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

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Abstract

This paper investigates the impact of a reduction in low-skilled Temporary Foreign Workers (TFWs) on the vacancies in the manufacturing sectors in South Korea. Using a quasi-experimental event, the initiation of a quarantine policy due to COVID-19 in January 2020, the study aims to isolate the causal effect of TFWs on labor shortages. The paper employs vacancies as a proxy measure for labor shortages and focuses on E9 visa holders, who constitute the majority of TFWs in the South Korean manufacturing sector. Through Difference-in-Difference (DD) regressions, the study finds that sectors heavily reliant on TFWs experienced a significant increase in vacancies a year after the COVID-19 outbreak. The results suggest that firms faced challenges in finding full-time workers, leading to a higher ratio of part-time to full-time employees. The paper also utilizes Structural Vector Autoregression (SVAR) and Local Projection (LP) methods to reinforce these findings. Our results contribute to the existing literature by confirming that a reduction in TFWs results in an immediate increase in vacancies, and by challenging the claim that native workers can readily fill the positions left vacant by TFWs, especially in terms of full-time employment. (JEL J18, J21, J22, J23, J61, J63)

*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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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, 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 $\frac{\text{Number of unfilled vacancies}}{\text{Number of employees}} \times 100$.

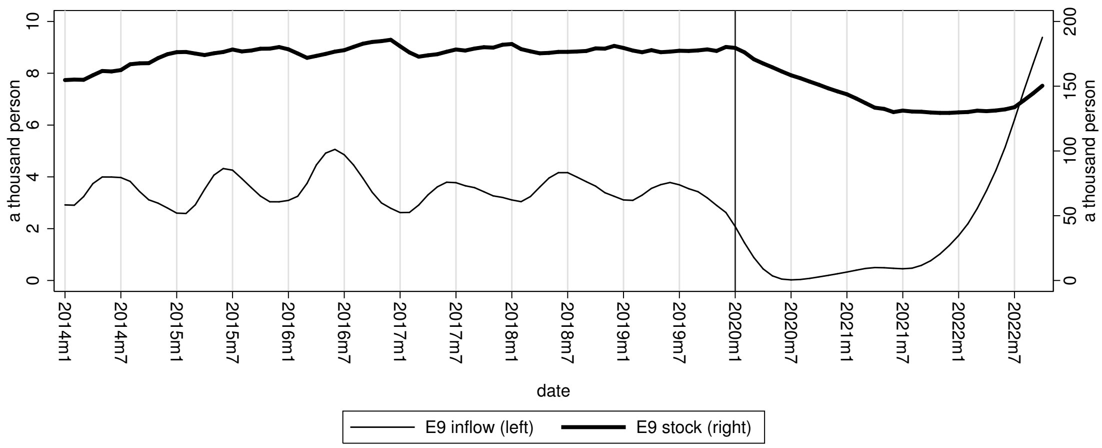
This paper examines the short-term (two-year) impact of a decrease in low-skilled TFWs on manufacturing sector vacancies in South Korea. A complicating factor is reverse causality: the government's TFW policy is informed by vacancy rates, which in turn impact the number of TFWs. A quasi-experimental 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.

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

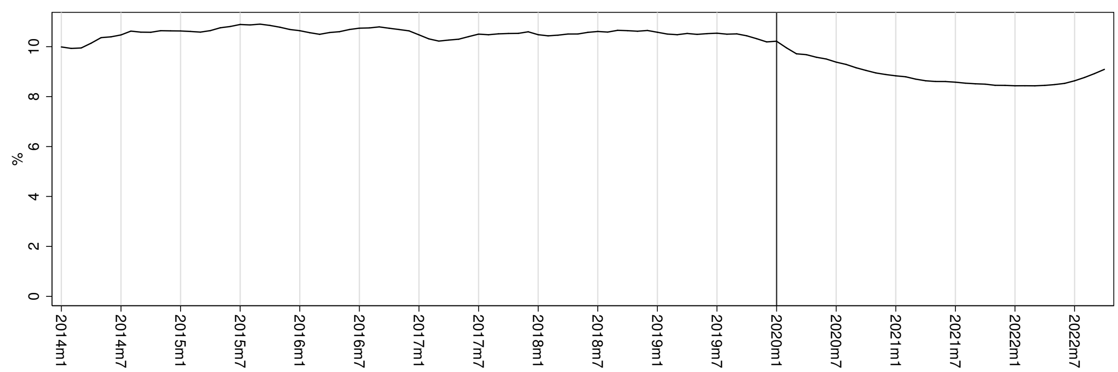
Figure 1

(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

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) 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)).

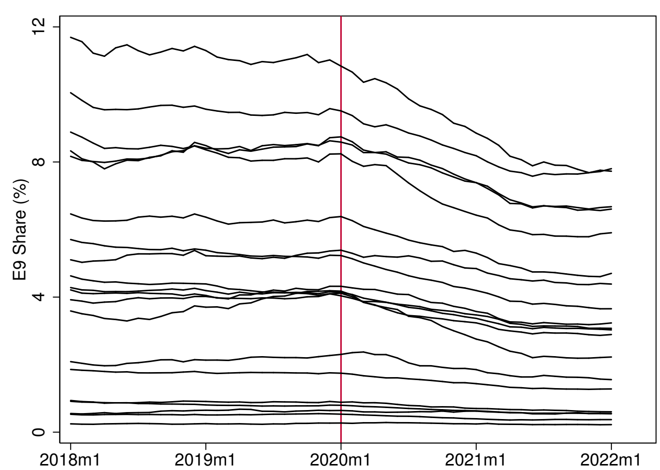
Goldsmith-Pinkham et al. (2020) discuss how the identification of the shift-share instrument comes from the 'share' part: using the shift-share instrument is equivalent to using local 'shares' as the instrument. Therefore, it is valid for this paper to use the 'share' part, which corresponds to the share of E9 workers before the onset of COVID. Furthermore, Jaeger et al. (2018) against using the shift-share instrument when the coun-

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: Share of E9 by sectors



$$\text{Share of E9} = \frac{\text{Number of E9 workers in 2019m8}}{\text{Number of total workers in 2019m8}} \times 100$$

try 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.

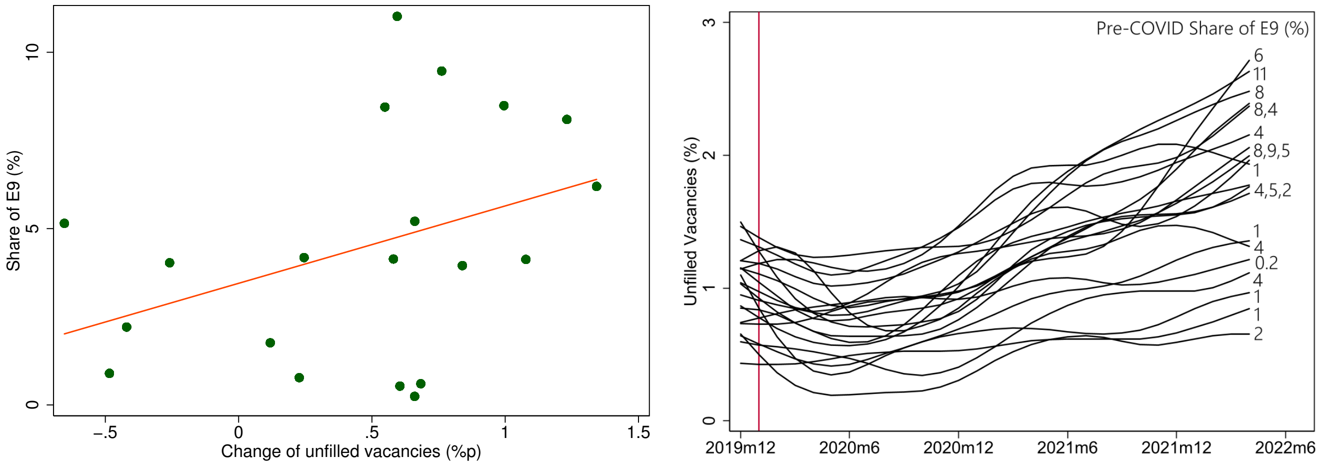
However, the validity of DD depends on the assumption that the post-pandemic decline of E9 workers due to stringent quarantine measures is the only event differentiating the control and treatment groups. If other factors differ across sectors and time, the identification of the DD effect will be compromised. COVID-19 has introduced multiple confounding factors, such as unemployment insurance benefits, labor demand shocks, and excess retirements, which will be rigorously addressed in the remainder of this paper (Section 4).

The DD regressions offer key insights into the labor market dynamics following

Figure 3

(a) Share of E9 and Change of Vacancies

(b) Unfilled Vacancies by sectors



$$\text{Share of E9} = \frac{\text{Number of E9 workers in 2019m8}}{\text{Number of total workers in 2019m8}} \times 100$$

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

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 (as illustrated in 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] Post-pandemic, these firms encountered considerable challenges in recruiting full-time workers, even as they found it relatively easier to hire part-time workers. As a result, the ratio of part-time to full-time workers has experienced a significant upturn.

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.

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

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.

The structure of the paper proceeds as follows: Section 2 provides detailed explanations for the empirical literature discussed in Introduction. Section 3 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 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 Literature Review

Through a careful review of the existing literature, four 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 refugee influx lasted about two years before 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. His findings are presented in Figure 5 of his paper. In the event of a foreign labor inflow shock, (1) unemployment increases both in the short- and long-term for ten years; (2) the vacancy rate *drops* in the first three years, then *bounces 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 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 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-term assumptions, which include fluid capital movements. 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-term impact of the increase in immigrants during 2012-2016 using the search and matching model.

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*.

To summarize this section, the three studies discussed (Anastasopoulos et al. (2021),

[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.

Schiman (2021), and Iftikhar and Zaharieva (2019)), along with the search and matching model by Howitt and Pissarides (2000), 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 both Structural Vector Autoregression (SVAR) and Local Projection (LP) approaches to analyze the impact of labor inflows on vacancy rates. Our 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 term, *bounces up* in the long term, and eventually converges to *zero*.

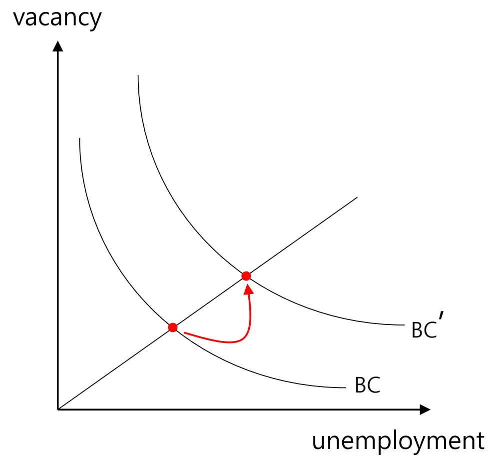
3 The Search and Matching Model

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 4(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 7 summarizes notations). The influx of immigrants leads to the birth rate (b) increase. In the long-run, the model predicts as in Figure 4(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 4(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 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

Figure 4: Search and Matching Model



When large influx of labor

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*.

4 Confounding Factors

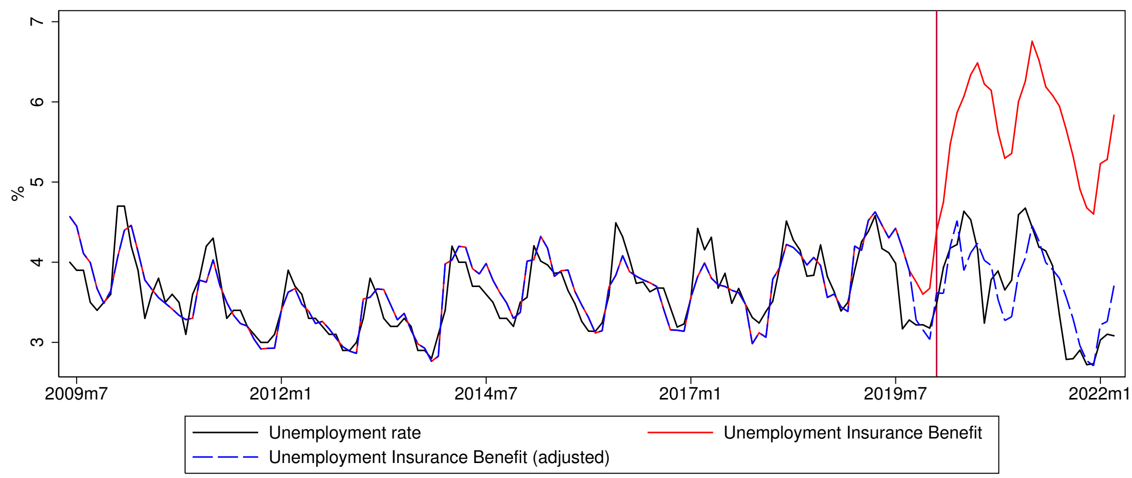
The COVID-19 pandemic has exerted multifaceted impacts on the South Korean economy. Several potential factors may have contributed to the rise in vacancy rates in South Korea: 1) unemployment insurance benefits, 2) labor demand shock, and 3) excess retirement. Throughout the paper, these confounding factors are rigorously accounted for as control variables.

Unemployment insurance benefits: the government increased unemployment insurance benefits (UIB) to help recipients cope with the pandemic (Figure 5). 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 6(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 7(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 7(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.

Figure 5: Unemployment rate and UI rate

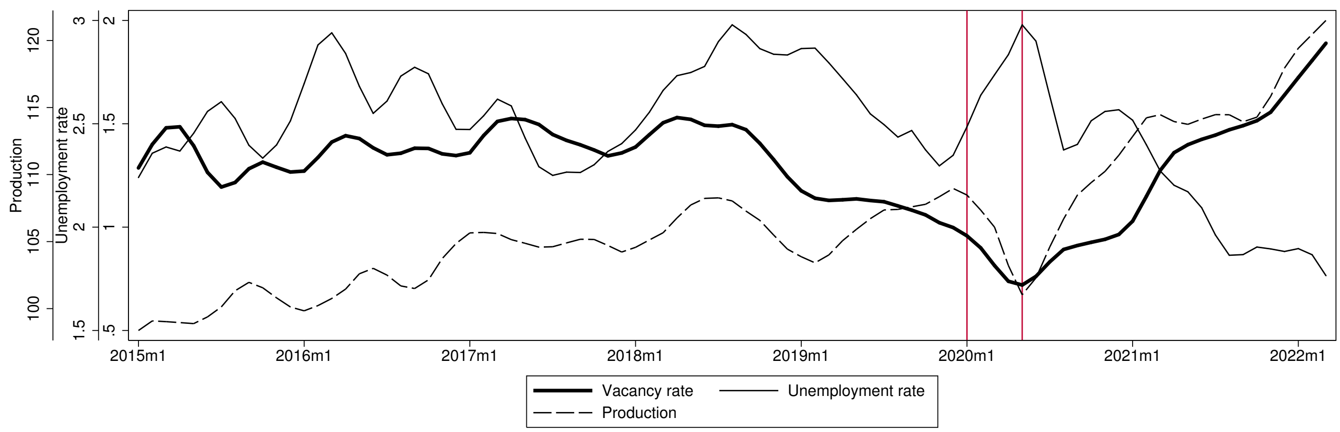


5 Time Frame

It is possible to identify two distinct phases during the COVID-19 pandemic (Figure 6). 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 6(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)). As of June 2022, 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.

Figure 6: Two Phases since COVID-19

(a) South Korean manufacturing case



(b) The USA case

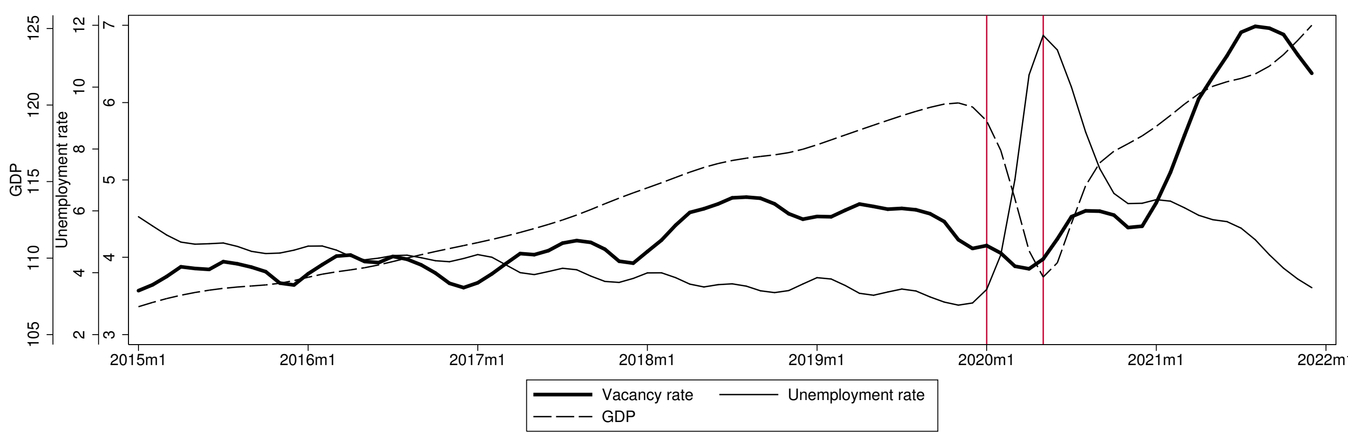
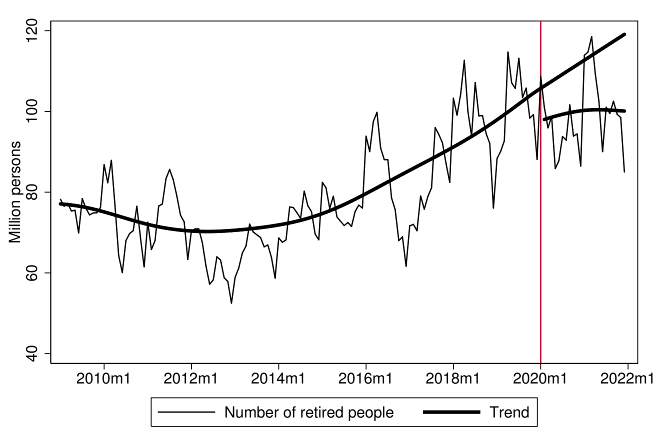
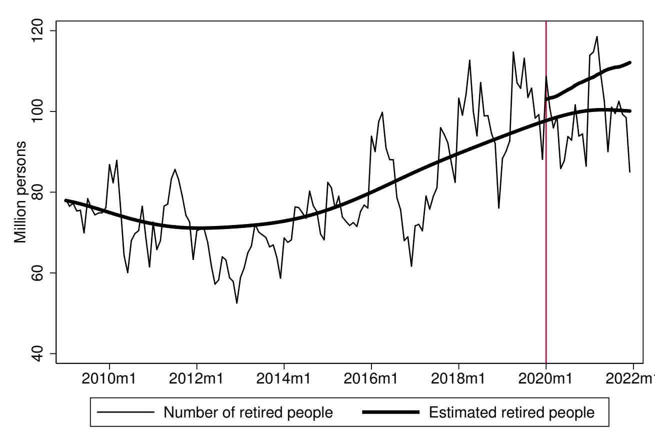


Figure 7

(a) Retirement Trend using Extrapolation



(b) Retirement Estimation using Age Cohort



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 B, 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 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 Appendix Table 6. Figure 5 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.[7]

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

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

[7] 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

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.

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

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
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

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

AR coefficients and their sum.

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 4, the paper includes Table 3, a reduced form estimation that directly uses the instrumental variable as an explanatory variable.

Table 3

	(1) Tightness	(2) Vacancy	(3) Vacancy(Full)	(4) Vacancy(Part)	(5) Part/Full	(6) Wage(Full)	(7) Hour(Full)
E9SHARE × 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

Standard errors in parentheses

S_i and T_t included but not reported.

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

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, 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 8. X_{it} are the same

Table 4

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Tightness	Vacancy	Vacancy(Full)	Vacancy(Part)	Part/Full	Wage(Full)	Hour(Full)
E9CHG × 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.

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

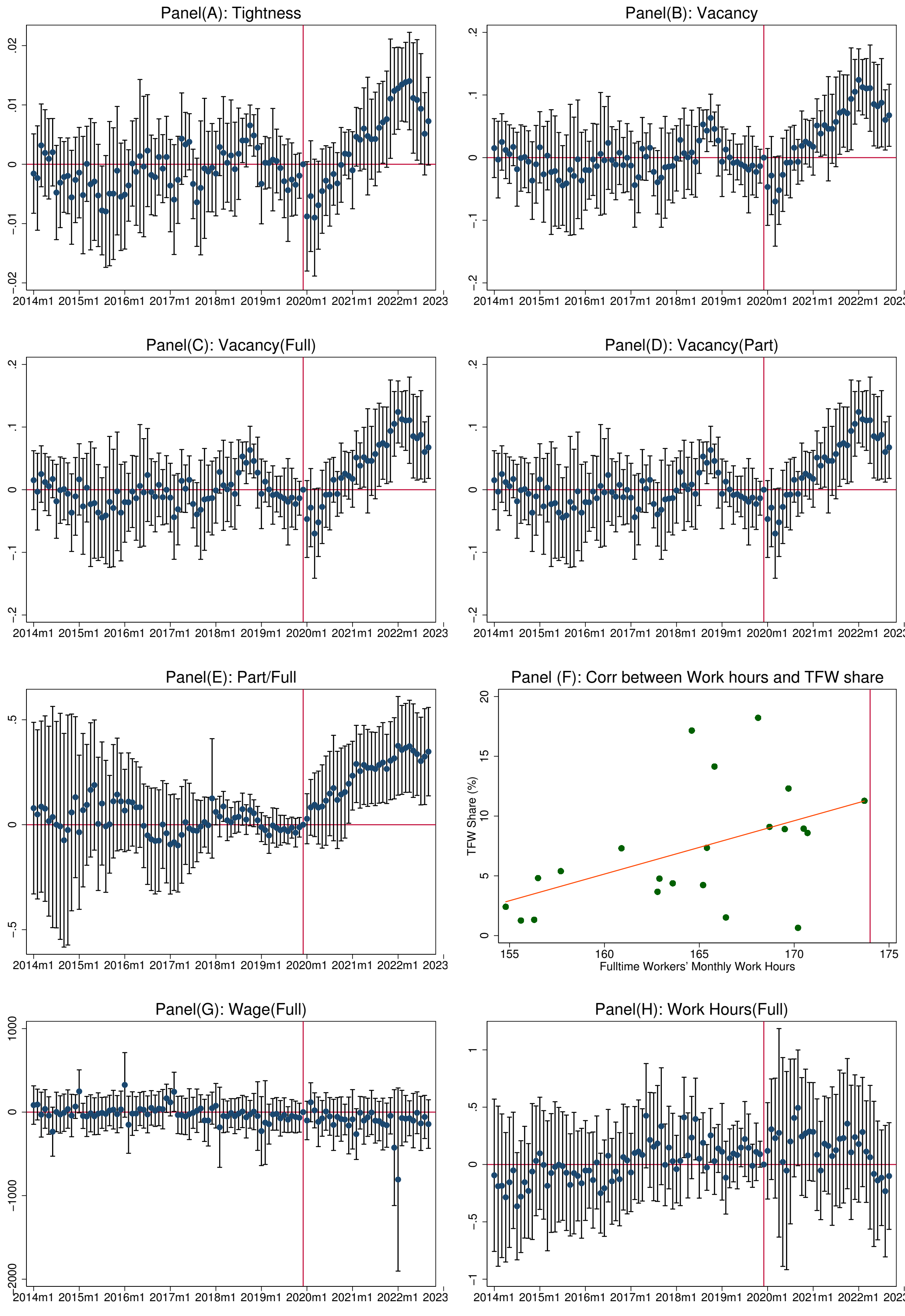
control variables as in the previous equation.

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

The figures are consistent with the regression results in Table 4. 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

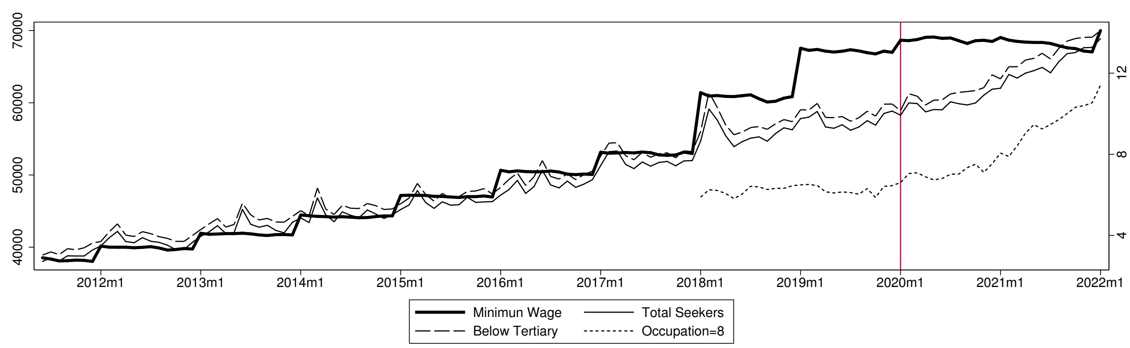
Figure 8: DD regressions



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 9 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).

Figure 9: The proportion of part-time job-seekers



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

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. $B_0 Y_t$ is included in the explanatory side because the variables may have a contemporaneous effect on each other. One important assumption is that ε_t is a white noise, with a zero covariance of $\mathbb{E}(\varepsilon_t \varepsilon_t')$.

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

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 objective of this subsection is to offer a comparative analysis by presenting Figure 10, which parallels Figure 5 in the paper by Schiman (2021). To ensure a precise comparison, I adopt the identical settings used by Schiman (2021). Specifically, the shocks, variables included, sign and narrative restrictions, and the lag length (denoted as $(l = 6)$) are all maintained. A forecast horizon of 120 months is utilized for this study. Details on the sign and narrative restrictions deployed in this paper[8] can be found in Table 5. Notably, the TFW supply shock serves as the most important contributor to TFW, conforming to the Type A restriction by Antolín-Díaz and Rubio-Ramírez (2018a).

In summary, every setting aligns perfectly with those in Schiman (2021).

Figure 10

(a) IRFs using narrative sign restrictions

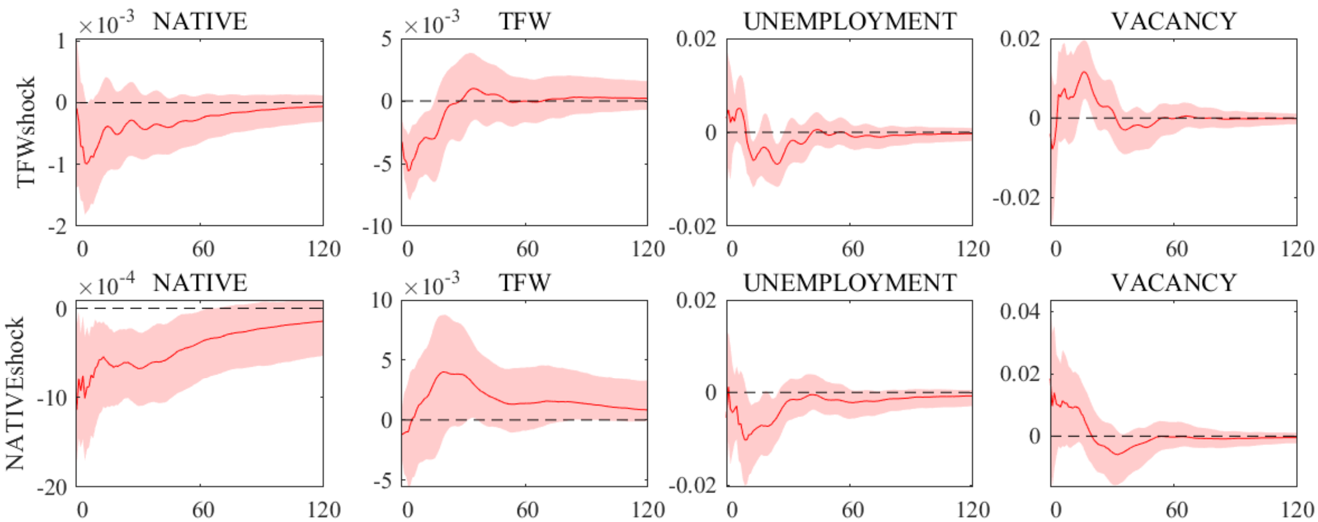


Table 5: Impact sign restrictions, 4-dimensional VAR

<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 10 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

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

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 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.

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

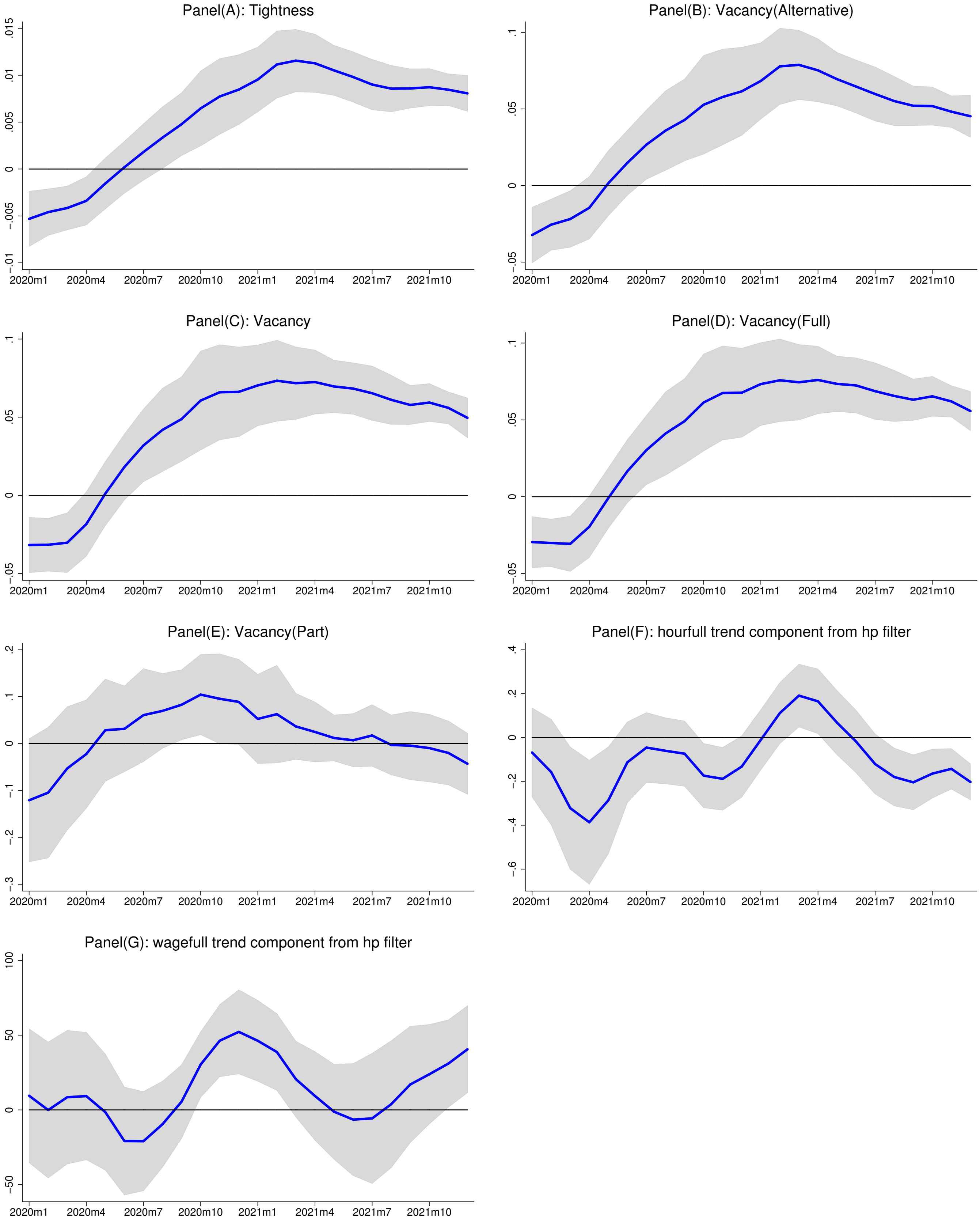
The time frame (t) spans as follows: $D_t = 0$ for 2019m3 to 2019m12, and $D_t = 1$ for 2020m1 to 2020m10. The forecast horizon (h) spans until $H - 1$(2022m9), which is the most recent data available. The number of h is 24 (including $h = 0$). The forecast horizon needs to have already taken place at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

Figure 11 shows the IRFs using the LP method. Panels A through D initially start from negative, reflecting the Shock Phase described in Section 5 (Figure 6). 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

Figure 11: IRFs using LP



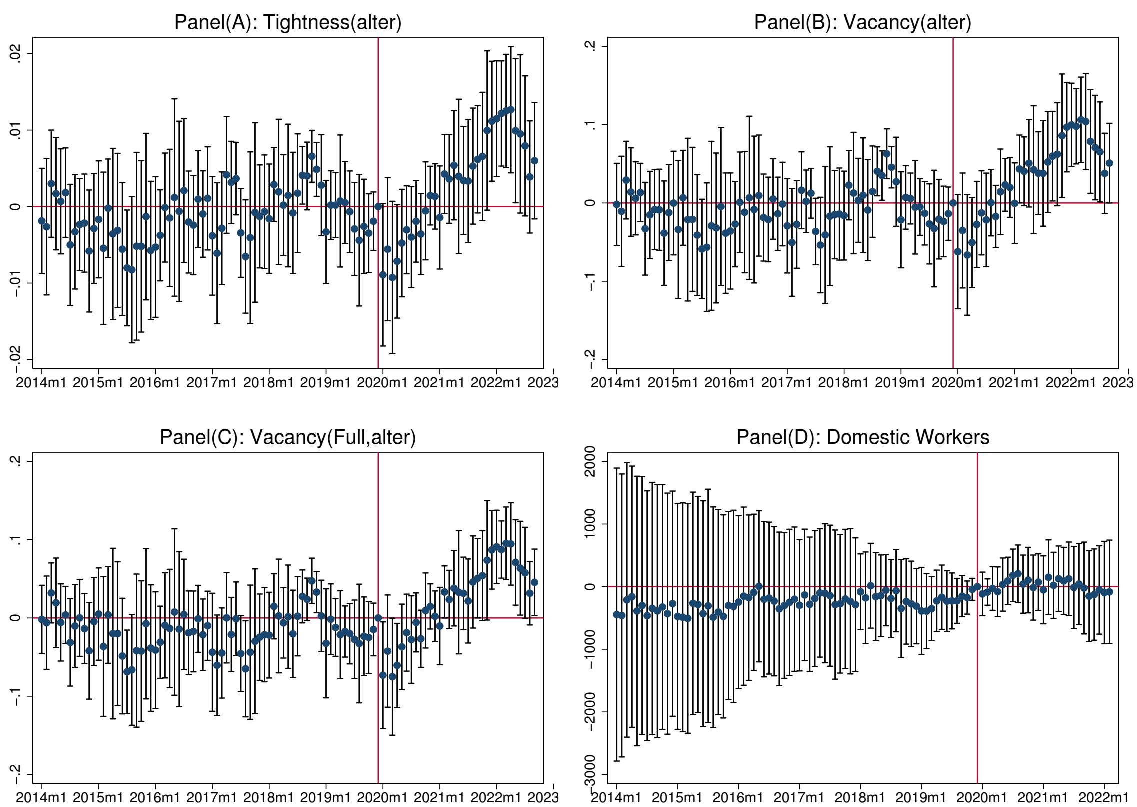
sectors, because in this case, the DD will cancel out the differences. On the contrary, it is problematic if the number of domestic workers has decreased (or increased) more in the manufacturing sectors that relied more on TFWs.

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 12 show the same DD regression as Figure 8. The only difference is that Figure 12 is using valter_{it} instead of the vacancy rate. Comparing Figure 8 and Figure 12, one can see that the figures are almost identical.

Figure 12: DD (Robustness Check)



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:

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

Equation 6 shows the estimated number of domestic workers for two-digit sectors level. Panel D of Figure 12 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

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 DD, SVAR, and LP methodologies, this paper validates these trends in the short run and observes a statistically insignificant *drop* in the long-run vacancy rate, according to SVAR results.

The empirical findings reveal that natives predominantly fill the vacancies as part-time workers, thereby exacerbating the difficulty firms face in recruiting full-time workers. Consequently, the ratio of part-time to full-time workers has seen a substantial increase. Manufacturers have not ameliorated this challenge by raising wages or extending working hours. A possible explanation here could be that they have already reached the maximum number of working hours.

This study endorses South Korea's 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.

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. Following this line of thought, an intriguing avenue for future research could be the impact of reduced TFW numbers post-pandemic on the adoption of labor-substituting technologies in manufacturing.

Furthermore, 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 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.

B 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.

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 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

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

can work anywhere they want, as long as it belongs to Elementary occupations.

Unauthorized workers

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

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

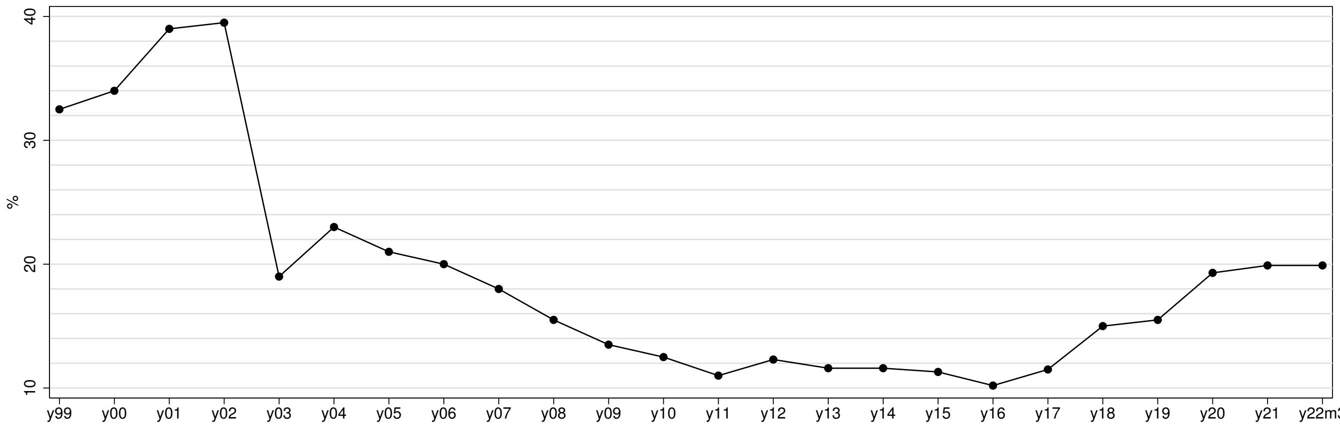
First, Korea Immigration Service Statistics (KISS) from Ministry of Justice provides information about people in Category A. Figure 13 shows that the share of overstaying foreign residents to the total non-immigration residents. It plummeted in year 2003 due to a legalization policy and strong enforcement. 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.

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

[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 immigrants; Source: Pew Research Center.

Figure 13: Share of Overstaying Residents



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

C Appendix: Derivation of Search and Matching Model

Notations are the same as Howitt and Pissarides (2000) and is summarized in Table 7. The people and firms' flow is depicted in Figure 4(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). So $L_{t+1} = L_t(1 + b_t - d_t)$. This means that firms' entrance is unlimited, but the number of people is strictly projected by the birth and death rate. The total number of employed workers is $(1 - u_t)L_t$, the total number of unemployed people is u_tL_t, and the total number of vacant firms is v_tL_t. This is because v_t is defined as the number of vacant firms per one mass of the population.

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

Table 7: 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

$m(u_t, v_t)$ 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.

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

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

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 $u_{t+1} = u_t$,

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

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.

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

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:

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

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

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

$$w = p \cdot \text{FDR} - \frac{pc(r+\lambda+d)}{q} \tag{JC}$$

$$w = z + \beta(p \cdot \text{FDR} - z + \theta pc) \tag{WC}$$

$$u = \frac{\lambda+b}{\lambda+b+q} \tag{BC}$$

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 **??**(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).

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