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The Analysis of Labor Market Efficiency Driven by the Eastern Economic Corridor (EEC)

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Abstract

This paper aims to study the efficiency of labor market, investigate the determinants of job employment in the Eastern Economic Corridor, and forecast the trend of job employment. The monthly data from January 2016 to September 2021 were collected to explore the long-run relationship among variables in the aggregate matching function. The finding results indicate that job employment, job vacancy, and unemployment are cointegrated in the long run. The market efficiency is approximately 1.15 percent, with the decreasing returns to scale matching technology. Regarding the short-run relationship, estimated by the vector error correction model, the employment rate is statistically affected by the unemployment rate and the widespread period of the COVID-19 pandemic. Finally, the forecasting result illustrates that the number of job employments will gradually decline in the 2022-2023 period. Despite an upward trend of job vacancies, the number of unemployed workers will continue to rise in 2022.

Keywords: Matching function, labor market efficiency, Johansen cointegration, vector error correction, Eastern Economic Corridor.

1. Introduction

Since 2016, the concept of Thailand 4.0 has been acknowledged and implemented nationally as a 20-year strategy that can transform the country from a middle-income country into a high-income one. This strategy aims to enhance industrial productivity through advanced technological innovation together with fundamental infrastructure investment. To practically pursue the strategy, the government chose the Eastern Economic Corridor (EEC), which consists of three provinces, namely Chachoengsao, Chonburi, and Rayong, to be a regulatory sandbox for intensively driving technological and innovative "S-curve" industries.

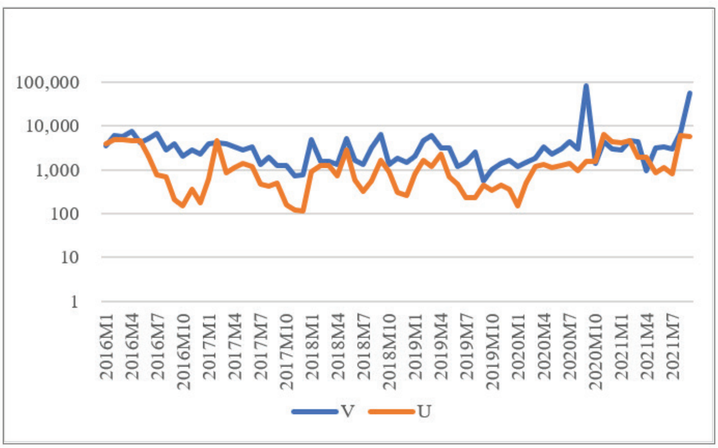
Although several factors can determine the success of this strategy, it cannot be denied that the labor market in the EEC is a key success of the S-curve industry. Consequently, the EEC organization (EECO) has continually generated the policy to stimulate both labor demand and labor supply in this area. For instance, a tax incentive is provided to private companies and multinational enterprises when establishing the company and hiring local workers. Multiple series of short courses are promoted to both employed and unemployed workers to upgrade new skills required for job positions in the S-curve industry (Eastern Economic Corridor Office of Thailand, 2017).

Once new job positions are opened, and more skilled laborers are ready to work, it can be expected that the number of job employments should be increased. However, the empirical evidence indicates the number of job employments remains fluctuating, and there is a significant gap between labor demand and labor supply in the EEC. During 2016-2021, the number of job vacancies was on average larger than the number of unemployed workers (Figure 1), and there were still unemployed workers mismatched with vacant positions (National Statistical Office of Thailand, 2021). Thus, the problem of matching efficiency occurred in the labor market. In addition, the COVID-19 pandemic and the trade war between the United States of America and the

Republic of China might be important factors having a negative impact on job employment and matching efficiency in the EEC.

According to the existing literature, the matching function was employed to estimate the matching efficiency and find the determinants of job employment in both aggregate and regional labor markets. By using the ordinary least squares (OLS) method, the matching efficiency can be estimated through the aggregate matching function (Petrongolo & Pissarides, 2001), the Beveridge curve relationship (Daly et al., 2012), and the modified matching function (Liu, 2013; Fedorets et al., 2019). However, the estimated result suffered from the endogeneity problem (See Borowczynski-Martin et al., 2013; Sedláček, 2016).

Figure 1. The gap between vacant jobs and unemployed workers



Source: National Statistic Office, Thailand (2021).

The aim of this paper is to study the efficiency of labor market, investigate the determinants of job employment in the EEC by using a well-known matching function of Petrongolo and Pissarides (2001), and forecast the trend of labor employment after the COVID-19 pandemic. Firstly, to make the contribution, the aggregate matching function is employed to study the matching efficiency in a special economic zone in Thailand. Secondly, to avoid the endogeneity problem, the vector error correction model is applied to measure the matching efficiency and to find the determinants of job employment in both the short- and long-run periods.

The main finding of this article is that job employment in the EEC is negatively affected by job vacancies but positively affected by unemployment and the COVID-19 pandemic. All variables are cointegrated in the long run, and the matching efficiency is about 1.15 percent, with the decreasing returns to scale technology. Although the matching efficiency steadily increases under the operation of the EECO, the pattern of matching efficiency has changed. Before the pandemic, the matching efficiency peaked from April to May every year, but during the pandemic, the highest level of matching efficiency occurs from October to November every year. Finally, the forecasting result indicates that the number of job employments will decline in 2022 and remain stable in 2023. In contrast, both job vacancies and unemployed workers will have an upward trend in 2022 and then converge to a new trend in 2023.

The paper is organized as follows. The existing literature on various types of matching function and their application are reviewed in Section 2. In Section 3, the research methodology is characterized while the results and interpretation are described in Section 4. Finally, the conclusion is exhibited in Section 5.

2. Literature Review

The theoretical model that studies the matching efficiency between labor demand and labor supply is mainly developed from the seminal works of Diamond (1982), Mortensen (1982), and Pissarides (1984). According to the neoclassical hypothesis, workers will apply to and accept the offered jobs on the condition that the lifetime present value of the benefit from working is greater than the cost required to sacrifice for job procurement. Likewise, firms will open vacant positions as long as the net benefit from the value of productivity and the maintaining cost of the job position remains profitable. Although there are available vacant jobs and unemployed workers, there is still a mismatch between them due to the problem of asymmetric information. As a result, the phenomenon of frictional unemployment possibly occurs in Thailand's economy.

In the late 1990s, the pattern of matching function and the determinants of job employment were investigated by a large number of labor economists. New hires were set to be a dependent variable while job vacancy and unemployment were introduced as the independent variables together with some exogenous variables (see Cole & Smith, 1996; Pissarides, 2011). By employing the ordinary least squares (OLS) estimation and other estimation techniques, both job vacancy and unemployment were key important factors that had a positive impact on job employment. Although some papers concluded that the matching technology can be increasing returns to scale (Warren, 1996; Yashiv, 2000) or decreasing returns to scale (Burda & Wyplosz, 1994), the majority of researchers indicated that the matching technology was a constant returns to scale, and the elasticity of job employment with respect to unemployed worker was around 0.5-0.7 (Petrongolo & Pissarides, 2001). Therefore, the matching function can be written as a Cobb-Douglas function as shown in equation (1):

$$M = AU^{\alpha}V^{1-\alpha} \tag{1}$$

where A is the efficiency of labor market, M is the number of job employments, U is the number of unemployed workers, and V is the number of job vacancies. The positive externalities on job matching are defined by the elasticity of job employment with respect to unemployed worker (α) and vacant jobs (1-α), respectively (Dixon et al., 2014). In addition, the matching function is similar to the production function. The stock of unemployed workers and job vacancies are counted as the input, while a flow of job employment is the output of the matching process (Ilmakunnas & Pesola, 2003).

The application of the matching function can be divided into four strands (Albrecht, 2011). Firstly, it is used to measure the efficiency of labor market through the Beveridge curve, where the negative relationship between vacancy rate and unemployment rate is established (Beveridge, 1944). By employing the property of homogenous degree one to transform the matching function, the market efficiency can be estimated from the relationship between the job procurement rate and the degree of market tightness using the OLS technique (Daly et al., 2012). However, the estimated parameter of the market efficiency may be biased and inefficient. Since the degree of market tightness is affected by the matching efficiency of labor market, it can be implied that market efficiency has both direct and indirect impacts on the procured job rate (Borowczyk-Martin et al., 2013). Furthermore, some economists theoretically argue that considering only the Beveridge curve may be insufficient to explain the labor market equilibrium and the market efficiency. It should be considered with the Nash bargaining process between firms and unemployed workers reflected by the job creation line to determine the equilibrium of employment (Elsby et al., 2015).

Secondly, labor market efficiency can be measured by using the aggregate matching function. To begin with the transformation of the matching function into natural logarithm form, the OLS estimation is employed to estimate the coefficient of unemployment and job vacancy. The market efficiency can be easily calculated as a percentage from the estimated parameter of the intercept. Nonetheless, the empirical work of Sedláček (2016) suggests that the estimated result of the aggregate matching function may suffer from the problem of omitted variable bias. Regarding the fact that both unemployed and non-unemployed workers may send their job application forms to firms, considering only the number of unemployed workers will lead to the underestimation of matching efficiency. Moreover, there has been a debatable argument among economists about the similarity between the matching and production functions. A stock-stock matching should result in a decrease in both unemployed workers and vacant jobs, but in reality, the number of unemployed workers is still high. Thus, the matching between vacant jobs and unemployed workers should be in a form of stock-flow matching rather than a stock-stock matching, as represented in the production function (Gregg & Petrongolo, 2005; Coles & Petrongolo, 2008).

The analysis of market efficiency in the regional labor market is the third approach that embraces the matching function as an important tool. Job vacancy and unemployment are considered determinants of new hires together with other exogenous variables. For example, regarding the work of Fedorets et al. (2019), the pooled OLS and the fixed effect model were employed to estimate the market efficiency and relevant parameters. They concluded that the number of unemployed workers and vacant jobs had a direct effect, whereas the regional proximities and the occupational similarities had an indirect effect on job employment. Nonetheless, it is worth mentioning that both job vacancy and unemployment are not purely exogenous variables. They are affected by many factors corresponding to business cycles. The number of unemployed workers is affected by the heterogeneity of laborers, e.g., skills, reservation wage, and degree of job tolerance (Liu, 2013). Meanwhile, the number of vacant jobs is remarkably affected by the level of market segmentation and the degree of competitiveness among industries (Barnichon & Figura, 2015). Additionally, research evidence from the fourth approach also supports that the possibility of job procurement is influenced by individual factors. Such factors may have an impact on matching efficiency, job vacancy, and unemployment (Faggian, 2014).

The common problem of estimating the market efficiency and finding factors that determine job employment in four approaches is endogeneity. Both job vacancy and unemployment are affected by other variables; therefore, they are obviously endogenous variables. To avoid the endogeneity problem, the matching function can be tackled and estimated by either the Generalized Method of Moment (GMM) method or the Vector Autoregression (VAR)/Vector Error Correction Model (VECM). Since both methods treat all variables as dependent variables, there would be no endogeneity problem. Nevertheless, the main difference between GMM and VAR/VECM is the empirical data used in the economic methods. Longitudinal/panel data should be analyzed by the GMM model, while the time-series data should be scrutinized by the system of multivariate simultaneous equations and the VAR/VECM technique. As a consequence of using time-series data of the labor market in the EEC, the VECM method is applied in this paper to investigate the efficiency of labor market and to find the determinants of job employment.

3. Research Methodology

3.1 Data Source and Explanation

In this paper, the time-series data were used, having been collected monthly from January 2016 to September 2021. All variables were gathered from the National Statistics Office of Thailand (NSO), the Department of Employment, Ministry of Labour, Thailand (DOE), and the Provincial Employment Offices (PEO) in Chacheongsao, Chonburi, and Rayong. Job matching/placement (M) was used as a proxy for job employment, while job vacancy (V) could be obtained from the number of vacant positions. The number of job applications was employed as a suitable proxy for the number of unemployed workers (U), which can be accounted for both registered and unregistered laborers. Since the available data of the variables were flow variables, we incorporated the initial data of job vacancies and job applications from 2015 to transform the flow variables into the stock variables. Furthermore, the dummy variables, such as the COVID-19 pandemic (d_{cv}) and the trade war between the United States of America and the Republic of China (d_{tw}), were chosen to detect the unusual macroeconomic effect on the labor market in a specific period.[1]

3.2 Stationary Test and Optimal Lag Length Selection

All variables are conducted with the stationary test by using the Augmented Dickey-Fuller (ADF) test and can be written as shown in equation (2):

[1] See Appendix I for further details.

$$\Delta y_t = \delta_0 + \delta_1 t + \delta_2 y_{t-1} + \sum_{i=1}^{P} \mu_i \Delta y_{t-i} + \varepsilon_t \quad (2)$$

where is the dependent variable and is the intercept (drift). ε_t is a disturbance term, and it is assumed to be independently and identically distributed ($\varepsilon_t \sim iid(0,\sigma^2)$). If the variable has no deterministic trend, δ_1 is restricted to be zero. μ_i is a coefficient that indicates the correlation between the first-difference variable and its lagged variables when a lag order (P) is chosen. Accordingly, the null hypothesis (H_0), $\delta_2 = 0$ means the dependent variable is (trend) stationary, while the alternative hypothesis (H_1), $\delta_2 < 0$ indicates the dependent variable is not (trend) stationary.

Once all dependent variables are stationary at the same level, the optimal lag length is chosen regarding the fact that the current variable may be affected by the past variables. To determine the lag length, the matching function is augmented and log-linear transformed into the unrestricted Vector Autoregression (VAR) model generated by equations (3) – (5).

$$\sum_{h=1}^{L} \alpha_{1h} m_{t-h} + \sum_{i=1}^{L} \alpha_{2i} v_{t-i} + \sum_{j=1}^{L} \alpha_{3j} u_{t-j} + d_{cv} + d_{tw} + e_{1t} \quad (3)$$

$$\sum_{h=1}^{L} \beta_{1h} m_{t-h} + \sum_{i=1}^{L} \beta_{2i} v_{t-i} + \sum_{j=1}^{L} \beta_{3j} u_{t-j} + d_{cv} + d_{tw} + e_{2t} \quad (4)$$

$$\sum_{h=1}^{L} \gamma_{1h} m_{t-h} + \sum_{i=1}^{L} \gamma_{2i} v_{t-i} + \sum_{j=1}^{L} \gamma_{3j} u_{t-j} + d_{cv} + d_{tw} + e_{3t} \quad (5)$$

After obtaining the estimated result of VAR, the information criteria, i.e., Akaike Information Criterion (AIC), Schwarz's Bayesian Information Criterion (SBIC), and Hannan-Quinn Information Criterion (HQIC), are compared to select the optimal lag length.

3.3 Johansen Cointegration Test

The long-run relationship between dependent variables can be estimated by using the Johansen cointegration test that employs the maximum likelihood method to estimate the parameters. According to the hypothesis testing of the long-run relationship proposed by Johansen (1991), the VAR equations should be rewritten as represented in the vector equation (6):

$$\Delta z_t = \varphi + \Pi z_{t-1} + \sum_{i=1}^{L-1} \Gamma_i \Delta z_{t-i} + \varepsilon_t \tag{6}$$

where $\Pi = \sum_{i=1}^{L} \omega_i - I$ and $\Gamma_i = -\sum_{j=i+1}^{L} \omega_j$. ω is a coefficient matrix, whose dimension is 3x3, and z is a 3x1 vector that contains all dependent variables.

If the long-run relationship among variables exists, the matrix Π should be rank-deficient. To investigate this, trace statistics is employed to determine the number of cointegrating vectors (r) from the eigenvalues (λ), and then r is compared with a maximum number of rows (k) in the square matrix Π. The null hypothesis (H_0) states that r≤r*, while the alternative hypothesis (H_1) asserts that r>r*, r*=1,2,3. In addition, the maximum eigenvalue test is adopted to recheck the number of ranks of the matrix, where the null hypothesis (H_0) and the alternative hypothesis (H_1) are r = r* and r = r*+1, respectively. Both tests can be explicitly written as follows.

Trace Statistics: $\lambda_{trace}(r|k) = -T \sum_{j=r+1}^{k} \ln(1 - \hat{\lambda}_j)$

Max-Eigenvalue Statistics: $\lambda_{max}(r|r+1) = -T ln(1 - \hat{\lambda}_{r+1})$

On the condition that there is at least one cointegrating equation, the long-run relationship between variables and the efficiency of labor market can be measured through the normalized cointegrating equation as represented in equation (7):

$$m_t = \rho_0 + \rho_1 v_t + \rho_2 u_t + e_t \tag{7}$$

where ρ_0 indicates the percentage of market efficiency.

3.4 VECM and Granger Causality Test

To explore the speed of adjustment and the short-run relationship, the dependent variables, integrated into order one, are rearranged into the form of the Vector Error Correction Model (VECM). The VECM consists of a system of equations, which can be written in equations (8) – (10):

$$\Delta m_t = a + \sum_{h=1}^{L} \alpha_{1h} \Delta m_{t-h} + \sum_{i=1}^{L} \alpha_{2i} \Delta v_{t-i} + \sum_{j=1}^{L} \alpha_{3j} \Delta u_{t-j} + d_{cv} + d_{tw} + \theta_1 ecm_{t-1} + \epsilon_{1t} \tag{8}$$

$$\Delta v_t = b + \sum_{h=1}^{L} \beta_{1h} \Delta m_{t-h} + \sum_{i=1}^{L} \beta_{2i} \Delta v_{t-i} + \sum_{j=1}^{L} \beta_{3j} \Delta u_{t-j} + d_{cv} + d_{tw} + \theta_2 ecm_{t-1} + \epsilon_{2t} \tag{9}$$

$$\Delta u_t = c + \sum_{h=1}^{L} \gamma_{1h} \Delta m_{t-h} + \sum_{i=1}^{L} \gamma_{2i} \Delta v_{t-i} + \sum_{j=1}^{L} \gamma_{3j} \Delta v_{t-j} + d_{cv} + d_{tw} + \theta_3 ecm_{t-1} + \epsilon_{3t} \tag{10}$$

where θ is the speed of adjustment from a short run to a long run. Note that ecm_{t-1} should be added to the equations if the cointegration among variables exists.

The causal relationships among the variables in the short run are postulated and estimated by the VEC Granger causality test. Meanwhile, the null hypothesis (H_0) asserts that one dependent variable does not Granger cause another one; the alternative hypothesis (H_1) admits that the dependent variable does Granger cause another variable.

3.5 Impulse Response Function

After the VECM is validated by the diagnostic tests, the impulse response function (IRF) is conducted to observe the movement of a selected dependent variable when the exogenous shock has an instantaneous impact on another variable. According to Granger's representation theorem, the vector of dependent variables (z_t) can be written as equation (11):

$$z_t = z_0 + \Theta \sum_{i=1}^{t} e_i + \sum_{j=0}^{\infty} \Theta_j \, e_{t-j} \tag{11}$$

where z_0 is a 3x1 vector of the initial values, and e_t is a 3x1 vector of disturbance term. In equation (11), the third term will converge to zero for $j \rightarrow \infty$ due to the absolute summability of Θ_j. Thus, a one-time standard deviation shock will have a long-run effect through the second component.

Using the B-model setup from the structural VAR literature, the structural shock (u_t) is introduced into equation (11), and the reduced form shock (e_t) is equal to Bu_t. While B is a 3x3 matrix, u_t has a zero mean and a unit variance ($u_t \sim (0,I_3)$). Thus, $\sum_e = BB'$, where $\sum_e$ is a symmetric and positive-definite matrix. The long-run effect that captures the common trend will be:

$$\Theta \sum_{i=1}^{t} e_i = \Theta B \sum_{i=1}^{t} u_i \tag{12}$$

where $\Theta = \vartheta_{\perp}(\theta_{\perp}^{'} (I_K - \sum_{i=1}^{L-1} \Gamma_i) \vartheta_{\perp})^{-1} \theta_{\perp}^{'}$, ϑ is a vector of the long-run coefficients, and $\perp$ refers to the orthogonalized components.

In the system of three endogenous variables, three independent restrictions are required to identify the structural shocks. However, the cointegrating structure indicates two restrictions regarding a reduced rank of , and there is only one restriction left for identification. Supposing there exists one (r = 1) cointegrating relationship, the rank of ΘB is 2. This means there are one transitory shock and two permanent shocks (Gonzalo & Ng, 2001). After applying zero restrictions on both ΘB and B, only one additional restriction for one permanent shock is required by the system (Lütkepohl, 2006). Therefore, the Cholesky factorization technique is employed to impose further restriction on B afterward. Regarding the demand-driven policy implemented by the EECO, firms will open vacant jobs based on their experience in job matching. Then, unemployed workers can apply for the open positions. For this reason, the Cholesky ordering should be m, v, and u, respectively.

4. Empirical Results and Interpretation

4.1 Descriptive Statistics

All variables are first characterized by the descriptive statistics as presented in Table 1. From January 2016 to September 2021, the average number of job employments (M) in the EEC was 2,512 positions per month. Its maximum number reached 6,060, while the minimum number was only

673 positions per month. Despite the number of job vacancies (V), which was about 95,729 positions on average, the average stock of unemployed workers (U) was 49,433 per month.

Table 1. Descriptive statistics

Variables	Mean	Max	Min	S.D.	Skewness	Kurtosis
M	2,512.06	6,060	673	1,373.21	0.8883	2.9674
V	95,729.43	231,882	63,439	40,578.28	1.6462	4.2661
U	49,432.78	78,303	32,859	11,806.92	0.5914	2.6369
d_{cv}	0.2754	1	0	0.4500	1.0058	2.0116
d_{tw}	0.5652	1	0	0.4994	-0.2631	1.0692

Source: Author's calculations.

As shown in Table 1, job vacancy has the largest statistical dispersion followed by unemployment and job employment, since the values of standard deviation are 40,578, 11,806.92, and 1,373.21, respectively. According to the values of skewness and kurtosis, one can conclude that all dependent variables are non-normally distributed.

4.2 Stationary Test and Optimal Lag Length Selection

After transforming the matching function into the logarithmic form, all variables are detected at the stationary level by using the ADF test. The estimated result illustrates that job employment (m), job vacancy (v), and unemployment are stationary at the first-difference level, as shown in Table 2.[2] It is worth mentioning that the number of lags is selected by the Akaike Information Criterion (AIC).

[2] The robustness of the unit root test can be found in Appendix II.

Table 2. Augmented Dickey-Fuller (ADF) test

Variables	Level I(0)		First Difference I(1)	
	No. of Lags	t-statistics	No. of Lags	t-statistics
m	2	-0.3082	1	-8.1250***
v	0	-0.7318	0	-7.3192***
u	9	-2.1068	0	-4.0058***
d_{cv}	0	-0.5971	0	-8.1240***
d_{tw}	0	-1.1277	0	-8.1240***

Notes: *** indicates the statistical significance at the 1% level.
Source: Author's calculations.

To find the optimal lag length, the unrestricted VAR is estimated, and the optimal lag length is specified by the information criteria. From Table 3, AIC, SBIC, and HQIC indicate that the appropriate lag length is equal to 1 regarding the fact that AIC, SBIC, and HQIC have the lowest values at lag 1 when compared to other lags. Thus, the first-lag interval of variables is employed to explore the long-run relationship among variables.

Table 3. Optimal lag length selection

Lag	LogL	LR	FPE	AIC	SBIC	HQIC
0	21.6497	-	0.0001	-0.4288	-0.1119	-0.3051
1	**167.6170**	**262.2463***	**1.26E-06***	**-5.0718***	**-4.4379***	**-4.8243***
2	170.8311	5.4477	1.54E-06	-4.8756	-3.9249	-4.5045
3	180.3050	15.0940	1.53E-06	-4.8917	-3.6240	-4.3969
4	185.7042	8.0530	1.76E-06	-4.7696	-3.1851	-4.1511
5	189.0892	4.7046	2.19E-06	-4.5793	-2.6778	-3.8370
6	199.0754	12.8636	2.20E-06	-4.6127	-2.3943	-3.7468
7	205.8810	8.0745	2.49E-06	-4.5383	-2.0030	-3.5487

Source: Author's calculations.

4.3 Long-run relationship among variables

The long-run relationship among job employment, job vacancy, and unemployment is verified by the Johansen cointegration test. According to the estimated results in Table 4, the trace statistics confirm there are two cointegrating equations at the 5% significance level. In contrast, the maximum-eigenvalue statistics indicate the existence of one cointegrating equation at the 5% significance level. Despite the different number of cointegrating equations, it can be concluded that there is at least one cointegrating equation (r = 1) that exhibits in the long-run relationship (Killian & Lütkepohl, 2017).

Table 4. Trace statistics and maximum-eigenvalue statistics

Number of Cointegrating Equations (CEs)	Eigenvalue	Trace Statistics	Maximum Eigenvalue Statistics
None	0.268147	34.82983***	20.91581**
At most 1	0.139273	13.91402**	10.04855*
At most 2	0.056061	3.865476*	3.865476*

Notes: ***, ** and * indicates the significance level at 1%, 5% and 10% respectively.
Source: Author's calculations.

According to the existence of a cointegrating equation, the long-run relationship between variables can be measured by the normalized cointegrating equation represented in equation (13):

$$m_t = 3.3626 - \underset{[-2.4332^{**}]}{1.2715\, v_t} + \underset{[2.8684^{***}]}{1.7445\, u_t} + e_t \qquad (13)$$

where t-statistics is presented in the [ ] parenthesis. ***, **, and * indicate the significance level at 1%, 5%, and 10%, respectively.[3]

[3] Despite the super-consistent coefficient estimators in equation (13), the standard inference of t-statistics would be wrong when there is a serial correlation.

According to equation (13), job employment is statistically affected by both job vacancy and unemployment at the 5% significance level. When the number of unemployed workers increases by 1%, job matching will increase by 1.7445%. Oppositely, a 1% increase in the number of vacant jobs leads to a decrease in job matching by 1.2715%. The decreasing returns to scale matching technology is exhibited in the labor market due to the fact that the sum of coefficients in equation (13) is equal to 0.4730. This result is consistent with the empirical research of Burda & Wyplosz (1994). They found that the matching technology in France, Germany, Spain, and the United Kingdom is equal to 0.61, 0.95, 0.26, and 0.89, respectively. For the market efficiency, it can be interpreted by the intercept term, which is 3.3626. This means that market efficiency leads to new hires of approximately 29 positions per month. In other words, the efficiency of labor market accounts for 1.15 percent per month when compared to the average of job hiring monthly.

4.4 Short-run relationship and Granger Causality

The short-run relationship between job employment and other variables can be estimated through the VECM as shown in equation (14).

$$\begin{aligned} \Delta m_t = &- 0.2805 + 0.0430\, \Delta m_{t-1} + 0.1568\, \Delta v_{t-1} + 4.4742\, \Delta u_{t-1} \\ &[-2.6878^{***}]\ \ [0.3428]\ \ [0.2274]\ \ [2.5684^{**}] \\ &+ 0.5056\, d_{cv} + 0.2598\, d_{tw} - 0.6026\, ecm_{t-1} + e_{1t} \\ &[2.5623^{**}]\ \ [1.8992^{*}]\ \ [-4.6691^{***}] \end{aligned} \qquad (14)$$

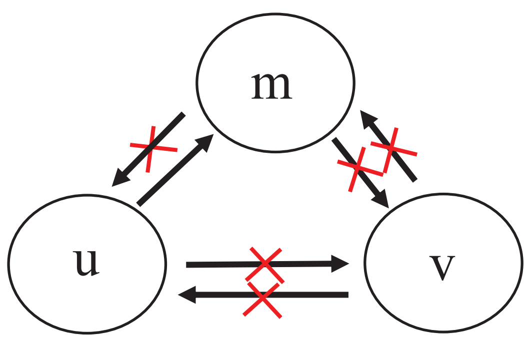
R-square = 0.3399, Adjusted R-square = 0.2738, and F-statistics = 5.1481***

where the t-statistics is represented in the [ ] parenthesis. ***, **, and * indicate the significance level at 1%, 5%, and 10%, respectively.

According to equation (14), job employment is affected by unemployed workers, the COVID-19 pandemic, and the error correction term at the

5% significance level. An increase in unemployed workers will enhance the opportunity for job matching because of a high number of job applications. This evidence is consistent with the results of existing research papers (See Petrongolo & Pissarides, 2001; Liu, 2013; Fagian, 2014). Surprisingly, the COVID-19 pandemic had a positive impact on job employment. The reason behind this could be the effectiveness of upskill and reskill policies, e.g., EEC Type B courses and training courses for delayed unemployment, for local workers during the pandemic. The skill improvement may bring about an increased possibility of job matching in the EEC (Katchwattana, 2020). Due to the negative coefficient of the error correction term, it can be interpreted that the dynamic movement of variables in the short-run will converge to the long-run equilibrium with the speed of adjustment at 60.26 percent. Furthermore, the estimated result of VEC Granger causality confirms that unemployment statistically causes job matching in the short-run, while job vacancy does not at the 5% significance level.[4] Thus, the short-run causality among variables can be depicted in Figure 2.

Figure 2: Short-run causality among dependent variables



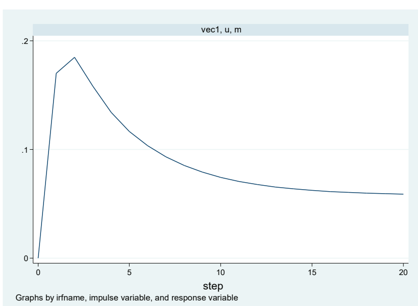
Source: Author's calculations.

[4] See Appendix III (Table A.4) for the result.

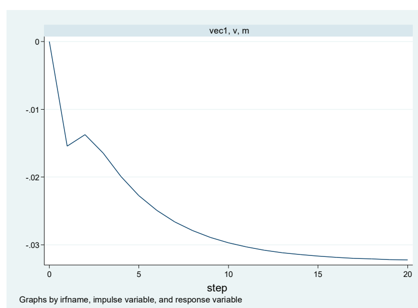
4.5 Impulse Response Function

In this section, the response of job matching to the exogenous shock through other variables is analyzed by using the impulse response function. Since there is at least one cointegrating relationship among variables (r = 1), there are one transitory shock and two permanent shocks in our system. With the positive impact of 1 standard deviation (S.D.) shock on job vacancy, job employment will sharply decrease in the first two months as shown in Figure 3.1. It will gradually decline and converge to the new long-run equilibrium due to the permanent effect of shocks. This is probably because there is a mismatch between the required skills from job positions and the skills possessed by workers, especially new graduates. Despite a large number of new vacant jobs, new graduates may encounter the problem of skills mismatch and become unemployed workers due to horizontal educational inconsistency (Pholphirul et al., 2016).

Figure 3. The impulse response of job employment



(3.1)



(3.2)

Source: Author's calculation.

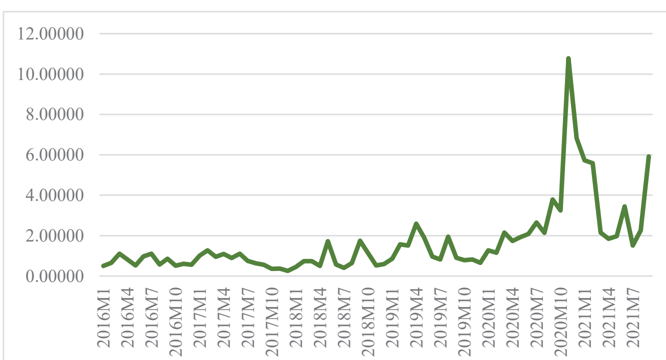
In Figure 3.2, job employment will rapidly increase during the first three months when there is a positive impact of one S.D. shock on unemployment. After that, job employment will decline and converge to the new long-run equilibrium. Since an increase in unemployment creates a higher possibility of job matching, job employment will undoubtedly increase at first glance.

4.6 Market Efficiency and Forecasting

The efficiency of labor market in each period can be calculated by using the parameters from the normalized cointegrating equation and the real value of variables. The market efficiency in the EEC has a slightly upward trend, as depicted in Figure 4. From 2016-2021, the highest efficiency was approximately 10.78 percent, while the lowest efficiency accounted for was 0.25 percent. Before the COVID-19 pandemic, market efficiency reached a high level in April and May every year due to the graduation period. Instead, the high level of market efficiency exhibited in October and November during the pandemic regarded the employment policies implemented by the EECO.

After examining the possible problems by the diagnostic tests and checking for model stability,[5] the forecasting result of macroeconomic variables in the labor market is illustrated in Figure 5. Accordingly, job employment will decline in 2022-2023, with a 95% confidence interval. On the contrary, job vacancy has an upward trend in the next two years owing to the possibility of vacant jobs related to the targeted (S-curve) industries. As for unemployment, it will slightly increase in 2022 due to the COVID-19 pandemic but will remain unchanged in 2023.

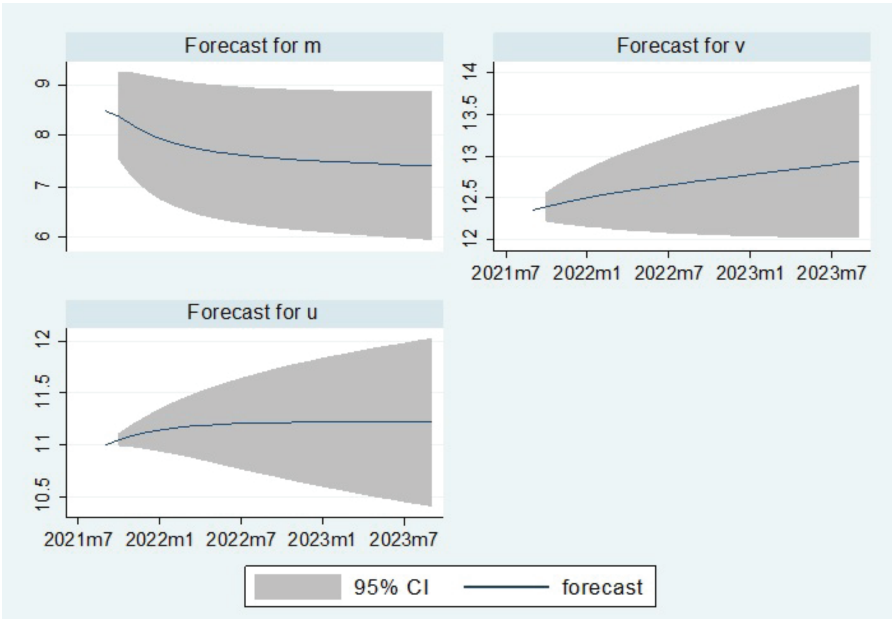
Figure 4. Market efficiency in the EEC



Source: Author’s calculation.

[5] The results of diagnostic and stability tests are explained in Appendix IV.

Figure 5. Macroeconomic forecasting in the labor market



Source: Author's calculation.

Although the estimated result is quite robust, it should be interpreted with caution. Since the purpose of this paper is to measure the efficiency of labor market in the EEC under the supervision of the EECO, the limitation of this study is a small sample size (69 observations). Therefore, in the model setup, the problem of structural break is not accounted for. This is because breaking a sample into subsamples may lead to an insufficient number of observations and alter the validity of statistical inference. Note that if the structural break exists, other cointegration tests (i.e., Gregory-Hansen cointegration test, etc.) may be more appropriate, and the estimated result will change.

5. Conclusion

The market efficiency and the relationship among macroeconomic variables in the EEC are investigated by employing the Johansen cointegration test and the vector error correction model. The same stationary level, job employment, job vacancy, and unemployment are cointegrated in the long run. Despite a negative relationship between job matching and job vacancy, an increase in unemployed workers will increase the number of job employments. The matching between vacant jobs and unemployed workers exhibits decreasing returns to scale technology where the market efficiency is approximately 1.15 percent per month. According to the short-run relationship, job matching is positively affected by unemployment and the COVID-19 pandemic. Such a relationship is also statistically confirmed by the Granger causality test. When job vacancy and unemployment are individually affected by the exogenous shock, the magnitude of response of job matching will be enlarged during the first three months. Then, it will decline and converge to the long-run equilibrium. Furthermore, the efficiency of the labor market had a marginally upward trend from 2016-2021. The market efficiency reached the highest level from April to May before the pandemic but was at the highest level from October and November during the pandemic. Finally, the forecasting result indicated that job employment had a decreasing trend, while vacant jobs and unemployed workers had an increasing trend in 2022. For the policy recommendation, the government and the EECO should revise the policy, such as the tax incentive, the up-skill and re-skill courses, and the matching platform for targeted industries to improve the matching technology and enhance the labor market efficiency.

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Appendices

Appendix I: Data and variables

Table A.1. Variables' sources and explanations

Variable	Explanation	Type of Variable	Data Source
Job Employment (M)	Job employment is a result of the matching process between vacant jobs and job applicants in the EEC.	Flow (Endogenous)	NSO/DOE/POE
Job Vacancy (V)	The number of vacant jobs proposed by firms in the EEC.	Flow (Endogenous)	NSO/DOE
Unemployment (U)	The number of job applications submitted by unemployed workers and workers who are willing to change jobs.	Flow (Endogenous)	NSO/DOE/POE
The Pandemic of Coronavirus (d_{cv})	The COVID-19 pandemic in Thailand from March 2020 to September 2021.	Dummy (Exogenous)	Time period of the pandemic
Trade War between US and China (d_{tw})	The period of trade war between U.S. and China from July 2018 to June 2020.	Dummy (Exogenous)	Time period of the trade war

Notes: Although job vacancy and unemployment are flow variables, they can be transformed into stock variables by using the stock of job vacancy and unemployment from 2015 as the initial data.

Appendix II: The robustness check for the stationarity of dependent variables

Table A.2. Unit root tests for the stationarity of dependent variables

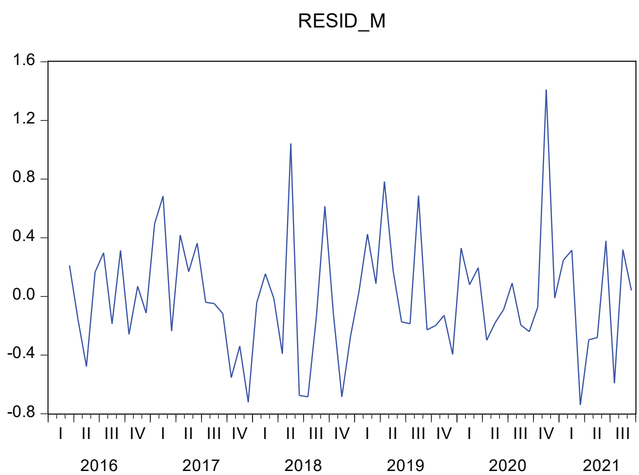
Variables	Integrated order	ADF t-statistics	PP Adj. t-statistics	KPSS LM statistics
m	I(0)	-0.3082	-0.2984	0.3969*
	I(1)	-8.1250***	-13.8592***	0.1996***
v	I(0)	-0.7318	-0.8926	0.8434
	I(1)	-7.3192***	-7.3189***	0.2979***
u	I(0)	-2.1068	-1.2664	0.7359
	I(1)	-4.0058***	-3.9294***	0.4341**

Notes: ***, **, and * indicate the significance level at 1%, 5%, and 10%, respectively. Due to the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, it can be concluded that m, v, and u are all stationary at first-difference level.

Source: Author's calculations.

Appendix III: The long-run relationship and causality among variables

Figure A.1 Graph of the residuals of the cointegrating equation



Source: Author's calculations.

Table A.3. Stationary test for the residuals of the cointegrating equation

Variables	ADF test		PP test	
	t-statistics	p-value	Adj. t-statistics	p-value
RESID_M	-8.3147***	0.0000	-8.3322***	0.0000

Notes: The null hypothesis of the stationary test is the residuals are non-stationary at level I(0), while the alternative hypothesis is the residuals are stationary at level I(0). ***, **, and * indicate the significance level at 1%, 5%, and 10%, respectively.

Source: Author's calculations.

Table A.4. VEC Granger Causality

Dependent variable: Δm			
Variable	Chi-square	df	Prob.
Δv	0.051727	1	0.8201
Δu	6.596631**	1	**0.0102**
All	**6.691457****	**2**	**0.0352**
Dependent variable: Δv			
Excluded	Chi-square	df	Prob.
Δm	0.230182	1	0.6314
Δu	0.123539	1	0.7252
All	0.376514	2	0.8284
Dependent variable: Δu			
Excluded	Chi-sq	df	Prob.
Δm	0.649717	1	0.4202
Δv	0.003843	1	0.9506
All	0.665569	2	0.7169

Note: ***, **, and * indicate the significance level at 1%, 5%, and 10%, respectively.

Source: Author's calculations.

Appendix IV: Diagnostic tests

Table A.5. Lagrange Multiplier (LM) test

Lag	Chi-square	df	Prob.
1	9.2002	9	0.4190
2	22.1595	18	0.2250
3	24.6022	27	0.5967
4	31.6177	36	0.6771
5	41.9341	45	0.6026
6	56.1262	54	0.3951
7	60.0418	63	0.5824
8	71.2930	72	0.5014
9	82.5004	81	0.4327
10	87.1584	90	0.5652
11	107.6798	99	0.2589
12	131.7025	108	0.0603

Notes: Within the range of lag 1 to 12, the LM test indicates there is no autocorrelation problem.

Source: Author's calculations.

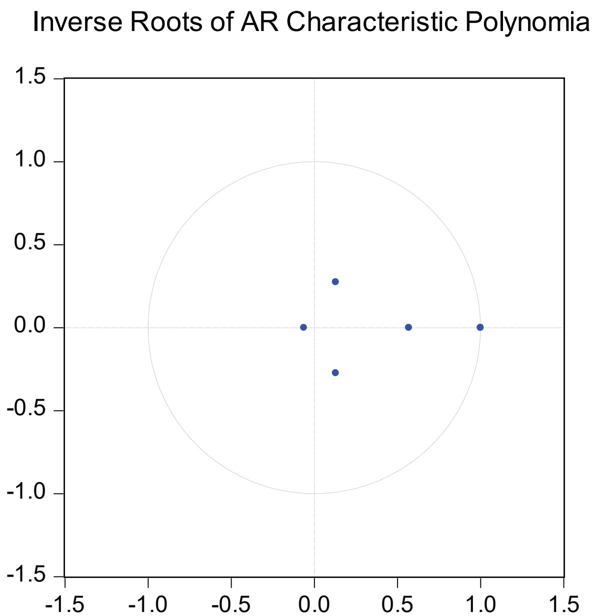
Table A.6. Normality test

Component	Jarque-Bera	df	Prob.
1	9.138364**	2	0.0104
2	5247.193***	2	0.0000
3	84.91733***	2	0.0000
Joint	5,341.249***	6	0.0000

Notes: ***, **, and * indicate the significance level at 1%, 5%, and 10%, respectively. The Jarque-Bera statistics confirms that the disturbance term in the model is non-normally distributed. However, one can say that the disturbance term is an asymptotical normal distribution since the sample size is large enough (69 months).

Source: Author's calculations.

Figure A.2. Stability test of Vector Error Correction Model (VECM)



Notes: Under the condition of the AR equation with 3 endogenous variables and 1 cointegrating equation, all eigenvalues lie within a unit circle. Therefore, the model is stable.

Source: Author's calculations.