How the reduction of Temporary Foreign Workers led to a rise in vacancy rates in the South Korean manufacturing industry

Version 10.0 *

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1 Introduction

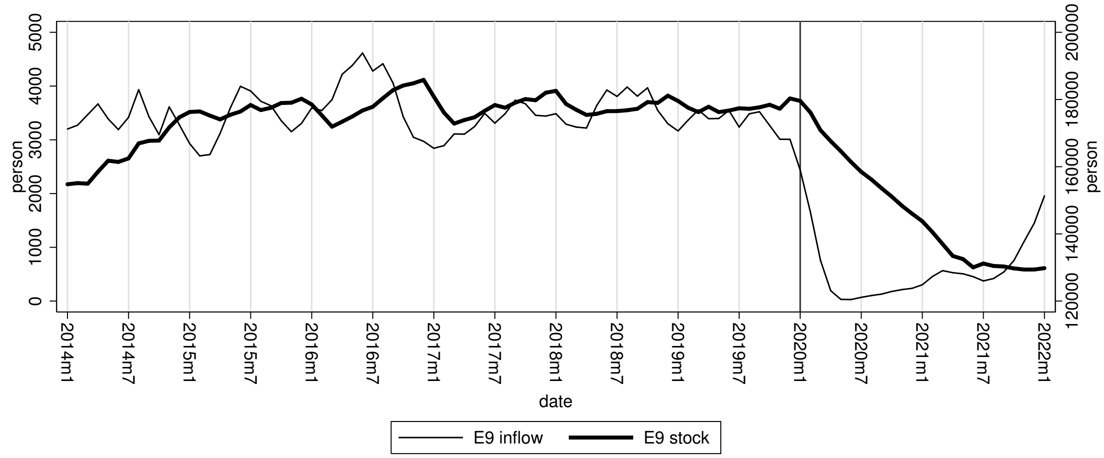
The South Korean government allows for an inflow of low-skilled temporary foreign workers (TFWs) only when there is a labor shortage. This TFW policy is grounded in the notion that accepting TFWs helps to alleviate employers' difficulties in finding low-skilled workers. Opponents of the TFW policy, however,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

Defining the labor shortage is the first step of this study. The literature has actively discussed the definition of the labor shortage (Martin Ruhs and Bridget Anderson (2019); Constant and Tien (2011); and Barnow et al. (2013)). The studies agree that there is no clear-cut definition, but that the issue of vacancy is important. Vacancy rates measure the degree of how difficulty it is for employers to find workers. Vacancy in this study follows the same definition of 'Job openings' used in the JOLTS (Job Openings and Labor Turnover Survey): "positions that are open on the last business day of the reference month, and the job could start within 30 days.'' To sum, this study will use vacancies as a proxy to measure the labor shortage.

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

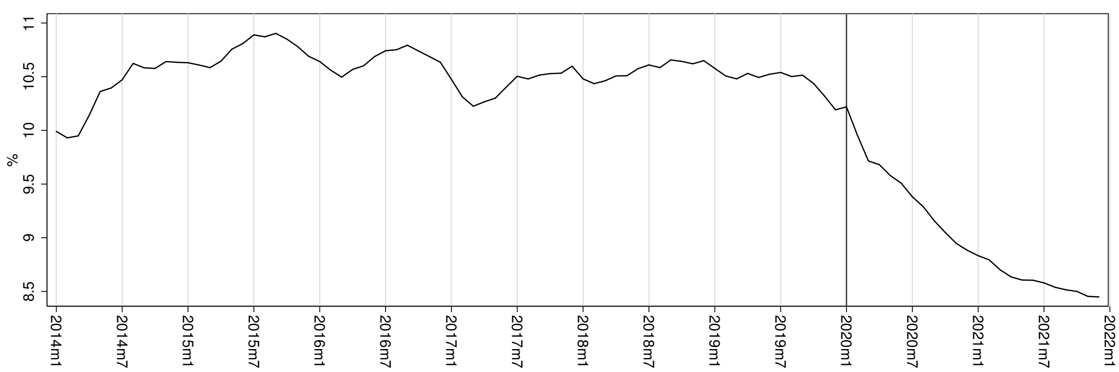
Figure 1

(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

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

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

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

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]

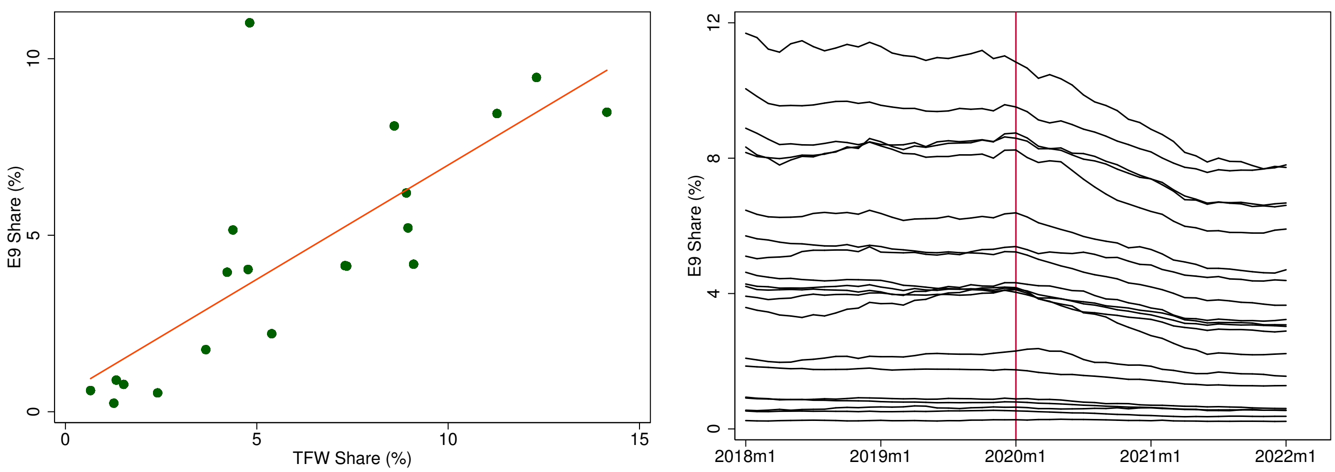
Meanwhile, the identification of DD crucially depends on the assumption that a single event is the only difference between the control and treated. If this is not the case —that is, if any other events differ by sectors and time during the period after this single event— the identification of DD will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

DD regressions show the following results. The sectors that heavily relied on TFWs encountered a large increase in vacancies a year after COVID-19. These sectors have historically featured an intense workload; the sectors with a heavy reliance on TFWs

Figure 2

(a) Correlation between E9 and TFW

(b) E9Share by sectors



include a higher monthly average of working hours. Therefore, when the vacancy issues arose, these firms could not increase the number of working hours, as they were already at a maximum. Furthermore, 90.19% of TFWs were full-time workers before COVID-19 (as of 2019h2).[2] After COVID-19, firms that heavily relied on TFWs have faced difficulties finding full-time workers, while finding part-time workers was easier. Consequently, the ratio of part-time to full-time workers had significantly increased. Reading these results together, this paper concludes that TFWs are indispensable members of South Korean society, especially in the manufacturing sector which faces competition from low-wage countries like China and Vietnam.

This paper uses DD approach as the main analysis since it is the most appropriate setting that reflects the COVID-19 incident. However, in addition to DD regression analysis, this paper explores two additional and different approaches. The first is Impulse Response Functions (IRF) using Structural Vector Autoregression (SVAR). The result is consistent with existing literature. The reason why the paper added this SVAR approach is that Schiman (2021) used the same approach. By using the same method, the paper provides a comparison between the South Korean context and the Austrian context.

Second, the paper explores IRF using the Local Projection (LP) method. The results are again consistent with all of the aforementioned results. The reason why the paper added this LP approach is that there is a growing literature on this method in place

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

of the SVAR approach. Moreover, the LP approach has many advantages that the SVAR approach does not have. For instance, the LP approach can incorporate the DD approach as well as panel settings.

The findings in this paper contribute to the scarce literature about the effect of immigration on vacancies. Through a careful review of the literature, it is possible to identify four existing studies. First, Anastasopoulos et al. (2021) found that labor inflow from Mariel Boatlift in Miami led to a vacancy *drop*. On the contrary, Schiman (2021) showed that labor inflow to Austria due to EU enlargement led to a vacancy *rise*. Third, Iftikhar and Zaharieva (2019) demonstrated a vacancy *rise* when high-skilled immigrants flow into the manufacturing sector in Germany. Finally, Kiguchi and Mountford (2019) showed the vacancy results in three different scenarios, which will be explained in the next section.

Although the findings of the first three studies (Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019)) may initially seem contradictory, they are actually consistent. Therefore, finding and identifying this consistency is one more contribution to the literature made by this paper. To begin, Anastasopoulos et al. (2021) study job vacancies, comparing the synthetic control and Miami treated (Figure 3 Panel A of their paper). The Mariel Boatlift occurred between April and October, 1980, and the influx of refugees lasted about two years until many left Miami to go to other cities. The figure shows that the vacancy *dropped* until 1988, but then *bounced up* afterwards.

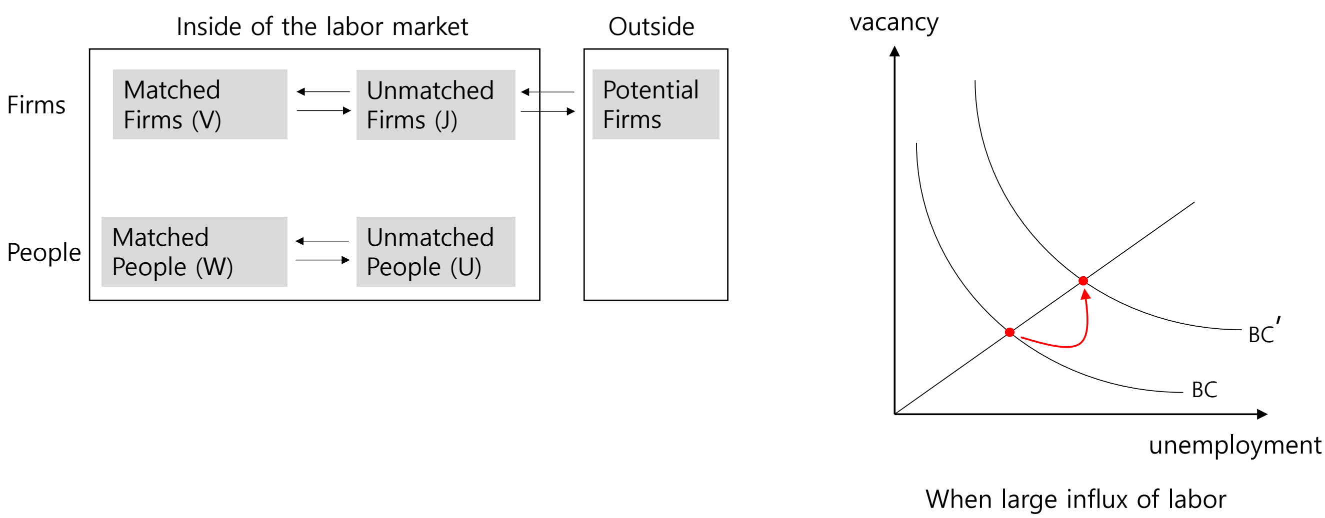
Meanwhile, the case studied by Schiman (2021) shows a similar pattern (Figure 5 of his paper). Due to EU enlargement, a labor influx to Austria began in 2004 and accelerated from 2011 onwards (Figure 2 in his paper). This influx has persisted for more than a decade and is still ongoing at the time of writing. In the figure where the impulse response function is shown using Structural Vector Autoregression (SVAR), vacancy initially *drops* for about three years and then *bounces up* afterwards. It eventually converges to zero within ten years. In other words, vacancy *drops* in the short-run (0-3 years), *bounces up* in the long-run (4-6 years), and finally converges to *zero* (7-10 years).

Finally, Iftikhar and Zaharieva (2019)'s results are also consistent with the pattern identified above. They analyzed the effect of a 25% increase in immigrants in Germany (2012–2016) and found that —after 2016— the average duration of vacancies almost tripled. This vacancy *rise* represents a long-run result, as they used a typical search and matching model. In other words, they analyzed the effect of an increase in immigrants during 2012-2016 (in the short run) on the steady-state equilibrium (in the long run).

The search and matching model by Howitt and Pissarides (2000) predicts the same pattern. In the short-run, where capital is fixed, firms cannot enter and exit the labor market (Figure 3(a)). Therefore, potential firms outside the labor market cannot enter the labor market, even though there is an influx of unmatched people. As a result, the vacancy rate *drops* in the short run (this is formally explained in Appendix D). However, in the long-run, potential firms outside the labor market can enter, as they expect increased profit by matching more people to jobs. As a result, the vacancy rate *rises*, as shown in Figure 3(b).

Figure 3: Search and Matching Model

(a) Model flows (b) Long run



In all, the vacancy pattern is consistent across the three studies (Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019)) as well as within the search and matching model (Howitt and Pissarides (2000)). This paper will contribute to the existing literature by providing analysis results using DD, SVAR, and LP approaches. In the short-run, all of the results from DD, SVAR, and LP approaches are consistent with the vacancy pattern found in the literature: the vacancy rate *surged* in the short-run when there was an outflow of TFWs.

This paper provides a long-run result by using SVAR approach (the top of the forth column in Figure 9). The figure depicts that the vacancy rate does not *drop* in the long-run (4-6 years after the TFW shock) but converges to *zero* (7-10 years after the TFW shock). The long-run result is not consistent with the vacancy pattern found in the literature, especially by Schiman (2021). The reason for this contradictory result could be due to the lack of long-run data in this paper: a dataset was available until two years after the shock (short-run) but unavailable afterwards (long-run). This is a weakness of this paper.

The structure of the paper proceeds as follows: Section 2 provides more detailed explanations for the literature discussed in Introduction. Section 3 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-present). This paper will focus the analysis on the Recovery Phase. Section 4 explains background information about TFWs in South Korea, as it helps to understand underlying implications from the analysis results. Section 5 presents various datasets that the paper will use. Section 6 sets out the empirical model (DD, SVAR, and LP) and identification assumptions. Then it will provide the analysis results. Section 7 checks the robustness of the main results, and Section 8 concludes.

2 Literature Review

Typical search and matching models aim to analyze the long-run consequences when capital is extremely fluid. 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 a new steady-state equilibrium under conditions of extremely fluid capital. A curved arrow line in Figure 3(b) depicts this unique path.

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 of these implicitly assume an extremely fluid capital. Therefore, the search and matching model is more relevant for long-run analysis.

As noted in the Introduction, I have identified four studies about the effects of immigration on vacancies. First, Anastasopoulos et al. (2021) used DD regression as Equation 1 in their paper. Table 1 in their paper reports the regression results. Compared to the treated group (Miami), the synthetic control group shows that vacancies declined by over 20% in 1981-1982, and over 40% in 1985.

Meanwhile, Schiman (2021) studied the impact of foreign labor inflow from Eastern European countries into Austria due to EU enlargement, beginning in 2011. Unlike the Mariel event, the mass migration to Austria persisted for over a decade, and is ongoing. He used Structural Vector Autoregression (SVAR) with sign restrictions for the study. His findings are presented in Figure 5 of his paper. When there is a foreign inflow shock, (1) unemployment increases both in the short- and long-run for ten years; (2) vacancy rate *drops* in the first three years, then *bounce up* for another three years, and then eventually converges to *zero*. His study has two more findings that are provided in the footnotes.[3]

Literature about the effect of immigration on vacancies using the search and matching framework is rare. However, one exception can be found in the work of Chassamboulli and Palivos (2014), although they focus on unemployment and wage outcomes rather than the vacancy rate. The same applies to Liu (2010). Therefore, the closest study that focuses on vacancies is the work of Iftikhar and Zaharieva (2019). They analyze the implications of a 25% increase in immigrants in Germany from 2012-2016.

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

Meanwhile, Kiguchi and Mountford (2019) studied the impact of immigration on economic outcomes, particularly on unemployment and vacancy rates, with annual data from the United States from 1950 to 2005. Their simulation consists of three scenarios.[4] In terms of vacancy rate simulation, none of their three scenarios is consistent with the pattern discussed in the Introduction. For instance, the vacancy rate in the second scenario *drops* in the short run and converges to zero, but never *bounces up* in the long-run.

To summarize this section, the vacancy pattern is consistent across the three studies (Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019)) as well as within the search and matching model (Howitt and Pissarides (2000)). One exception

[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 foreign workers' labor supply shock (not due to reallocation, aggregate activity, or domestic labor supply shocks). His third finding is 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.

[4]The baseline scenario assumes immigrants' entering the market with unemployed status with a low job-finding probability (Figure 4 of their paper). The second scenario assumes they enter the market with employed status (Figure B.1 of their paper). This can be interpreted as employment-based immigration where employers sponsor immigrant workers for green cards. Finally, the third scenario assumes they enter the market with unemployed status with a high job-finding probability (Figure B.2 of their paper).

is the study by Kiguchi and Mountford (2019).

3 Time Frame

It is possible to identify two distinct phases during the COVID-19 pandemic (Figure 4(a)). 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 4(b)). Most of the existing studies about the COVID-19 pandemic focus on the Shock Phase (Borjas and Cassidy (2020); Mongey et al. (2020); Cajner et al. (2020); Coibion et al. (2020); Forsythe et al. (2020)). Studies that focus on the Recovery Phase are relatively rare (Jeong (2022); 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 offers a novel focus on the Recovery Phase.

4 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.

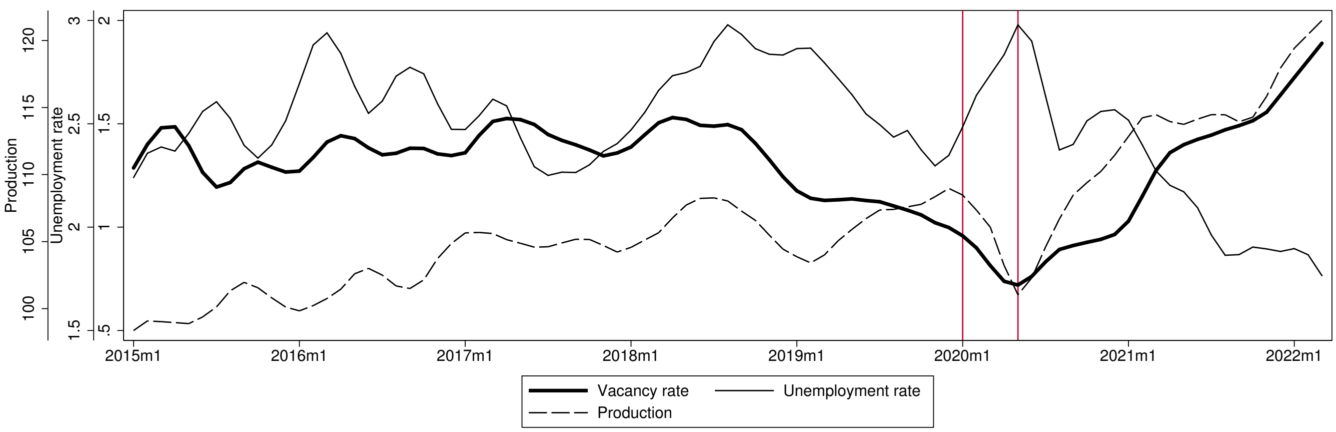
The most important criteria for E9 visa applicants is the Korean language test score: most E9 workers can speak Korean at the elementary level. When admitted, E9 workers will enter South Korea only as full-time workers. Moreover, they are required to leave the country after three years, which means that 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.

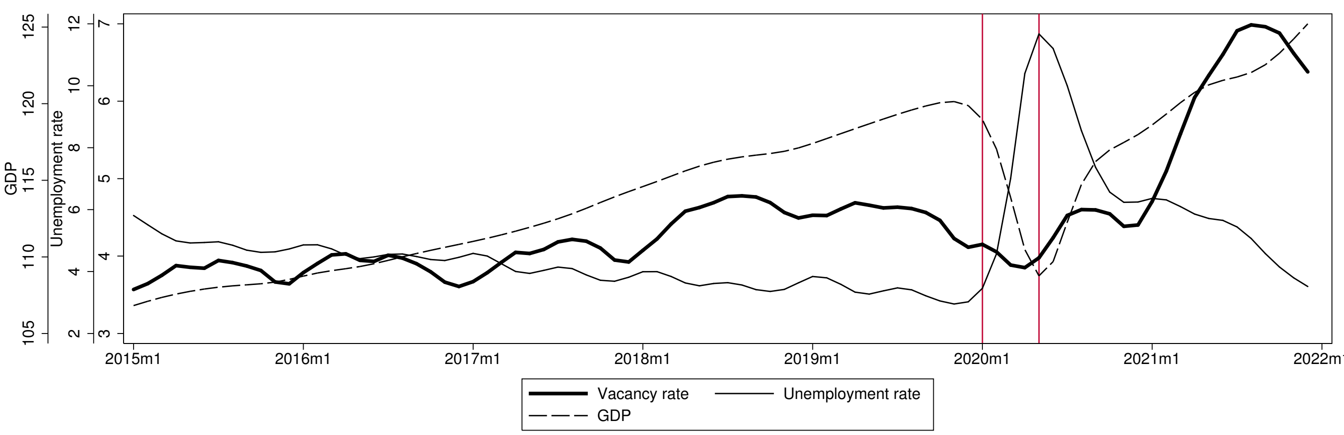
The issue of unauthorized workers would impact the validity of this paper. Lee (2020) estimates the number of unauthorized foreign residents in 2020. According to his findings, the number of unauthorized E9, H2, and F4 visa holders is small. Among the unauthorized foreign residents in 2020, 43.8% fall within the Visa Exemption category (B1), 20.1% have Temporary Visit visas (C3), 12.0% are from the Non-professional

Figure 4: Two Phases since COVID-19

(a) South Korean manufacturing case



(b) The USA case



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.

5 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.[5]

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.[6] Subscript i represents twenty subgroups of manufacturing industries, as shown in Table 7 in Appendix G. Figure 5 shows that the unemployment and UI rates are serially correlated. Therefore, the rate of UI benefits[7] 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 UI benefits rate as a proxy for u_i (unemployment rate for the two-digit manufacturing sectors).

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

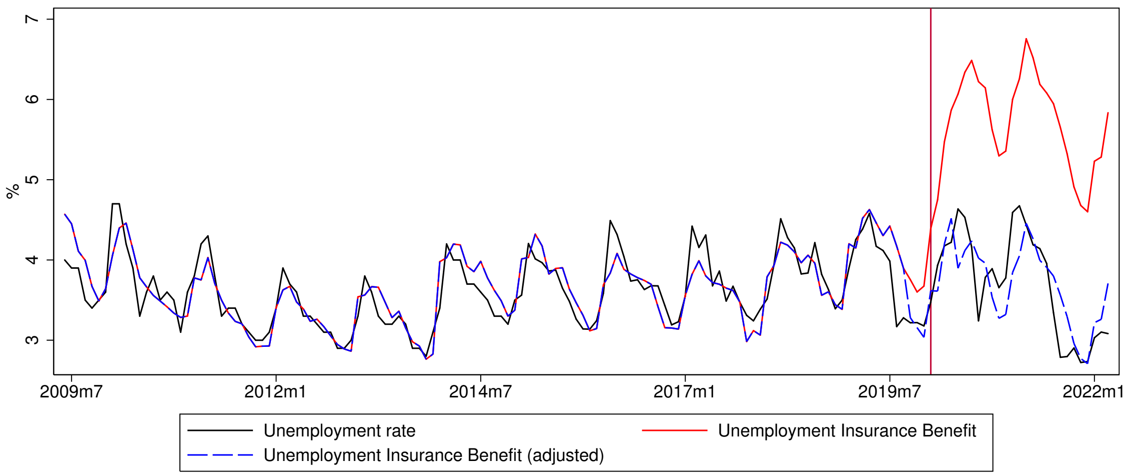
[5] https://www.bls.gov/news.release/empsit.t14.htm

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

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

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

Figure 5: Unemployment rate and UI rate



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 deseasonalizing procedures used by statistical agencies introduce an upward bias on the estimates of the AR coefficients and their sum.

6 Results

6.1 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).

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 2017m1∼2019m12 (pre-COVID), and $D_t = 1$ for the period of 2021m8 $\sim$

2022m04 (post-COVID). The period between 2019m12 and 2021m8 is omitted for 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).

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
Matching efficiency	Explained in detail in Appendix E	LFSE, EAPS
Termination	Explained in detail in Appendix F	LFSE, EAPS

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.

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 -0.241 in the second column means that the

Table 3

	(1) Tightness	(2) Vac	(3) Vac(Full)	(4) Vac(Part)	(5) Part/Full	(6) Wage(Full)	(7) Hour(Full)	(8) MatchEff	(9) Termination
E9SHARE × D	0.007*	0.061*	0.069*	-0.031	0.288*	-0.173*	-0.133	0.018	0.001
	(0.003)	(0.025)	(0.026)	(0.068)	(0.109)	(0.075)	(0.372)	(0.009)	(0.001)
UIB	-0.059	0.362	0.474	-2.010	-0.090	0.334	-9.129*	-0.395*	0.025**
	(0.033)	(0.222)	(0.277)	(1.044)	(1.238)	(1.685)	(3.970)	(0.162)	(0.007)
ProdDomestic	0.001**	0.006*	0.006*	0.012	0.000	-0.003	0.027	0.001	0.000
	(0.000)	(0.002)	(0.002)	(0.011)	(0.006)	(0.005)	(0.026)	(0.001)	(0.000)
ProdAbroad	0.000	0.002	0.003	-0.010	0.021	0.009	0.008	0.002*	0.000
	(0.000)	(0.002)	(0.002)	(0.008)	(0.011)	(0.011)	(0.014)	(0.001)	(0.000)
ProdOperation	0.001	0.006	0.006	0.006	0.010	-0.011	0.071	-0.005*	-0.000
	(0.001)	(0.004)	(0.005)	(0.020)	(0.014)	(0.017)	(0.059)	(0.002)	(0.000)
Observations	820	820	820	820	820	820	820	820	820
R^2	0.352	0.316	0.339	0.093	0.379	0.499	0.931	0.114	0.221

Standard errors in parentheses

S_i and T_t included but not reported.

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

Table 4

	(1) Tightness	(2) Vac	(3) Vac(Full)	(4) Vac(Part)	(5) Part/Full	(6) Wage(Full)	(7) Hour(Full)	(8) MatchEff	(9) Termination
E9CHG × D	-0.027*	-0.241*	-0.274**	0.122	-1.141**	0.687*	0.527	-0.073*	-0.004*
	(0.013)	(0.098)	(0.101)	(0.272)	(0.433)	(0.298)	(1.496)	(0.036)	(0.002)
UIB	-0.051	0.427*	0.548*	-2.043	0.222	0.146	-9.273*	-0.375*	0.026***
	(0.032)	(0.206)	(0.261)	(1.055)	(1.220)	(1.708)	(4.120)	(0.157)	(0.007)
ProdDomestic	0.001**	0.006**	0.006**	0.012	0.002	-0.005	0.026	0.001	0.000
	(0.000)	(0.002)	(0.002)	(0.011)	(0.006)	(0.005)	(0.027)	(0.001)	(0.000)
ProdAbroad	0.000	0.003	0.003	-0.010	0.023	0.009	0.007	0.002*	0.000
	(0.000)	(0.002)	(0.002)	(0.008)	(0.012)	(0.011)	(0.015)	(0.001)	(0.000)
ProdOperation	0.000	0.006	0.006	0.006	0.009	-0.011	0.071	-0.005*	-0.000
	(0.001)	(0.004)	(0.005)	(0.020)	(0.014)	(0.016)	(0.060)	(0.002)	(0.000)
Observations	820	820	820	820	820	820	820	820	820
R^2	0.3474	0.3120	0.336	0.093	0.376	0.500	0.931	0.116	0.217
First-stage F	184.49	184.49	184.49	184.49	184.49	184.49	184.49	184.49	184.49

Standard errors in parentheses

S_i and T_t included but not reported.

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

industrial sectors that experienced a larger decrease of E9 workers had a larger increase in vacancies. Under the valid DD assumptions, one can infer that the decrease in TFWs caused the increase in vacancies.

Column 8 of Table 4 shows how the sectors that heavily relied on TFWs experienced higher matching efficiency. This result may reflect the fact that the matching efficiency increases if the firms are desperate enough to lower their expectation. The related conclusion I can draw is that matching efficiency has increased due to the higher acceptance of part-time workers. This finding is consistent with the result in Column 9, where the termination rate has increased. In other words, firms accept the workers more readily by lowering their expectations, and the accepted workers more frequently quit their jobs.

Equation 2 is a reduced form DD regression model for Figure 6. X_{it} are the same control variables as in the previous equation.

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

The figures are consistent with the regression results in Table 4. In concert, the figures and tables imply that full-time workers' hourly wages decreased when the number of foreign workers goes down to levels lower than those experienced previously. This is an unexpected result, because one could imagine that wages increase when finding workers is more difficult. One possibility is that the vacancy rate does not identify the labor shortage well: the vacancy rate is defined by the number of vacant spots divided by the total number of employees. It can increase when the number of employees decreases, even if the vacant spots stay the same. 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 G of the figure shows that the sectors with a higher number of TFW workers also feature higher work hours. In 2021, the legal maximum number of work hours was 174 per month. If these include overtime payments, the legal maximum is 226 hours. The figure shows that sectors with higher dependence on TFWs also require a number

Figure 6: DD regressions

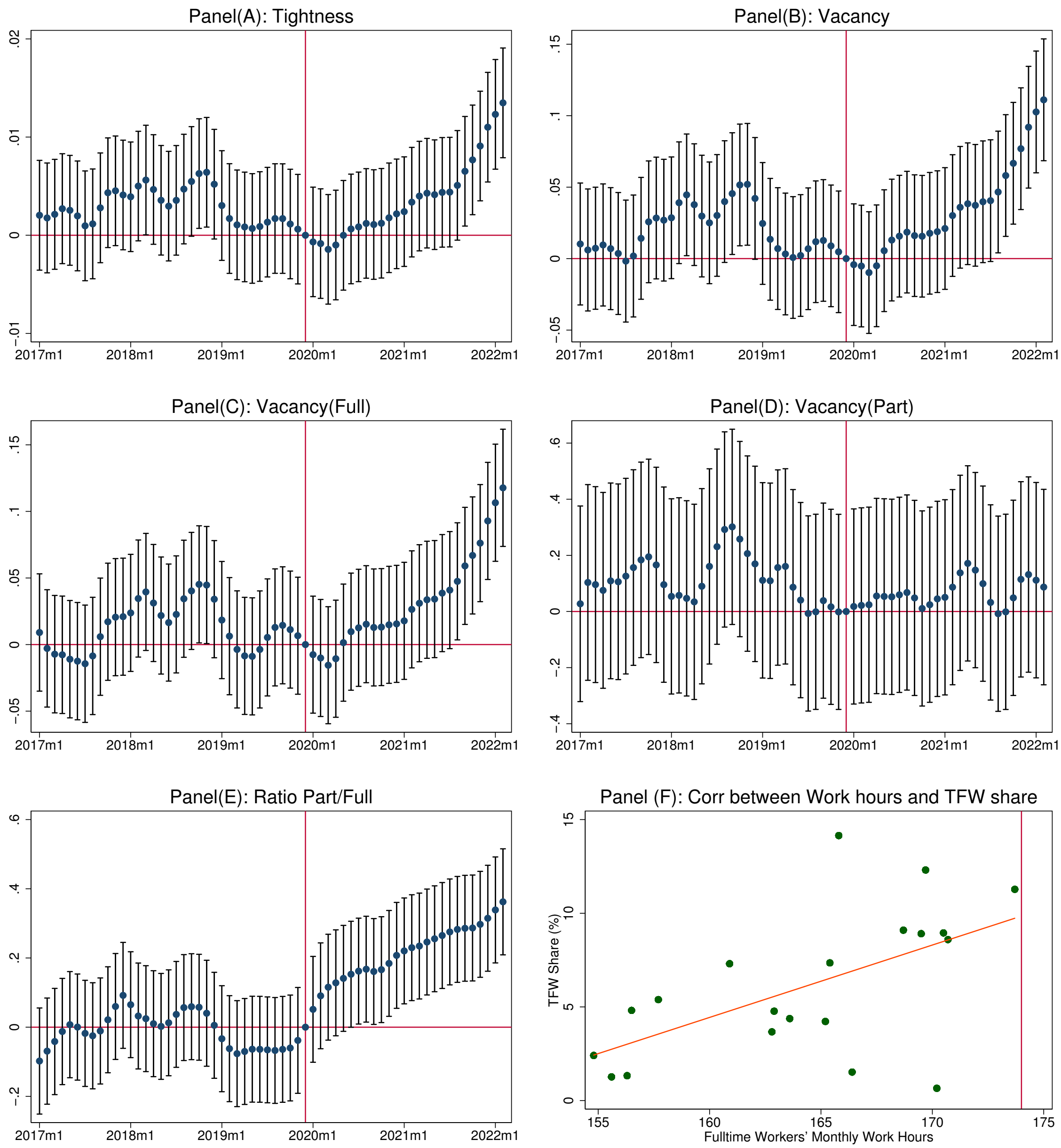
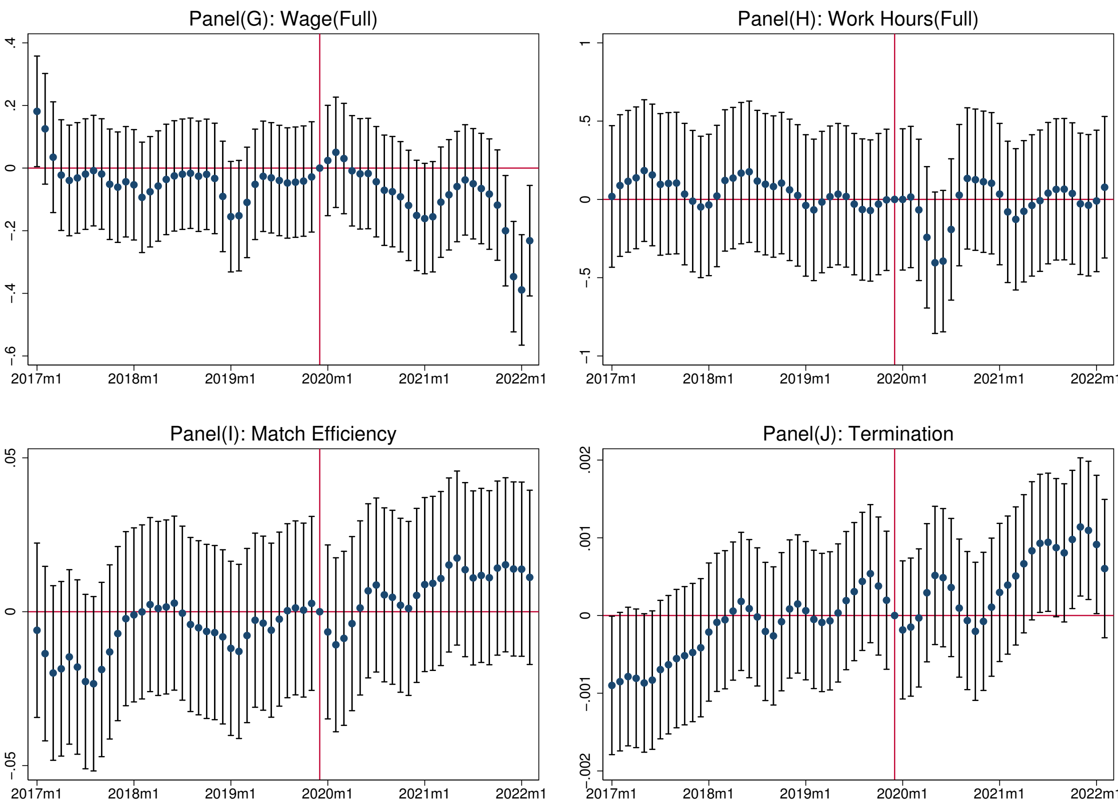


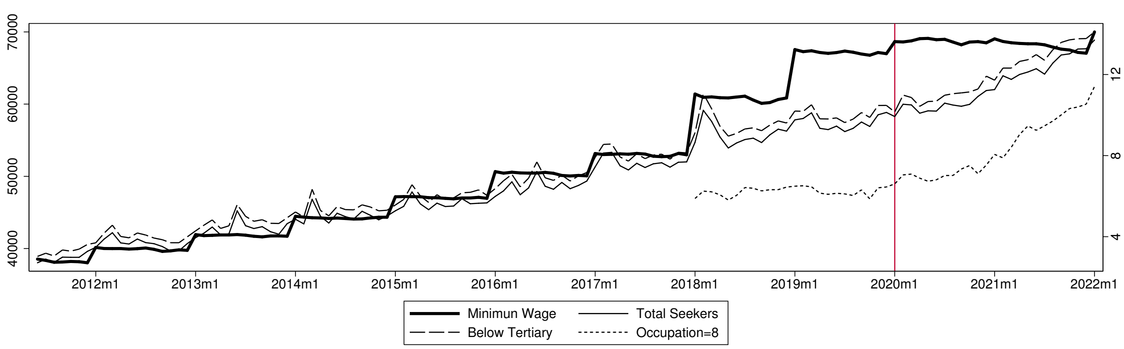
Figure 7: DD regressions (Continued)



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 C), they do have troubles when it comes to finding full-time workers (Panel B). Consequently, the ratio of part-time workers to full-time workers increases significantly in these sectors (Panel D). Manufacturers do not respond to this difficult situation by extending working hours (Panel F) or raising wages (Panel E). Surprisingly, the wages they pay to the currently employed full-time workers actually decreased (Panel E). 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.

Figure 8 shows the increasing proportion of part-time jobseekers. It was around 3.0% in 2011m6, but increased to 13.7% in 2022m1. This trend may have exacerbated the difficulties of finding full-time workers. The increased minimum (real) wage may be attributed to the increasing trend of part-time applicants. The minimum wage in the figure includes an legally mandated extra allowance that any worker, including daily workers, who work more than 15 hours per week should get paid. This allowance is not negligible, and the law is strictly enforced. For instance, in 2021 the minimum hourly wage was \$7.30 if a person worked fewer than 15 hours a week, but increased to \$8.80 if they worked more than 15 hours. In the figure, the total number of jobseekers and the number of below-tertiary seekers does not differ much. Occupation=8 seekers are those who belongs to 'Installation, maintenance, and manufacturing works' in the Korean Employment Classification of Occupations (KECO) . The full classification of KECO is provided in Table 8 of Appendix G.

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



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

6.2 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.

Figure 9 shows IRFs over ten years, using the monthly dataset that ranges from 2012m1 to 2022m3 (123 observations). The dashed lines are 68% error bands, as is considered standard. The figure shows that vacancy rate rises in the short run (three years) when there is a *negative* TFW shock. This is consistent with the other results presented in this paper (DD and LP).

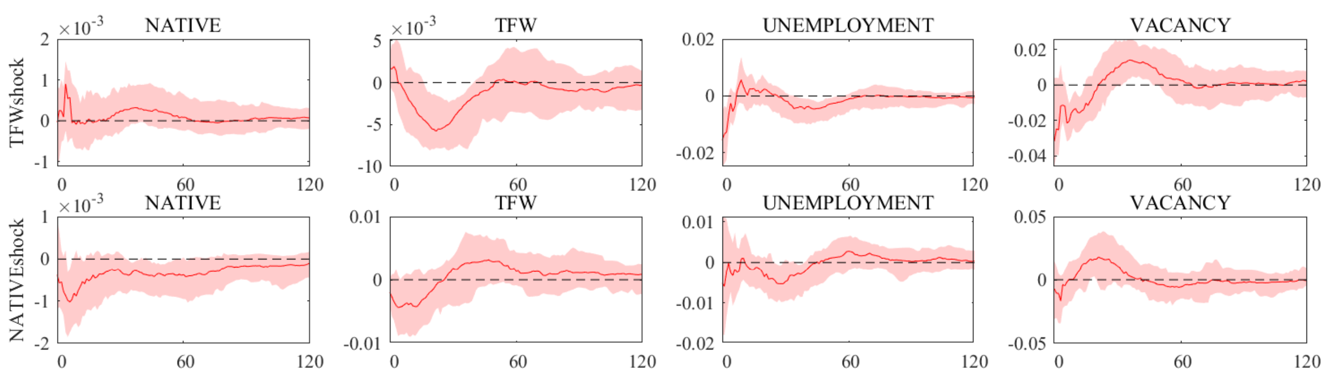
The figure uses the same settings as Schiman (2021). Specifically, shocks, included variables, the sign and narrative restrictions, and the lag length ($l = 6$) are the same. Like Schiman (2021), this paper also uses 120 months (10 years) as a forecast horizon. The sign and narrative restrictions used in this paper[8] are provided in Table 5, which are the same as those used in Schiman (2021)'s argument, although the directions are opposite: the negative supply shock of foreign labor would have a positive effect on the domestic employment, a negative effect on unemployment, and an undetermined effect on vacancy rate. The TFW supply shock is the most important contributor to TFW (Type A restriction by Antolín-Díaz and Rubio-Ramírez (2018a)).

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 9

(a) IRFs using narrative sign restrictions



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

6.3 IRF using the Local Projection Method

As briefly mentioned in the previous section, Jordà (2005) proposed the Local Projection method (LP), which is an alternative method for IRF. Indeed recently, LP has become a more popular method than SVAR. One of the advantages of LP is its flexible applications to situations when an exogenous shock is identified. Once an exogenous shock is identified, IRF can be directly estimated using OLS regressions (Adämmer, 2019). Another merit of LP is that it can be used to a panel dataset (Owyang et al. (2013); Jordà et al. (2015)). Furthermore, LP can be applied to the difference in difference (DD) settings. Moreover, LP is more robust than VAR, especially when VAR is misspecified (Jordà, 2005). In sum, LP results are more reliable than VAR because this paper has DD settings with panel dataset.

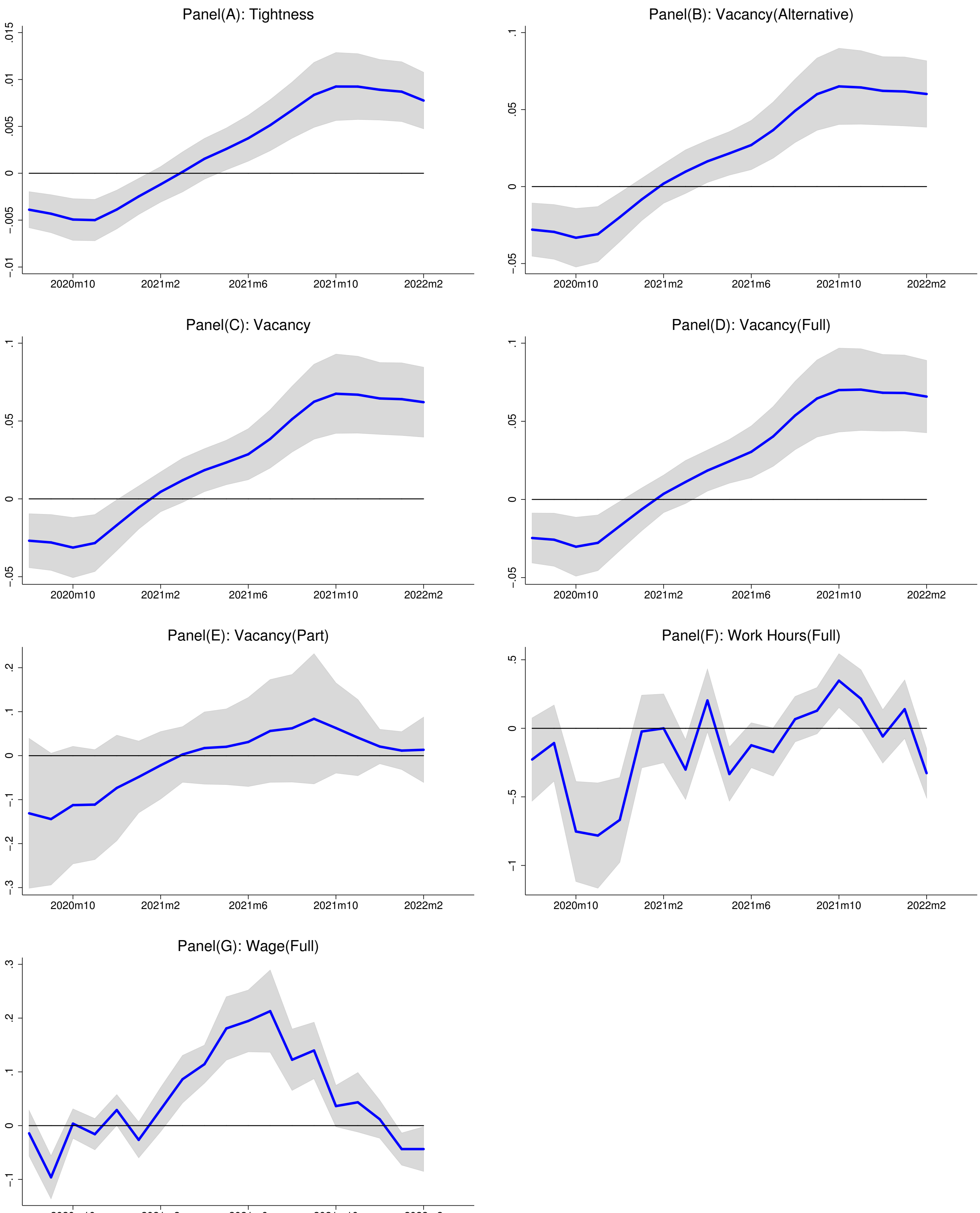
Equation 5 is for the LP estimation, and uses effectively the same setting as the DD regression (Equation 1). The coefficient β^h is the response of $y_{i,t+h}$ to the exogenous shock at time t. The LP estimation is clustered by industrial sectors, as accounting for the heteroskedasticity and serial 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 $H - 1$(2022m4), which is the most recent data available. The number of h is 19 (including $h = 0$). The forecast horizon needs to have already taken place at the time of the study. Therefore, any further long-run analysis is yet not possible due to data unavailability.

Figure 10 shows the IRFs using the LP method. Panels A through D initially start from negative, reflecting the Shock Phase described in Section 3 (Figure 4). Then they bounce up, reflecting the Recovery Phase. These are consistent with the findings from the previous sections (DD and SVAR). Meanwhile, Vacancy rate (part-time) and Work hours (full-time) oscillate around zero. On the contrary, Wages (full-time) surge for a while. This is not consistent with Panel G of Figure 7, where the DD coefficient drops in the end. These inconsistencies may result from the fact that the two regression settings and time frames are not identical.

Figure 10: IRFs using LP



7 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, the previous section 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:

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

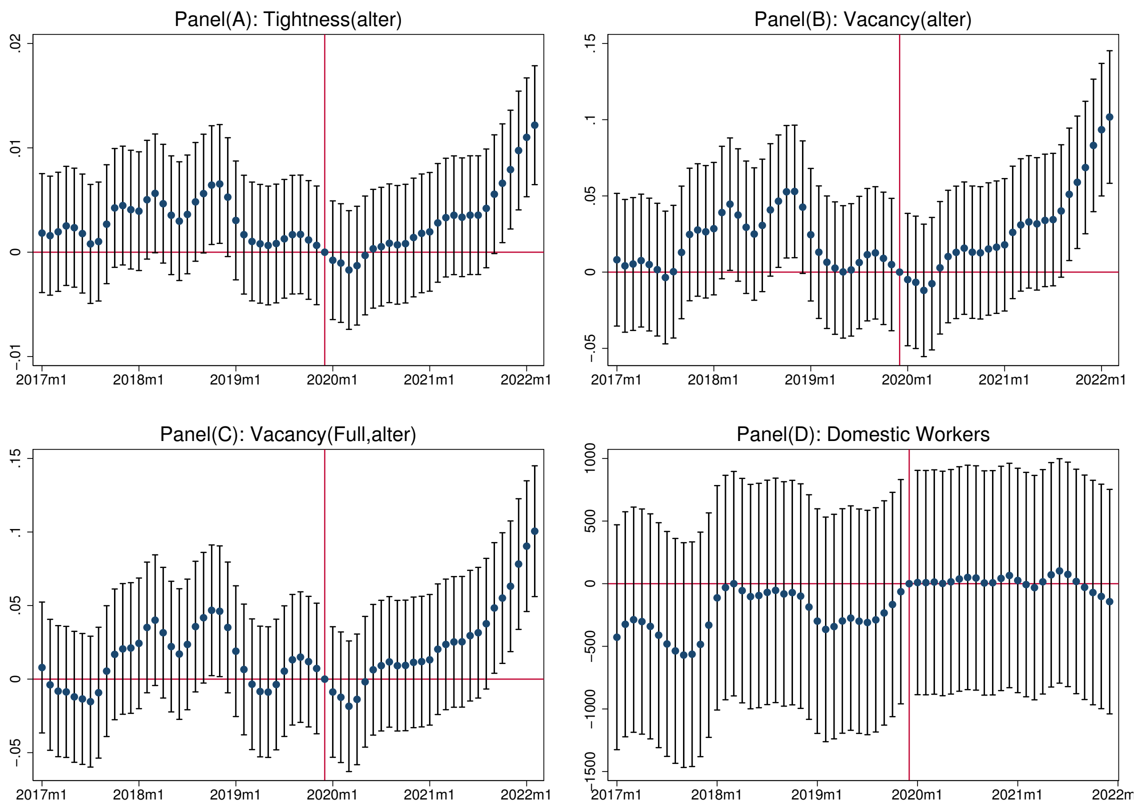
Panels A, B, and C of Figure 11 show the same DD regression as Figure 6. The only difference is that I am using valter_{it} instead of the vacancy rate. Comparing Figure 6 and Figure 11, one can see that the figures are almost identical.

Another way to check the robustness is by performing the same DD regression as Equation 2, but instead to use the number of domestic workers as a dependent variable. Unfortunately, the exact number of TFWs is known only for the total manufacturing sector (TFW_t). For two-digit sectors level, only the number of E9 workers is known (E9_{it}). Therefore, the paper assumes for now that the proportion of TFWs across sectors is the same as that of E9 workers. Under this assumption, TFW_{it} can be estimated as follows:

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

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

Figure 11: DD (Robustness Check)



8 Conclusion

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

The paper identified that the vacancy pattern is consistent across the three studies (Anastasopoulos et al. (2021), Schiman (2021), and Iftikhar and Zaharieva (2019)) as well as within the search and matching model (Howitt and Pissarides (2000)). This paper contributes to the existing literature by providing analysis results using DD, SVAR, and LP approaches. In the short-run, all of the results from DD, SVAR, and LP approaches are consistent with the vacancy pattern found in the literature: the vacancy rate *surged* in the short-run when there was an outflow of TFWs.

Specifically in the short-run, Natives filled the vacant spots primarily as part-time workers, and firms have had difficulty finding full-time workers. Consequently, the ratio of part-time to full-time workers has surged. Moreover, the sectors that heavily relied on TFWs experienced higher matching efficiency. This result may reflect the fact that the matching efficiency increases if the firms are desperate enough to lower their expectation. The related conclusion I can draw is that matching efficiency has increased due to the higher acceptance of part-time workers. This finding is consistent with the result that termination rate has increased. In other words, firms accept the workers more readily by lowering their expectations, and the accepted workers more frequently quit their jobs.

This paper provides a long-run result by using SVAR approach (the top of the forth column in Figure 9). The figure depicts that the vacancy rate does not *drop* in the long-run (4-6 years after the TFW shock) but converges to *zero* (7-10 years after the TFW shock). The long-run result is not consistent with the vacancy pattern found in the literature, especially by Schiman (2021) and the search and matching models. The reason for the inconsistent result could be the lack of long-run data in this paper: data were available until two years after the shock (short-run) but unavailable afterwards (long-run). This is a weakness of this paper.

Existing studies that use the search and matching model may predict that in the long-run, there is a possibility that vacancies would drop. If this were to happen, many firms would exit the market in the long-run, and the industries that face labor shortage will shut down. This finding implies that the labor shortage may accelerate the deterioration of the manufacturing sector. Therefore, if unskilled people from outside South Korea can freely join the manufacturing sector, the sector may experience a less dramatic decline. Indeed, studying this possibility would make for interesting future research.

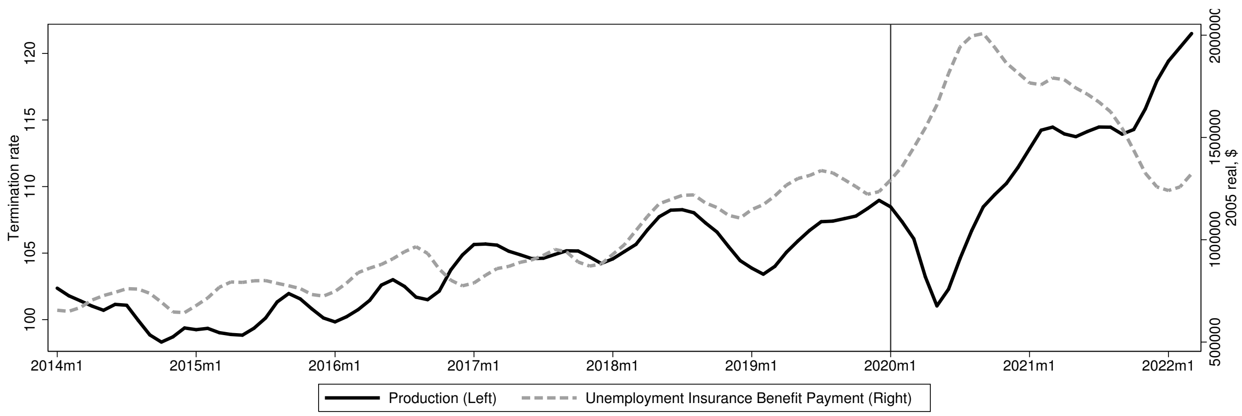
The findings in this paper also present policy implications. The TFW policy has helped alleviate the labor shortage issue in the manufacturing sector in South Korea. Therefore, even if there is sentiment against foreigners among natives, this paper provides findings that encourage this TFW policy. Specifically,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

A Appendix: Confounding Factors

COVID-19 has had a variety of impacts on every aspect. There are some possible determinants that caused vacancy rise: 1)*Unemployment insurance benefits* , 2)*labor demand shock*, and 3) *Excess retirement*. These confounding factors should be handled properly. Otherwise, the identification fails and the causal interpretation is not persuasive. Throughout the paper, these confounding factors are properly added as control variables.

Unemployment insurance benefits: the government eased requisites for unemployment insurance benefits (UIB) right after the COVID-19 outbreak to help recipients cope with the hardship (Figure 12). Larger UIB, however, may induce people to be economically inactive (lesser desperate to search for other jobs). UIB variable is available for panel dataset, which varies by sector and time. Therefore, UIB will be added as a control variable.

Figure 12

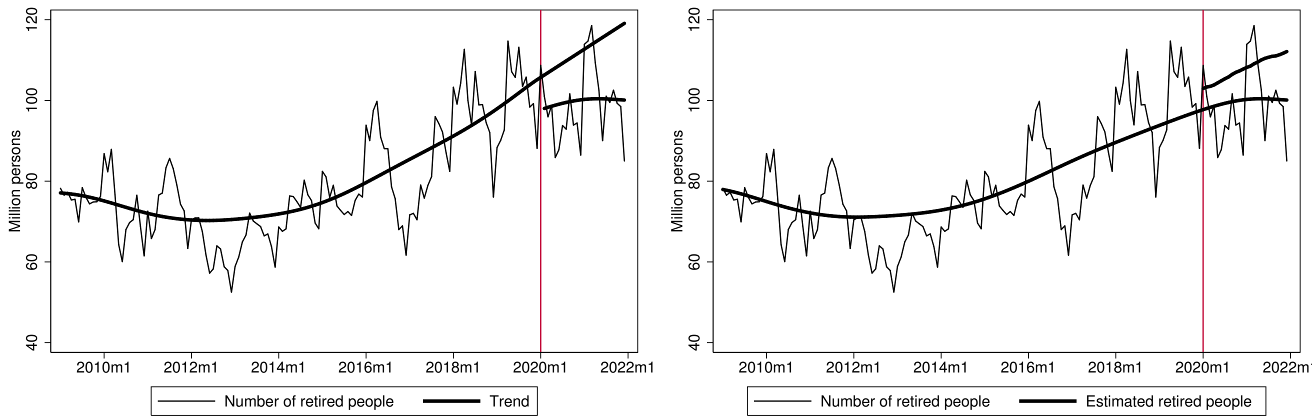


Labor demand shock: the production suddenly plummeted for about 5 months since the outbreak, and then recovered to its previous level (Figure 12). There will be three control variables to handle this labor demand shock: the level of shipment to domestic, the level of shipment to abroad, and the level of operation intensity (the ratio of real production to total production ability).

Excess retirement: The study measures *Excess retirement*, the actual number of retired people minus a trend absence of COVID-19. Figure 13(a) shows that there was a retirement drop after COVID-19 compared to the imaginary trend without COVID-19. So it shows that *Excess retirement* did not happen. Using the trend extrapolation may not be accurate. Therefore, Figure 13(b) shows an alternative estimation using five years of age cohort. In each cohort, first calculate the probability of being retired in year 2019,

Figure 13

(a) Retirement Trend using Extrapolation (b) Retirement Estimation using Age Cohort



before COVID-19. Second, multiply the probability by the actual total population after COVID-19. The result is similar to the result using trend extrapolation.

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 (Figure **??**) as government promotes F4 visa application.

F4 visa holders can enter South Korea whenever they want and work almost wherever they want. Therefore, they are technically foreigners but similar to domestic citizens. Strictly speaking, F4 visa holders are illegal to work in the Elementary Occupations.[10] However, there has not been any law enforcement until now, and most of F4 holders are actually working in elementary occupations. Therefore, the study treats that F4 visa holders who work in elementary occupations as realistically legal.

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

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.

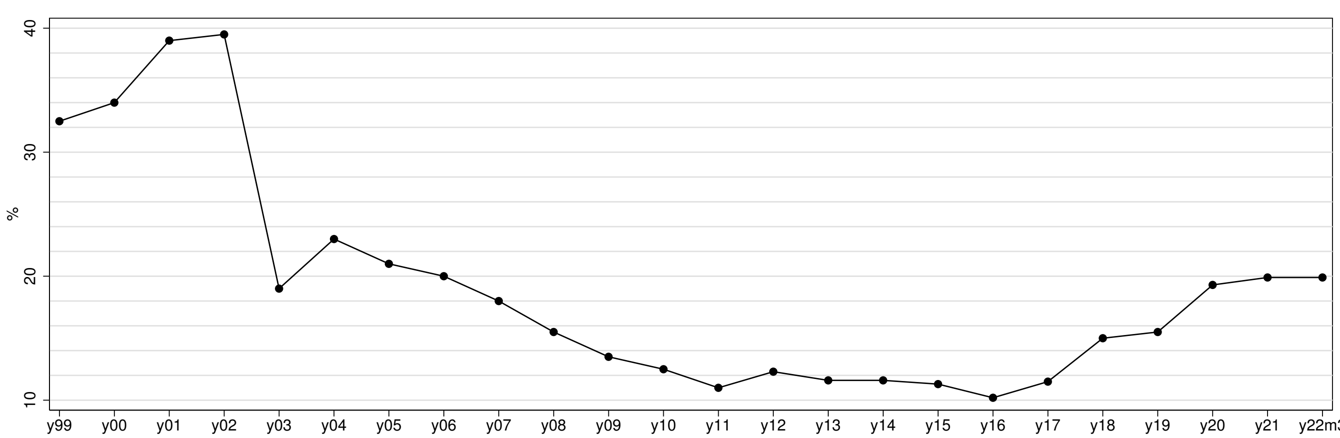
[9] 1) the ratio of currently hired number of E9 workers to the number of maximum allowance for E9 workers —the lower the ratio, the higher the score, 2) the number of additionally hired natives before requesting E9 workers —the larger the number, the higher the score, 3) the number of excellent dormitory 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.

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 14 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.

Figure 14: Share of Overstaying Residents



Second, Lee (2020) studies people in Category B using data from Employment Permit

[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.

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

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

C Appendix: Derivation of Search and Matching Model

The notations are the same as Howitt and Pissarides (2000) and is summarized in Table 6. The people and firms' flow is depicted in Figure 3(a). Each firm hires only one worker. The firms outside the market can freely enter the market, and the firms inside the market can also freely exit the market. Therefore, when firms expect a large profit increase or decrease, numerous firms can enter or exit the market immediately (long run environment).

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

$m(u_t, v_t)$ is the arrival rate of matching. Therefore, $m(u_t, v_t)L_t$ is the total number of matching at time t. There are many versions of matching functions, but this paper will use the most common and simplest Cobb-Douglas version, $m = au^{1-\eta}v^{\eta}$. a is matching efficiency. Therefore, the matching rate per one person is Equation 7, and the matching

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

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

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 $u_{t+1} = u_t$,

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

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

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

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

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

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

In order to calculate these values, a Poisson and an Exponential distributions are used. Suppose a random variable x follows a Poisson distribution with the arrival rate of λ, then the distribution is Equation 10. Then it can convert to an Exponential distribution as in Equation 11

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

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

Using these distribution functions with an arrival rate of λ, the probability that an event never happens until time t equals as $x = 0$, which is Equation 12. And the probability that an event happens for the first time at time t is Equation 13.

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

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

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

V will eventually be zero.

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

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

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

The value function of W can be calculated as below.

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

The value function of U can be calculated as below.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

The above three equations are the final result. Equation JC and WC are both the function of w and θ. θ is typically called as the market tightness. The tighter θ implies firms' difficulty of finding workers. The intersection of Equation JC and WC yields an equilibrium (steady-state) wage(w) and market tightness(θ), as shown in Figure 15(a). After optimal θ is determined, the intersection of a tangent line of θ and Equation BC yields an equilibrium (steady-state) unemployment(u) and vacancy(v) as in Figure 15(b).

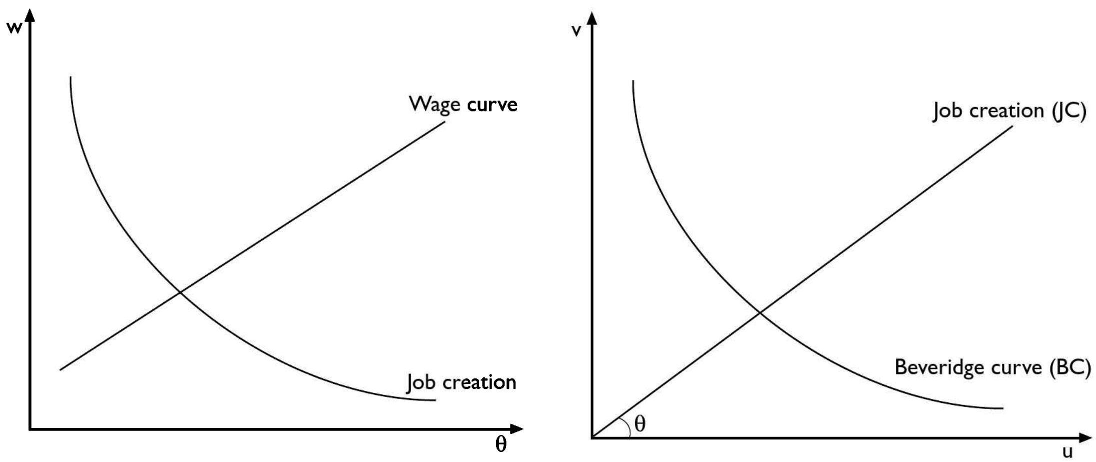
D Appendix: Comparison between long and short run

It is important to note that results in Appendix A are steady-state equilibrium, which assumes the extremely fluid capital adjustment (long run). The long and short run results are distinct. Suppose there is an influx of immigrants so that the birth rate (b) increases. Then the long run model predicts as Figure 3(b). The Beveridge curve (BC) moves *outward* when the birth rate(b) increases. Firms anticipate the increased availability of people, so many enter into the labor market. As a consequence the vacancy *rises*.

However, firms cannot enter the labor market in the short run. Furthermore, many people are searching for jobs. So the vacancy *drops*. Formally speaking, k^* from Equation k does not change unless $f(\cdot),\ r,$ or δ change. K^* is also fixed in the short run. Assume

Figure 15

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



that there is no production shock, p. In the short run, when there is a labor supply shock such that N changes, the only way to achieve k^* is to recover to the initial N^*. For instance, if there is an influx of labor so that N increases, the vacancy should *drop*.

E Appendix: Calibration of Matching Efficiency

After the disconnection of the employer-employee relationships, it naturally takes time to be matched again. The search and matching models by Howitt and Pissarides (2000) introduce the matching efficiency. This section explains the basic calibration method in detail. Matching efficiency represents the matching speed per job seeker and employer. It can go down for many reasons: the job matching system becomes inefficient, or job seekers and employers become pickier or less desperate when finding matches. Let $m(u_t, v_t)$ in Equation 14 as the arrival rate of matching. This is the most frequently used one in literature.

$$m(u_t, v_t) = {u_t}^{1-\eta} {v_t}^{\eta} \tag{14}$$

Let a_t as the matching efficiency. In general, it is the inserted into Equation 14 as a form of $m(a_t u_t, a_t v_t)$.[12] The idea is that matching efficiency (a_t) is commonly shared by job seekers and employers. Therefore, the matching function becomes

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

Calibration of matching efficiency (a_t) has been actively discussed in literature since it is the core of any studies with the search and matching model. The commonly used method is as follows: the time(t) will be omitted for notational convenience throughout this section. The first step is estimating L_t, the total number of people in the labor market. Let EMP the total number of matched workers, which is available in LFSE dataset. Furthermore, EIS dataset provides u. Therefore, L can be calculated as follows:

$$\begin{aligned} \text{EMP} =&(1-u)L \\ \Leftrightarrow L =&\frac{\text{EMP}}{1-u} \end{aligned} \tag{16}$$

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

$$\begin{aligned} M &= m(au, av)L \\ \Leftrightarrow \frac{M}{uL} &= \frac{m(au, av)}{u} \\ \Leftrightarrow \frac{M}{uL} &= a \cdot \theta^{\eta}, \text{where } \theta \equiv \frac{v}{u} \\ \Leftrightarrow \ln\left(\frac{M}{uL}\right) &= \ln(a) + \eta \ln(\theta) \\ \Leftrightarrow \ln\left(\frac{M}{uL}\right) &= \ln(a_0) + \eta \ln(\theta) + \ln(\varepsilon) \end{aligned} \tag{17}$$

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

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

The above method is the basic calibration method. However, it has an endogeneity issue: In Equation 17, the past market tightness(θ) may affect the current number of matching(M), and vice versa. In other words, if finding workers was tighter in the past, then it may increase(or decrease) the matching. As a result, the error term is correlated with the market tightness, resulting in biased estimation of η. Borowczyk-Martins

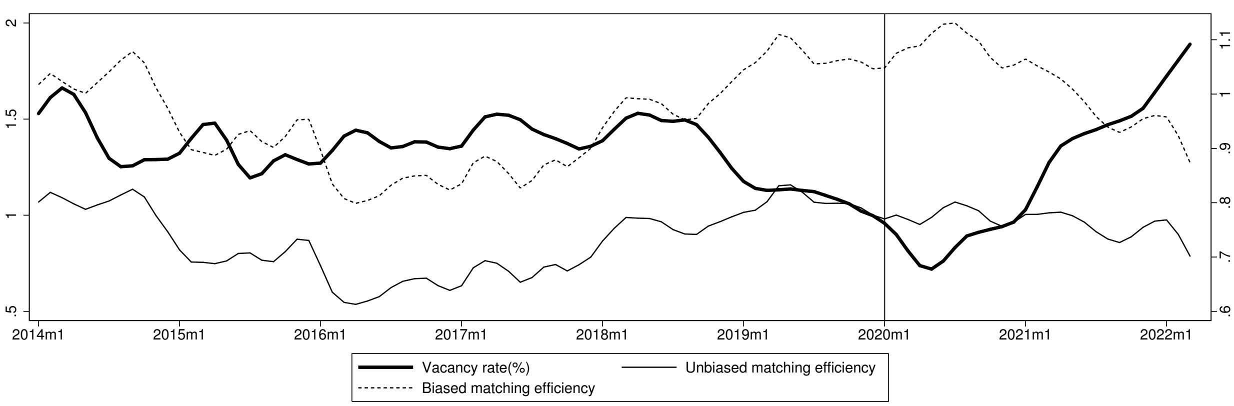
[12] Howitt and Pissarides (2000) has suggested dividing the matching efficiency into job seekers' side and employers' side (Chapter 5). Specifically, $m(s_t u_t, a_t v_t)$, where s_t is suppliers' job search intensity, and a_t is demanders' job advertising intensity. By firm's free entry assumption, a_t becomes invariant to other shocks. There is also a version that only considers firms' side: $m(u_t, a_t v_t)$ (Chapter 6.2 of Elsby et al. (2015)). This becomes meaningful in the presence of inelastic entry, such as the model with entry cost. Anyway, the paper will use the most widely used version (Equation 15).

et al. (2013) summarizes this issue as follows: "the search behavior of firms and/or job seekers implies that labor market tightness and the job finding rate are simultaneously determined as functions of the unobserved efficiency of the matching process. As a consequence, the standard practice of regressing the job finding rate on a measure of labor market tightness using, e.g., OLS, is exposed to a simultaneity bias."

Therefore, estimating a matching efficiency that removed the endogeneity bias is the key to this study. This paper will use a biasedness corrected matching efficiency proposed by Borowczyk-Martins et al. (2013). To correct this biasedness, Borowczyk-Martins et al. (2013) proposed a method using an ARMA process.[13] They impose an ARMA structure on matching efficiency as in Equations 7 and 8 of their paper. Using this ARMA structure, they transform from Equation 17 in my paper to Equation 9 in their paper. Then they estimate the transformed equation by the generalized method of moments (GMM), using lags of the labor market tightness and/or the job finding rate as instrumental variables.

Figure 16 compares the matching efficiency between biased and unbiased. Although not shown in the paper, the time series cross-correlation between the matching efficiency and the vacancy is much lower for the unbiased case than biased one.

Figure 16: Comparison of Matching Efficiencies



F Appendix: Calibration of Termination Rate

The employer-employee relationships had disconnected more frequently since COVID-19 until 2021m11 (Figure 12). In Equation 18, the termination rate represents this disconnection. The paper uses 'the number of separations' as the number of employees separated from the payroll during the month, which is the same definition as JOLTS. The

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

calibration of 'the number of people in the labor market', L_{it}, was explained in Appendix E.

$$\begin{aligned} \text{Number of separations}_{it} =& \text{Termination rate}_{it} \times L_{it} \\ \Rightarrow \text{Termination rate}_{it} =& \frac{\text{Number of separations}_{it}}{L_{it}} \end{aligned} \tag{18}$$

G Appendix: Tables

Table 7: Share of TFW Workers on Total Workers in 2019h2

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

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

Table 8: Korean Employment Classification of Occupations (KECO)

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

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