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

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Abstract

This study investigates the causal relationship between the reduction of low-skilled temporary foreign workers (TFWs) and job vacancies in South Korea's manufacturing sectors, utilizing the COVID-19 quarantine policy as a natural experiment. Employing a Difference-in-Differences methodology, the research reveals that sectors with high dependence on TFWs, particularly to fill permanent positions, experienced significantly elevated vacancy rates for a two-year period following the onset of the pandemic. The inability of native workers to fill these positions highlights the critical role of foreign labor in mitigating labor shortages. Notably, vacancy rates began to decline only after the government relaxed quarantine restrictions, facilitating the re-entry of TFWs into the country. These findings are corroborated by Local Projection methods.

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

1 Introduction

The South Korean government allows the inflow of low-skilled temporary foreign workers (TFWs) only when a labor shortage exists. This TFW policy is based on the idea that admitting TFWs eases the challenges employers face in finding low-skilled workers. However, critics of the TFW policy argue that it diminishes employment opportunities

[*]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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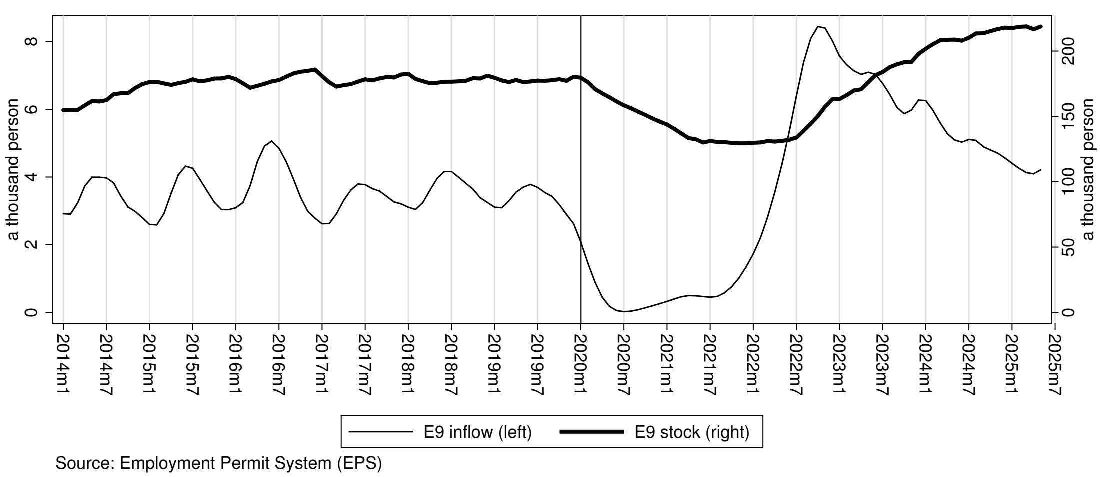
for native workers. Therefore, it is crucial to examine the validity of the critics' arguments. If a labor shortage occurs due to a reduction in TFWs, this would suggest that native workers are not adequately able to fill the available jobs.

This paper exploits a quasi-natural experiment in South Korea to examine whether reducing the inflow of TFWs causes labor shortages in the form of unfilled positions (vacancies). One complicating factor is reverse causality: the government's TFW policy is informed by vacancy rates, which in turn impact the number of TFWs allowed in the country. To address this complication, the study examines a quasi-experimental event: the COVID-19 pandemic. Beginning in January 2020, the COVID-19 pandemic prompted the government to impose strict border controls that effectively halted the entry of new low-skilled foreign workers (Figure 1). This sudden suspension of TFW inflows was unrelated to conditions in specific industries, providing an exogenous shock to labor supply. The paper leverages this event by implementing a difference-in-differences (DD) strategy across manufacturing sectors with varying pre-pandemic reliance on TFWs. Sectors with a larger share of foreign workers before COVID-19 experienced a greater loss of labor when the inflow ceased (Figure 2), enabling the study to identify the causal impact of the TFW reduction on vacancies.

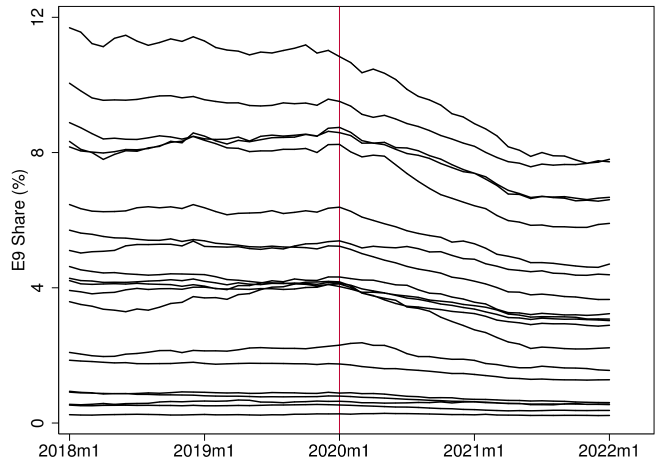
Figure 1: Inflows and Stocks of E9 Workers in Manufacturing Sector



The pandemic led to the implementation of stringent quarantine measures beginning in January 2020, preventing TFWs who had already secured contracts from entering the country.

The analysis reveals that the interruption of TFW inflows led to a pronounced increase in unfilled positions in high-exposure sectors. In the two years following the border closure, vacancy rates in sectors that had depended heavily on foreign workers rose significantly relative to less-exposed sectors, indicating substantial labor shortages.

Figure 2: Share of E9 by sectors



Share of E9 $= \frac{\text{Number of E9 workers}}{\text{Number of total workers}} \times 100,$ Source: EPS
Sectors that have traditionally relied on E9 workers have recently witnessed a notable decline in their numbers.

These unfilled openings were concentrated in permanent positions, suggesting that native workers did not substitute for the absent foreign labor. Vacancy rates began to normalize only after foreign worker inflows resumed. Notably, the study does not observe commensurate increases in wages or domestic hiring during the short-run shortage, implying that firms struggled to attract replacement workers for these difficult-to-fill positions.

Figure 1 demonstrate that the shock commenced in January 2020, reached its peak in January 2022, and was subsequently eliminated by approximately January 2024. Moreover, Panel (a) of Figure 6 in Section 6, which presents the impulse response function (IRF) using the Local Projection (LP) method, indicates that the vacancy rate exhibited a positive response until January 2022, followed by a negative response that persisted until approximately January 2024. Based on this comprehensive analysis of observed patterns, this paper delineates three distinct temporal windows: the short-run, spanning from January 2020 to January 2022; the medium-run, extending from January 2022 to January 2024; and the long-run, commencing from January 2024 onward.

It is important to note that only the *inflow* of E9 workers was restricted after the pandemic began in January 2020. Conversely, the government did not interfere with the *outflow*, meaning that it did not force TFWs to leave. As a result, the number of E9 workers gradually decreased, as shown in Figure 1. Consequently, the significant decline commenced in July 2020, rather than January 2020 when the pandemic initially emerged.

Furthermore, determining whether the shock remained confined to the short-run or persisted over an extended period warrants examination. In the case examined in this paper, the shock intensified progressively throughout the short-run, culminating at its peak at the conclusion of this period. Subsequently, the shock began to attenuate during the medium-run, with complete dissipation occurring by the end of this phase. Consequently, the shock persisted for approximately four years, after which an opposing trend emerged, characterized by an influx of foreign workers that exceeded pre-shock levels. The occurrence of a reverse shock in the long-run has important implications for the interpretation of long-run analysis results, necessitating careful consideration when drawing conclusions from these findings.

This paper employs the LP method to examine the dynamic effects of an exogenous negative shock to TFWs on labor market outcomes. The LP approach, which offers significant advantages over traditional SVAR methods in difference-in-differences settings with panel data, allows for tracing impulse response functions across short-, medium-, and long-run horizons. The identification strategy exploits pre-COVID variation in TFW employment shares across industries, providing exogenous variation to estimate causal effects.

The empirical results reveal distinct temporal patterns in response to TFW shortages. Vacancy rates exhibit a three-phase dynamic: an initial rise in the short-run, a subsequent decline in the medium-run, and eventual convergence to zero in the long-run. While permanent positions show significant responses, fixed-term employment vacancies remain largely unaffected. Furthermore, domestic workers show no immediate substitution effect but experience reduced employment in the medium-run in industries with greater TFW shortages. Firm profits respond immediately with significant declines in sectors more dependent on foreign labor, suggesting substantial short-run adjustment costs that cannot be mitigated through immediate labor substitution.

Three empirical studies examine labor inflows and job vacancies with contrasting findings. Anastasopoulos et al. (2021) and Schiman (2021) documented vacancy declines following the Mariel Boatlift and EU enlargement-driven migration, respectively —with Miami experiencing 20-40% drops and Austria showing three-year declines before rebounds. Conversely, Iftikhar and Zaharieva (2019) found vacancy increases from high-skilled immigration to Germany's manufacturing sector, attributed to long-run capital adjustments.

These patterns align with Search and Matching theory (Howitt and Pissarides 2000), which predicts short-run vacancy declines due to market rigidity, followed by medium-run increases as firms enter anticipating higher matching profits. This framework, supported by recent theoretical work (Kindberg-Hanlon and Girard 2024; Hornstein, Krusell, and Violante 2007), suggests a consistent trajectory: positive labor shocks initially reduce vacancies, which subsequently rise before converging to equilibrium.

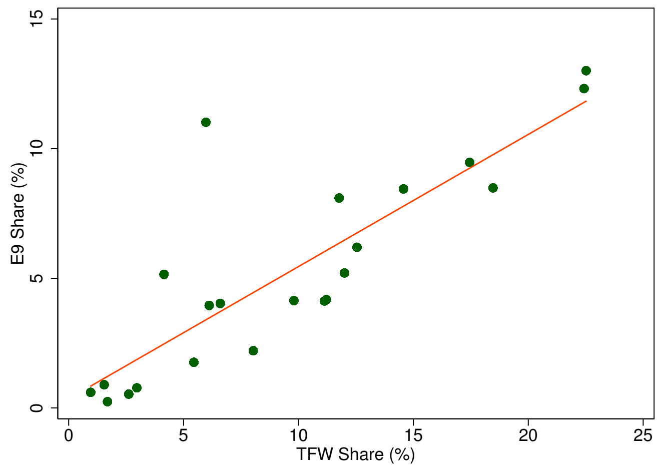
This study contributes by examining the reverse scenario —a negative labor supply shock. While previous research shows immigration reduces vacancies as foreign workers fill positions (Anastasopoulos et al. 2021; Schiman 2021), this analysis demonstrates that sudden foreign worker absence causes vacancy surges. This mirror-image result reinforces that TFWs alleviate genuine hiring frictions rather than displacing native workers, consistent with Search and Matching predictions where labor supply contractions increase unmet demand until shock reversal. Using the LP approach, the findings confirm the inverse pattern: negative foreign labor shocks produce short-run vacancy increases, medium-run declines, and eventual convergence to zero in the long-run.

Synthesizing these findings, this investigation concludes that domestic workers were unable to adequately fill positions vacated by E9 workers following the COVID-19 pandemic. The remainder of the paper is structured as follows. Section 2 provides background on South Korea's TFW program and describes the data and time frame of the analysis. Section 3 outlines the empirical strategy, including the DD design and identification assumptions. Section 4 presents the main empirical results. Section 5 discusses robustness checks and extensions, including Local Projections to see the long-run outcomes. Section 6 explicates the mechanisms and rationales underlying the observed vacancy fluctuation patterns. Finally, Section 7 concludes with policy implications and broader perspectives.

2 Background and Data

This section provides context on South Korea's TFW program and the role of foreign workers in the manufacturing sector, then describe the data sources. The proportion of TFWs within the total workforce decreased from 10.44% in December 2019 to 8.21% in December 2021, as illustrated in Appendix Figure 8. TFWs in the country's manufacturing sectors comprise primarily E9, F4, and H2 visa holders. Among these, E9 workers constitute 53% of total TFWs (Appendix Table 4). 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. According to administrative data, the share of E9 workers among total manufacturing employment and the share of all TFWs among total manufacturing employment exhibit strong correlation (Figure 3).

Figure 3: Share of E9 versus share of TFWs



Source: EPS & Korea Immigration Service

The share of E9 workers among total workers and the share of TFWs among total workers are closely correlated.

2.1 E9 Workers

It is essential to delineate the characteristics of these foreign workers within the context of South Korea's labor market. In the United Kingdom, the Migration Advisory Committee (MAC) compiles a list of occupations for which the government should facilitate immigration to address labor shortages, exempting them from labor market tests (Sumption 2011). The labor market test mandates that employers demonstrate unsuccessful recruitment efforts for domestic workers despite comprehensive hiring initiatives.

Similarly, South Korea's policy for E9 visa workers involves an expert committee that annually establishes sector-specific E9 visa quotas based on reported labor shortages. Employers must advertise open positions for 14 days via the Korea Employment Information Service (KEIS) before they are permitted to hire foreign labor, thereby ensuring that local workers have the first opportunity to fill vacancies.

The government subsequently matches employers with E9 visa applicants using a scoring system that evaluates several factors. For employers, criteria include the current ratio of E9 workers to the allowable maximum, recent hiring of additional native workers prior to seeking E9 workers, the quality of dormitory accommodations provided for foreign workers, compliance with safety and labor regulations, and tax compliance history. For E9 applicants, the primary criterion is their score on a Korean language proficiency test.

Once a prospective match is identified, both the employer and the E9 candidate must agree to the employment arrangement. If either party rejects the match, the process terminates for that pairing. Upon successful matching, E9 workers enter South Korea as permanent employees but are required to depart after three years. They cannot obtain permanent residency or change employers freely (except under special permission). If an E9 worker's employment is terminated, that worker must leave the country.

2.2 F4 and H2 Workers

By contrast, F4 and H2 visa holders are ethnic Koreans (foreign-born descendants) who are typically fluent in the Korean language, making them close substitutes for domestic workers in certain roles (particularly service occupations requiring communication). Obtaining an H2 visa is generally more accessible than an F4 for these individuals, since many documentation requirements are waived, but since 2015 there has been a policy shift encouraging increased F4 visa issuance over H2.

F4 visa holders can enter and leave South Korea at will and may work in nearly any sector. Technically, F4 holders are prohibited from employment in Elementary Occupations[1] , but in practice enforcement is minimal and most F4s do work in such low-skilled positions. Thus, in effect, F4 visa holders face virtually no labor market restrictions (they are foreigners in legal status but their labor market access resembles that of citizens). The F4 visa has no expiration, whereas the H2 visa expires after three years (with a one-time extension of 22 months possible). H2 visa holders are permitted to work only in sectors classified as Elementary Occupations, and they must renew or depart once their term ends.

2.3 Unauthorized Workers

The presence of unauthorized foreign workers could potentially confound the analysis. A detailed discussion of this issue is provided in Appendix B. Lee (2020) estimates that a significant portion of unauthorized residents fall under Visa Exemption (B1) status, with 43.8% of these overstaying or working illegally. In contrast, the numbers of unauthorized E9, H2, and F4 visa holders in 2020 were relatively small. Meanwhile, Lim (2021) found a high incidence of illegal workers in the agricultural sector, which is less regulated compared to the manufacturing sector. Since my study utilizes data on E9 workers (where government monitoring is stringent), and focuses on the manufacturing sector (where

1. International Standard Classification of Occupations, Major Group 9

enforcement is relatively robust), the potential bias from unobserved illegal workers should be minimal.

2.4 Definition of Labor Shortage

This subsection defines what constitutes a labor shortage. Existing literature provides multiple perspectives on the subject, yet are in agreement about the importance of unfilled vacancies as a key metric (Martin Ruhs and Bridget Anderson 2019; Constant and Tien 2011; Barnow, Trutko, and Piatak 2013). Here, the term 'vacancies' captures the extent to which employers struggle to find suitable employees. The present 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 the 'vacancy rate' as $\frac{\text{Number of unfilled vacancies}}{\text{Number of employees}} \times 100$.

2.5 Data

This study employs 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 Insurance System (EIS).

No single data source contains all the variables of interest, necessitating the construction of a panel by combining multiple sources. For example, vacancy information derives from the LFSE, the number of E9 workers from the EPS, and unemployment rates from the EAPS. Each dataset provides monthly observations for South Korea's two-digit manufacturing sectors, which this study merges by sector and month.

The LFSE provides establishment-level data on employment, vacancies, hires (matching), and separations. It is a monthly survey sampling approximately 50,000 establishments with at least one employee (including both permanent and fixed-term workers). The LFSE serves as the South Korean counterpart to the U.S. Job Openings and Labor Turnover Survey (JOLTS), adopting similar variables and definitions. For instance, a vacancy in the LFSE corresponds to a job opening in JOLTS (a position open at the end of the month that could start within 30 days), and accordingly this study defines the vacancy rate as $\frac{\text{Number of unfilled vacancies}}{\text{Number of employees}} \times 100$. Similarly, matching in LFSE corresponds to hires in JOLTS, and separation corresponds to separations. As with JOLTS, microlevel LFSE data are not publicly available. One distinction is that the LFSE reports these variables disaggregated by detailed industry (two-digit manufacturing subsectors) and by employment type (permanent vs. fixed-term positions).

This study defines a permanent worker as one with a contract extending for more than a year or for an indefinite term, while a fixed-term 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 permanent workers stood at 1.9%, whereas it stood at 43.6% for fixed-term workers. This high turnover rate among fixed-term workers implies shorter tenures and reduced job proficiency, as these workers leave their jobs more frequently.

The EPS, maintained by KEIS, records the number of E9 and H2 visa workers employed. This study utilizes only the number of E9 workers, as the EPS closely tracks the monthly stock and flow of E9 workers by detailed industry. Although the EPS also collects H2 worker data, it is less reliable because only approximately 10% of H2 visa holders voluntarily report their employment to the system.

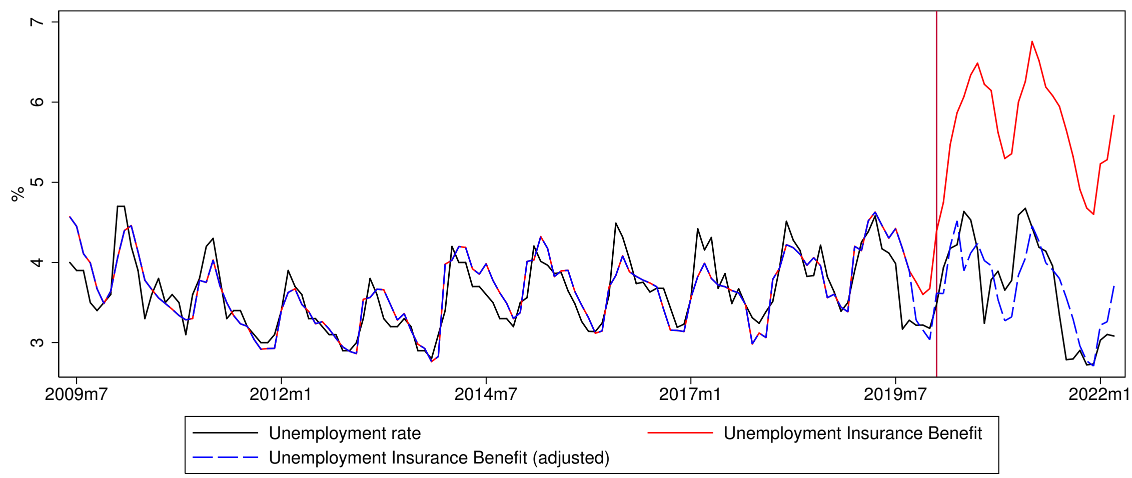
The MSMM provides various production-related indicators, including domestic and international shipment indexes. Compiled by Statistics Korea, the MSMM data are integral to the Bank of Korea's GDP calculations.

The EAPS supplies unemployment rates. It is analogous to the U.S. Current Population Survey (CPS), with a similar sampling design and variable definitions. The EAPS is essentially a survey of households (primarily native residents, since foreign residents are underrepresented in the sample). The EAPS does not explicitly distinguish foreign vs. native respondents, but given the sampling, officials treat EAPS-based measures (like unemployment) as reflecting outcomes for native workers. Although the EAPS only publishes unemployment rates for broad sectors (e.g., total manufacturing), the EIS administrative data enable this study to proxy monthly unemployment at a finer industry level. Specifically, this study utilizes the counts of unemployment insurance (UI) recipients from the EIS,[2] which are available by two-digit industry. This study finds that the UI recipiency rate in each sector is highly correlated with the sector's unemployment rate from the EAPS (Figure 4), suggesting the UI data provide a reasonable proxy for unemployment conditions by sector. Unfortunately, a level shift occurred in October 2019 due to an expansion of UI coverage and generosity (the red line in Figure 4 shows the raw UI rate); This study correct for this by subtracting the mean increase (estimated

2. For each two-digit manufacturing sector i, this study defines the UI benefits rate as $\frac{\text{UI recipients in sector } i}{\text{Employment in sector } i + \text{UI recipients in sector } i}$. This parallels the standard unemployment rate definition $\frac{\text{Unemployed}}{\text{Employed} + \text{Unemployed}}$.

via a dummy variable for post-2019m10) so that the series remains consistent over time. Therefore, this study employs the adjusted UI benefits rate as our measure of u_{it} (sectoral unemployment rate).

Figure 4: Unemployment Rate vs. UI Benefits Rate



Source: EAPS and EIS.

This figure shows the close correspondence between the official unemployment rate and the unemployment insurance (UI) recipiency rate across the manufacturing sector. This study uses the UI recipiency rate (adjusted for a policy change in late 2019) as a proxy for the unemployment rate by detailed industry.

Throughout the analysis, this paper applies seasonal adjustments using seasonal dummies.

3 Empirical Strategy

3.1 Difference-in-Differences Design

Sectors that have traditionally relied on E9 workers experienced a notable decline in their foreign workforce after 2020, whereas sectors with minimal prior reliance on E9 workers experienced relatively small changes. This variation serves as a continuous treatment intensity in a DD framework. The share of E9 workers in each sector *before* the pandemic corresponds to the 'share' component of a Bartik-style shift–share instrument (Bartik 1991). Therefore, the treatment variable is effectively uncorrelated with any sector-specific demand shocks during the pandemic, satisfying the exogeneity requirement for the DD identification (Goldsmith-Pinkham, Sorkin, and Swift 2020; Jaeger, Ruist, and Stuhler 2018).

Goldsmith-Pinkham, Sorkin, and Swift (2020) emphasize that the identifying power of a shift–share instrument derives predominantly from its cross-sectional 'share' component —utilizing such an instrument is essentially equivalent to using the pre-shock shares as an instrumental variable. Consequently, employing the pre-pandemic E9 share of each sector as an instrument in this study's setting is both valid and informative. Moreover, Jaeger, Ruist, and Stuhler (2018) caution that the shift–share approach can be problematic if the origin composition of foreign workers remains stable over time. In this study's context, however, the COVID-19 border closure constituted a sudden, national-level shock, which fulfills the conditions for treating the pre-COVID E9 share as an exogenous predictor of the foreign worker reduction.

Equation (1) presents the DD regression model used for the instrumental-variable estimation in the baseline specification:

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

In Equation (1), the treatment intensity $\mathrm{E9CHG}_i$ constitutes a sector-level measure of the shock, varying across sectors i while remaining constant over time. By construction, $\mathrm{E9CHG}_i$ measures the percentage change in sector i's E9 workers from immediately before the pandemic (end of 2019) to the post-shock trough (early 2022). More negative values of $\mathrm{E9CHG}_i$ indicate larger losses of foreign workers attributable to the entry ban. Since $\mathrm{E9CHG}_i$ incorporates a post-treatment outcome in its definition, it may suffer from endogeneity (for example, sectors experiencing pandemic-related difficulties might have lost more foreign workers while simultaneously experiencing vacancy changes for unrelated reasons). This study therefore instrument $\mathrm{E9CHG}_i$ with $\mathrm{E9SHARE}_i$, the pre-pandemic proportion of foreign workers. As $\mathrm{E9SHARE}_i$ is determined prior to COVID-19, it is unlikely to be influenced by pandemic-era shocks beyond the foreign labor supply shock itself. Essentially, $\mathrm{E9SHARE}_i$ captures pre-existing reliance on TFWs and serves as a proxy for sectoral exposure to the shock. Sectors with higher $\mathrm{E9SHARE}_i$ experienced larger declines in foreign workers, establishing $\mathrm{E9SHARE}_i$ as a strong predictor of $\mathrm{E9CHG}_i$.

The definitions of each dependent variable Y_{it} are summarized in Table 1. For example, when Y_{it} represents the vacancy rate, β measures the causal effect of a sector's TFW reduction on its vacancy rate. In this study's setting, D_t is a post-pandemic dummy ($D_t = 0$ for the period 2017m10–2019m12, and $D_t = 1$ for 2020m7–2022m12; the brief 2020m1–2020m6 shock phase is omitted as discussed in Appendix C). Sector fixed effects (S_i) and time fixed effects (T_t) absorb any static differences across sectors and any shocks common to all sectors in each month, respectively. For the covariates, X_{it}, this study employs the international shipments index and unemployment insurance benefits, which were selected according to the criteria delineated in Appendix D. Standard errors are clustered by industrial sector throughout this paper to account for serial correlation.

Table 1: Definition of Variables

Variables	Definitions	Main source of data
E9CHG_i	$\frac{\text{(E9 in 2022m1)}-\text{(E9 in 2019m12)}}{\text{Total workers in 2019m12}} \times 100$	EPS
E9SHARE_i	$\frac{\text{E9 in 2019m12}}{\text{Total workers in 2019m12}} \times 100$	EPS, LFSE
X_{it}	ProdAbroad_{it} = The index of shipment to abroad	MSMM
	UIB = UIB payment (base year=2005, \$) With sector interaction term	EPS

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(Perm)	Permanent workers' vacancy	LFSE
Vacancy(Fixed)	Fixed-term workers' vacancy	LFSE
Fixed/Perm	$\frac{\text{Number of fixed-term workers}}{\text{Number of permanent workers}}$	LFSE
Wage	Log of hourly real wage	LFSE
Work hours	Log of monthly working hours	LFSE

Note: This table provides definitions of variables that appear in Equations (1) and (2).

4 Results

4.1 Graphical Two Way Fixed Effect Regressions

This section presents the empirical findings. Prior to presenting the main results in regression table format, I begin with a graphical two-way fixed-effects (TWFE) DD analysis to illustrate the effects of the TFW shock on vacancies and to validate the parallel trends assumption. Specifically, I estimate a TWFE DD model following the specification outlined in Equation (2):

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

Subscript i represents manufacturing sectors, and t represents monthly time. S_i and T_t are sector and time fixed effects, respectively. τ_t denotes dummy variables for quarterly seasonal periods. Standard errors are clustered by industrial sector to account for serial correlation.

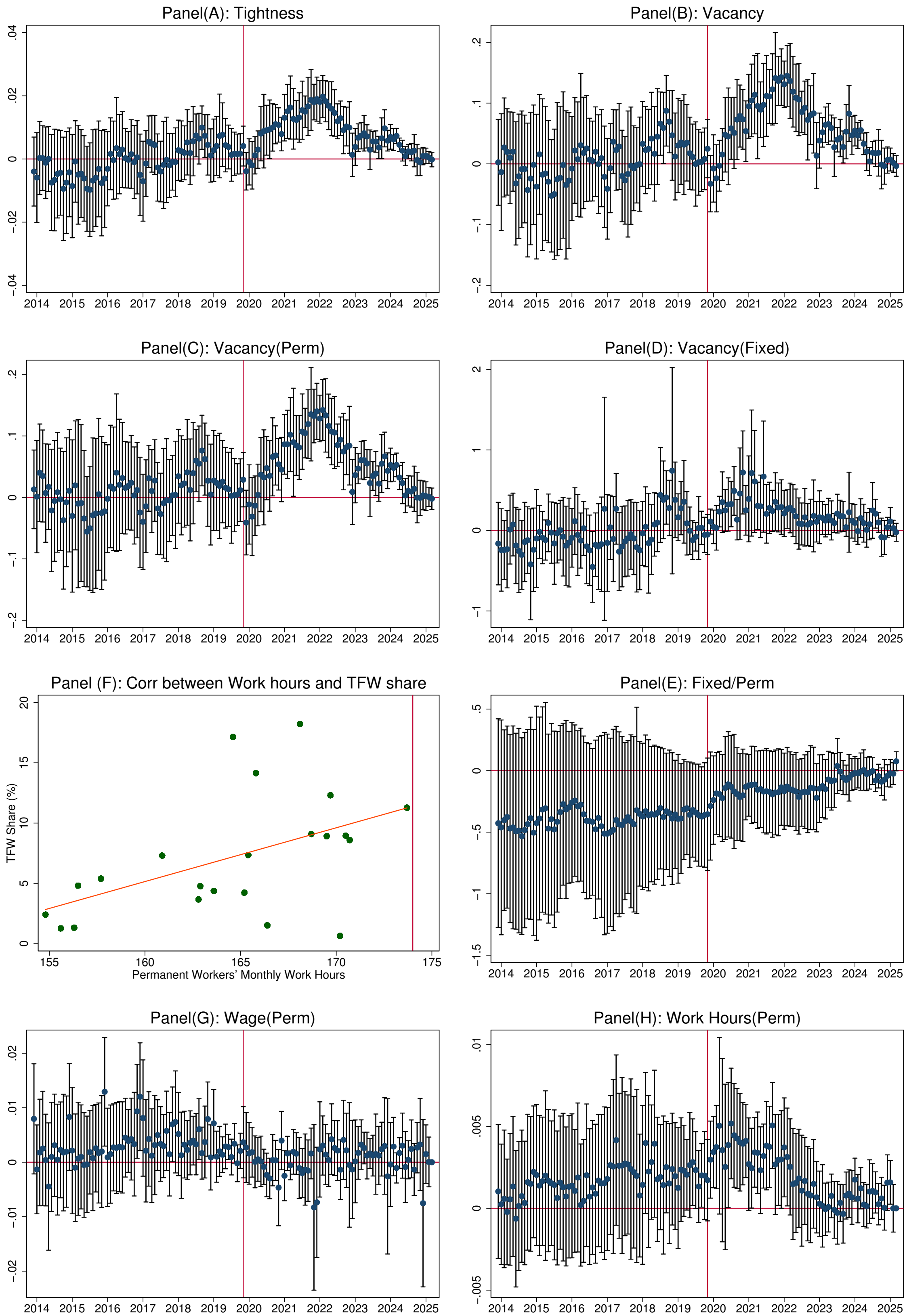
Figure 5 presents the estimated treatment effects on various outcomes, confirming that sectors with greater dependence on TFWs experienced significantly larger increases in unfilled positions following the pandemic. While estimates for months prior to 2020 generally remain near zero, validating the parallel trends assumption, it is important to acknowledge a notable spike in vacancy measure between 2018 and 2019. This observation indicates that the pre-trend is not entirely flat and constitutes a limitation of the present study. The cause of these fluctuations remains unclear, precluding the possibility of adjusting for a perfectly flat trend. Nevertheless, the overall pattern supports the validity of the identification strategy, with the pre-pandemic period exhibiting relatively stable trends despite this isolated deviation.

Notably, in panels (A) through (C), the initial few months exhibit below zero estimates, although these values are statistically insignificant. This phenomenon can be attributed to the following: as depicted in Figure 1, the cessation of TFW inflow did not necessitate their departure from the country. Consequently, the figure illustrates a gradual decline in the total number of foreign workers. Thus, during the early stages of the COVID-19 pandemic, firms reduced their workforce due to apprehension, while foreign workers remained abundant, explaining the negative vacancy rate observed in the initial period.

In Panels (A) through (C), the estimated values reach their peak around January 2022 (short run), followed by a subsequent decline until January 2024 (medium run). This temporal evolution aligns precisely with the documented trajectory of TFW stock levels. These empirical findings suggest that TFW shocks generate immediate effects on vacancy rates, with both the initial impact and subsequent reversal occurring without temporal lags. This evidence supports the conclusion that labor market adjustments to TFW shocks are characterized by contemporaneous responses rather than delayed effects.

To illustrate the interpretation of the aggregate measure, Panel (B) demonstrates that a one percentage point increase in E9Share is associated with an approximately 0.13 percentage point rise in the vacancy rate, as observed in January 2022 when vacancy rates reached their peak. Panel (C) of Figure 5, which analyzes unfilled vacancy rates specifically for permanent employees, exhibits patterns consistent with those observed in Panel (B). In contrast, Panel (D) reveals that the unfilled vacancy rate for fixed-term workers remained stable despite the absence of TFWs.

Figure 5: Two way fixed effect DD results



The empirical narrative unfolds as follows: Panel (F) illustrates that sectors with a higher concentration of TFWs also exhibit elevated work hours. In 2021, the statutory maximum work hours in South Korea were 174 per month, extending to 226 hours when including overtime. The figure indicates that sectors heavily reliant on TFWs tend to approach these legal maxima, suggesting potentially demanding working conditions for employees. While these sectors do not encounter difficulties in recruiting fixed-term workers (Panel D), they face substantial challenges in securing permanent employees (Panel C). Consequently, the ratio of the number of fixed-term to permanent workers marginally increases in these sectors, although this trend is statistically insignificant (Panel E).

The data reveal a notable absence of conventional responses to recruitment challenges from manufacturers. Panel (G) demonstrates that wage increases are not employed as a strategy to attract labor. Similarly, Panel (H) illustrates that extending working hours is also not much utilized as a solution although there is a slight increase. The lack of traditional adaptive measures may be attributed to two factors: first, these sectors may have already reached the legal maximum of permissible working hours; second, they may face constraints in offering higher wages due to competitive pressures from nations with lower labor costs.

4.2 Difference-in-Difference Regressions

For more formal quantification, Table 2 reports regression results from the DD specification shown in Equation (1). Here, the actual percentage change in E9 employment in each sector (E9CHG_i) is instrumented by the pre-pandemic share (E9SHARE_i). The first stage F-statistic is larger than 10, the rule of thumb claimed by Stock, Wright, and Yogo (2002).

The results demonstrate a substantial and significant impact of the TFW shock on vacancies and labor market tightness. In sectors experiencing larger declines in foreign workers, vacancy rates increased markedly and the tightness ratio (vacancies relative to unemployed workers) rose correspondingly. Market tightness captures the difficulty of finding workers and represents the most critical factor in the Search and Matching Model. This measure provides a more realistic assessment of recruitment difficulties compared to the vacancy rate, as it incorporates the unemployment rate in the denominator rather than simply dividing vacant positions by the current total workforce.

The effect concentrates on permanent positions (Column (3)) whereas the effect on fixed-term vacancies remains statistically insignificant (Column (4)). Consequently, the ratio of fixed-term workers to permanent workers increased when the negative shock was imposed (Column (5)). Consistent with the graphical evidence, this study find no compensating wage increase or working hours decrease in response to the shock (Columns (6) and (7)).

Table 2

	(1) Tightness	(2) Vacancy	(3) Vacancy(Perm)	(4) Vacancy(Fixed)	(5) Fixed/Perm	(6) Wage(Perm)	(7) Hour(Perm)
E9CHG $\times$ D	-3.813**	-32.366***	-33.078***	-37.789	-64.501*	0.307	20.947
	(1.530)	(12.011)	(12.386)	(25.733)	(38.256)	(0.790)	(61.761)
ProdAbroad	1.016	5.852	7.453	-14.547	87.060***	-0.398	22.460
	(0.970)	(7.467)	(8.587)	(30.910)	(19.878)	(0.522)	(46.670)
UIB	-1.815*	1.312	2.418	11.145	120.456***	0.452	-166.430***
	(0.949)	(6.565)	(5.945)	(41.592)	(27.436)	(0.701)	(37.074)
Observations	1254	1254	1254	1254	1254	1254	1254
R^2	0.606	0.551	0.568	0.130	0.433	0.635	0.918
First-stage F	399.65	399.65	399.65	399.65	399.65	399.65	399.65

Standard errors in parenthesis are clustered by sector.

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

Sector interactions with UIB are not reported.

Fixed effects are not reported.

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

Note: The results demonstrate a substantial and significant impact of the TFW shock on vacancies and labor market tightness. In sectors experiencing larger declines in foreign workers, vacancy rates increased markedly and the tightness ratio (vacancies relative to unemployed workers) rose correspondingly.

Table 3 presents a reduced-form version of the analysis, employing the pre-pandemic E9 worker share (E9SHARE$_i$) directly as an explanatory variable. The estimates align closely with the IV results. It should be noted that the coefficient signs appear opposite between Tables 2 and 3 due to the methodological distinction: the former employs the actual decline in foreign workers (negative values indicating larger drops), while the latter utilizes the initial share (a positive measure of exposure). In this specification, a one percentage-point increase in E9 share in 2019 corresponds to an approximately 0.092 percentage-point increase in the post-pandemic vacancy rate.

Regarding labor market tightness and permanent vacancies, this study observes significant positive effects of TFW reliance: a one percentage-point increase in E9 share in 2019 is associated with an approximately 0.011 percentage-point increase in post-pandemic market tightness, and an approximately 0.094 percentage-point increase in the post-pandemic vacancy rate for permanent positions. Furthermore, both the IV and reduced-form specifications yield insignificant results for hourly wages and working hours. A notable distinction emerges concerning the ratio of fixed-term to permanent workers: while the IV results indicate significance at the 10% level, the reduced-form results show no statistical significance. Consequently, this study interprets these findings as marginally significant.

Table 3

	(1) Tightness	(2) Vacancy	(3) Vacancy(Perm)	(4) Vacancy(Fixed)	(5) Fixed/Perm	(6) Wage(Perm)	(7) Hour(Perm)
E9SHARE $\times$ D	1.080**	9.169**	9.371**	10.706	18.273	-0.087	-5.934
	(0.430)	(3.439)	(3.555)	(7.190)	(10.730)	(0.225)	(17.547)
ProdAbroad	0.908	4.931	6.512	-15.623	85.224***	-0.390	23.056
	(0.910)	(6.864)	(8.038)	(30.835)	(19.608)	(0.532)	(46.990)
UIB	-2.442***	-4.008	-3.019	4.934	109.854***	0.502	-162.987***
	(0.749)	(4.779)	(4.415)	(41.078)	(22.964)	(0.706)	(41.377)
Observations	1254	1254	1254	1254	1254	1254	1254
R^2	0.623	0.569	0.582	0.133	0.450	0.635	0.918

Standard errors in parenthesis are clustered by sector.

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

Sector interactions with UIB are not reported.

Fixed effects are not reported.

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

Note: This table presents a reduced-form version of the analysis, employing the pre-pandemic E9 worker share ($E9SHARE_i$) directly as an explanatory variable. The estimates align closely with the IV results. It should be noted that the coefficient signs appear opposite between Tables 2 and 3 due to the methodological distinction.

As shown in Figure 2, as of 2019m12, immediately preceding the COVID-19 outbreak, E9SHARE_i stands at approximately 12% in the top group, whereas E9SHARE_i remains at approximately 1% in the bottom group. Given this disparity, when E9SHARE_i increases from 1% to 12% (an 11 percentage point change), the unfilled vacancy rate increases by 1.01 percentage points. As vacancy rates vary from 0.4% to 2.2%, an increase of 1.01 percentage points represents a substantial change. Similarly, the table results can be interpreted from a different perspective. For the furniture manufacturing sector, E9SHARE_i declined from 12.15% (2019m12) to 8.81% (2022m1), representing a difference of 3.34 percentage points. When E9SHARE_i decreases by 3.34 percentage points, the vacancy rate correspondingly increases from 2.22% to 2.53%, representing approximately a 14% increase in the vacancy rate.

5 Robustness and Extensions

5.1 Wild Cluster Bootstrap

Several robustness checks are conducted to ensure the results are not driven by spurious factors and to explore their broader implications. One concern involves the reliability of inference with only 22 sectoral clusters. As MacKinnon and Webb (2018, 2020) note, standard cluster-robust errors can over-reject the null hypothesis when the number of clusters is small. Therefore, a wild cluster bootstrap-t procedure (using 9,999 replications) is implemented as recommended by Roodman et al. (2019) to validate the significance of the estimates. The bootstrapped p-values (reported in Appendix Table 5) confirm that the impact on vacancy rates and tightness remains significant at the 5% level.

Next, verification is undertaken to ensure the findings do not result from artifacts in vacancy rate measurement. If total employment declined disproportionately in high-TFW sectors, the vacancy rate could rise mechanically even without genuine increases in unfilled positions. To put it another way, the result 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, the result is problematic if the number of domestic workers has decreased (or increased) more in the manufacturing sectors that relied more on TFWs.

To address this concern, the vacancy rate is recomputed using a fixed pre-pandemic employment level in the denominator. 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:

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

The resulting estimates (Appendix Figure 9, panels (A)–(C)) are virtually identical to the main graphical results in Section 4.1, indicating that uneven workforce changes did not drive the vacancy surge.

5.2 Domestic Employment

Direct examination of changes in domestic employment reveals no significant relative increase in the number of domestic workers in high-TFW sectors following the shock, as illustrated in Appendix Figure 9, panel (D). Native workers did not significantly occupy positions vacated by TFWs. Although a marginal increase in domestic employment was observed during the Shock phase (2020-2021), this change failed to achieve statistical significance. This analysis confirms the absence of confounding factors that could have generated fluctuations in the domestic workforce and subsequently influenced vacancy rates. The methodological approach employed to estimate domestic worker numbers at the two-digit sector level is documented comprehensively in Appendix E.

5.3 Local Projection

While the preceding analysis focused primarily on short-run effects, examining medium- and long-run responses to a single shock through impulse response functions (IRF) constitutes an important area of academic inquiry. The graphical DD regression demonstrated that negative TFW shocks produce immediate effects that synchronously diminish as the shock attenuates in the medium run. To investigate the dynamic trajectory of these effects over extended horizons, this section employs Local Projection (LP) methodology as an alternative to traditional Vector Autoregression approaches.[3]

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

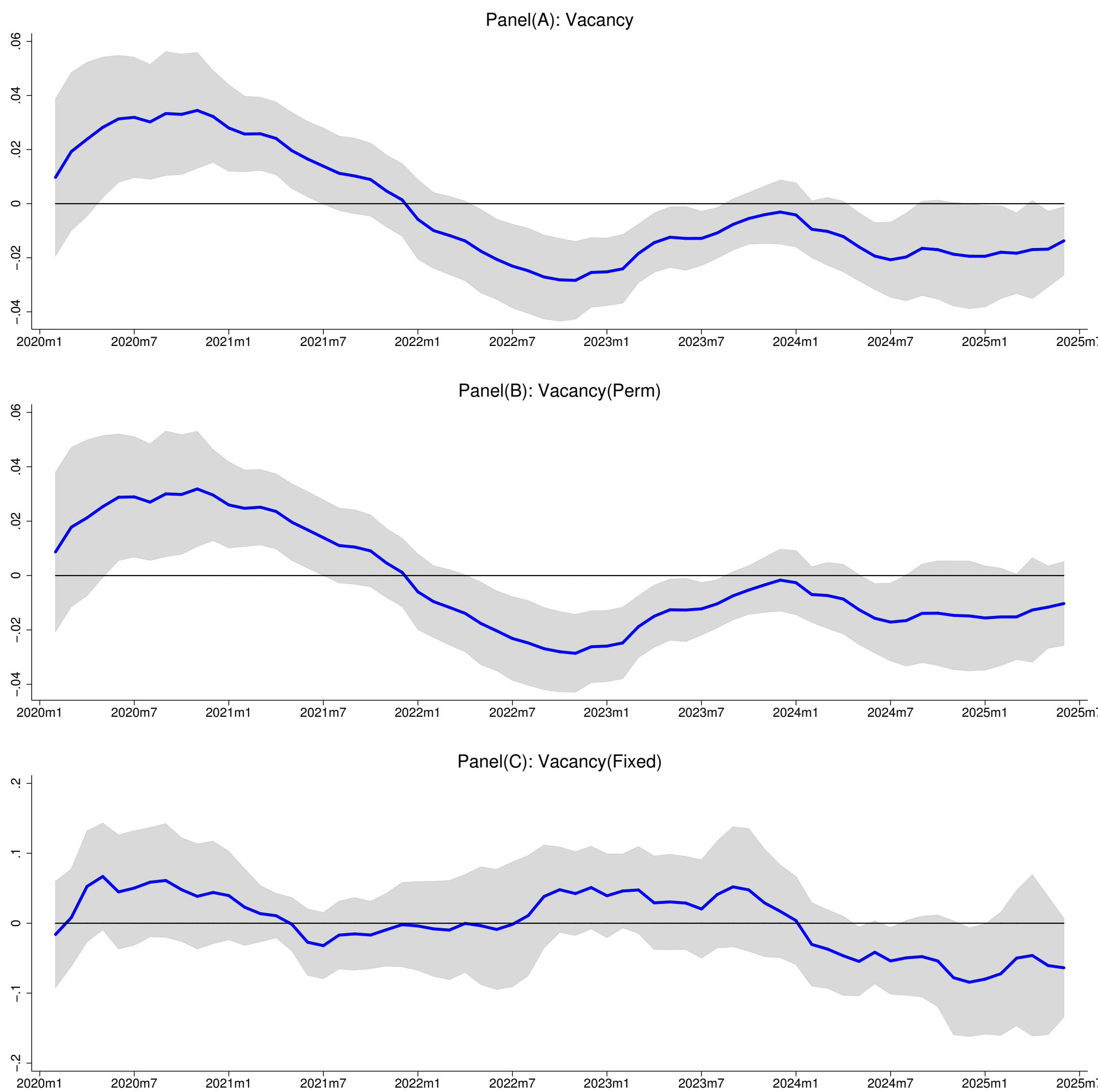
Equation (3) outlines the LP estimation and employs settings similar to those in the DD regression shown in Equation (1).[4] The key identification assumption for the LP method is the exogeneity of $\text{E9SHARE}_i \cdot D_t$. Given that E9SHARE_i includes only pre-COVID information, it satisfies the identification criteria. The coefficient β^h represents the response of $Y_{i,t+h}$ to the exogenous shock at time t. The LP estimation is clustered by industrial sectors, as accounting for the heteroskedasticity and serial autocorrelation

3. In his work, Jordà (2005) introduced the Local Projection (LP) method as an alternative to the Structural Vector Autoregression (SVAR). Recently, LP has gained popularity over SVAR due to its numerous advantages. One significant advantage of LP is its flexibility in applications where an exogenous shock is identified, allowing for direct estimation of impulse response functions (IRF) using OLS regressions, as noted by Adämmer (2019). Additionally, LP is adaptable to panel datasets, as demonstrated by Owyang, Ramey, and Zubairy (2013) and Jordà, Schularick, and Taylor (2015). LP can also be employed in DD settings, enhancing its applicability (Dube et al. 2023). Moreover, LP is more robust than VAR, particularly when VAR models are misspecified (Jordà 2005). Given that this paper involves DD settings with a panel dataset, the results derived from LP are inherently more reliable than those from VAR.

4. Even in the absence of staggered treatment timing, the Local Projections Difference-in-Differences (LP-DD) approach provides substantial analytical advantages. Traditional DD specifications incorporate all leads and lags as dummy variables within a single comprehensive regression model. Moreover, the beta coefficient for any given month is derived exclusively from the corresponding monthly dummy variable, rather than utilizing information from a temporal window. In contrast, the LP-DD methodology circumvents potential mis-specification issues by estimating the treatment effect at each horizon independently. This approach maintains a consistent two-year window for the treatment indicator D_t across all horizon-specific regressions.

is important for the LP method. S_i^h and T_t^h are sector and time fixed effects, respectively. The time frame (t) spans as follows: $D_t = 0$ for 2018m11 to 2019m12, and $D_t = 1$ for 2020m1 to 2021m2. The forecast horizon (h) spans until $H - 1$(2025m5), which is the most recent data available. The number of h is 66 (including $h = 0$).

Figure 6: Impulse Response Functions Estimated Using Local Projections



The results show that the vacancy rate initially rises, subsequently drops, and eventually converges at zero. Meanwhile, the vacancy rate for fixed-term employment is relatively insignificant, which corroborates the results from the DD regression analysis.

The results are provided in Figure 6, which reveal a distinct temporal pattern in vacancy rate responses. In the short run, vacancy rates exhibit a substantial positive response, subsequently transitioning to negative values in the medium run, before converging toward zero. Notably, the long-run trajectory demonstrates a slight negative deviation, attributable to the reversal of the initial TFW shock from negative to positive as border restrictions were lifted and TFW inflows resumed. This pattern suggests that the initial labor shortage-induced vacancy surge was followed by a compensatory adjustment period, with the eventual normalization and slight overshooting reflecting the restoration of TFW flows to pre-pandemic levels.

Notably, no significant long-run changes emerge in fixed-term vacancies, corroborating the DD findings. Regarding potential confounding factors, manufacturing industries may have exhibited heterogeneous pandemic responses that could theoretically bias the results. However, Appendix Figure 10 demonstrates that the number of active firms remained stable in high-TFW sectors, indicating that subsequent vacancy reductions cannot be attributed to firm closures. These analyses collectively support a causal interpretation: the TFW reduction generated genuine and significant increases in unfilled positions that cannot be explained by concurrent sectoral shocks or domestic labor substitution.

5.4 Local Projection on Domestic Workers and Profits

The impact of a negative TFW shock on domestic workers and firms' profits through its impulse response constitutes an intriguing area of investigation. This paper has primarily concentrated on examining the short-run causal effects of shocks on unfilled vacancies. However, the implications of such shocks for long-run human capital formation and economic growth remain a compelling area of inquiry. For example, Monras (2021) and Ehrlich and Pei (2021) both examine the long-run impacts of immigration shocks[5]

While the graphical DD illustration for domestic workers has been presented in Section 5.2, examining impulse responses through LP methodology offers a distinct analytical perspective. This distinction arises from the fundamental differences in the structural frameworks of DD and LP methodologies. Specifically, TWFE-DD estimation derives

5. Ehrlich and Pei (2021) demonstrate that the prohibition of low-skilled immigration diminishes the immigration surplus in the destination country during the static short-run period. In the long-term equilibrium, when the destination country exclusively permits high-skilled migrant inflows while prohibiting all low-skilled immigration, both average human capital and physical capital accumulation increase, consequently elevating per capita income levels in the destination economy. Moreover, Ehrlich and Pei (2021) establish that regulatory constraints on high-skilled migration attenuate knowledge spillover effects and subsequently reduce long-term per capita income growth. Therefore, although Monras (2021) provides empirical evidence that wage levels in Miami experienced an initial decline following the Mariel Boatlift before achieving substantial recovery by 1990, Ehrlich and Pei (2021) emphasize that long-term per capita income may experience adverse effects when *overall* immigration flows —particularly those comprising high-skilled workers— are restricted. These analytical perspectives should be understood as complementary contributions to the literature rather than conflicting interpretations.

multiple coefficients through dummy variables within a single regression framework, whereas LP estimates individual coefficients through separate regressions at each horizon. Consequently, the impulse response functions derived from LP are analogous to those obtained from structural vector autoregression models.

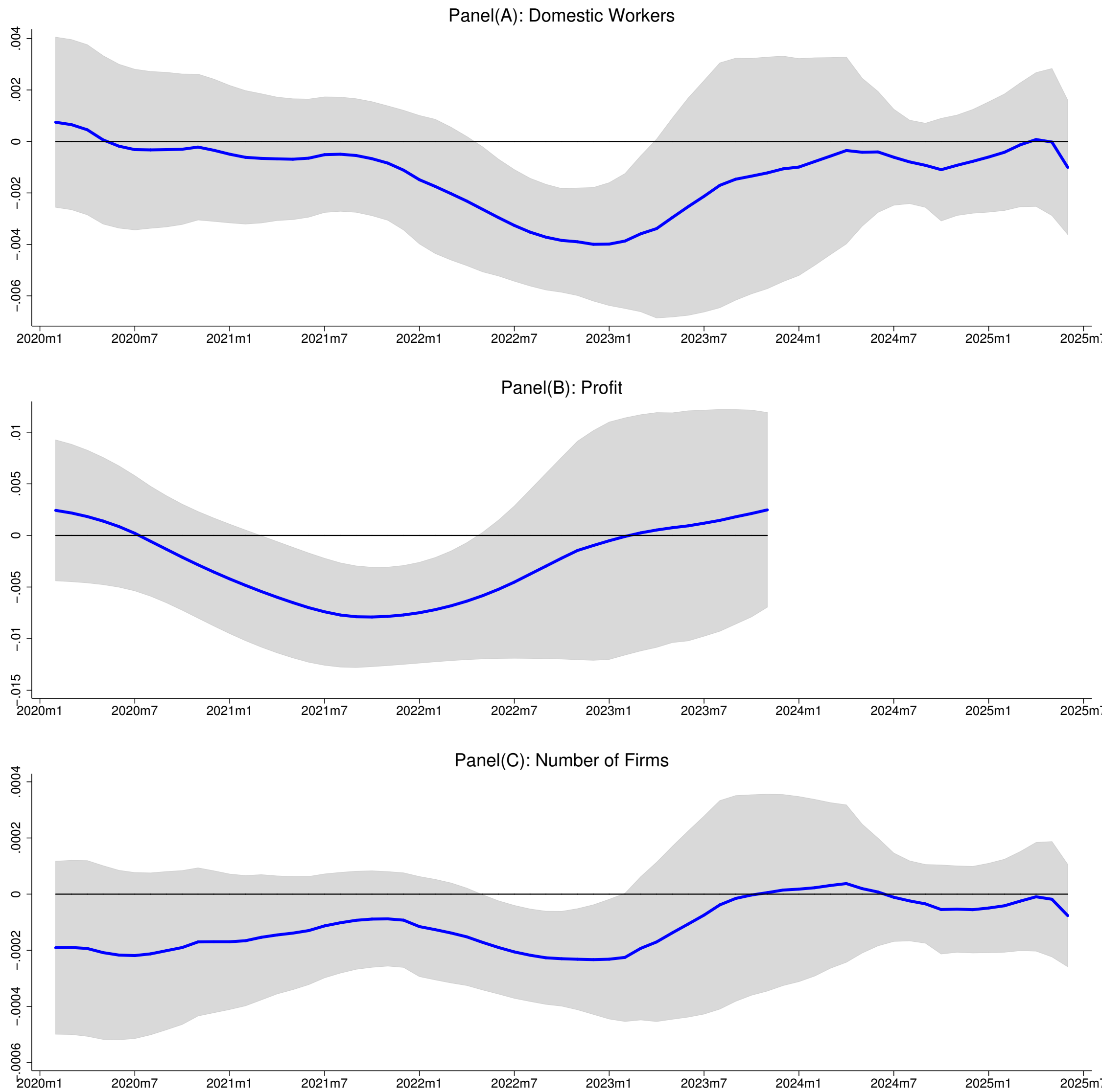
Figure 7 presents the LP results for domestic workers, profits (measured as value added), and the number of firms by employing the same specification as Equation (3). Following a negative TFW shock, domestic workers exhibit no significant response in the short-run. However, in the medium-run, industries experiencing greater TFW shortages demonstrate a pattern of reduced domestic worker employment. In the long-run, no significant response is observed. Panel (B) illustrates the profit (value-added) response function. Due to data availability constraints, with profit data only available through December 2023, subsequent IRF estimation was not feasible. The results indicate an immediate negative profit response in the short-run, demonstrating that industries with greater TFW shortages experience more severe profit declines. In Panel (C), the number of firms demonstrates patterns analogous to those observed for domestic workers in Panel (A). Specifically, modest firm attrition emerges during the medium-run period, coinciding with the recovery of TFWs inflows.

Meanwhile, heterogeneous variation in domestic workers across sectors could potentially affect the vacancy rate, as domestic workers are incorporated in the denominator of this metric. Similarly, the number of firms, defined as the sum of employees and unfilled vacancy positions following the search and matching model framework, could introduce bias. These LP results support the assertion that, during short-run analysis, neither domestic workers nor the number of firms constitutes a confounding factor that would bias the main specification presented in the primary tables and graphical difference-in-differences figures. Conversely, during short-run analysis, profits emerge as a potential confounding factor. This consideration motivated the exclusion of the profit variable from the covariate set to avoid bad control bias. The instrumental variable E9SHARE_i addresses this potential bias arising from heterogeneous profit responses across industries.

6 Mechanisms and Reasons for the Vacancy Pattern

The theoretical framework provided by the Search and Matching model, as elucidated by Howitt and Pissarides (2000), offers a robust analytical approach for examining the long-run dynamics of job vacancies precipitated by the outflow of foreign labor. A compre-

Figure 7: Impulse Response Functions Estimated Using Local Projections



Panel A: *After a negative TFW shock, domestic workers show no immediate response. In the medium run, industries with larger TFW shortages reduce domestic employment. Long-run effects are insignificant.* ***Panel B:*** *Industries with greater TFW shortages experience immediate profit declines. Analysis limited to December 2023 due to data constraints.* ***Panel C:*** *The number of firms demonstrates patterns analogous to those observed for domestic workers in Panel A. Specifically, a slight firm attrition appears during the medium-run period.*

hensive exposition of the standard Search and Matching model is presented in Appendix F, which introduces the essential notations employed throughout this section.

This paper incorporates short-run dynamics into the Search and Matching model. In the short-run, firms cannot exit the labor market. Furthermore, fewer people are searching for jobs. Therefore, the vacancy rate *rises* according to the model. From a theoretical perspective, the 'optimal capital-labor ratio' —determined ex ante through firms' profit maximization decisions— remains invariant unless the production function, interest rate, or depreciation parameters are changed. Therefore, 'optimal capital-labor ratio' constitutes a fixed factor in the short run. When a negative labor supply shock reduces the workforce, the sole mechanism for maintaining the optimal capital-labor ratio becomes the restoration of the initial employment level. This restoration can only be achieved through an elevation in the vacancy rate. A rigorous mathematical formalization of this mechanism is presented in Appendix F.

Similar arguments are made by few studies. First, Kindberg-Hanlon and Girard (2024) argue that a labor supply shock, like the post-pandemic worker shortage, can increase the marginal product of the remaining labor (MPL) if other factors like capital are relatively fixed in the short run. This higher MPL increases the potential profit from a new match, incentivizing firms to post more vacancies. Second, Hornstein, Krusell, and Violante (2007)'s model introduces vintage capital, where capital cannot be adjusted after investment, creating rigidity in the short run. This directly supports the claim about fixed capital per job and firms being unable to adjust capital stock instantly.

Conversely, the long-run recovery of the vacancy rate can be elucidated through various mechanisms within the Search and Matching model. Two principal factors warrant consideration. Firstly, if the decline in the birth rate (represented by TFW in this context) is transient, a subsequent rebound in the birth rate would result in the Beveridge Curve (BC) returning to its initial state. During the period of temporarily reduced birth rates, the long-term vacancy rate experiences a downward adjustment. Upon birth rate recovery, the vacancy rate gradually converges to its original equilibrium, effectively neutralizing the temporary perturbation. Secondly, even in the case of a permanent decline in the birth rate, which would cause the BC to contract towards the origin, the free exit of firms facilitates an adjustment in θ, the market tightness parameter. Specifically, the new equilibrium market tightness is determined by the interaction of Equations (WC) and (JC) shown in Appendix F. Despite a potentially permanent contraction of the BC, the alteration in θ leads to an adjustment in the vacancy rate.

Meanwhile, the conceptualization of 'firms' within the Search and Matching framework diverges significantly from the traditional understanding of establishments employing multiple individuals. In this model, 'firms' are defined as the aggregate of employed workers and unfilled vacant positions. Even if the conventional number of establishments remains constant, a reduction in the sum of employed workers and unfilled vacancies would be interpreted as a decline in 'firms' according to the Search and

Matching model. This approach is justifiable, as the critical factor is not the conventional quantity of establishments, but rather, the actual number of worker positions, both filled and potential.

This study investigates whether the observed recovery in vacancy rates can be attributed to the re-entry of TFWs (analogous to a recovery in birth rates within the Search and Matching model's conceptual framework) or to the exit of 'firms.' An examination of Figure 1 reveals that E9 workers began to re-enter the labor market in May 2022. The Korean government initiated a significant policy shift in May 2022, implementing measures to substantially increase the influx of TFWs into the country. This observation aligns with the data presented in Panel (B) of Figure 5, which indicates a commencement of vacancy rate decline in the same month. The temporal correlation between these events suggests a potential causal relationship, rather than mere coincidence.

This study further investigates whether the exit of firms could be an additional factor contributing to the decline in the unfilled vacancy rate. As previously defined, the number of firms is calculated as the sum of the number of workers and the number of vacant positions. The analysis employs the same equation as Equation (2), with a modification so that the dependent variable is now log of the number of firms. Appendix Figure 10 presents the results of this analysis. The data does not indicate a significant reduction in the number of firms. Notably, the firm count remains consistent even in the post-pandemic period. These findings suggest that firm attrition is not a contributing factor to the observed decline in the vacancy rate.

In conclusion, while the resurgence of TFWs following the end of the pandemic has contributed to a decline in the vacancy rate, firm attrition does not appear to be a significant factor. The evidence suggests that without TFWs, the vacancy rate would likely have remained elevated for a prolonged period, with a considerably slower decline in unfilled positions. The data indicates that domestic labor force participants demonstrated limited interest in filling these employment opportunities (Appendix Figure 9 (D)).

7 Conclusion

This study provides clear evidence that South Korea's Temporary Foreign Workers (TFW) program has been effective in alleviating labor shortages in the manufacturing sector. The natural experiment caused by COVID-19 border closures demonstrated that when the inflow of low-skilled foreign workers was abruptly halted, sectors previously reliant on TFWs experienced significant increases in unfilled job vacancies. Domestic workers did not step in to fill the gap left by absent foreign workers —particularly for permanent positions— leading to a surge in vacancies that only began to abate after the government reopened borders and allowed TFW arrivals to resume. This outcome directly challenges the criticism that foreign workers displace native workers, instead indicating that TFWs fulfill genuine labor demand that the native workforce cannot meet.

The analysis reveals a distinct dynamic pattern in vacancy rates following the TFW shock. In the short-run (approximately 2020–2022), the sudden reduction of foreign labor caused vacancy rates to spike in high-exposure industries, signaling acute labor shortages concentrated in permanent jobs, while vacancies for fixed-term positions remained relatively stable. Employers did not respond to the hiring crunch by markedly raising wages to attract local workers or significantly extending working hours beyond small adjustments, as many affected industries were already operating near legal maximum working hours and facing competitive pressures that limited wage growth. This constrained firms' ability to improve job conditions sufficiently to attract domestic workers, leaving crucial positions unfilled until foreign workers could re-enter. Firms in TFW-dependent sectors essentially faced a choice between enduring labor shortfalls or risking higher costs, with evidence showing they largely could not mitigate the shortfall without the return of foreign labor.

These findings align with predictions from job matching theory and mirror the inverse of outcomes observed in earlier studies of immigration shocks. Search and Matching models (Howitt and Pissarides 2000; Kindberg-Hanlon and Girard 2024; Hornstein, Krusell, and Violante 2007) suggest that a *positive* labor supply shock (an influx of workers) tends to initially reduce vacancies, followed by a gradual rise as the market adjusts, eventually returning to equilibrium. This study documents the flip side: a negative labor supply shock —the sudden removal of foreign workers— causes an immediate increase in vacancies, which later declines as adjustments occur, eventually converging back toward zero once the shock is reversed. The short-run surge and medium-run fall in vacancies observed here perfectly reflect this theorized trajectory, representing a mirror image of effects documented in prior empirical research.

Given these insights, important policy implications emerge for South Korea's labor market and immigration strategy. The evidence indicates that maintaining a stable and sufficient inflow of foreign workers is crucial for sectors facing chronic labor shortages, particularly in less-desirable permanent jobs that domestic workers are unwilling or unable to fill. Overly restrictive TFW policies can unintentionally induce significant labor market slack through unfilled jobs, hampering production and economic growth, while a well-calibrated TFW program can relieve these shortages without substantially harming native employment opportunities. South Korean authorities might consider making the TFW program more flexible and responsive to industry needs —for instance, by extending the residency period for *temporary* foreign workers in sectors demonstrating proven labor deficits. The observed inability or unwillingness of firms to adjust wages upward indicates that reliance on market forces alone to attract native workers may prove unrealistic in certain sectors. While improvements to working conditions and the provision of training programs or incentives for domestic workers could serve as strategies for addressing long-term structural issues, such measures may prove insufficient to fully bridge existing labor gaps. Consequently, a pragmatic policy approach necessitates facilitating the timely inflow of foreign workers to address urgent vacancy pressures.

Finally, this study opens avenues for future research. Over the five-year period examined, vacancy rates eventually declined from their peak and began to normalize as the shock dissipated, with acute shortages easing by the end of the medium-run (2024). The long-run adjustment may partly reflect the re-introduction of foreign workers (a "reverse shock" as inflows rebounded above pre-pandemic levels), but could also involve deeper economic adjustments. Persistent labor scarcity can spur firms to restructure, automate, or exit the market, as historical episodes demonstrate: the sudden loss of immigrant labor in U.S. agriculture in the 1920s prompted farmers to adopt more capital-intensive techniques (Abramitzky et al. 2019), and the end of the Bracero program in the 1960s led to greater mechanization in previously labor-reliant farms (Clemens, Lewis, and Postel 2018).

In the Korean manufacturing context, chronic labor shortages may lead to long-run sectoral contraction or transitions toward more capital-intensive production methods (between-sector transition), ultimately eroding competitiveness relative to other countries. The shipbuilding industry exemplifies this risk: contrary to common perception, shipbuilding remains surprisingly labor-intensive, and Korea's shipbuilding sector currently relies heavily on TFWs. Without this workforce, the industry risks following the trajectory of its American and Japanese counterparts, which have largely disappeared. Fostering and maintaining manufacturing capacity represents a critical policy priority, as emphasized by the Trump administration. Therefore, ensuring rapid and sufficient replenishment of foreign worker stocks becomes essential for industrial sustainability. This may necessitate modifications to the current TFW (E9) system, which mandates departure from Korea after three years. Institutional reforms might include provisions for visa extensions based on demonstrated work performance and safety records during the initial three-year period, thereby retaining skilled and reliable workers who have already integrated into the manufacturing ecosystem.

A Appendix: Tables and Figures

Figure 8: TFWs in Manufacturing Sector

The proportion of TFWs in South Korea's total manufacturing workforce declined from 10.44% in December 2019 to 8.21% in December 2021 as a result of the entry freeze.

Table 4: Workers by Visa Type in 2019 (%)

	Visa	Proportion in Manufacture	Proportion in 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

TFWs in the country's manufacturing sectors comprise primarily E9, F4, and H2 visa holders. Among these, E9 workers constitute 53% of total TFWs.

B Appendix: Unauthorized Workers

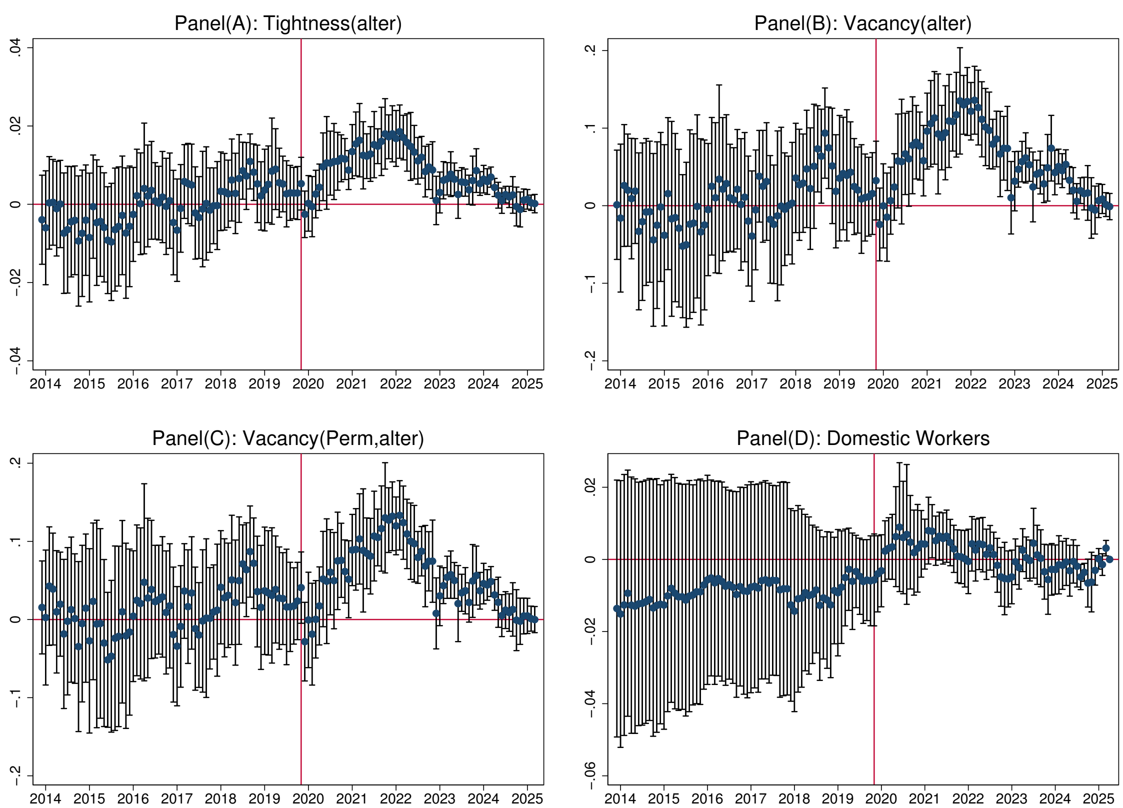
The Survey on Immigrants' Living Conditions and Labor Force, initiated in 2012, excludes temporary foreigners from its sample. Additionally, it lacks a variable indicating whether a respondent is an unauthorized resident. Therefore, this survey is unsuitable for studying unauthorized workers. Given the absence of a survey specifically designed

Table 5: Result for wild cluster bootstrap-t

	Table 2 (Instrumented) Explanatory variable: E9CHG		Table 3 (Reduced form) Explanatory variable: E9Share	
	p-value	confidence interval	p-value	confidence interval
Tightness	0.013	[-0.0681, -0.0081]	0.019	[0.0019, 0.0196]
Vacancy rate	0.007	[-0.5591, -0.0883]	0.014	[0.0208, 0.1625]
Vacancy rate (Perm)	0.008	[-0.5735, -0.0880]	0.015	[0.0204, 0.1670]
Vacancy rate (Fixed)	0.142	[-0.8823, 0.1265]	0.148	[-0.0411, 0.2552]

The results from the wild cluster bootstrap-t test show that the p-value for the coefficient on the share of E9 workers remains statistically significant at the 5% level (except for Fixed-term), confirming the robustness of the findings despite the small number of clusters.

Figure 9: DD (Robustness Check)

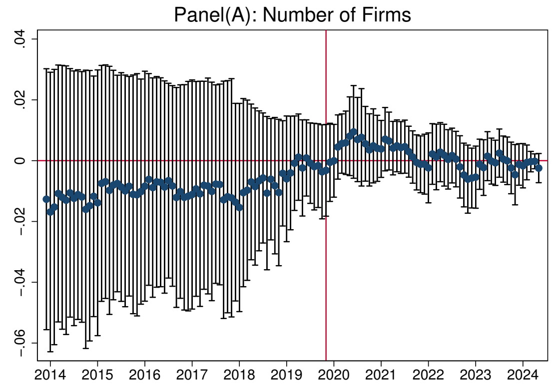


Panel (A) through (C) are using valter$_{it}$ instead of the vacancy rate. Comparing Figure 5 and Figure 9, the figures are almost identical.

to study unauthorized foreign workers in South Korea, researchers must rely on various indirect sources to estimate their numbers.

Unauthorized workers in South Korea fall into one of four categories: A) individuals

Figure 10: DD (A test for market attrition)



Source: LFSE (firms)

The firm count remains consistent even in the post-pandemic period. This finding suggests that firm attrition is not a contributing factor to the observed decline in the vacancy rate.

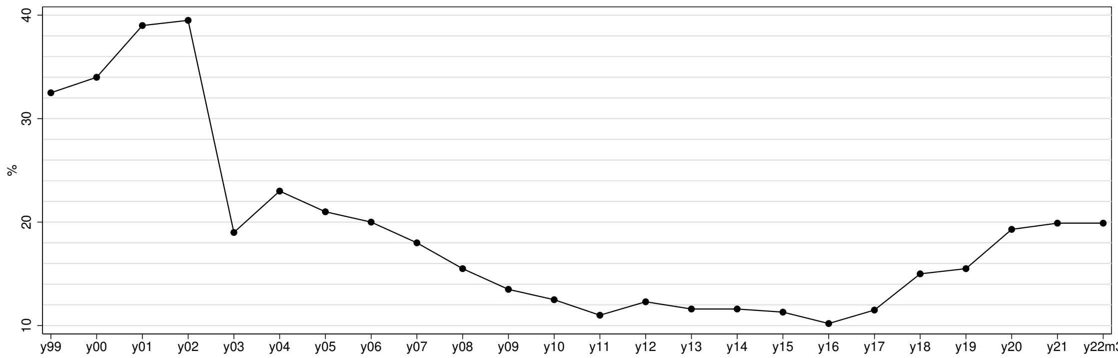
who stay beyond their permitted period, B) individuals who leave their legally assigned establishments to work elsewhere illegally, C) individuals who work without the necessary work authorization, and D) individuals who enter South Korea illegally without a visa.

First, the Korea Immigration Service Statistics (KISS) from the Ministry of Justice provides information about individuals in Category A. Figure 11 illustrates the proportion of overstaying foreign residents relative to the total non-immigration residents. This proportion significantly decreased in 2003 due to a legalization policy and robust enforcement efforts. However, it began to rise again from 2018 due to the more generous issuance of Visa Exemption (B1) and Temporary Visit (C3) visas, a policy change initiated in response to the Winter Olympic Games hosted in South Korea in 2018. In 2020, the share was 19.3%, comparable to the USA, which recorded 21.2% in 2019.[6] Utilizing KISS, Lee (2020) estimates that among the unauthorized foreign residents in 2020, 43.8% originated from Visa Exemption (B1), 20.1% from Temporary Visit (C3), 12.0% from Non-professional Employment (E9), and 0.7% from Working Visit (H2). He also estimates that among Visa Exemption (B1) residents, about 72.4% are from Thailand, many of whom are employed in the illegal massage service industry. As B1 visa holders are not authorized to work, these individuals also fall into Category C.

Second, Lee (2020) analyzes unauthorized foreign workers using data from the Employment Permit System (EPS). As previously mentioned, E9 workers are required not

6. 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 11: Share of Overstaying Residents



This figure illustrates the proportion of overstaying foreign residents relative to the total non-immigration residents. This proportion significantly decreased in 2003 due to a legalization policy and robust enforcement efforts. However, it began to rise again from 2018 due to the more generous issuance of Visa Exemption (B1) and Temporary Visit (C3) visas.

to change their place of employment and must leave South Korea immediately upon termination of their employment. He estimates that among unauthorized E9 workers, approximately 79.4% fall into Category A, while 20.6% fall into Category B. Thus, the issue of unauthorized status is predominantly associated with Category A rather than Category B.

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

C Appendix: Time Frame

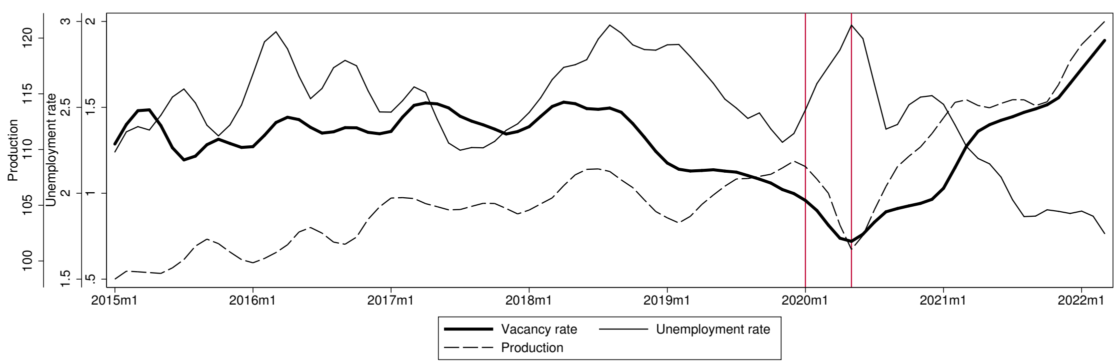
It is possible to identify two distinct phases during the COVID-19 pandemic (Appendix Figure 12(a)). The first is the Shock Phase (2020m1-2020m6) and the second is the Recovery Phase (2020m7-2022m12). In the United States, these two phases are even starker

6. Category 9 of the International Standard Classification of Occupations (ISCO)

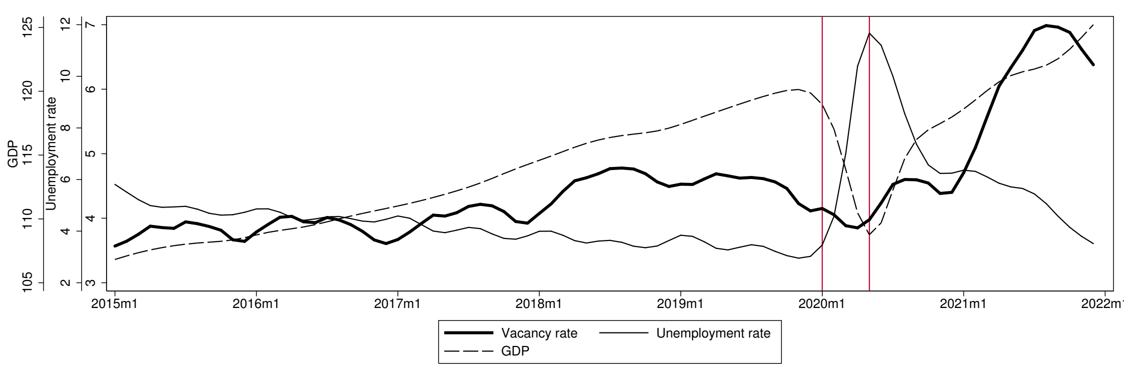
(Appendix Figure 12(b)).[7] Various macroeconomic indicators demonstrated contrasting trajectories between the Shock phase and the Recovery phase. Specifically, the vacancy rate exhibited a decline during the Shock phase, followed by a subsequent rebound throughout the Recovery phase. Production levels displayed an analogous pattern of initial contraction and subsequent expansion. Conversely, the unemployment rate followed an inverse trajectory, experiencing an increase during the Shock phase before declining in the Recovery phase. These findings indicate that the two phases are characterized by diametrically opposed economic dynamics.

Figure 12: Two Phases since COVID-19

(a) South Korean manufacturing case



(b) The USA case



Source: LFSE, EAPS, MSMM (KOREA); JOLTS, CPS, BEA (USA)

It is possible to identify two distinct phases during the COVID-19 pandemic. The first is the Shock Phase (2020m1-2020m6) and the second is the Recovery Phase (2020m7-2022m12). In the United States, these two phases are even starker.

It is important to note that only the *inflow* of E9 workers was restricted after the

7. Many of the existing studies about the COVID-19 pandemic focus on the Shock Phase (Borjas and Cassidy 2020; Mongey, Pilossoph, and Weinberg 2020; Cajner et al. 2020; Coibion, Gorodnichenko, and Weber 2020; Forsythe et al. 2020). Studies that focus on the Recovery Phase include Bishop and Rumrill (2021), Alvarez and Pizzinelli (2021), and Handwerker, Meyer, and Piacentini (2020)). Some studies distinguish the two phases and analyze them separately (Rothstein and Unrath (2020); Goda et al. (2021)).

pandemic began in January 2020. Conversely, the government did not interfere with the *outflow*, meaning that it did not force TFWs to leave. As a result, the number of E9 workers gradually decreased, as shown in Figure 1(a). Consequently, the significant decline commenced in July 2020, rather than January 2020 when the pandemic initially emerged. This temporal point of July 2020 marks the commencement of the Recovery phase. Therefore, this paper concentrates on the Recovery Phase to compare vacancy rates before and after the COVID-19 pandemic.

D Appendix: Robustness Check for Control Variables

The inclusion of control variables may inadvertently introduce 'bad controls' if such variables exhibit correlations with both the dependent variable and the primary explanatory variable of interest (Angrist and Pischke 2008). In such instances, selection bias emerges because of these inappropriate controls. Within the context of this study, a control variable is deemed unsuitable if it lacks orthogonality to the instrumental variable, specifically the pre-pandemic share of E9 employees. Indeed, the potential for bad controls exists, as factors such as profits and production are susceptible to pandemic-induced fluctuations, while the proportion of E9 workers may contribute to reduced labor costs, thereby potentially enhancing profitability or production.

It is therefore imperative to examine the correlation between the instrumental variable and the candidates of control variables (profit growth rate, shipment index, and Unemployment Insurance Benefits (UIB) growth rate). All of these candidates are time-varying and extend into the post-treatment period, potentially being differentially influenced by the exposure share. To address this methodological concern, I employ a diagnostic approach wherein candidates are regressed on the treatment variable (E9SHARE $\times$ Pandemic dummy) to identify whether these variables are endogenous to the treatment. As illustrated in Equation (4), the potential control variable candidates are incorporated as dependent variable, Y_{it}. Subscript i represents manufacturing sectors, and t represents monthly time. S_i and T_t are sector and time fixed effects, respectively. τ_t denotes dummy variables for quarterly seasonal periods. Thus, this equation is a dynamic two-way fixed-effects (TWFE) DD regression for the placebo exogeneity test.

$$
\begin{aligned}
Y_{it} = S_i + T_t + &\sum_{t \in \text{Pre}} \beta_t (\text{E9SHARE}_i \cdot T(\text{month} = t)) \\
&+ \sum_{t \in \text{Post}} \beta_t (\text{E9SHARE}_i \cdot T(\text{month} = t)) \\
&+ \tau_t + \varepsilon_{it}
\end{aligned} \tag{4}
$$

Figure 13 illustrates the analytical findings, which demonstrate that both profits and domestic shipments experienced greater declines in firms with high E9 concentration when COVID-19 emerged, indicating that these variables represent outcomes influenced by the treatment rather than stable control parameters. Consequently, incorporating these variables as controls in the vacancy regression would likely attenuate the treatment effect, resulting in biased coefficient estimates. The analysis identifies no significant impact on UIB, suggesting that E9 exposure did not directly alter patterns of layoffs or benefit distribution. This observation indicates that UIB may not lie on the causal pathway. Similar conclusions can be drawn regarding international shipments, which also appear to be independent of the causal mechanism under investigation.

E Appendix: Estimating Domestic Labors in Two-Digit Industry Sectors

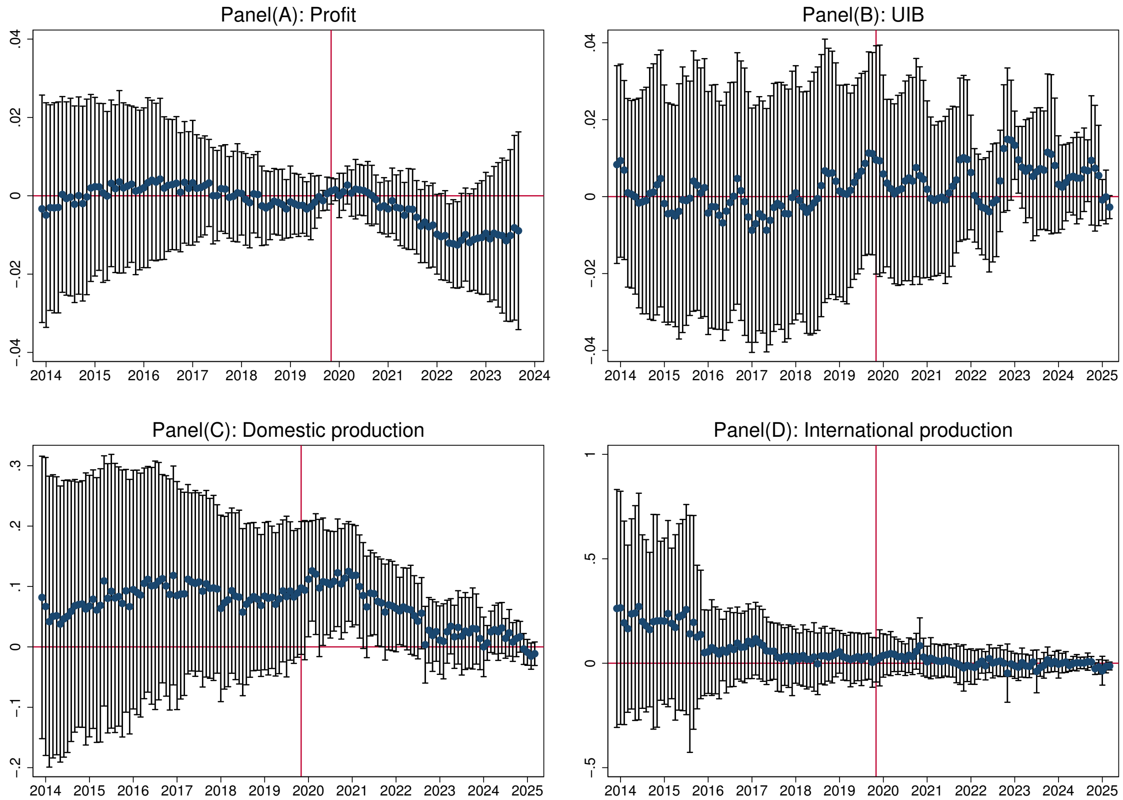
Unfortunately, the exact number of TFWs is known only for the total manufacturing sector (TFW_t). For two-digit sectors level, only the number of E9 workers is known (E9_{it}). Therefore, the paper assumes for now that the proportion of TFWs across sectors is the same as that of E9 workers. Under this assumption, TFW_{it} can be estimated as follows. Equation (5) shows the estimated number of domestic workers for two-digit sectors level.

$$
\begin{aligned}
\text{TFW}_{it} &= \text{TFW}_t \times \frac{\text{E9}_{it}}{\sum_i \text{E9}_{it}} \\
\Rightarrow \text{Domestic Workers}_{it} &= \text{Total Workers}_{it} - \text{TFW}_{it}
\end{aligned} \tag{5}
$$

F Appendix: Conventional Search and Matching Model

Following Howitt and Pissarides (2000), this section 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

Figure 13: Robustness Check for Control Variables

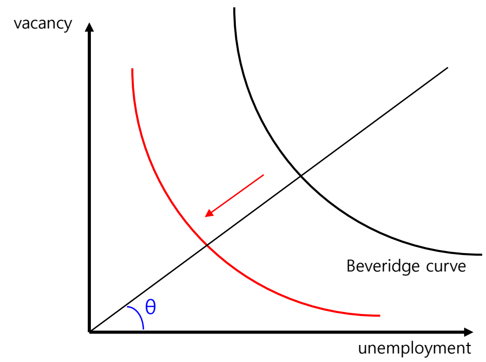


These figures are TWFE DD regressions for the placebo exogeneity test. They show that incorporating profits or domestic shipments as controls in the vacancy regression would likely attenuate the treatment effect, resulting in biased coefficient estimates.

and Matching models. There are numerous versions of the Search and Matching models, including in Howitt and Pissarides (2000), Elsby, Michaels, and Ratner 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 14 depicts this unique path.

This standard Search and Matching model can explain the trajectory of vacancies *in the long-run* when there is a *permanent* outflow of foreign workers (Table 6 summarizes notations). The outflow of immigrants leads to the birth rate (b) decline. In the long-run, the model predicts as in Figure 14. Many firms exit the labor market as they anticipate the decreased availability of people. Consequently, the Beveridge curve (BC) moves *inward*, and the vacancy rate *drops*.

Figure 14: Search and Matching Model



The outflow of immigrants leads to the birth rate (b) decline. In the long-run, the model predicts as in this figure: many firms exit the labor market as they anticipate the decreased availability of people. Consequently, the Beveridge curve (BC) moves inward*, and the vacancy rate* drops.

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

Table 6: Definitions

a	Matching efficiency
b	Birth rate (enter the labor market)
β	Worker's bargaining power
c	Search cost
d	Death rate (exit the labor market)
δ	Depreciation rate
λ	Job termination rate
K	Representative firm's capital
N	Representative firm's employees
FDR	$f(k) - \delta k - rk$
p	Labor augmented productivity
r	Interest rate
z	Unemployment benefit

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

$m(u_t, v_t)$ is the arrival rate of matching. Therefore, $m(u_t, v_t)L_t$ is the total number of matching at time t. There are many versions of matching functions, but this paper will use the most common and simplest Cobb-Douglas version, $m = au^{1-\eta}v^{\eta}$. a is matching efficiency. Therefore, the matching rate per one person is Equation (6), and the matching rate per one firm is Equation (7), where $\theta \equiv \frac{v}{u}$. Conventionally, $\frac{m}{u}$ is represented as q, and $\frac{m}{v}$ is represented as θq.

$$\frac{mL}{uL} = \frac{m}{u} = a\left(\frac{v}{u}\right)^{\eta} = a\theta^{\eta} \equiv q \tag{6}$$
$$\frac{mL}{vL} = \frac{m}{v} = a\left(\frac{v}{u}\right)^{\eta-1} = a\theta^{\eta-1} \equiv \theta q \tag{7}$$

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

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

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

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

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

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

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

$$
\begin{aligned}
&\frac{F}{N} - \frac{\delta K}{N} - \frac{rK}{N} - w \\
&\Leftrightarrow pf(k) - \delta pk - rpk - w \\
&\Leftrightarrow p[\text{FDR}] - w, \text{ where FDR} \equiv f(k) - \delta k - rk
\end{aligned} \tag{8}
$$

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 (9). Then it can convert to an Exponential distribution as in Equation (10). Denote the distribution function as $g(\ )$.

$$
g(x) = \frac{\lambda^x e^{-\lambda}}{x!} \tag{9}
$$

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

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

$$
g(0) = e^{-\lambda t} \tag{11}
$$

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

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

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

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

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

The value function of W can be calculated as below.

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

The value function of U can be calculated as below.

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

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). 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).

In the short-run, firms cannot exit the labor market. Furthermore, fewer people are searching for jobs. Therefore, the vacancy rate *rises* according to the model. From a formal perspective, k^* in Equation (k) remains constant unless alterations occur in $f(\cdot)$, r, or δ. Thus, k^* is fixed in the short run. When a negative labor supply shock occurs, causing N to decrease, the sole method to achieve k^* is to restore the initial N^*. The only viable approach to increase N is by elevating the vacancy rate.

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