The reduction of Temporary Foreign Workers led to vacancy rise in South Korea

Jay Jeong

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1 Introduction

[1] Literature about the effect of immigration on vacancy is scarce, and the results are diverging. Anastasopoulos et al. (2018) showed that labor inflow from the Mariel Boat-lift event in Miami led to a vacancy drop. On the contrary, Schiman (2021) showed that labor inflow from EU enlargement led to a vacancy rise in Austria. Using the fixed effect with instrumental variable regression, this study will show that reducing Temporary Foreign Workers(TFW) led to a vacancy increase.

Moreover, the study will show that the mechanism through which reducing the TFWs led to vacancy rise was a termination rate increase but not a matching efficiency decrease. Anastasopoulos et al. (2018) proposed an idea that the increase in labor supply due to the Mariel Boat-lift event might have increased the matching efficiency. Nonetheless, it was their conjecture without an analysis since the data during the 1980s were not ample. In line with their idea, this study analyzed the reason for the vacancy rise. It turned out that the matching efficiency was not the reason. To the best of my knowledge, this study is the first to analyze the mechanism through which the TFW's reduction led to vacancy rise.

The issue in this study is the reverse causality of vacancy on TFWs: For fifteen years, the vacancy has determined the inflow of TFWs. The South Korean government has decided the number of TFWs based on vacancy. In January 2020, when COVID-19 broke out, however, TFWs could not enter South Korea because of a quarantine policy, which was exogenous from vacancy. In other words, TFWs suddenly dropped due to outside reasons from the vacancy. This event allows seeing the causal effect of TFW's reduction on vacancy.

[1] It is possible to replicate all of the results from a Stata code link below:
https://raw.githubusercontent.com/jayjeo/public/master/LaborShortage/LScode.do

E9, H2, and F4 visa workers consist of about 9% of workers in the manufacturing sector. Figure 1 shows E9 visa workers' reduction since the outbreak. Although the number of H2 and F4 workers in the manufacturing sector is not available, the total number of E9, H2, and F4 visa holders staying in South Korea is available. According to Figure 2, it is possible to guess that H2 workers in the manufacturing sector also have decreased a lot.

Figure 1: E9 Workers in Manufacturing Sector

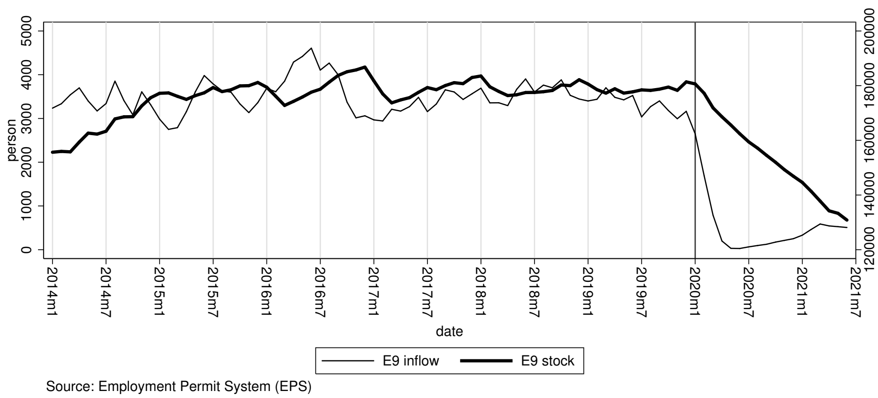
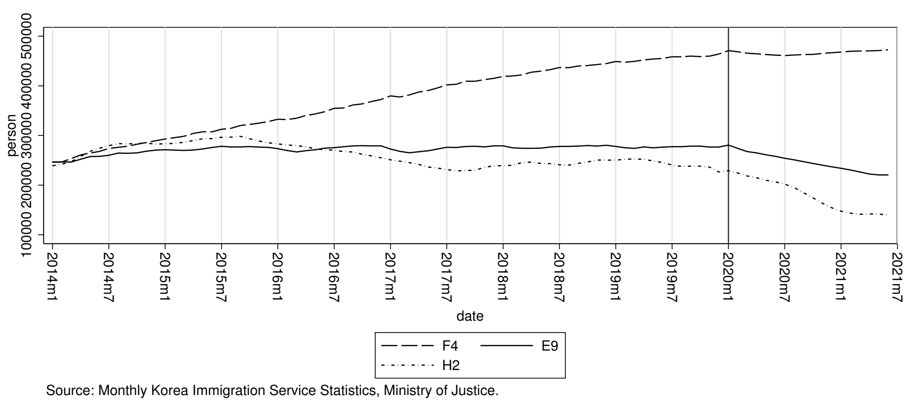


Figure 2: Visa Holders Staying in South Korea

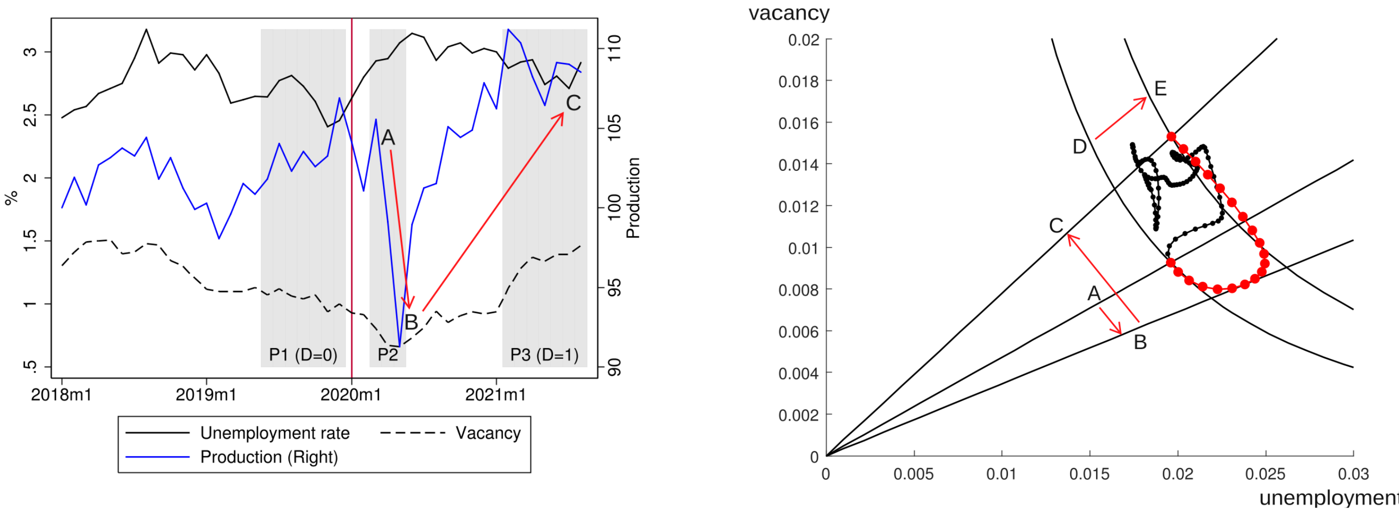


After controlling any other COVID-19 related shocks, the study wants to see the effects of foreign labor supply on vacancy change. The hurdle for this study is the coexistence of the labor demand side impact during COVID-19. The left panel of Figure 3 shows a sharp drop in the production level right after the outbreak event (from point A to B). The right panel also shows the drop of market tightness (the slope of lines from the origin). This market tightness is known to be highly correlated with the production level. After a few months have passed, the production recovers to point C. Fortunately, the recovery is fast. However, the sharp production drop (point A to B) may still have a lagged effect on vacancy. How to properly control this production shock is key to this study.

Meanwhile, the right panel shows that BC shifted outward from origin (point D to E).[2] The black dots indicate vacancy-unemployment relationships from 2011m1 to 2019m12 (until the COVID-19 outbreak). The red dots indicate the relationships from 2020m1 to 2021m8 (until present). Either a decrease in matching efficiency or an increase in termination rate moves BC outward from origin. The study will show that the increase in termination rate was the reason for the BC movement.

Figure 3

(a) Production (b) Beveridge Curve



2 Literature Review

To the best of my knowledge, there are two studies about the effect of immigration on vacancy. One is Anastasopoulos et al. (2018) and another is Schiman (2021). This study contributes to the literature by adding one more case study regarding the causal relationship of immigration on vacancy. Furthermore, this study analyzes the mechanism of the causal relationship and finds that the rise of the termination rate is the reason for the vacancy rise. Up to now, none of the previous studies have analyzed the mechanism of the causal relationship.

Anastasopoulos et al. (2021) studied the Mariel boatlift event in Miami in the 1980s. Mariel supply shock lasted only briefly (less than a year). Under this

[2]One caveat is that this movement is a short-term observation.

environment, their study focused on the longer term of the vacancy effect, which is 1∼10 years after the Mariel supply shock. Using Difference-in-Difference, they concluded that the refugees' influx led to a vacancy drop.

Furthermore, they compared Beveridge curves (BC) of many regions, including Miami. They found that Miami's BC moved inward to origin while BCs in other regions moved outward from origin (Figure 10(c) of their study). They surmised that the increase of the matching efficiency could be the reason for Miami's movement: "heterogeneity in search behavior between immigrants and natives might shift the BC because the matching function of the new arrivals differs from that of pre-existing workers. Such a difference could arise, for example, if the immigrants have a different reservation wage than natives. (Anastasopoulos et al., 2021)" It might be that the newcomers from Mariel were economically desperate, so they quickly found the job. Nonetheless, it was their conjecture without an analysis since the data during the 1980s were not ample.

Meanwhile, Schiman (2021) showed that the labor inflow shock from Eastern Europe temporarily increased Austria's unemployment by 25% and vacancy by 40%. EU enlargement to Eastern European countries resulted in a large influx of labor force to Austria from 2011. Unlike the Mariel supply shock event, the mass migration to Austria persisted for over a decade, so the increase in labor supply rate had long lasted. Unfortunately, his analysis did not include the matching efficiency or termination rate.

He used a structural vector autoregression (SVAR) with sign restrictions. The key to his study is the validity of the structural modeling and sign restriction since the results will largely depend on it. However, his study did not explain these thoroughly. Without a valid explanation using theoretical reasoning, this SVAR could be less persuasive. This is because the results of SVAR depend so much on which ordering and sign restrictions are used. Sims (1980) first introduced Vector autoregression (VAR) to provide forecasting methods without relying on identifying assumptions. Later, the SVAR method was invented, which entails solid structural assumptions based on macroeconomics theory.

Christl (2020) also studied the labor inflow shock from Eastern Europe to Austria. He showed that since 2011 the labor supply shock had played a role in unemployment rate rise. He also showed that since 2014 the decrease of matching efficiency played an exclusive role in the unemployment rate rise. He used the decomposing method first proposed by Barnichon and Figura (2012).

There are several studies on Beveridge curve movement and matching efficiency.

Barnichon and Figura (2012) showed that lower labor supply led to BC's shift toward origin in the USA from 1976 to 2010 (CPS and Help-Wanted-Index). They also showed that matching efficiency was not a factor for this BC movement.

Klinger and Weber (2016) showed that improvement of matching efficiency accounts for half of the substantial decline in unemployment during 2005 to 2011 in Germany. They claimed that matching efficiency has improved due to Hartz reforms which aimed at raising incentives for more intense job search and helping the matching process. They analyzed German BC between 1980 and 2013 using the unobserved components (UCs) method proposed by Sedláček (2014). German BC had shifted inwards from 2005 to 2011 for the first time in decades.

Literature about the effect of immigration on the termination rate is scarce. However, the literature is active in decomposing the unemployment rate into two components: job-finding rate (JF) and job-leave rate (JL). JL and termination rate are almost similar definitions. Shimer (2005) and Hall (2005) claimed that JL plays almost no significant role and that JF dominates JL. Later, a number of follow up study rejected this idea (Petrongolo and Pissarides, 2008); (Elsby et al., 2009); and (Fujita and Ramey, 2009). Specifically, they claimed that both JF and JL matter. "The separation rate (JL) accounts for just under half of unemployment variance and leads cyclical changes in unemployment" (Smith, 2011).

Immigration literature has been concerned to adverse effects of foreign workers' inflow on the natives' outcomes such as wage or employment. The answers are mixed and still in debate. Latif (2015) and Fromentin (2013) studied the effect on natives' unemployment. Carrasco et al. (2004) studied the effect on natives' employment opportunity. The studies on natives' wage are follows: (Peri, 2017), (Borjas, 2017), (Ottaviano and Peri, 2012), (Bratsberg and Raaum, 2012), (Cohen-Goldner and Paserman, 2011), and (Orrenius and Zavodny, 2007). Lastly, the studies on natives' out-migration or displacement are follows: (Martins et al., 2018), (Peri and Sparber, 2011), (Crowder et al., 2011), (Mocetti and Porello, 2010), (Card, 2001), and (Card and DiNardo, 2000).

Politically, immigrants' adverse effects are the issue. Moreover, there are anti sentiments toward foreign workers since many think foreigners take the natives' jobs. However, some parties advocate TFWs, such as employers. As a result, policymakers face a trade-off situation and listen to both parties. To minimize the adverse effects on natives, many countries, including South Korea, have TFW programs that restrictively permit temporary foreign workers. United Kingdom has Migration Advisory Committee(MAC), a group of five economists who produce a list of occupations that recommends facilitating immigration (Sumption, 2011). When determining the list of occupations, they use quantitative and qualitative data, and vacancy is a crucial variable. The occupations included in the list are exempted from the labor market test, which is employers' demonstration that they could not find native workers even after some period of effort to hire.

Similar to MAC, South Korea has a committee with twenty experts. However, the procedure of accepting TFWs is different from the United Kingdom. Firstly, the committee decides the quota of E9 visas, an employer-sponsored visa for temporary workers with low-skilled jobs. In addition to this quota, employers should make 14 days of announcements on the Korea Employment Center to hire native workers (labor market test). Then the government arranges a connection between the employer and applicant for E9 visa. In short, the committee decides the quota of E9 visas based on the labor shortage.

As explained above, determining the presence of the labor shortage is an important topic since it is a basis for accepting immigration. The literature have actively discussed the definition of labor shortage (Martin Ruhs and Bridget Anderson, 2019); (Constant and Tien, 2011); and (Barnow et al., 2013). The studies agree that there is no consensus of the definition. However, one consensus is that vacancy plays an important role in the definition. Therefore, this study will use vacancy to proxy the labor shortage.

3 Data

This paper uses mainly five datasets: The Labor Force Survey at Establishments (LFSE), Employment Permit System (EPS), Monthly Survey of Mining And Manufacturing (MSMM), Economically Active Population Survey (EAPS), and Employment Information System (EIS).

LFSE provides datasets of employment, vacancy, matching, and separation variables. LFSE is a South Korean version of the Job Openings and Labor Turnover Survey (JOLTS). LFSE replicates the list of variables and definitions from JOLTS. It is a monthly survey and has a 50,000 sample size on establishments with more than one any-type of worker — either full-time or temporary workers.

EPS provides datasets of the number of E9 and H2 workers. This paper will use only the number of E9 workers. Korea Employment Information Service (KEIS) supervises every single flow of E9 visa holders. Although EPS also provides the data for H2 visa holders, it is unreliable. Only about 10% of H2 workers voluntarily report to the EPS system.

MSMM provides a dataset of production levels. MSMM, conducted by Statistics Korea, is the vital data source when the Bank of Korea calculates Gross Domestic Product.

EAPS provides datasets of the unemployment rate for the manufacturing sector. It is a South Korean version of the Current Population Survey (CPS) in the USA. It replicates the list of variables and definitions from CPS. EAPS asks the unemployed or inactive surveyee about the previous job information, including the type of industrial sectors. Assuming that most people are looking for jobs in the same industrial sectors they previously worked in, it is possible to calculate the unemployment rate by industrial sectors. Similar to EAPS, the USA and Canada also provide the unemployment rate by industrial sectors.[3]

The shortcoming of EAPS is that it only provides unemployment rates by large categories of industries, such as agriculture, manufacturing, and service sector. On the contrary, EIS provides unemployment insurance (UI) recipients by detailed category of industries.[4] Subscript i represents twenty-three subgroups of manufacturing industries as shown in Table 1.

The figure shows that the unemployment and UI rates are serially highly correlated. Therefore, UI benefits rate[5] can be a good proxy for the unemployment rate (Figure 4). Unfortunately, there was a time break from 2019m12 because of the UI policy change. The policy has become more generous. The dashed blue line is the actual UI rate, and the study adjusted it by multiplying 0.7 after the UI policy change from 2019m12. To sum up, this paper will use UI benefits rate as u_i.

Using UI Benefit rate as a proxy for detailed manufacturing subsectors might be a too strong assumption. This is because people may move from a sector to other sectors quickly. Therefore, this paper will also use an alternative unemployment rate for a robustness check. In other words, this paper will use an alternative unemployment rate $u_i = u$ for all i, where u is the unemployment for the entire manufacturing sector.

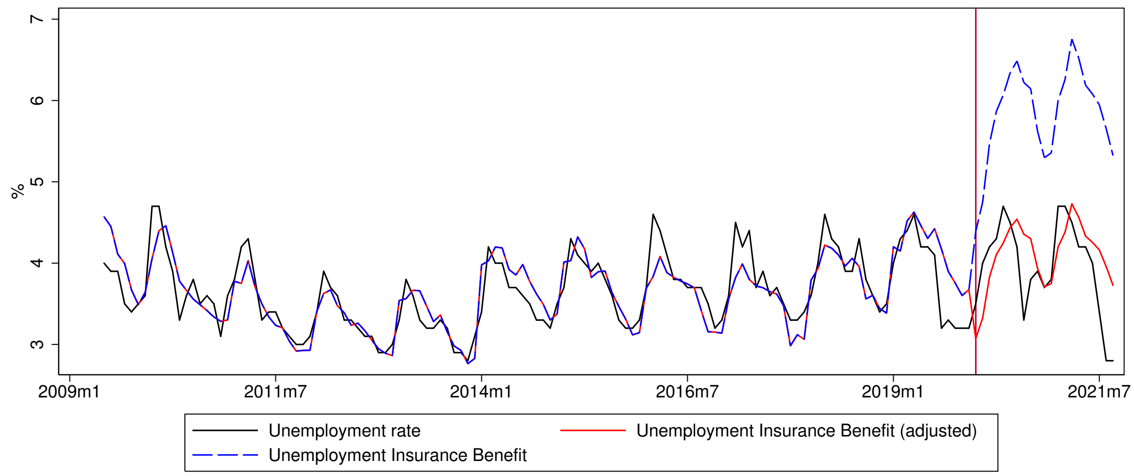
[3] https://www.bls.gov/news.release/empsit.t14.htm

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

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

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

Figure 4: Unemployment rate and UI rate



4 Search and Matching Model

This section aims to explain how the matching efficiency and the termination rate are calibrated. These variables will be calibrated by twenty-three industrial sectors and by each month. Also, these calibrated results will be used as dependent variables for the regression analysis in the next section.

The first step of this section is to introduce the Search and Matching model. This study will use the basic model containing the birth and the death rate (Chapter 4 of Howitt and Pissarides (2000)). The birth rate drop leads to the Beveridge curve's (BC) inward movement, which causes vacancy drop. However, this study will show that TFWs' drop (the same as the birth rate drop) moved BC outward, which caused a vacancy rise. Therefore, there should be other reasons —aside from the birth rate— that moved BC outward from origin. The possible canditates of the other reasons are the matching efficiency decrease or the termination rate increase.

Matching efficiency represents the matching speed per job seeker and employer. It can go down for many reasons: the job matching system becomes inefficient, or job seekers and employers become pickier or less desperate when finding matches. Among these various reasons, one possible story during the quarantine policy is the following: 'the TFWs had been promoting the job matching by accepting the difficult and dirty jobs that domestic workers were reluctant to work. However, after TFWs reduction, this promotion disappeared, and consequently, the matching efficiency went down.'

The above was the possible scenario, but the fixed effect with instrumental variable regression (FEIV) will show that this scenario is not the case: the industries heavily relying on TFWs have not experienced the reduction of matching efficiency. This implies that domestic workers may have quickly replaced the previously filled jobs by TFWs.

Meanwhile, the job termination rate represents the termination of the matching status either by workers' or by employers' reason: workers may leave the job voluntarily, or employers may fire the employee. The termination rate is a distinct definition of the death rate. Both job termination and death result in job separation. However, they are different in that workers are still economically active after the termination while they become economically inactive after the death. However, the death rate is known to be relatively stable, so the study assumed that the variation of job separation and job termination are the same.

Using the FEIV method, this study will show that the industries which primarily rely on TFWs are experiencing an increase in the termination rate. This means that TFWs' drop due to the quarantine policy caused an increase in termination rate. Moreover, this explains the vacancy rise and the Beveridge curve's outward movement from origin. One possible story is that domestic workers who replaced the jobs that TFWs initially filled could not endure the harsh conditions. The vacancy has risen because of the quick termination of the matched status.

To fully describe these terminologies, the study introduces the notations as follows, which are the same notations as Howitt and Pissarides (2000): the economically active population (L_t), the number of vacant firms per one mass of population (v_t), and the number of unemployed workers per one mass of population (u_t). Therefore, at time t, the total number of employed workers is $(1 - u_t)L_t$, the total number of unemployed people is $u_t L_t$, and the total number of vacant firms is $v_t L_t$. Also there are birth rate (b_t), death rate (d_t), and the job termination rate (λ_t). Here, the birth and death rates do not mean that people are born or die. It means that people move in and out from the economically active status.

Let EMP_t the total number of workers, which is provided by LFSE dataset. Furthermore, EIS provides u_t. Therefore L_t can be calculated as follows:

$$\begin{aligned} \text{EMP}_t =& (1 - u_t)L_t \\ \Leftrightarrow L_t =& \frac{\text{EMP}_t}{1 - u_t} \end{aligned} \tag{1}$$

$m(u_t, v_t)$ is the arrival rate of matching. This paper will use as in Equation 2, which is most frequently used formation in the literature. There is other types of matching function such as $m(u_t, v_t) = \frac{u_t v_t}{u_t + v_t}$. The overall results in this paper does not change by which functions are used.

$$m(u_t, v_t) = {u_t}^{1-\eta} {v_t}^{\eta} \tag{2}$$

Secondly, the type of matching efficiency needs to be selected. The most widely used one is a general efficiency, $m(a_t u_t, a_t v_t)$. The idea is that matching efficiency (a_t) is commonly shared by job seekers and employers. The paper will use this one. Therefore, the matching function now becomes

$$m(a_t u_t, a_t v_t) = a_t {u_t}^{1-\eta} {v_t}^{\eta} \tag{3}$$

Howitt and Pissarides (2000) has suggested to differentiate between job seekers' side and employers' side (Chapter 5). Specifically, $m(s_t u_t, a_t v_t)$, where s_t is suppliers' job search intensity, and a_t is demanders' job advertising intensity. By firm's free entry assumption, a_t becomes invariant to other shocks. There is also a version that only considers firms' side: $m(u_t, a_t v_t)$ (Chapter 6.2 of Elsby et al. (2015)). This becomes meaningful in the presence of inelastic entry, such as the model with entry cost.

Anyway, the paper will use the most widely used version (Equation 3). Then the arrival rate of matching per unemployed person is

$$\begin{aligned}
\frac{m(u_t, v_t) L_t}{u_t L_t} =& \frac{m(u_t, v_t)}{u_t} \\
=& \frac{a_t {u_t}^{1-\eta} {v_t}^{\eta}}{u_t} \\
=& a_t (\frac{v_t}{u_t})^{\eta} \\
=& a_t {\theta_t}^{\eta}, \text{ where } \theta_t \equiv \frac{v_t}{u_t}
\end{aligned}$$

The people's inflow to unemployed status is $\lambda_t(1 - u_t)L_t + b_t L_t$. The first term is by the termination of job. The second term is by the birth. The people's outflow from unemployed status is $a_t {\theta_t}^{\eta} u_t L_t + d_t u_t L_t$. The first term is by job matching. The second term is by death. Therefore, the total flow of unemployed people is

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

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

$$\begin{aligned}
\Leftrightarrow (b_t - d_t)u_t =& \lambda_t(1-u_t) + b_t - a_t{\theta_t}^{\eta}u_t - d_tu_t \\
\Leftrightarrow u_t =& \frac{\lambda_t + b_t}{\lambda_t + b_t + a_t{\theta_t}^{\eta}} \\
\Leftrightarrow v_t =& \left(\frac{(\lambda_t + b_t)(1-u_t)}{a_t{u_t}^{\eta}}\right)^{\frac{1}{\eta}}
\end{aligned} \tag{BC}$$

Equation BC is the Beveridge curve. It moves inward to origin when a_t increases and moves outward from origin when λ_t or b_t increases.

4.1 Calibration of Matching Efficiency

Calibration of matching efficiency (a_t) has been actively discussed in literature since it is the core of any studies regarding the Search and Matching model. There is a consensus on the simple and basic calibration method. However, it has an endogeneity issue. As a result, the matching efficiency becomes serially correlated with the market tightness. To correct this biasedness, Borowczyk-Martins et al. (2013) proposed a method using an ARMA process.[6] Sedláček (2014) and Dixon et al. (2014) proposed another alternative method using the unobserved components (UCs) model. This paper will use the basic calibration method for now and will update it to an advanced method when possible.

The first step of matching efficiency calibration is the estimation of η. For notation convenience, time(t) subscript is omitted. Denote M as total matchings per month, which is provided by LFSE dataset. L is acquired from Equation 1. From $m(au, av) = a \cdot u^{1-\eta}v^{\eta}$, it follows that

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

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

The last equation is the regression model, where η can be estimated. Then matching efficiency for each subsector of the manufacturing industry are as follows:

$$\begin{aligned} M_i &= m(a_i u_i, a_i v_i)L_i \\ \Leftrightarrow M_i &= a_i \cdot u_i^{1-\eta} v_i^{\eta} L_i \\ \Leftrightarrow a_i &= \frac{M_i}{u_i^{1-\eta} v_i^{\eta} L_i}. \end{aligned}$$

4.2 Calibration of Termination Rate

Job termination rate, λ_i, is an arrival rate that terminates job matched status. In the birth and death rate model, a matched status can be separated either by job termination or death. Assuming that the variation of death rate is relatively small, it becomes possible to estimate the variation of the job termination rate. Let EXIT_i be the number of separations in each subsector, provided by LFSE dataset. Then it follows that

$$\begin{aligned} \text{EXIT}_i &= \lambda_i L_i \\ \Leftrightarrow \lambda_i &= \frac{\text{EXIT}_i}{L_i} \end{aligned}$$

5 Regression Models and Results

Equation 4, 5, and 6 will be the regression models throughout the study. Dependent variables will be the vacancy rate, unemployment rate, matching efficiency, and termination rate. Subscript i represents twenty-three subgroups of manufacturing industries as shown in Table 1. Subscript t represents months (either $D_t = 0$ or $D_t = 1$). The shaded areas in Figure 5 show that $D_t = 0$ if month is 2019m6 $\sim$ 2019m12; and $D_t = 1$ if month is 2021m2 $\sim$ 2021m8. S_i and T_t are the industry and time fixed effect, respectively.

$$Y_{it} = S_i + T_t + \beta(\text{E9CHG}_i \cdot D_t) + \gamma\text{PROD}_{it} + \varepsilon_{it} \tag{4}$$

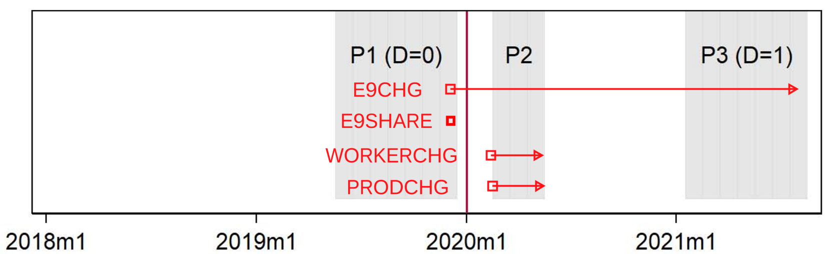
$$Y_{it} = S_i + T_t + \beta(\text{E9CHG}_i \cdot D_t) + \theta(\text{PRODCHG}_i \cdot D_t) + \gamma\text{PROD}_{it} + \varepsilon_{it} \tag{5}$$

$$Y_{it} = S_i + T_t + \beta(\text{E9CHG}_i \cdot D_t) + \theta(\text{WORKERCHG}_i \cdot D_t) + \gamma\text{PROD}_{it} + \varepsilon_{it} \tag{6}$$

, where definitions are provided below:

$$\text{E9CHG}_i \equiv \frac{(\text{E9 in 2021m8}) - (\text{E9 in 2019m12})}{\text{Total workers in 2019m12}} \times 100$$
$$\text{E9SHARE}_i \equiv \frac{\text{E9 in 2019m12}}{\text{Total workers in 2019m12}} \times 100$$
$$\text{WORKERCHG}_i \equiv \frac{(\text{Total workers in 2020m5}) - (\text{Total workers in 2020m3})}{\text{Total workers in 2020m3}} \times 100$$
$$\text{PRODCHG}_i \equiv \frac{(\text{Production in 2020m5}) - (\text{Production in 2020m3})}{(\text{Production in 2020m3})} \times 100$$
$$\text{PROD}_{it} \equiv \text{Production at time t}$$
$$V_{it} \equiv \frac{\text{Number of vacant spots at time t}}{\text{Number of workers at time t}} \times 100$$

Figure 5: Time range of the definitions



All of the models above use fixed effect assumptions with industry clustered. To be specific, this study uses a serially correlated cluster-robust covariance matrix estimator. The key assumptions are (1) (Y_i, X_i, Z_i, S_i) is iid for all i, where $W_i \equiv [w_{i1}, w_{i2}, w_{i3}, ..., w_{iT}]$, and (2) the strict exogeneity with respect to ε_{it}.

Meanwhile, all of the models use Difference-in-Difference (DD) idea. E9CHG_i is a treatment intensity that is a continuous variable. It varies by industrial sectors but is constant across time. $\text{E9CHG}_i \cdot D_t$ is the interaction term for DD regression. This interaction term will be instrumented by $\text{E9SHARE}_i \cdot D_t$. The idea is that the industries that have relied more on TFWs in Period 1 would have experienced more actual drop from Period 1 to Period 3 (Figure 5). Since the instrument uses the data only from Period 1, before the outbreak event, it can be fully free from potential endogeneity issues that can arise if the data is otherwise used from Period 2 or 3. The idea of using the instrument is similar to Card (1992), where he used the proportion of teenagers laborforce earning less than \$3.80, all of which are measured before the event of minimum wage increase.

Table 1: Share of E9 Workers on Total Workers

Industries	E9SHARE(%)
Pharmaceuticals, Medicinal Chemicals and Botanical Products	0.27
Medical, Precision and Optical Instruments, Watches and Clocks	0.54
Beverages	0.64
Electronic Components, Computer, Radio, Television Equipment	0.80
Wearing apparel, Clothing Accessories and Fur Articles	0.91
Coke, hard-coal and lignite fuel briquettes and Refined Petroleum Products	1.36
Electrical equipment	1.76
Tanning and Dressing of Leather, Luggage and Footwear	2.27
Chemicals and chemical products except pharmaceuticals, medicinal chemicals	4.10
Motor Vehicles, Trailers and Semitrailers	4.10
Other Machinery and Equipment	4.16
Other Transport Equipment	4.19
Food Products	4.32
Basic Metal Products	5.24
Printing and Reproduction of Recorded Media	5.37
Other Non-metallic Mineral Products	6.35
Textiles, Except Apparel	8.23
Fabricated Metal Products, Except Machinery and Furniture	8.63
Pulp, Paper and Paper Products	8.72
Rubber and Plastic Products	9.58
Other Manufacturing	11.02
Furniture	12.15
Wood Products of Wood and Cork; Except Furniture	13.11
Total Manufacturing	4.86

Consequently, these regression models are the fixed effect with instrumental variable (FEIV). Therefore, the validity of the instrument is crucial for this paper. Although the models use DD regression idea, they are essentially not DD but FEIV model. Therefore, the parallel assumption crucial in DD regression has less importance in this paper.

$\text{E9SHARE}_i \cdot D_t$ is a valid instrument for $\text{E9CHG}_i \cdot D_t$. First, $\text{E9SHARE}_i \cdot D_t$ and $\text{E9CHG}_i \cdot D_t$ are highly correlated: -0.984. Also the first-stage F values are far above 10, the rule of thumb number that avoids weak IV issue. Second, the instrumental variable satisfies the exclusion restriction: $\text{Cov}(\text{E9SHARE}_i \cdot D_t,\ \varepsilon_{it}|X_{it}) = 0$, where X_{is} is a vector of control variables. In other words, the instrumental variable affects the dependent variable only indirectly through the channel of instrumented variable. The instrument uses the values only from Period 1 while the instrumented uses the values from both Period 1 and 3. The idea is similar to using the lagged variables as instrument variables (Arellano and Bond, 1991).

When $D_t = 0$, both instrument and instrumented are zero. When $D_t = 1$, instrument becomes E9SHARE_i and instrumented becomes E9CHG_i. Instrumented may not be orthogonal to the error term in Period 3 since it is using the values from Period 3. On the contrary, instrument only uses the values in Period 1. Therefore, it is orthogonal to the error term in Period 3. Moreover, the control variables,

$\text{PRODCHG}_i \cdot D_t$ and $\text{WORKERCHG}_i \cdot D_t$, also uses the values from Period 2 and 3, but not from Period 1. Therefore, it is possible to claim that $\text{Cov}(\text{E9SHARE}_i \cdot D_t,\ \varepsilon_{it}|X_{it}) = 0$.

Table 2 is the regression result using vacancy as a dependent variable. Equation 4 disentangles the production shock by using production level as a control function. Equation 5 additionally uses $\text{PRODCHG}_i \times D_t$ to account for the lagged effect: production drop during Period 2 might have lagged effects until Period 3 (Figure 3). Equation 6 uses $\text{WORKERCHG}_i \times D_t$ to account for the lagged effect. Whichever methods are used to account for the production drop, the coefficient estimates for $\text{E9CHG}_i \cdot D_t$ are negative and significant. It implies that industries that have relied on more TFWs are experiencing severe vacancy issues. As far as the instrument is valid, the reduction of TFWs caused a vacancy rise.

Table 2

	Equation 4 Vacancy	Equation 5 Vacancy	Equation 6 Vacancy
E9CHG × D	-0.299**	-0.292**	-0.339***
	(0.110)	(0.110)	(0.102)
PRODCHG × D		-0.006	
		(0.009)	
WORKERCHG × D			0.108*
			(0.052)
Production	0.018***	0.017***	0.015*
	(0.005)	(0.005)	(0.006)
Observations	322	322	322
R^2	0.439	0.444	0.480
First-stage F	109.98	121.88	99.37

Standard errors in parentheses

S_i and T_t included but not reported.

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

Table 3 is the regression result using the unemployment rate as a dependent variable. Unlike vacancy, the results for the unemployment rate are insignificant. This means that TFWs' reduction did not cause the unemployment rate to change.

Table 4 is the regression result using matching efficiency as a dependent variable. If TFWs reduction caused matching efficiency to drop, it could explain the BC's outward shift from origin. However, the results are insignificant. This means that TFWs' reduction did not cause a matching efficiency drop. Moreover, it means that matching efficiency was not the reason for the BC's outward movement.

Table 3

	Equation 4 Unemployment	Equation 5 Unemployment	Equation 6 Unemployment
E9CHG × D	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
PRODCHG × D		0.000	
		(0.000)	
WORKERCHG × D			-0.000
			(0.001)
Production	-0.000*	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)
Observations	322	322	322
R^2	0.540	0.558	0.542
First-stage F	109.98	121.88	99.37

Standard errors in parentheses
S_i and T_t included but not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 4, the first three columns use the unemployment rate acquired by Unemployment Insurance (UI) Benefit rate, as explained in the Dataset section. This UI rate is a good proxy for the unemployment rate and provides values for each subsector of manufacturing industries (u_i for each subsector). However, this can be a too strong assumption since people may quickly move from one sector to another. Therefore, this paper will also use an alternative assumption for robustness check ($u_i = u$ for all i). In other words, the last three columns used u as the commonly shared unemployment rate for the entire manufacturing sector.

Finally, Table 5 is the regression result using termination rate as a dependent variable. Whichever models are used, the results show that the coefficient estimates for $\text{E9CHG}_i \cdot D_t$ are negative and significant. It implies that industries that have relied on more TFWs are experiencing a severe termination problem. One possible story is that domestic workers who filled in place of TFWs could not endure. The reason could be an unsatisfactory environment, such as low wages compared to challenging workloads.

Figure 6 additionally explains the previous results. Red(blue) lines are industries that heavily(lightly) relied on TFWs. The left panel shows the matching efficiencies. Although red lines are more volatile than the blue lines, they do not significantly increase after the COVID-19 outbreak. On the contrary, the termination rate on the right panel shows a significant increase after the outbreak. This implies that

Table 4

	u_i for each subsector			$u_i = u$ for all i		
	Equation 4 Match Eff	Equation 5 Match Eff	Equation 6 Match Eff	Equation 4 Match Eff	Equation 5 Match Eff	Equation 6 Match Eff
E9CHG × D	-0.164	-0.169	-0.176	-0.119	-0.134	-0.141
	(0.093)	(0.086)	(0.096)	(0.096)	(0.089)	(0.101)
PRODCHG × D		0.005			0.013	
		(0.015)			(0.017)	
WORKERCHG × D			0.031			0.060
			(0.109)			(0.113)
Production	0.012	0.013	0.011	0.004	0.006	0.003
	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
Observations	322	322	322	322	322	322
R^2	0.150	0.152	0.152	0.104	0.116	0.113
First-stage F	109.98	121.88	99.37	109.98	121.88	99.37

Standard errors in parentheses

S_i and T_t included but not reported.

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

Table 5

	u_i for each subsector			$u_i = u$ for all i		
	Equation 4 Termination	Equation 5 Termination	Equation 6 Termination	Equation 4 Termination	Equation 5 Termination	Equation 6 Termination
E9CHG × D	-0.005*	-0.006**	-0.006**	-0.005*	-0.006**	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PRODCHG × D		0.000			0.000	
		(0.000)			(0.000)	
WORKERCHG × D			0.002			0.002
			(0.002)			(0.002)
Production	0.000*	0.000*	0.000	0.000*	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	322	322	322	322	322	322
R^2	0.285	0.311	0.330	0.283	0.310	0.327
First-stage F	109.98	121.88	99.37	109.98	121.88	99.37

Standard errors in parentheses

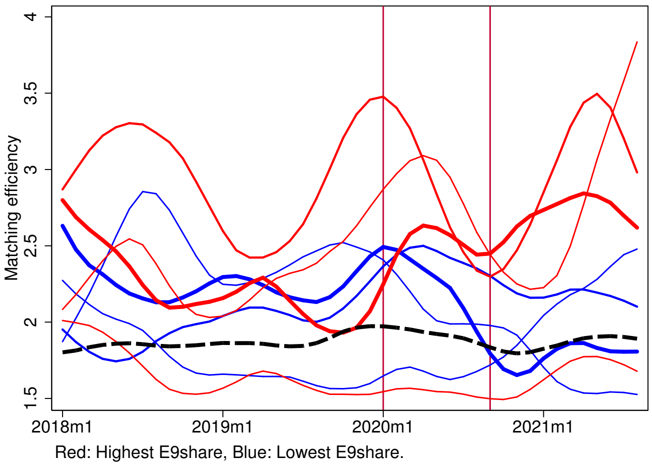
S_i and T_t included but not reported.

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

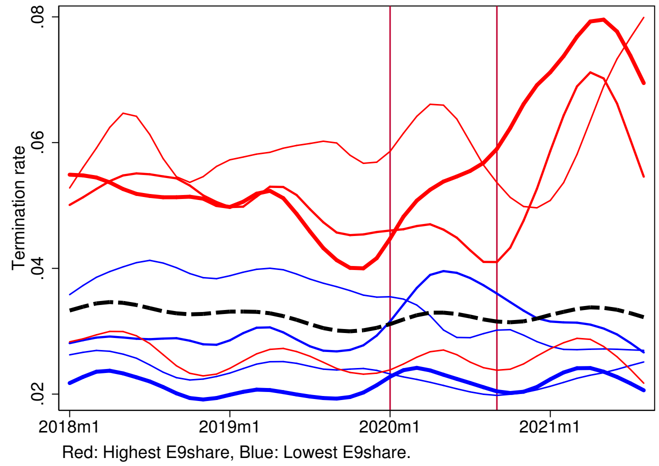
industries that heavily rely on TFWs are having an issue that workers do not stay long.

Figure 6

(a) Matching efficiency



(b) Termination rate



6 Conclusion

Due to the quarantine policy after COVID-19, Temporary Foreign Workers(TFWs) significantly dropped because they could not enter South Korea. This outbreak event allows to see the causal effect of drop in TFWs on vacancy. Among the manufacturing industries, the sectors that heavily relied on TFWs experienced a vacancy increase. Using the fixed effect with instrumental variable(FEIV) method, the study concludes that the reduction of TFWs caused the vacancy rise.

The following research question was how and why the vacancy has increased. The possible candidates were either the decrease of matching efficiency or the increase of the termination rate. The study showed that a decrease in matching efficiency was not the case: the industries heavily relying on TFWs have not experienced the reduction of matching efficiency. This implies that domestic workers may have quickly replaced the jobs previously filled by TFWs.

On the contrary, the study showed that the industries that mainly relied on TFWs experienced an increase in termination rate. This means that TFWs' drop due to the quarantine policy caused an increase in termination rate. Moreover, this explains the vacancy rise and the Beveridge curve's outward movement from origin. One possible story is that domestic workers who replaced the jobs initially filled by

TFWs could not endure the harsh conditions in the workplace. The vacancy has risen because of the quick termination of the matched status.

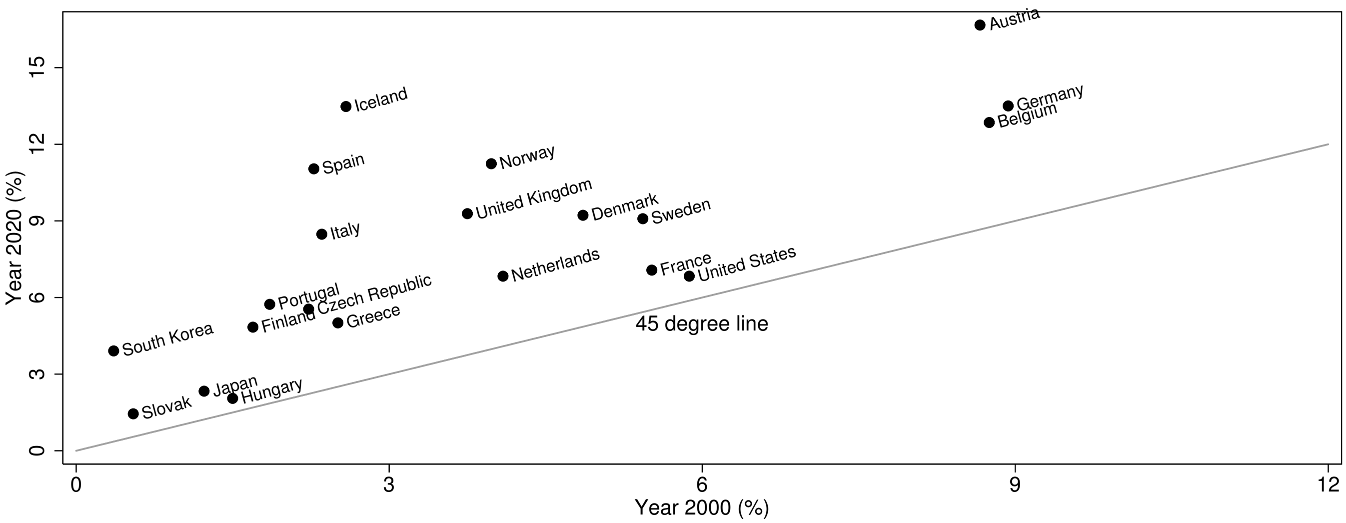
Based on the results found in this study, the role of TFWs in South Korea should not be disregarded. Even though there is anti sentiment to foreign workers among natives, it is evident that TFWs are an indispensable member of South Korean society. South Korean government started to open its border to foreigners in 2005. Since then, the number of foreign workers has dramatically increased. However, their proportion is still low compared to other advanced countries (Figure 7). South Korea has been experiencing the population aging issue for a long time. The number of South Korean citizens aged from 20 to 65 has begun to decline since 2020. Moreover, the percentage of the population aged 25 to 65 who has attained tertiary education in 2020 in South Korea is 50.7% (38.6% in the OECD average).[7] Therefore, it will become harder to find low-skilled workers if the South Korean government is reluctant to open its labor market abroad.

One point worth noting is that the results and the policy implications should vary across countries and periods. Each country confronts unique economic circumstances, so generalizing the result is inappropriate. For instance, the labor supply shock in the Mariel boatlift event lasted for only a year, whereas the labor supply shock in Austria due to EU enlargement lasted over a decade. Also, these shocks increased labor supply in overall sectors, but in South Korea, TFWs' drop majorly affected only in manufacturing sectors. This is because foreign workers in the service sectors consist of only about 1%.[8] This was the reason why this study has only focused on manufacturing sectors.

[7] Education at a Glance, OECD Statistics

[8] E9 workers are legally not allowed to work in the service sectors. Most foreign workers in service sectors are F4 visa holders who are distinct from other TFWs. F4 visa holders are more akin to permanent residents since they are Korean descendants, fluent in the Korean language, and free to stay and work whenever and wherever they want (Strictly speaking, they are legally not allowed to work in the manual low-skilled job, but there have not been any law enforcement case until now). Even during this COVID-19 quarantine policy era, they could enter South Korea.

Figure 7: Proportion of Immigrants in Total Population



Source: OECD Statistics
Greece used data from 2017 instead of 2020

References

Jason Anastasopoulos, George J Borjas, Gavin G Cook, and Michael Lachanski. Job Vacancies, the Beveridge Curve, and Supply Shocks: The Frequency and Content of Help-Wanted Ads in Pre-and Post-Mariel Miami. Technical report, 2018.

L Jason Anastasopoulos, George J Borjas, Gavin G Cook, and Michael Lachanski. Job Vacancies and Immigration: Evidence from the Mariel Supply Shock. *Journal of Human Capital*, 15(1): 1–33, 2021. ISSN 1932-8575.

Manuel Arellano and Stephen Bond. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies*, 1991. ISSN 00346527. doi: 10.2307/2297968.

Regis Barnichon and Andrew Figura. The determinants of the cycles and trends in US unemployment. *Unpublished manuscript, CREI*, 2012.

Burt S Barnow, John Trutko, and Jaclyn Schede Piatak. *Conceptual Basis for Identifying and Measuring Occupational Labor Shortages*, volume 1. 2013. ISBN 9780880994132. URL https://research.upjohn.org/up_press/220/(accessed20September2018)(accessed.

G.J. Borjas. The Wage Impact of the Marielitos: A Reappraisal. *ILR Review*, 70(5):1077–1110, 2017. doi: 10.1177/0019793917692945.

Daniel Borowczyk-Martins, Gregory Jolivet, and Fabien Postel-Vinay. Code and data files for "Accounting For Endogeneity in Matching Function Estimation", 2012.

Daniel Borowczyk-Martins, Grégory Jolivet, and Fabien Postel-Vinay. Accounting for endogeneity in matching function estimation. *Review of Economic Dynamics*, 16(3):440–451, 2013. ISSN 1094-2025.

Bernt Bratsberg and Oddbjørn Raaum. Immigration and Wages: Evidence from Construction. *Economic Journal*, 2012. ISSN 00130133. doi: 10.1111/j.1468-0297.2012.02540.x.

D. Card. Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, 19(1):22–64, 2001. doi: 10.1086/209979.

D. Card and J. DiNardo. Do immigrant inflows lead to native outflows? *American Economic Review*, 90(2):360–367, 2000. doi: 10.1257/aer.90.2.360.

David Card. Using Regional Variation in Wages to Measure the Effects of the Federal Minimum Wage. *Industrial and Labor Relations Review*, 46(1):22, 1992. ISSN 00197939. doi: 10.2307/2524736.

Raquel Carrasco, Juan F Jimeno, and Ana Carolina Ortega Masague. The effect of immigration on the employment opportunities of native-born workers: some evidence for Spain. 2004.

Michael Christl. A Beveridge curve decomposition for Austria: did the liberalisation of the Austrian labour market shift the Beveridge curve? *Journal for Labour Market Research*, 54(1):1–15, 2020. ISSN 2510-5027.

Sarit Cohen-Goldner and M. Daniele Paserman. The dynamic impact of immigration on natives' labor market outcomes: Evidence from Israel. *European Economic Review*, 55(8):1027–1045, 2011. ISSN 00142921. doi: 10.1016/j.euroecorev.2011.05.002. URL http://dx.doi.org/10.1016/j.euroecorev.2011.05.002.

Amelie F Constant and Bienvenue N Tien. Germany's immigration policy and labor shortages. *IZA, DP*, 41(November), 2011.

Kyle Crowder, Matthew Hall, and Stewart E. Tolnay. Neighborhood immigration and native out-migration. *American Sociological Review*, 76(1):25–47, 2011. ISSN 00031224. doi: 10.1177/0003122410396197.

Robert Dixon, Guay C Lim, and John Freebairn. Regional Beveridge Curves: A latent variable approach. *Regional Studies*, 48(2):254–269, 2014. ISSN 0034-3404.

Michael W L Elsby, Ryan Michaels, and Gary Solon. The ins and outs of cyclical unemployment. *American Economic Journal: Macroeconomics*, 1(1):84–110, 2009. ISSN 1945-7707.

Michael W L Elsby, Ryan Michaels, and David Ratner. The Beveridge curve: A survey. *Journal of Economic Literature*, 53(3):571–630, 2015. ISSN 0022-0515.

Vincent Fromentin. The Relationship Between Immigration and Unemployment: The Case of France. *Economic Analysis and Policy*, 43(1):51–66, mar 2013. doi: 10.1016/S0313-5926(13)50003-8. URL https://www.sciencedirect.com/science/article/pii/S0313592613500038.

Shigeru Fujita and Garey Ramey. The cyclicality of separation and job finding rates. *International Economic Review*, 50(2):415–430, 2009. ISSN 0020-6598.

Robert E Hall. Employment efficiency and sticky wages: Evidence from flows in the labor market. *Review of Economics and statistics*, 87(3):397–407, 2005. ISSN 0034-6535.

Peter Howitt and Christopher A. Pissarides. *Equilibrium unemployment theory*. MIT press, 2000. ISBN 0262264064. doi: 10.2307/2555075.

Sabine Klinger and Enzo Weber. Decomposing Beveridge curve dynamics by correlated unobserved components. *Oxford Bulletin of Economics and Statistics*, 78(6):877–894, 2016. ISSN 0305-9049.

Ehsan Latif. The relationship between immigration and unemployment: Panel data evidence from Canada. *Economic Modelling*, 50:162–167, nov 2015. ISSN 0264-9993. doi: 10.1016/J.ECONMOD.2015.06.013. URL https://www.sciencedirect.com/science/article/pii/S0264999315001601.

Martin Ruhs and Bridget Anderson. Who Needs Migrant Workers? 2019.

Pedro S. Martins, Matloob Piracha, and José Varejão. Do immigrants displace native workers? Evidence from matched panel data. *Economic Modelling*, 72(July 2017):216–222, 2018. ISSN 02649993. doi: 10.1016/j.econmod.2018.01.019. URL https://www.sciencedirect.com/science/article/pii/S0264999317310970.

S. Mocetti and C. Porello. How does immigration affect native internal mobility? New evidence from Italy. *Regional Science and Urban Economics*, 40(6):427–439, 2010. doi: 10.1016/j.regsciurbeco.2010.05.004.

Pia M. P.M. Orrenius and Madeline Zavodny. Does immigration affect wages? A look at occupation-level evidence. *Labour Economics*, 14(5):757–773, 2007. ISSN 09275371. doi: 10.1016/j.labeco.2006.09.006.

G.I.P. Ottaviano and G. Peri. Rethinking the effect of immigration on wages. *Journal of the European Economic Association*, 10(1):152–197, 2012. doi: 10.1111/j.1542-4774.2011.01052.x.

G. Peri. The impact of immigration on wages of unskilled workers. *Cato Journal*, 57(3):449–460, 2017.

G. Peri and C. Sparber. Assessing inherent model bias: An application to native displacement in response to immigration. *Journal of Urban Economics*, 69(1):82–91, 2011. doi: 10.1016/j.jue.2010.08.005.

Barbara Petrongolo and Christopher A Pissarides. The ins and outs of European unemployment. *American economic review*, 98(2):256–262, 2008. ISSN 0002-8282.

Stefan Schiman. Labor supply shocks and the Beveridge Curve — Empirical evidence from EU enlargement. *Review of Economic Dynamics*, 40:108–127, 2021. ISSN 10942025. doi: 10.1016/j.red.2020.09.005.

Petr Sedláček. Match efficiency and firms' hiring standards. *Journal of Monetary Economics*, 62 (1):123–133, 2014. ISSN 03043932. doi: 10.1016/j.jmoneco.2013.10.001.

Robert Shimer. The cyclical behavior of equilibrium unemployment and vacancies. *American economic review*, 95(1):25–49, 2005. ISSN 0002-8282.

Christopher A Sims. Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, pages 1–48, 1980. ISSN 0012-9682.

Jennifer C Smith. The ins and outs of UK unemployment. *The Economic Journal*, 121(552): 402–444, 2011. ISSN 0013-0133.

By Madeleine Sumption. Filling Labor Shortages through Immigration : An Overview of Shortage Lists and their Implications. (February):1–9, 2011.