole differentiator between the control and treatment groups. However, if other variables that vary across sectors and over time are not canceled out by the DD method, this could compromise the accurate identification of the DD effect. The COVID-19 pandemic has exerted multifaceted impacts on the South Korean economy. Several potential factors may have contributed to the rise in vacancy rates in South Korea: 1) unemployment insurance benefits, 2) labor demand shock, 3) profits, and 4) excess retirement.

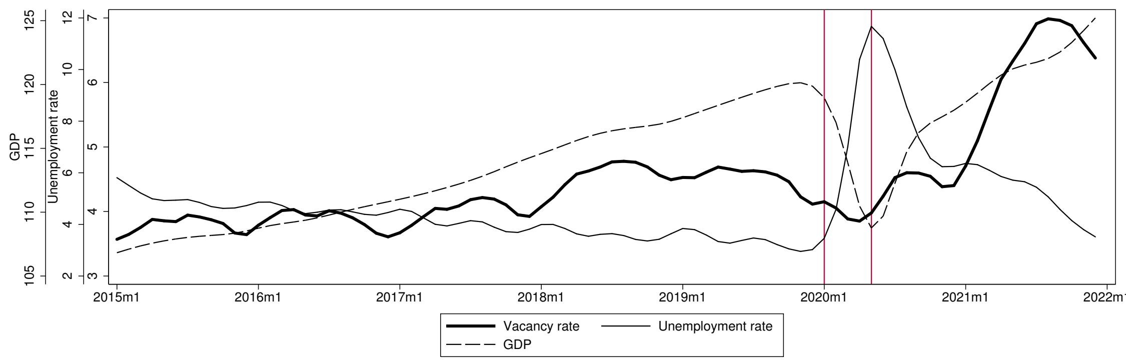
Unemployment insurance benefits: The government increased unemployment insurance benefits (UIB) to help recipients cope with the pandemic (Figure 5). Larger UIB, in return, may encourage people to be economically inactive (that is, less desperate to

Figure 4: Two Phases since COVID-19

(a) South Korean manufacturing case



(b) The USA case



search for other jobs). Since UIB is available as a panel dataset, it will be added as a control variable and is rigorously accounted throughout the paper.

Labor demand shock: At the beginning of the pandemic, the production level, which affects the labor demand, plummeted for about 5 months, and then recovered to its previous level (Figure 4(a)). There will be three control variables to handle this labor demand shock: (1) the level of shipment to domestic locations, (2) the level of shipment abroad, and (3) the level of operation intensity (the ratio of real production to total production ability). These control variables are also accounted throughout the paper.

Profits: Profitability is a crucial factor in a firm's long-term decisions to enter or exit the market. In the context of vacancies, it is plausible that profits influence market dynamics in a similar manner. Consequently, it is necessary to include profit, measured here as production minus total costs, as a variable that will be consistently accounted for throughout the paper.

Excess retirement: The paper quantifies excess retirement as the actual trend of retired individuals minus the expected trend had COVID-19 not occurred. Figure 6(a) shows the trend extrapolation. According to this figure, excess retirement might not happen in this period, and rather, that fewer people might have retired. Figure 6(b) conducts the following estimation that is alternative to Figure 6(a): 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 also suggests that excess retirement might not occur. Throughout this paper, excess retirement is not included as a control variable.

Figure 5: Unemployment rate and UI rate

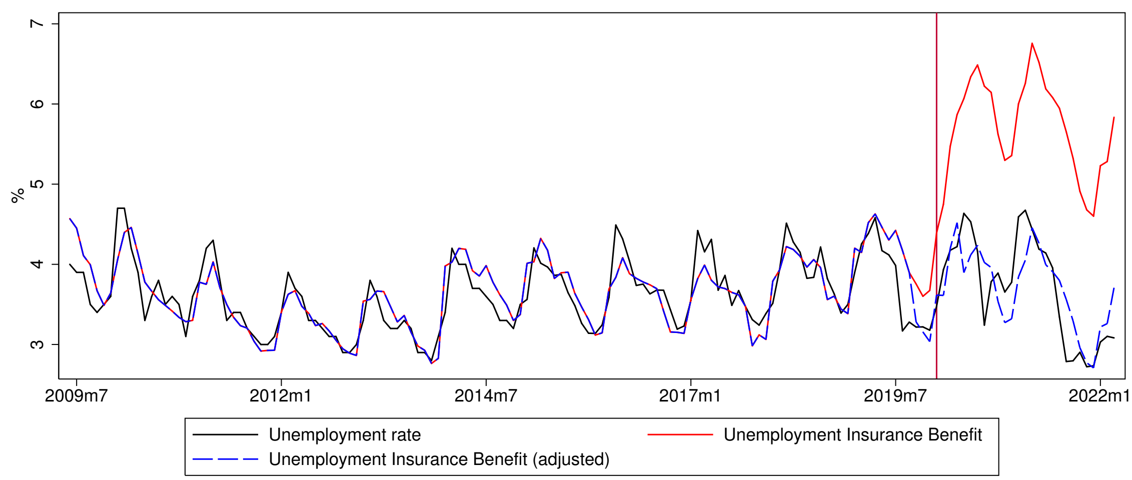
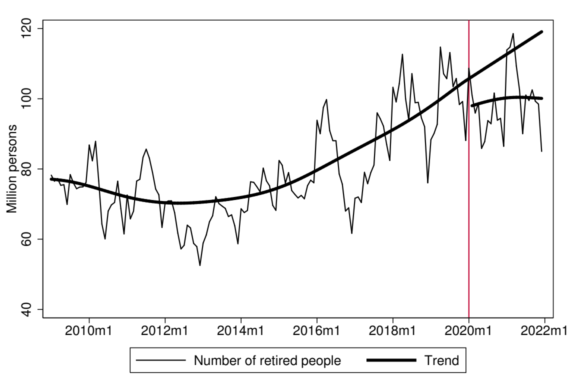
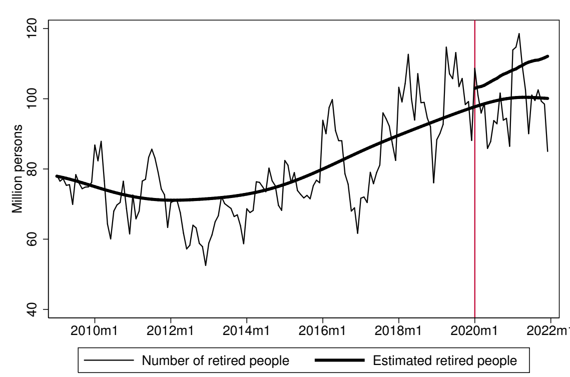


Figure 6

(a) Retirement Trend using Extrapolation



(b) Retirement Estimation using Age Cohort



5.2 Estimations using Difference-in-Differences

Equation (1) shows 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

Variables	Definitions	Main source of data
$\mathrm{E9CHG}_i$	$\frac{\text{(E9 in 2022m1)}-\text{(E9 in 2019m12)}}{\text{Total workers in 2019m12}} \times 100$	EPS
$\mathrm{E9SHARE}_i$	$\frac{\text{E9 in 2019m12}}{\text{Total workers in 2019m12}} \times 100$	EPS, LFSE
X_{it}	UIB = UIB payment (base year=2005, $)	EPS
	Profit = Production − Total cost	MSMM
	$\mathrm{ProdDomestic}_{it}$ = The level of shipment to domestic	MSMM
	$\mathrm{ProdAbroad}_{it}$ = The level of shipment to abroad	MSMM
	$\mathrm{ProdOperation}_{it}$ = 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

$\mathrm{E9CHG}_i$ 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 2014m1∼2019m12 (pre-COVID), and $D_t = 1$ for the period of 2020m5 $\sim$ 2022m09 (post-COVID). The period between 2020m1 and 2020m4, the Shock Phase, is omitted, with the reasons detailed in Section 4.2.

$\mathrm{E9SHARE}_i$ is an instrumental variable. As shown in Table 2, $\mathrm{E9CHG}_i$ is defined as $\frac{\text{(E9 in 2022m1)}-\text{(E9 in 2019m08)}}{\text{Total workers in 2019m08}} \times 100$, which includes a post-pandemic outcome. This outcome may not be orthogonal to the error term, even after controlling for various factors using control variables. Conversely, E9SHARE_i consists solely of pre-pandemic information, making it unlikely to be correlated with effects other than the exogenous decline in TFWs.

E9SHARE_i can be viewed as a variation of the shift-share instrument extensively analyzed in existing studies (Goldsmith-Pinkham et al., 2020; Jaeger et al., 2018). In this paper, E9SHARE_i functions as both the 'shift' and 'share' components. Clearly, it encompasses the 'share' component. The issue then becomes whether it also includes a 'shift' component. As illustrated in Figure 2, sectors with high E9SHARE_i have experienced a significant drop after the pandemic, and vice versa. Thus, their shifts can be accurately predicted by their share before the pandemic.

Before presenting the instrumental variable estimation in Table 4, the paper discusses Table 3, which features a reduced form estimation that directly uses the instrumental variable as an explanatory variable. Because it is not instrumented, the coefficients are straightforward to interpret. An increase of 1%p in E9SHARE_i across sectors in 2019m12 results in a vacancy rate change of 0.06316%p from pre- to post-COVID. Assuming this effect is consistent over different time spans, the overall change in E9SHARE from 4.90% in 2019m12 to 3.60% in 2022m3, a difference of 1.30%p, suggests that the vacancy rate in overall sectors should have changed by 0.082%p. The actual change observed was 0.086%p, which aligns with the predicted 0.082%p.

In Table 4, the research interests are the coefficients of $\text{E9CHG}_i \cdot D_t$, which represents the interaction term for DD. It is instrumented by $\text{E9SHARE}_i \cdot D_t$. The dependent variables for Tightness, Vacancy, and Vacancy(Full) are statistically significant.

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.

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

Figure 7 aligns with the regression results presented in Table 3 and 4. Together, the figures and tables suggest that finding workers post-pandemic was challenging. One potential issue is that the vacancy rate may not accurately reflect the labor shortage. Defined as the number of vacant positions divided by the total number of employees, the

Table 3

	(1) Tightness	(2) Vacancy	(3) Vacancy(Full)	(4) Vacancy(Part)	(5) Part/Full	(6) Wage(Full)	(7) Hour(Full)
E9SHARE × D	0.658**	6.316**	6.334**	7.925	18.504	-4.162	21.879
	(0.269)	(2.373)	(2.365)	(5.730)	(15.350)	(4.914)	(20.327)
UIB	-2.128***	-2.623	-0.891	-38.002	3.266	4.088	-182.037**
	(0.673)	(5.224)	(4.863)	(28.284)	(18.320)	(12.197)	(66.189)
Profit	3.508	38.784	27.339	-81.156	696.993*	777.269**	1009.181
	(10.084)	(56.216)	(55.592)	(185.052)	(354.020)	(332.128)	(634.960)
ProdDomestic	0.251	1.619	0.793	20.748	28.485	-19.636	26.298
	(0.544)	(3.478)	(3.230)	(14.094)	(21.714)	(13.888)	(72.224)
ProdAbroad	1.319***	8.138***	9.754***	-4.635	79.406*	-6.405	32.587
	(0.362)	(1.814)	(1.601)	(15.461)	(45.453)	(11.787)	(66.747)
ProdOperation	0.930*	6.934**	7.572**	0.592	-7.312	1.883	55.627
	(0.460)	(3.225)	(3.000)	(13.783)	(18.830)	(6.325)	(42.960)
Observations	2222	2222	2222	2222	2222	2222	2222
R^2	0.453	0.399	0.413	0.078	0.459	0.617	0.889

Standard errors in parenthesis are clustered by sector.

The coefficients and the standard errors have been multiplied by 100 for better readability.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4

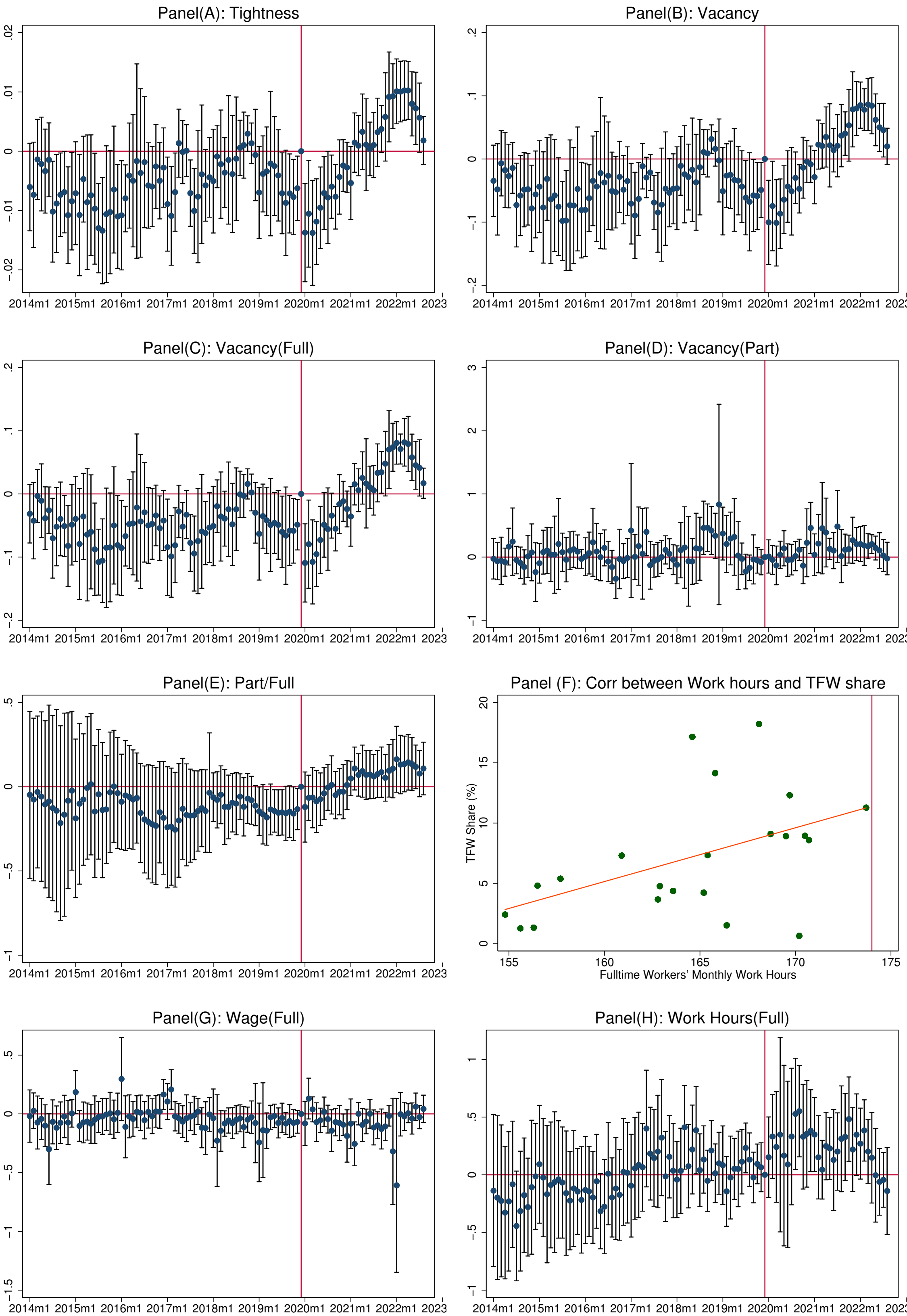
	(1) Tightness	(2) Vacancy	(3) Vacancy(Full)	(4) Vacancy(Part)	(5) Part/Full	(6) Wage(Full)	(7) Hour(Full)
E9CHG × D	-2.361**	-22.641***	-22.708***	-28.411	-66.336	14.920	-78.437
	(0.975)	(8.499)	(8.454)	(20.797)	(55.807)	(17.582)	(71.254)
UIB	-1.990***	-1.306	0.430	-36.349	7.126	3.220	-177.473***
	(0.728)	(5.939)	(5.558)	(29.061)	(20.274)	(12.074)	(66.505)
Profit	4.469	48.003	36.584	-69.589	724.001**	771.194**	1041.117
	(11.081)	(66.406)	(65.515)	(188.073)	(366.243)	(337.978)	(674.172)
ProdDomestic	0.221	1.325	0.498	20.378	27.622	-19.442	25.278
	(0.568)	(3.689)	(3.435)	(14.277)	(20.836)	(14.018)	(72.895)
ProdAbroad	1.412***	9.038***	10.656***	-3.506	82.043*	-6.998	35.704
	(0.356)	(1.862)	(1.751)	(15.150)	(46.642)	(11.587)	(66.605)
ProdOperation	0.940**	7.030**	7.668**	0.711	-7.033	1.820	55.957
	(0.463)	(3.295)	(3.074)	(13.798)	(19.043)	(6.215)	(42.728)
Observations	2222	2222	2222	2222	2222	2222	2222
R^2	0.446	0.391	0.406	0.076	0.454	0.617	0.888
First-stage F	281.50	281.50	281.50	281.50	281.50	281.50	281.50

Standard errors in parenthesis are clustered by sector.

The coefficients and the standard errors have been multiplied by 100 for better readability.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 7: DD regressions



vacancy rate can rise when the number of employees decreases, even if the vacant positions remain constant. Thus, an increase in the vacancy rate does not necessarily indicate that it is more difficult to find 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. 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 indicates that sectors with a higher reliance on TFWs tend to have work hours that approach the legal maximum. This suggests that these sectors may have challenging 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 slightly increases in these sectors (Panel E, although insignificant). Manufacturers do not react to this challenging situation by increasing wages, as shown in Panel G.[10] Instead, they slightly extend working hours, as indicated in Panel H, though the change is not particularly significant. A possible explanation is that these sectors have already reached the maximum number of allowable working hours, and they cannot offer higher wages due to competition from countries with lower wage standards.

Figure 8 illustrates the rising proportion of part-time jobseekers across categories such as Total Seekers, Below Tertiary Education, and Occupation=8[11] , as indicated in the legend. The proportion was around 3.0% in June 2011 but increased to 13.7% by January 2022. This trend may have exacerbated the difficulties in finding full-time workers. Additionally, the increase in the minimum (real) wage might be contributing to the growing trend of part-time applicants, as the trends of Minimum Wage and Total Seekers in the figure follow a similar path.

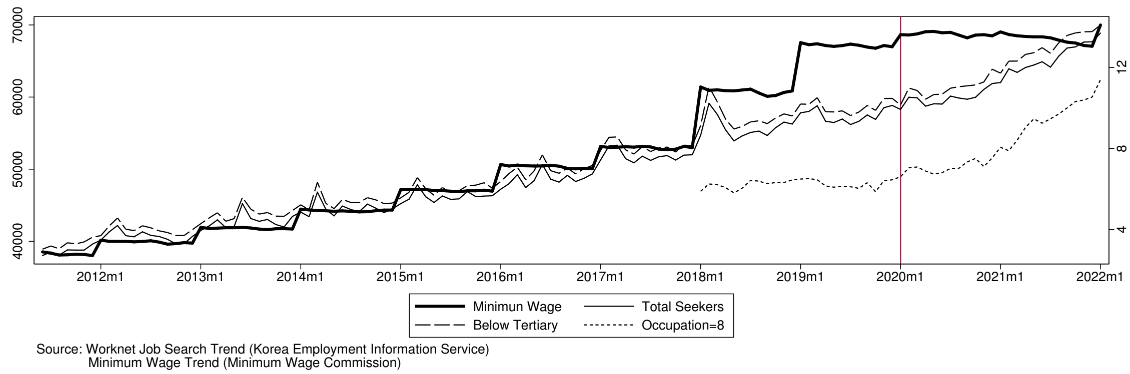
5.3 IRF using the Local Projection Method

Jordà (2005) introduced the Local Projection (LP) method as an alternative to the Structural VAR model (SVAR). Recently, LP has gained popularity over SVAR due to its numerous advantages. One significant advantage of LP is its flexibility in applications where

[10]In fact, according to Panel G and Table 4, there has even been a slight decrease in wages.

[11]Occupation=8 seekers are those who belongs to 'Installation, maintenance, and manufacturing works' in the Korean Employment Classification of Occupations (KECO).

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



an exogenous shock is identified, allowing for direct estimation of impulse response functions (IRF) using OLS regressions, as noted by Adämmer (2019). Additionally, LP is adaptable to panel datasets, as demonstrated by Owyang et al. (2013) and Jordà et al. (2015). LP can also be employed in Difference-in-Differences (DD) settings, enhancing its applicability. Moreover, LP is more robust than VAR, particularly when VAR models are misspecified (Jordà, 2005). Given that this paper involves DD settings with a panel dataset, the results derived from LP are inherently more reliable than those from VAR.

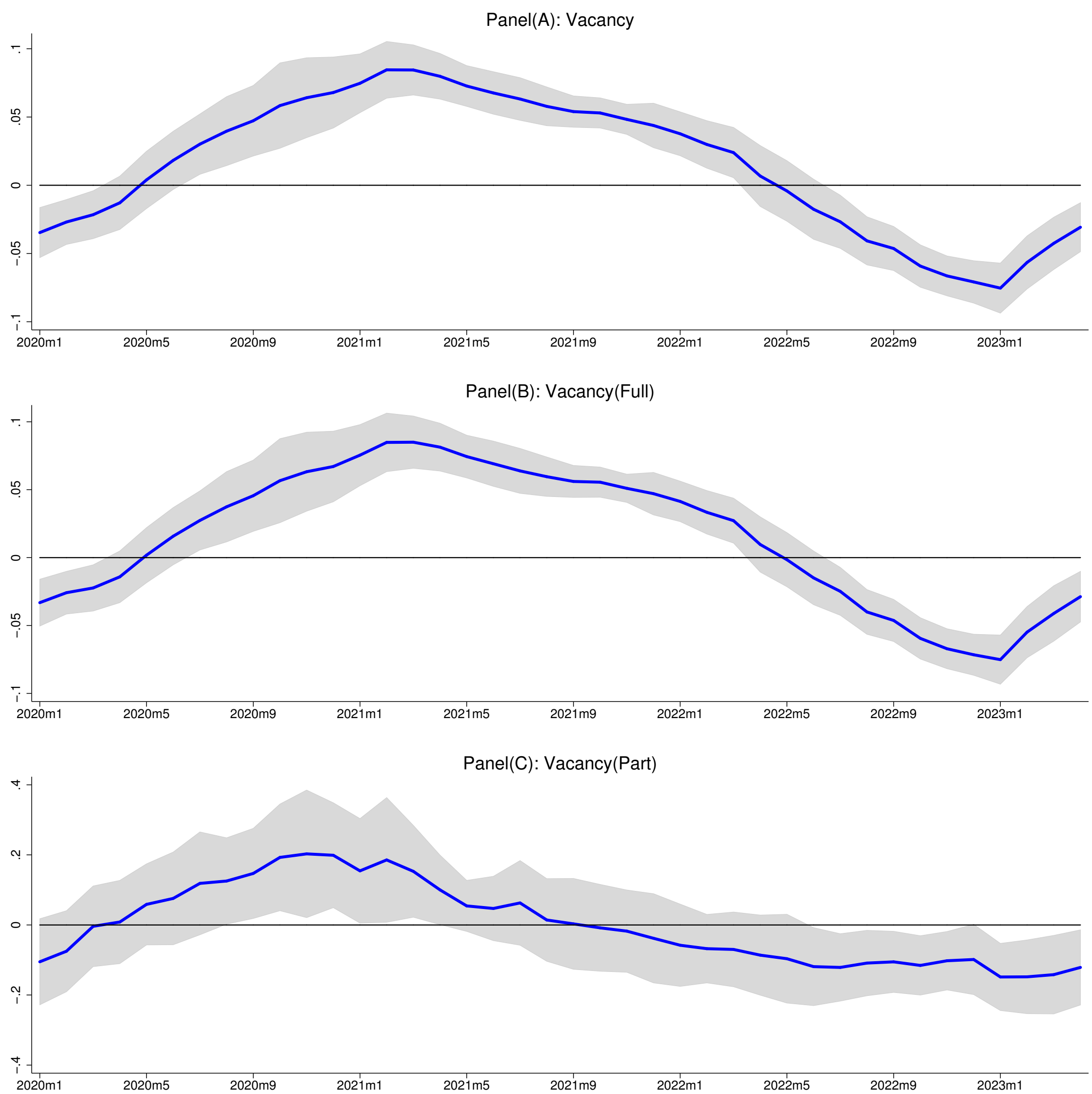
Equation (3) outlines the LP estimation and employs settings akin to those in DD regression shown in Equation (1). The key identification assumption for the LP method is the exogeneity of $\text{E9SHARE}_i \cdot D_t$. Given that E9SHARE_i includes only pre-COVID information, it satisfies the identification criteria. The coefficient β^h represents 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. The vector $X_{i,t}$ contains the control variables, consistent with those listed in Table 2. S_i^h denotes the sector fixed effect.

$$y_{i,t+h} = S_i^h + \beta^h(\text{E9SHARE}_i \cdot D_t) + \gamma^h X_{i,t} + \varepsilon_{i,t+h}^h, \quad h = 0, 1, ..., H-1 \tag{3}$$

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 $H - 1$(2024m2), which is the most recent data available. The number of h is 40 (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 9 presents the IRFs using the LP method. The results align with the findings from the Literature Review section: following a negative shock in foreign labor, the vacancy rate initially rises, subsequently drops, and eventually converges to zero. The figure does not fully depict this eventual convergence due to data limitations. Meanwhile, as Figure 9 (C) illustrates, the vacancy rate for part-time employment is relatively insignificant, which corroborates the results from the DD regression analysis discussed in the previous subsection.

Figure 9: IRFs using LP



As discussed in this section, once an exogenous shock is identified, the LP method offers significant advantages over the Structural VAR model (SVAR). Nonetheless, in Appendix E, I also present IRF using SVAR with Sign Restrictions. This is done purely to facilitate a direct comparison with the SVAR results reported by Schiman (2021).

6 Robustness Check

Throughout this paper, the vacancy rate has been measured by $\frac{\text{Number of vacant positions}_{it}}{\text{Number of total workers}_{it}}$. Using this variable, Section 5 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:

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

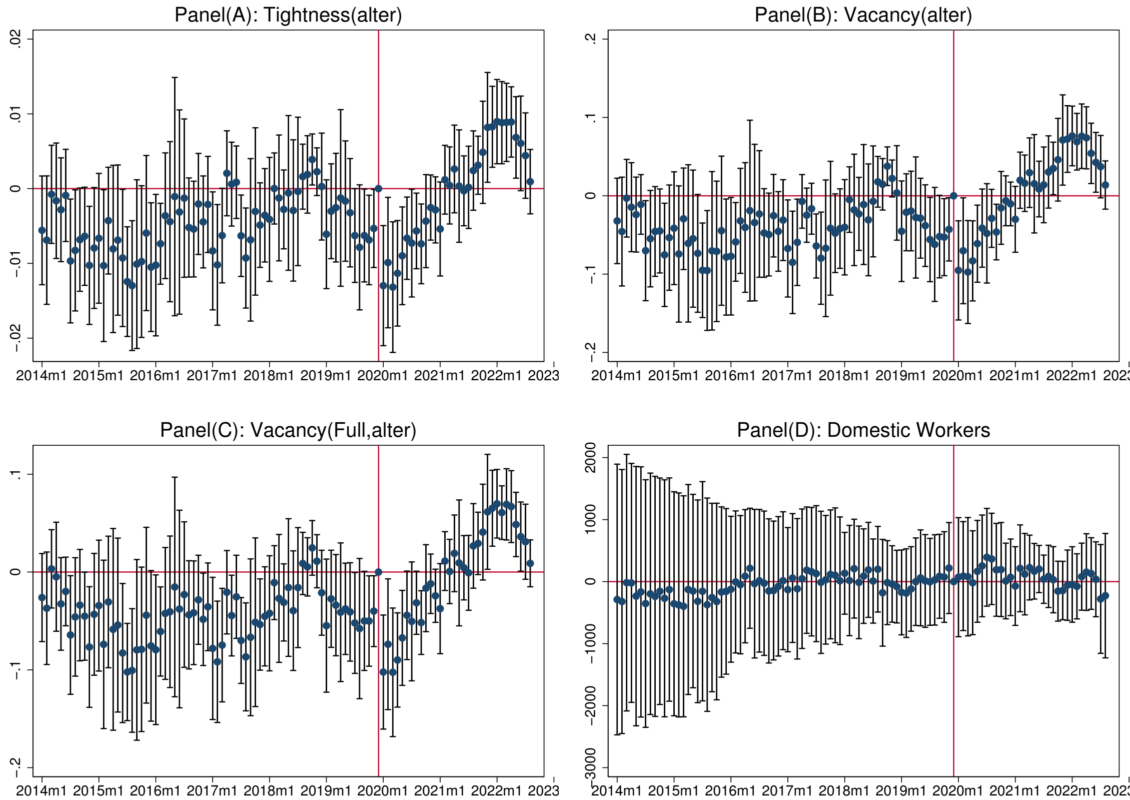
Panels A, B, and C of Figure 10 show the same DD regression as Figure 7. The only difference is that Figure 10 is using valter_{it} instead of the vacancy rate. Comparing Figure 7 and Figure 10, one can see that the figures are almost identical.

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:

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

Equation (4) shows the estimated number of domestic workers for two-digit sectors level. Panel D of Figure 10 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.

Figure 10: DD (Robustness Check)



7 Conclusion

This study endorses South Korea's temporary foreign workers (TFW) policy as an effective measure for alleviating labor shortages in the manufacturing sector. Despite prevailing anti-foreigner sentiment among natives, this paper highlights the insufficiency of the domestic workforce to meet the demand for full-time employment. Thus, the integration of TFWs into full-time roles could mitigate this labor market tightness.

The paper's empirical analysis show that sectors heavily reliant on TFWs frequently have working hours that are close to the legal maximum. This indicates that these sectors might have challenging working conditions. Although it is relatively easy for these industries to hire part-time employees, finding full-time workers is more challenging. In response to these challenges, manufacturers do not increase wages and only marginally extend working hours, indicating a slight but noteworthy adjustment. A potential explanation could be that these sectors have already reached the upper limit of permissible working hours and are unable to offer higher wages due to competition from countries with lower wage norms.

This paper establishes that vacancy patterns are consistent across three pivotal studies —Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019)— as well as within the framework of the Search and Matching model by Howitt and Pissarides (2000). Specifically, a shock causing a decrease in foreign workers leads to a *rise* in the vacancy rate in the short run, a *drop* in the long run, and eventually a convergence to *zero*. Employing the Difference-in-Differences and the Local Projection methodologies, this paper validates these trends in the short run and observes a statistically significant *drop* in the long-run vacancy rate, according to Local Projection results.

Previous research employing the Search and Matching model has posited that vacancies could decline in the long run due to an adjustment process, which may include firms shutting down or investing in labor-saving technologies. Acemoglu (2010) called for additional studies exploring the causal relationships between labor scarcity and technological adoption. Building on this idea, an interesting direction for future research could be to examine the effects of reduced TFW numbers in the post-pandemic era on the adoption of labor-substituting technologies in the manufacturing sector. Abramitzky et al. (2019) documented that the loss of immigrant labor in the U.S. in the 1920s led farmers to transition to more capital-intensive methods and resulted in the closure of mining sectors. Similarly, Clemens et al. (2018) found that states that had previously relied on Bracero labor were more likely to adopt technological advancements.

A Appendix: Table

Table 5: 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

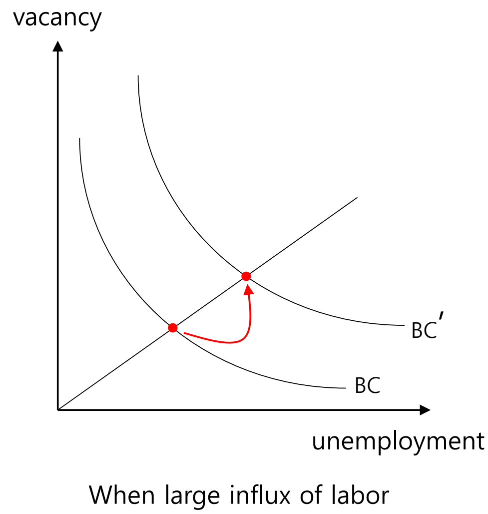
†: industries are removed because of scarce observations.

B Appendix: The Search and Matching Model

Following Howitt and Pissarides (2000), Appendix C 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 11(b) depicts this unique path.

The model explained in Appendix C can predict the trajectory of vacancies when there is an influx of foreign workers (Table 6 summarizes notations). The influx of immigrants leads to the birth rate (b) increase. In the long-run, the model predicts as in Figure

Figure 11: Search and Matching Model



11(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 11(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 model. Formally speaking, k^* from Equation k does not change unless $f(\cdot),\ r,$ or δ change (see Appendix C 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*.

C Appendix: Derivation of Search and Matching Model

Notations are the same as Howitt and Pissarides (2000) and is summarized in Table 6. The people and firms' flow is depicted in Figure 11(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).

The total number of people is L_t, and evolves by birth rate (b_t) and death rate (d_t).

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

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 $u_t L_t$, and the total number of vacant firms is $v_t L_t$. 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 (5), and the matching rate per one firm is Equation (6), where $\theta \equiv \frac{v}{u}$. Conventionally, $\frac{m}{u}$ is represented as q, and $\frac{m}{v}$ is represented as θq.

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

$$\frac{mL}{vL} = \frac{m}{v} = a\big(\frac{v}{u}\big)^{\eta-1} = a\theta^{\eta-1} \equiv \theta q \tag{6}$$

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:

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

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

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

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:

$$
\begin{aligned}
&\frac{F}{N} - \frac{\delta K}{N} - \frac{rK}{N} - w \\
&\Leftrightarrow pf(k) - \delta pk - rpk - w \\
&\Leftrightarrow p[\text{FDR}] - w, \text{ where FDR} \equiv f(k) - \delta k - rk && (7)
\end{aligned}
$$

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 (8). Then it can convert to an Exponential distribution as in Equation (9)

$$
f(x) = \frac{\lambda^x e^{-\lambda}}{x!} \tag{8}
$$

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

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 (10). And the probability that an event happens for the first time at time t is Equation (11).

$$f(0) = e^{-\lambda t} \tag{10}$$

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

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

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

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

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

The value function of W can be calculated as below.

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

The value function of U can be calculated as below.

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

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

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

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). 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).

D Appendix: Unauthorized Workers

The Survey on Immigrants' Living Conditions and Labor Force, initiated in 2012, excludes temporary foreigners from its sample. Additionally, it lacks a variable indicating whether a respondent is an unauthorized resident. Therefore, this survey is unsuitable for studying unauthorized workers. Given the absence of a survey specifically designed to study unauthorized foreign workers in South Korea, researchers must rely on various indirect sources to estimate their numbers.

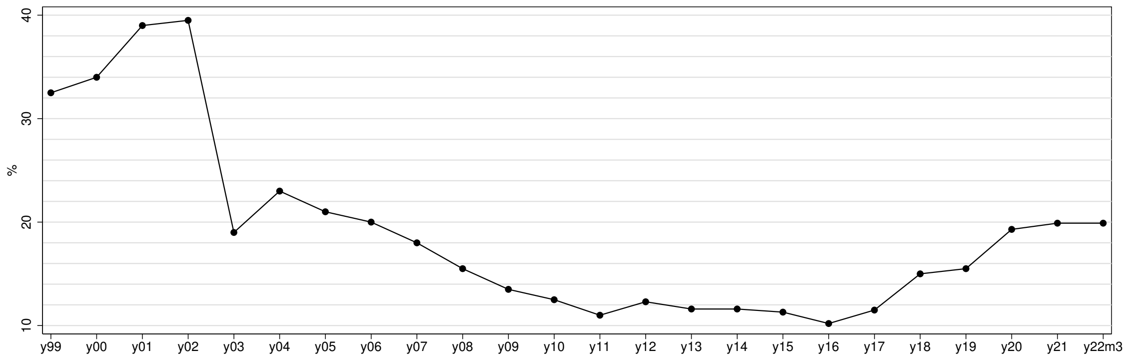
Unauthorized workers in South Korea fall into one of four categories: A) individuals who stay beyond their permitted period, B) individuals who leave their legally assigned establishments to work elsewhere illegally, C) individuals who work without the necessary work authorization, and D) individuals who enter South Korea illegally without a visa.

First, the Korea Immigration Service Statistics (KISS) from the Ministry of Justice provides information about individuals in Category A. Figure 12 illustrates the proportion of overstaying foreign residents relative to the total non-immigration residents. This proportion significantly decreased in 2003 due to a legalization policy and robust enforcement efforts. However, it began to rise again from 2018 due to the more generous issuance of Visa Exemption (B1) and Temporary Visit (C3) visas, a policy change initiated in response to the Winter Olympic Games hosted in South Korea in 2018. In 2020, the share was 19.3%, comparable to the USA, which recorded 21.2% in 2019[12]. Utilizing KISS, Lee (2020) estimates that among the unauthorized foreign residents in 2020, 43.8% originated from Visa Exemption (B1), 20.1% from Temporary Visit (C3), 12.0% from Non-professional Employment (E9), and 0.7% from Working Visit (H2). He also estimates that among Visa Exemption (B1) residents, about 72.4% are from Thailand, many of whom are employed in the illegal massage service industry. As B1 visa holders are not authorized to work, these individuals also fall into Category C.

Second, Lee (2020) analyzes unauthorized foreign workers using data from the Employment Permit System (EPS). As previously mentioned, E9 workers are required not to change their place of employment and must leave South Korea immediately upon termination of their employment. He estimates that among unauthorized E9 workers, approximately 79.4% fall into Category A, while 20.6% fall into Category B. Thus, the issue of unauthorized status is predominantly associated with Category A rather than

[12]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.

Figure 12: Share of Overstaying Residents



Category B.

Finally, estimating the number of people in Categories C and D is challenging due to the lack of official data. Nevertheless, one study conducted personal surveys of foreign workers, including those who are unauthorized (Lim, 2021). The sample size accounted for 8.7% of the total foreign population in 2020 in Nonsan City, which has a high concentration of foreigners in South Korea. The findings indicate that among the unauthorized foreign workers, 90% belonged to Category A. Additionally, 60% of these workers were employed in the agricultural industry, whereas only 10% were employed in the manufacturing sector. The researcher suggested that unauthorized workers are more prevalent in the agricultural sector due to the lack of active government supervision, in contrast to the strict enforcement observed in the manufacturing sector.

E Appendix: IRF using SVAR with Sign Restrictions

The Local Projection (LP) method offers significant advantages over the Structural VAR model (SVAR) once an exogenous shock is identified. This raises a valid question about the rationale for using SVAR in this Appendix. The purpose here is to present a result (Figure 13) that directly compares with the findings of Schiman (2021). To ensure this comparison is precise, I have replicated the identical settings used by Schiman (2021).

In SVAR, current period variables are included on the explanatory side as shown in Equation (12), where Y_t represents a vector of n endogenous variables. The term $B_0 Y_t$ is included in the explanatory side to account for the possibility of contemporaneous effects among the variables. A critical assumption of this model is that ε_t represents white noise, characterized by a zero covariance, denoted as $\mathbb{E}(\varepsilon_t \varepsilon_t') = 0$.

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

$$
\begin{aligned}
&Y_t = B_0 Y_t + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + \varepsilon_t && (12)\\
\Leftrightarrow &(I - B_0) Y_t = B(L) Y_t + \varepsilon_t \\
\Leftrightarrow &Y_t = (I - B_0)^{-1} B(L) Y_t + (I - B_0)^{-1} \varepsilon_t \\
\Leftrightarrow &Y_t = A_1 B(L) Y_t + \epsilon_t \ \text{, where } \ \epsilon_t = (I - B_0)^{-1} \varepsilon_t && (13)
\end{aligned}
$$

Equation (12) is transformed into Equation (13), its reduced form, to facilitate the estimation of coefficients using Ordinary Least Squares (OLS). However, the variance-covariance matrix of ϵ_t is no longer diagonal but contemporaneously correlated. Consequently, the innovations in ϵ_t lack structural interpretation, as noted by Breitenlechner et al. (2019). A common method to recover structural information from Equation (13) involves using the Cholesky decomposition of the covariance matrix $\mathbb{E}(\epsilon_t \epsilon_t')$. This approach, however, imposes the stringent assumption that shocks to one variable do not contemporaneously affect other variables, depending heavily on the ordering of variables. To mitigate this issue, alternative methods have been proposed that rely less on such assumptions. One such method involves applying sign restrictions, as suggested by Uhlig (2005), while another employs the Local Projection method proposed by Jordà (2005). The results derived from the Local Projection method will be detailed in a subsequent 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). Utilizing the narrative restriction method, Figure 5 in Schiman (2021)'s paper illustrates that following a *positive* shock of foreign labor, the vacancy rate initially decreases over the first three years, increases in the subsequent three years, and ultimately stabilizes at zero. As discussed in Introduction of this paper, this pattern is consistent with predictions from other existing studies and the Search and Matching model.

The objective of this subsection is to conduct a comparative analysis by presenting Figure 13, which corresponds to Figure 5 in the study by Schiman (2021). To ensure an accurate comparison, I have replicated the settings used by Schiman (2021). This includes maintaining the same shocks, variables, sign and narrative restrictions, and lag length. A forecast horizon of 120 months is employed in this analysis. Details regarding the sign and narrative restrictions utilized in this paper are provided in Table 7.[13] Notably, the

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

TFW supply shock, which is a critical factor in the TFW dynamics, adheres to the Type A restriction outlined by Antolín-Díaz and Rubio-Ramírez (2018a).

Figure 13

(a) IRFs using narrative sign restrictions

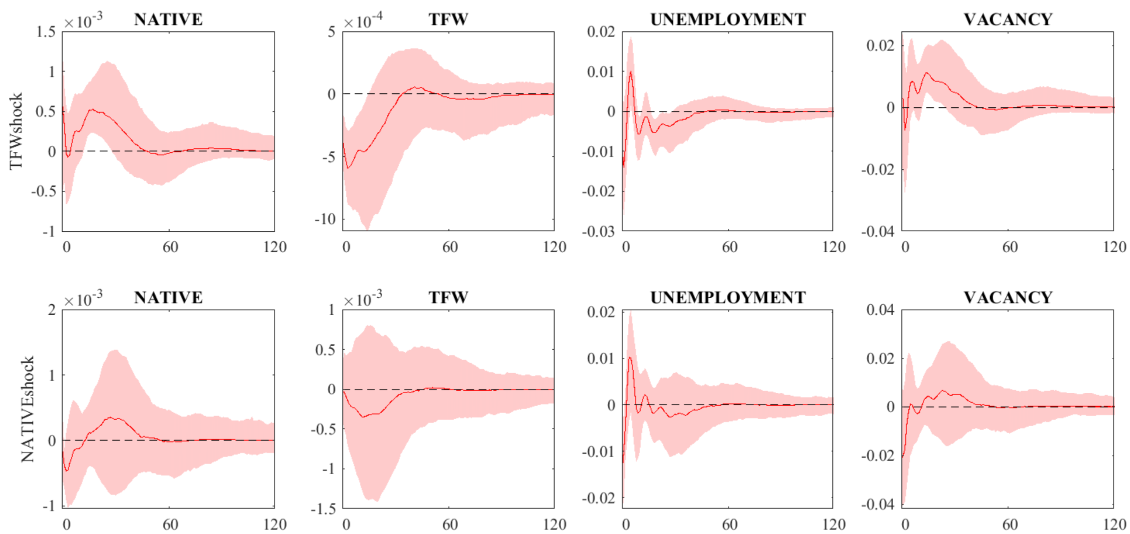


Table 7: Impact sign restrictions, 4-dimensional VAR

<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">Negative TFW supply shock</td><td colspan="2">$-$</td><td rowspan="2">$-$</td><td rowspan="2"></td></tr>
<tr><td>$b_{32} <$</td><td>$-$</td></tr>
<tr><td rowspan="2">Negative NATIVE supply shock</td><td colspan="2">$-$</td><td rowspan="2">$-$</td><td rowspan="2"></td></tr>
<tr><td>$-$</td><td>$b_{41} <$</td></tr>
</table>

Figure 13 shows IRFs over ten years, using the monthly dataset that ranges from 2012m1 to 2024m2 (146 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) and converges to *zero* eventually.

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