Short-run Dynamics of the Search and Matching Model: Exploring the Rise in Vacancies in Response to a Decrease in Foreign Workers *

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1 Introduction

Following the onset of the COVID-19 pandemic, the South Korean government implemented a quarantine policy that led to a reduction in the number of temporary foreign workers (TFWs) in the country. Specifically, there was a 2% decrease in TFWs employed in the manufacturing sector until March 2022, as depicted in Figure 1. Upon lifting the quarantine measures around March 2022, the number of TFWs began to rise once again. Figure 2 illustrates the trend in the number of E9 visa workers, a significant subset of TFWs, which closely mirrors the pattern observed in the previous figure. Jeong (2022) examined the impact of the reduction in temporary foreign workers (TFWs) using a difference-in-differences (DD) approach. The study found that, in the short term, the decrease in TFWs led to a notable *increase* in the vacancy rate. Specifically, a 2% reduction

[0]It is possible to replicate all of the results using Matlab codes below:
https://raw.githubusercontent.com/jayjeo/public/master/LaborShortage/SearchandMatching.zip
Download the zip file, unzip to the desired location, and open Readme.txt

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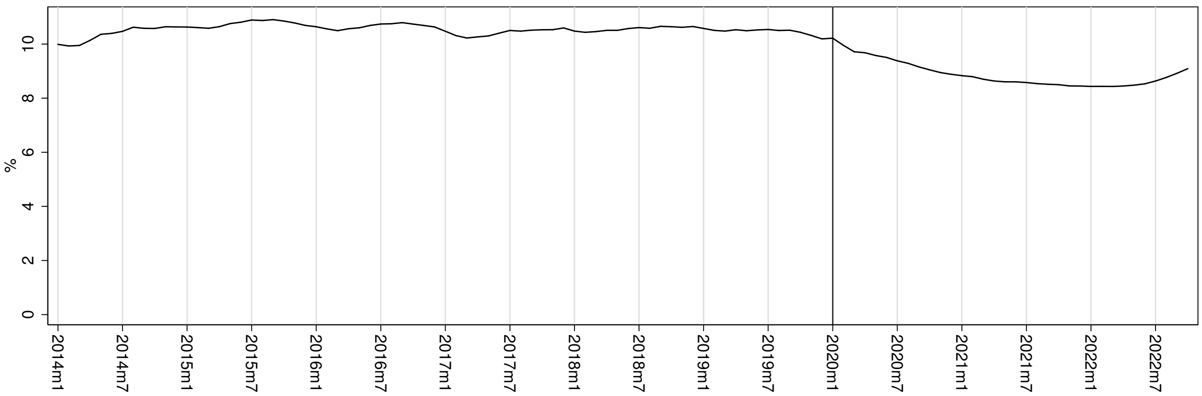
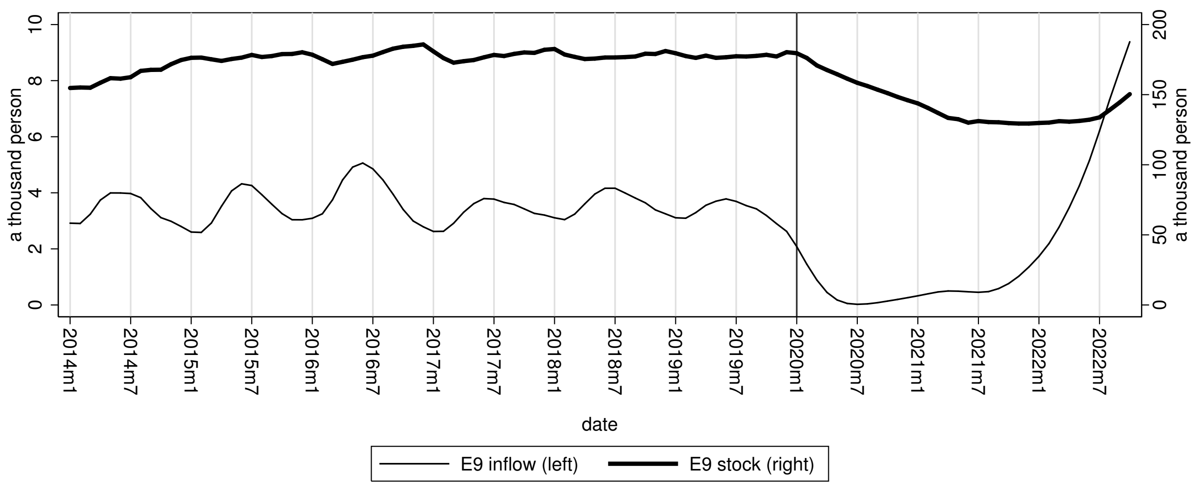
Figure 1: Proportion of Temporary Foreign Workers (TFW)



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

Figure 2: E9 Visa Workers



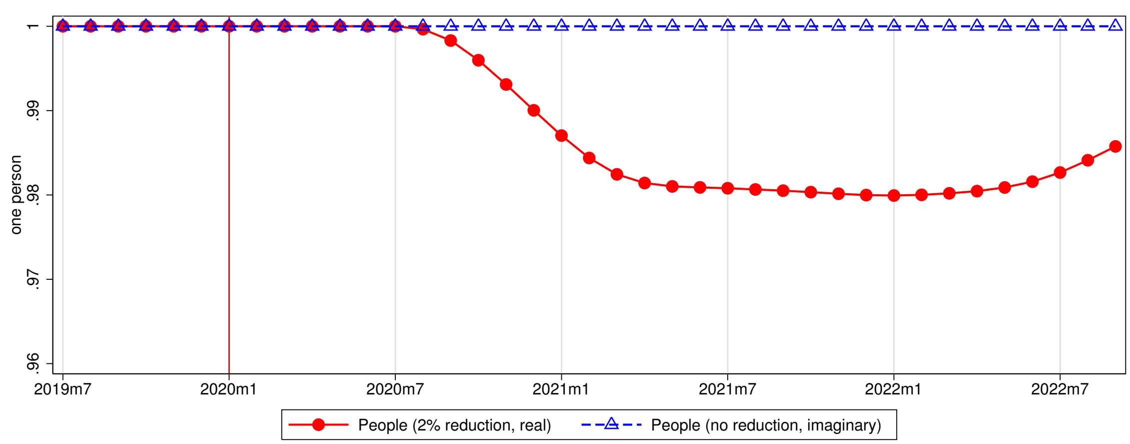
Source: Employment Permit System (EPS)

in workers resulted in a 0.6815 percentage point increase in the vacancy rate. Panel B of Figure 7 in the paper displays the monthly DD results, indicating that the vacancy rate began to rise with the onset of COVID-19 until March 2022. Following this period, the rate started to decline as the quarantine policy was lifted.

Investigating the underlying mechanism behind the short-term surge in the vacancy rate due to an exogenous reduction in the labor force presents an intriguing research question. One could initially consider the search and matching model (DMP model) as a theoretical basis. However, the standard search and matching model predicts a decrease in the vacancy rate when the population consistently declines (negative birth rate) due to the assumption of highly fluid capital in the long run. Various versions of search and matching models exist, including those in Howitt and Pissarides (2000), Elsby et al. (2015), Diamond (1982), and Mortensen and Pissarides (1994), but all of them implicitly assume fluid capital, even in dynamic analysis (out of steady-state) scenarios.

Thus, to understand the short-term surge in the vacancy rate, this paper will modify the standard search and matching model to better align with short-term dynamics. By employing this adjusted short-run model, the paper will simulate the vacancy rate, unemployment rate, and wage within the manufacturing sector in South Korea. The analysis will utilize data from January 2019 (the onset of COVID-19) through September 2022, covering the period when the quarantine policy was lifted and the population began to increase again. The simulation will compare two scenarios, as depicted in Figure 3: 1) the real situation where the population decreased by 2%, and 2) the hypothetical scenario where the population remained constant.

Figure 3: Number of Population



The proposed model diverges from the standard search and matching model. While retaining the dynamic path condition for the unemployment rate (denoted as Upath), the model introduces a new dynamic path condition for the vacancy rate (denoted as Vpath). This vacancy path is necessary because the model no longer permits unrestricted entry and exit of firms. In the standard model designed for long-run analysis, any number of firms can enter or exit within a single period (jump).

Consequently, the model no longer incorporates the Beveridge curve (BC), which describes a steady-state equilibrium condition for the unemployment and vacancy rates. The BC determines a stable condition over time, provided there are no additional shocks. In contrast, the present paper's model allows the unemployment and vacancy rates to continually change, following their respective paths (Upath and Vpath).

Although the model does not include the BC, it adheres to a simple rule: the sum of vacant positions and matched positions must be equal to the total number of positions offered by firms. In other words,

$$\text{Positions}_t = v_t L_t + (1 - u_t) L_t \tag{PO}$$

, where Positions_t is the total number of positions, v_t is the vacancy rate, and u_t is the unemployment rate. L_t is the total number of people on the market, normalized to one. The time-variant parameter Positions_t is derived from the ex-post value of the vacancy rate and the unemployment rate. Equation PO primarily determines the simulation results for the vacancy and unemployment rates. Although using Positions_t is a strong assumption, it alone cannot simulate the rates of vacancy and unemployment: the simulation also requires the Upath and Vpath equations.

It is important to note that Positions_t is not allowed to "jump," and its value is not fixed, even in the short run. Instead, it changes slowly over time. The search and matching model defines that **a** firm is matched to **a** person, so the number of "positions" may change even in the short run.

In the meantime, the model derives the wage curve (WC) similarly to the standard search and matching model. However, the equation is more complex since the assumption of free entry and exit ($V = 0$) does not apply. In the long run, when the free entry and exit condition is valid, $V = 0$ holds true. In that case, Equations J and V (defined in the next section) generate the Job Creation Curve (JC). Nonetheless, in the short-run model, such a JC does not exist. Table 1 summarizes the comparison between the short-run and long-run models.

Table 1: The comparison between short and long run models

Short-run		Long-run
PO	$\Rightarrow$	Holds, but meaningless
BC does not hold	$\Rightarrow$	**BC** holds in steady-state
Upath	$\Rightarrow$	**Upath** holds in dynamic state
Vpath	$\Rightarrow$	Does not hold anymore
WC is more complicated	$\Rightarrow$	**WC** holds in steady-state
JC does not exist	$\Rightarrow$	**JC** holds in steady-state

Following proper parameter calibration, the simulations provide adequate predictions for the vacancy and unemployment rates. The simulation reveals that the vacancy rate increased by 0.5405%p when the population decreased by 2%. This value is slightly lower than the DD result of 0.6815%p found by Jeong (2022). The reason for the rise in vacancies in the short run is that firms cannot fully adjust their positions. The simulation also demonstrates that the unemployment rate drops by 1.3408%p when the population decreases by 2%, as the number of unemployed individuals decreases when the population is smaller.

However, the simulation indicates that the wage increased by 24.61% compared to the constant population scenario. This finding contrasts with Panel G of Figure 7 in Jeong (2022), which shows, using the DD approach, that the wage difference is insignificant. Moreover, the wage simulation does not accurately predict the real value, as the real wage is relatively stable and sticky, while the simulated wage deviates from it.

To improve wage prediction, the model adopts the constant wage model presented by Hall (2005). This model offers a criterion within which a constant wage is possible. However, it does not explain why a constant value must specifically be a certain wage value. Thus, an alternative sticky wage structure is also introduced.

The long-run simulation results are presented as well. In the long run, the 2% population reduction is viewed as a one-time event that does not occur continuously. Consequently, the long-run Beveridge curve (BC) returns to the pre-COVID level, as the birth rate is zero. As a result, both the vacancy and unemployment rates will be the same as in the pre-COVID state, assuming that labor demand remains unchanged.

In the following sections, the paper will briefly introduce the dataset used (Section 2), explain the short-run model and results in detail (Section 3), and discuss the long-run model and its results (Section 4). Finally, Section 5 will address the contributions and limitations of this paper.

2 Data

This paper primarily employs two datasets: The Labor Force Survey at Establishments (LFSE) and the Economically Active Population Survey (EAPS). The LFSE, the Korean counterpart of JOLTS in the USA, closely follows JOLTS' definitions and methods, offering a wider variety of variables by industry sector. From the LFSE, this paper extracts the vacancy rate (v), the number of total employees in each month (Emp), wage (w), the number of newly matched people in a month (Matched), and the number of separated people in a month (Exit). Unlike JOLTS, LFSE provides these variables for two-digit industrial sectors.

The EAPS, a Korean version of CPS in the USA, replicates CPS with nearly identical variables and structures. This dataset provides the unemployment rate in the manufacturing sector.

The paper also utilizes several minor datasets. First, the Monthly Survey of Mining and Manufacturing (MSMM) offers labor productivity (p). Second, three datasets —EPS, KIMS, and SILC[1]— supply information on the exogenous reduction of TFWs due to COVID-19. The EPS provides the monthly number of E9 and H2 visa workers in South Korea, while KIMS offers monthly data on the number of temporary and permanent residents by visa type. Unlike EPS, which supplies the number of workers, KIMS only includes the number of visitors and residents. Lastly, SILC is an annual sample survey resembling the Economically Active Population Survey (EAPS). SILC provides a wealth of information about foreigners and naturalized citizens, including their employment status. Consequently, it is possible to calculate the employment and unemployment rates. By combining data from EPS, KIMS, and SILC, the study generates the exogenous monthly reduction of temporary foreign workers due to COVID-19.

In the subsequent sections, the paper will detail the data, the short-run and long-run models, and their respective results, as well as discuss the paper's contributions and limitations.

3 The Short-run Model

3.1 Environment

The short-run model builds on the framework of the standard search and matching model, following the same notation as Howitt and Pissarides (2000) unless specified otherwise. The model uses a discrete-time format with a monthly frequency. The matching technology is given by $m(u,v) = av^{\alpha}u^{1-\alpha}$. Consequently, the total number of matches is $m_t L_t$. For convenience, let $\theta \equiv \frac{v}{u}$, and $q \equiv a\theta^{\alpha-1}$. Therefore, the matching arrival rate per

[1]KIMS: Korea Immigration Service Monthly Statistics; SILC: Survey on Immigrant's Living Conditions and Labour Force

firm is q, while the matching arrival rate per person is θq.

The population (L_t) is normalized to one, meaning the total number of unemployed is u. With a 2% reduction in population, L_t is reduced from one to 0.98. A large number of firms each have one position, which can either be vacant or matched.

When a vacant position remains unfilled, the firm incurs a search cost equal to pc. Upon finding an unemployed individual, a job is formed, and the firm pays the worker a wage (w) determined by Nash bargaining when the two parties first meet. The bargaining power of workers is represented by η.

The destruction rate of existing jobs (λ) is exogenous. When a shock occurs, a match is terminated, causing the worker to become unemployed and receive a benefit of $z > 0$ per month. Additionally, when a matched job is destroyed, the position becomes vacant. While some vacant positions can exit the labor market, not all can. Specifically, the number of positions in the labor market is determined by a variable, Position_t. In this context, the number of positions is neither allowed to 'jump' indefinitely nor remain constant. If a vacant position persists in the market, it must attempt to find another match while paying the search cost, pc.

The model consists of three endogenous variables ($w, u,$ and v). Similar to the standard model in dynamics, the unemployment rate follows a predetermined path:

$$u_{t+1}L_{t+1} = u_t L_t - m_t L_t + \lambda_t(1 - u_t)L_t. \tag{Upath}$$

In contrast to the standard model, the vacancy rate must also adhere to a predetermined path:

$$v_{t+1}L_{t+1} = v_t L_t - m_t L_t + \lambda_t(1 - u_t)L_t. \tag{Vpath}$$

Equation PO naturally exists as an identity:

$$\text{Position}_t = v_t L_t + (1 - u_t) L_t. \tag{PO}$$

Since Position_t and L_t are known parameters, Equation PO represents the relationship between v_t and u_t. This relationship forms an upward line, which contrasts with the downward curve of the Beveridge curve. Equation PO is similar to market tightness (θ), which also defines an upward slope in the space of v_t and u_t.

Equation PO largely determines the simulation results for the vacancy and unemployment rates. For instance, the U-shaped simulation result observed around 2020m6 in Figure 4 can be attributed to Equation PO. Moreover, Position_t is a parameter that derives its value from the ex-post values of v_t and u_t, making it a strong assumption. However, Positions_t alone is insufficient for simulation; Equations Upath and Vpath are essential for the model to function properly.

Meanwhile, the following equations remain the same as those in the standard model. For the sake of notation convenience, let me omit the time subscript.

$$V = -pc + \beta\big(qJ + (1-q)V\big) \tag{V}$$

$$J = p - w + \beta\big(\lambda V + (1-\lambda)J\big) \tag{J}$$

$$W = w + \beta\big(\lambda U + (1-\lambda)W\big) \tag{W}$$

$$U = z + \beta\big(\theta q W + (1-\theta q)U\big) \tag{U}$$

, where β is a time discount factor. Nash bargaining solution yields Equation Nash.

$$\begin{aligned} &\arg\max_{w} (W-U)^{\eta}(J-V)^{1-\eta} \\ &\Rightarrow \frac{W-U}{\eta} = \frac{J-V}{1-\eta} \end{aligned} \tag{Nash}$$

A combination of Equations V, J, W, U, and Nash results in Equation WC. Since the assumption of free entry and exit for firms does not hold, V may not be zero, which complicates Equation WC as shown below:

$$w = \frac{\eta pMH + (1-\beta)(1-\eta)zMB + (1-\beta)\big(cB - \beta q\big)\eta pH}{MH - (1-\beta)(1-\eta)\beta\theta qM - (1-\beta)\beta q\eta H} \tag{WC}$$

, where

$$\begin{aligned} B &\equiv (1-\beta+\beta\lambda) \\ M &\equiv (1-\beta+\beta q)B - \beta^2\lambda q \\ H &\equiv (1-\beta+\beta\theta q)B - \beta^2\lambda\theta q \end{aligned}$$

The parameter $\beta = 0.9951$ is almost close to 1. Letting $\beta = 1$ simplifies Equation WC to $w_t = \eta p_t$. Consequently, one may guess that the simulated wage will depend only on p_t. However, this is not true. The shape of the simulated wage is mainly from θ_t, which is determined by v_t and u_t.

In summary, Equations PO, Upath, and Vpath determine v_t and u_t, which in turn decide θ_t. Then, θ_t determines the wage. Note that this sequence is in reverse order compared to the standard matching model. In the standard matching model, Equation WC and JC first determine θ_t and wage, and then θ_t and Equation BC establish v_t and u_t.

3.2 Calibration

Since deriving explicit solutions is impossible, a numerical approximation is necessary, which first requires proper calibration. The labor productivity (p_t) and the number of people on the market (L_t) are obtained from official data (time variants). The remaining parameters are time invariants. They are calibrated as shown in Tables 2 and 3. The bold text values are the ones this paper will use. Additionally, a, α, and λ can be calibrated (as presented in Table 3) so that the simulation results closely correspond

Table 2: Parameters

Parameter	Meaning	Value	Source
β	Discount factor	**0.995**	Hall (2005) and Shimer (2005)
		0.997	Thomas (2008)
c	Firm's search cost	**0.986**	Hall (2005)
z	Unemployment benefit	**0.4**	Hall (2005) and Shimer (2005)
		0.71	Hall and Milgrom (2008) and Pissarides (2009)
η	Worker's bargaining power	**0.72**	Shimer (2005)
		0.5	Gertler and Trigari (2009)

to the real ex-post values ($a = 0.180$, $\alpha = 0.147$, and $\lambda = 0.012$). This calibration leads to a good match with the real output (Figures 4 and 5). In these figures, the simulation result (red line with circle marks) follows the real output (black line) closely. However, these calibrated values are very different from the calibration values in the literature, as shown in Table 3. Let me denote these calibrations as 'bad calibration'.

On the other hand, a regression method can calibrate a, α, and λ. This calibration result is provided in Table 3 and will be primarily used in this paper. Let me denote these calibrations as 'good calibration'. The calibration method is explained as follows: Denote the total number of people working as 'Emp'; the number of people newly matched in each month as 'Matched'; the number of people separated each month as 'Exit'. The LFSE dataset, which is the Korean version of JOLTS, provides all of these variables as monthly data.

First, I can easily obtain λ as follows: Note that Exit $= \lambda(1-u)L$. Therefore, $\lambda = \frac{\text{Exit}}{(1-u)L}$. Second, I can determine L and $m(u, v)$ as follows: since Emp $= (1-u)L$, and thus $L = \frac{\text{Emp}}{(1-u)}$. Since $mL =$ Matched, it follows that $m = \frac{\text{Matched}}{L}$. Figure 6 shows $m(u, v)$ and λ by month. In the last two years, λ fluctuated primarily between 0.033 and 0.035.

[3] 0.72 that appears in Shimer (2005) is in terms of u, not v. Therefore, $1 - 0.72 = 0.28$ in terms of v.

[3] 0.12 (quarterly value) is transformed to 0.042 (monthly value) by the following calculation: solve($x + (1-x)x + (1-x)^2 x = 0.12$), then $x = 0.042$

Table 3: Parameters

Parameter	Source	Good or bad	Value
a	Shimer (2005)		1.355
	Gertler and Trigari (2009)		1
	Hall (2005)		0.947
	Calibration by author	Good calibration	**0.665**
	Calibration by author	Bad calibration	0.180
α	Thomas (2008) and Diamond and Blanchard (1989)		0.6
	Gertler and Trigari (2009)		0.5
	Petrongolo and Pissarides (2001)		0.5
	Gertler et al. (2008)		0.5
	Shimer (2005)		0.28 [2]
	Calibration by author	Good calibration	**0.319**
	Calibration by author	Bad calibration	0.147
λ	Blanchard and Galí (2010)		0.042 [3]
	Fujita and Ramey (2007)		0.039
	Gertler and Trigari (2009)		0.035
	Hall (2005)		0.034
	Shimer (2005)		0.034
	Calibration by author	Good calibration	**0.034**
	Calibration by author	Bad calibration	0.012

Figure 4: Vacancy rate (with bad calibration)

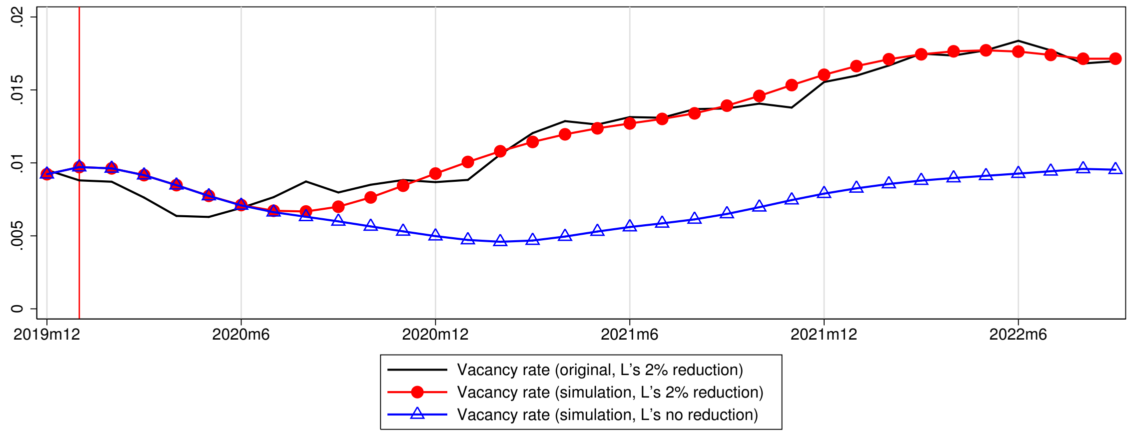
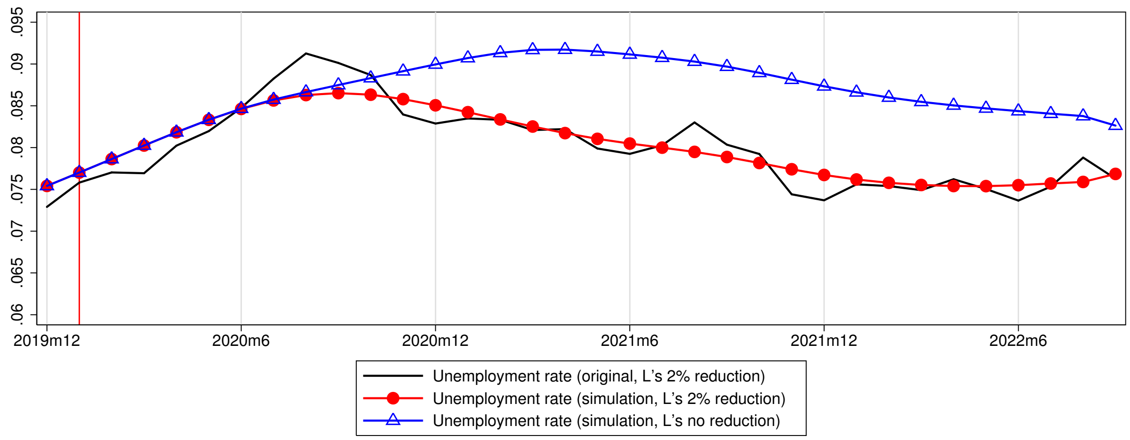


Figure 5: Unemployment rate (with bad calibration)

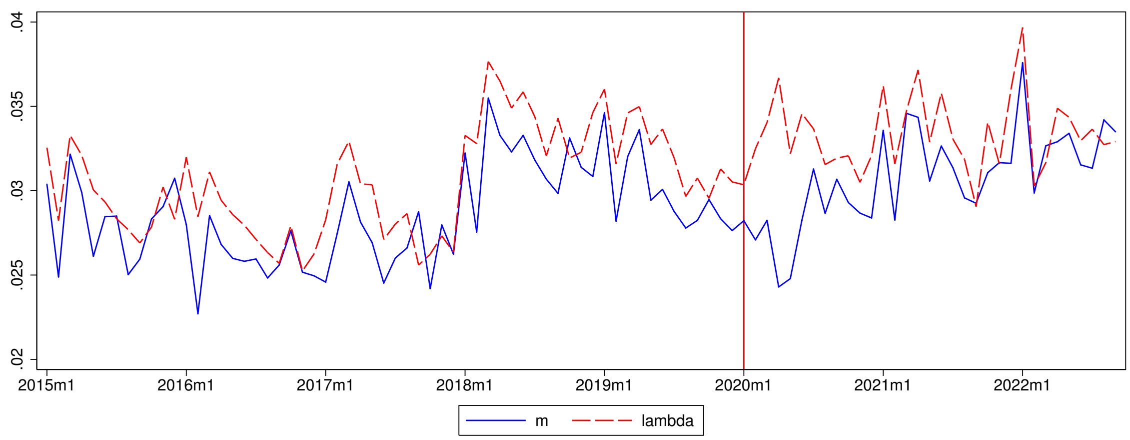


Therefore, let me calibrate λ as 0.034, as a time-invariant variable. The following explains how to calibrate a and α, which appear in Equation 1. By taking logs of this equation, I obtain Equation 2. I have all the values in the equation except $\ln a$ and α. Using a non-linear least-squares estimation[4] based on Equation 2, I derive $\ln a = -0.4074$ and $\alpha = 0.3187$. Consequently, $a = 0.6653$.

Although the value of a I obtain is slightly smaller than those in the literature, they are close. This difference might be attributed to the varying environments. My result focuses on the South Korean manufacturing

[4] In Stata, the regression command would be: nl $(\ln m = (\ln a = 1) + ((\alpha = 0.235) * \ln v) + ((1 - (\alpha = 0.235)) * \ln u))$. Download the zip file from Github, and run calibration.do for replication.

Figure 6: m and λ



sector. In the remaining sections, I will use the values of 'good calibration'.

$$m = av^{\alpha}u^{1-\alpha} \tag{1}$$

$$\ln m = \ln a + \alpha \ln v + (1-\alpha) \ln u \tag{2}$$

3.3 Simulation Results

Figure 7 illustrates the vacancy rate. In the figure, the black line represents the real outcome; the red line with circled marks represents the simulation when the population decreased by 2%; the blue line with triangle marks represents the simulation when the population remained constant. Similarly, Figure 8 shows the unemployment rate, and Figure 9 depicts the wage.

Figures 7 and 8 use the 'good calibration' values, while Figures 4 and 5 employ the 'bad calibration' values. The figures indicate that the former is less accurate than the latter. Although less accurate, I will use the former ('good calibration') since its calibration values are closer to those in the literature.

In Figure 7, when the population decreases by 2% (red line), the vacancy rate increases compared to when the population is constant (blue

Figure 7: Vacancy rate (with good calibration)

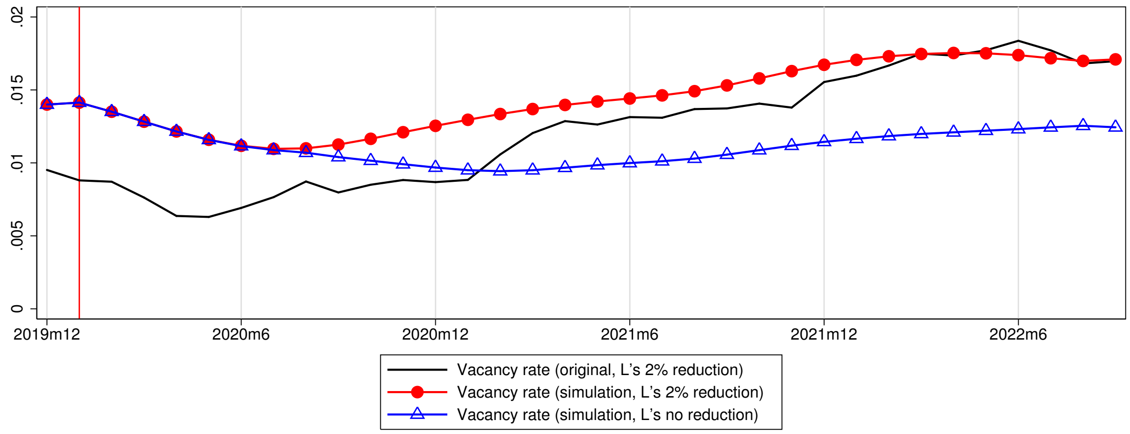
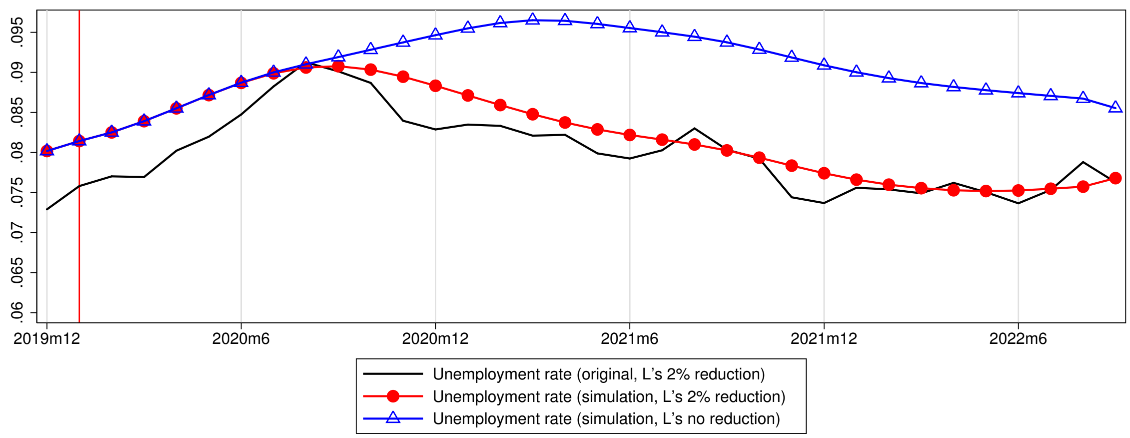


Figure 8: Unemployment rate (with good calibration)



line). As of 2022m1, the difference between the two vacancy rates is 0.5405%p. This value is lower than the DD result of 0.6815%p (Jeong, 2022). However, they are comparable.

When the population drops by 2%, the unemployment rate decreases by 1.3408%p (Figure 8 at 2022m1). The intuition is that a smaller population results in fewer unemployed individuals. When the population drops by 2%, the wage increases 24.61% compared to the wage of the constant population (Figure 9 at 2022m1). The intuition is that a tighter market leads to higher wages. However, the real wage (black line) appears to be sticky, and the simulated wage deviates from it.

Figure 9: Constant Wage by Hall (2005))

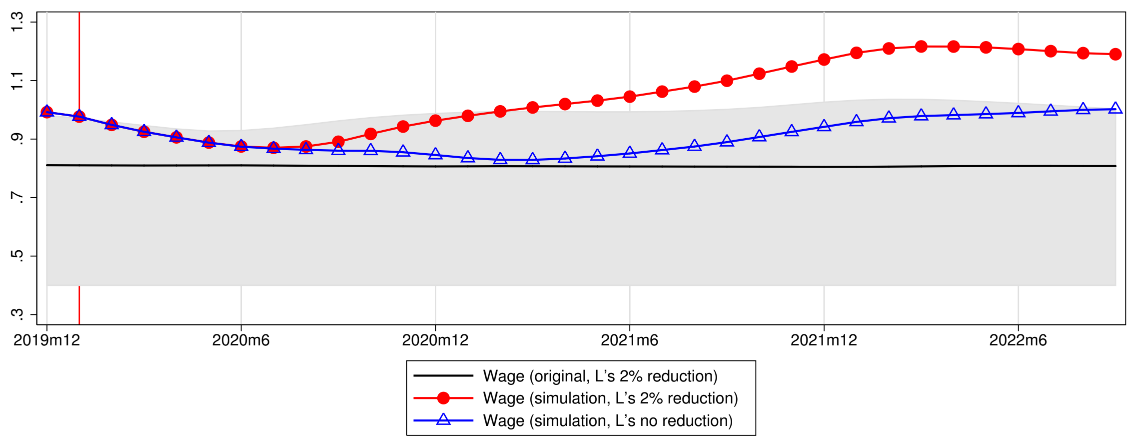
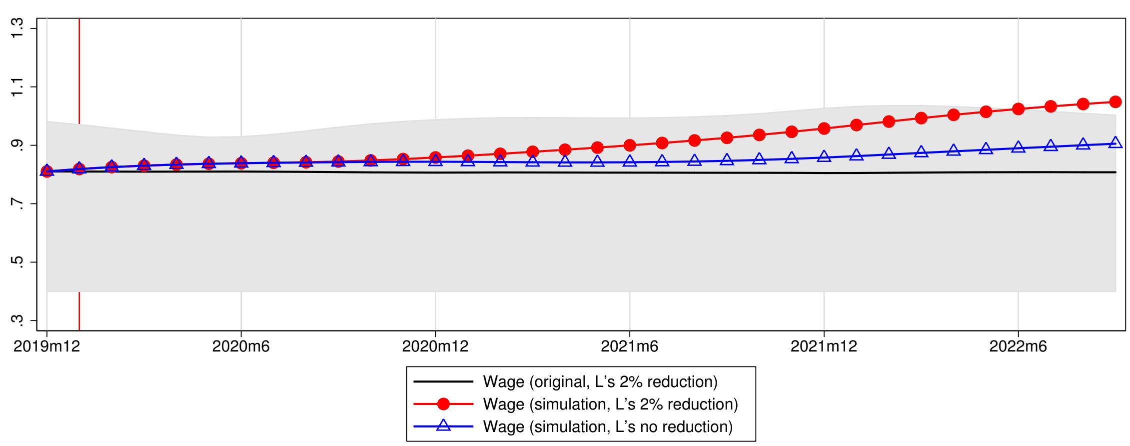


Figure 10: Sticky Wage ($\sigma = 0.99$)

Figure 11: Sticky Wage ($\sigma = 0.95$)



Moreover, the wage simulation is inconsistent with a DD analysis by Jeong (2022). The DD result revealed that the wage differences are insignificant, while the simulation demonstrates a significant difference. Therefore, alternative models are necessary for wage simulation.

One solution is a constant wage model by Hall (2005). He showed that any constant wage that satisfies Equation 3 is a Nash equilibrium. In his model, the Nash bargaining condition does not exist, which in turn, eliminates the Wage curve (WC). Consequently, Equation JC and the constant wage determine θ_t. Meanwhile, note that the Nash bargaining solution in the standard matching model is one of the solutions of the Nash equilibrium in Hall (2005). Also, note that a wage in his model is constant only between the contracting parties. Another contracting party in the next month may have a different wage contract, which will remain constant throughout their matching. Therefore, the wage in his model is neither perfectly constant nor as volatile as the standard matching model. In the standard model, the wage is constantly updated every period, leading to a more unstable wage.

$$z \leq w \leq \min_s [1-\beta(1-\lambda)]\tilde{J}_s \tag{3}$$

$$z \leq w \leq p \tag{4}$$

In my model presented in this paper, there are no multiple probability states, s. As a result, Equation 3 simplifies to Equation 4. The intuition is straightforward: any constant wage greater than the unemployment benefit and smaller than the labor productivity is a Nash equilibrium. In Figure 9, any constant wage within the gray area is the Nash equilibrium. This wage model simulates much better than the previous one.

One shortcoming of this constant-wage setting is that a constant value —for example, 0.81 in Figure 9— is arbitrary. For instance, Hall (2005) is silent about why a wage should specifically be at 0.81 when there are numerous other candidates for the wage in the range of $z \leq w \leq p$.

Therefore, I propose another simple solution that imposes weights on the current and past wages as follows:

$$w_{t+1} = \sigma w_t + (1 - \sigma)\mathrm{RHS}_t \tag{5}$$

, where RHS_t is the right-hand side of Equation WC, and σ is a weight, for example, 0.99. This sticky wage setting shows a good result. Figure 10 is the simulation result when σ is 0.99; Figure 11 is the result when σ is 0.95. According to these two figures, $\sigma = 0.95$ is not large enough to achieve a good result.

It is important to note that this sticky wage setting (as well as the constant wage setting by Hall (2005)) does not affect the simulation results of the vacancy and unemployment rates in this paper. This is because the model determines the vacancy and unemployment rates before determining the wage. Figures 7 and 8 are exactly the same as the simulation results from the sticky wage setting.

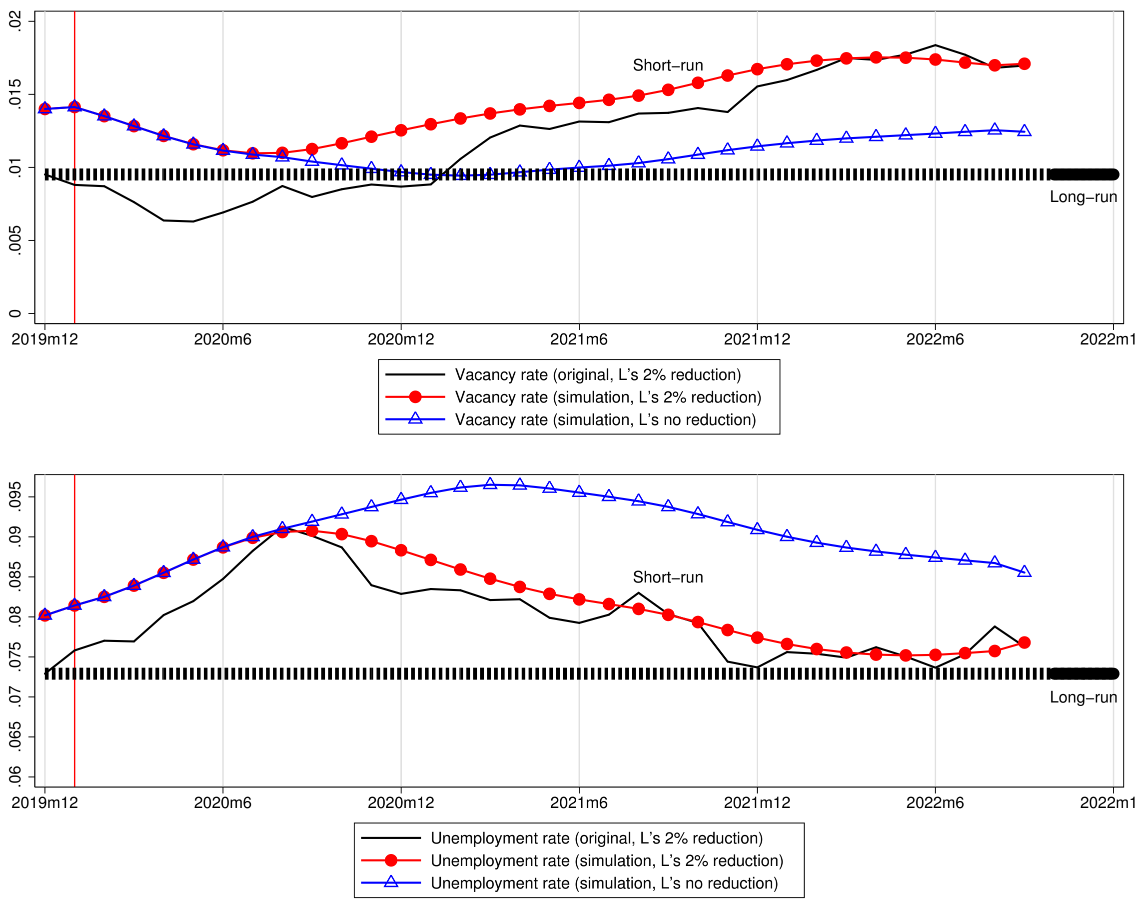
4 The Long-run model

The long-run model in this paper is the same as the standard model in Howitt and Pissarides (2000) (Ch.4), which includes a birth rate. If the population continues to decrease in the long run, the vacancy and unemployment rates will be lower. This result is due to the Beveridge curve (BC) moving closer to the origin (the negative birth rate).

In contrast, if the 2% population reduction is a one-time event (so that it stops decreasing), then the BC returns to its original level (the zero birth rate). Then, the vacancy and unemployment rates will be the same when the decreased case is compared to the constant populations case. Since the 2% population reduction should be considered a one-time event, the vacancy and unemployment rates will be the same as if nothing had happened to the population.

Suppose that labor productivity and firms' labor demand remain the same between 2019m12 (pre-COVID) and the long-run. Then, in the long-run, the vacancy and unemployment rates would be the same as in 2019m12. Figures 12 depict this.

Figure 12: Long-run simulation



The intuition is that in the short run, firms cannot adjust their positions, leading to a surge in vacancies. In contrast, in the long run, firms are aware of the more challenging matching conditions and reduce the number of positions accordingly.

5 Conclusion

First, this paper has policy implications. Some might argue that the recent issue of high vacancies is due to the labor demand side (production) rather than the reduction of foreign workers. Indeed, this paper demonstrated that some increase in vacancies can be attributed to the labor demand side. However, it also showed that the reduction of foreign workers exacerbated this surge. Therefore, accepting TFWs is essential for manufacturing firms to survive.

Second, this paper contributes to the understanding that the search and matching model can explain the increase in vacancies *in the short run*. The standard models could not explain this surge in vacancies because they primarily focus on the long run. Identifying that vacancies can move in the opposite direction in the short run compared to the long run is also a contribution to the literature.

Third, the DD result in Jeong (2022) and the simulation result in this paper are comparable. The DD result is that when 2% of workers decrease, the vacancy rate increases by 0.6815%p. In this paper, when 2% of the population decreases, the vacancy rate increases by 0.5405%p. This comparability ensures that both studies are valid and worth reading.

This paper has its weaknesses. As noted several times, Positions_t in Equation PO is a strong assumption. Positions_t is derived from the ex-post value of the vacancy and unemployment rate ($v_t L_t + (1 - u_t) L_t$). Consequently, the simulation results are not generated under a completely autonomous environment. Instead, they are largely guided by Positions_t. However, Positions_t alone cannot simulate anything. Moreover, without Equations Upath and Vpath, the simulation poorly matches the actual outcome. Therefore, a proper setting of Equations Upath and Vpath is essential for accurate simulation.

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