THE IMPACT OF CAUSAL FACTORS RELATIONSHIP RELATED TO GOVERNMENT'S SUSTAINABILITY POLICY IMPLEMENTATION IN THAILAND UNDER NATIONAL STRATEGY THAILAND 4.0

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Abstract

From past to present, the government of Thailand has been putting great efforts to achieve sustainable development. In order to simultaneously achieve economic, social, and environmental growth, it is necessary for the country to set plans that align with the national agenda. Every year, a plan assessment has been carried out. Former data showed that the national economy had grown tremendously and positively changed along with continuous social growth. However, this showed a negative impact on environmental damage as greenhouse effects increased continuously. Therefore, these three aspects through a relationship analysis was deemed important to the national development and management effectiveness. This research aimed to analyze the influence of the direct and indirect relationships of economic, social, and environmental factors as well as predicted their future effects by applying the path analysis-generalized method of moments (path analysis-GMM model). The model was believed to be the most effective in relationship analysis, and was capable of accurate prediction when compared to the original models. Most importantly, the model caned be applied to different contexts, benefiting the development areas of those contexts. Furthermore, the model was also found to be the best linear unbiased estimation (BLUE), suitable for long-term forecasting. However, the study's results reflected that the three latent variables of economic, social, and environmental factors had direct and indirect effects. In addition, both economic and social factors were found to have a causal relationship. This further

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adds another evidence in which the path analysis-GMM model was the most suitable in forecasting and contextual application to support the formulation of the national strategy in the future.

Keywords: Causal factors, Government's sustainability policy, Thailand 4.0, co-integration and error correction mechanism test

Introduction

In the implementation of social policies, Thailand had strived to create social development policies to continuously increase its growth rate [1,2], where the government plays a vital role in the formation of such policies. These policies cover the promotion of employment by a reduction in the unemployment rate, a protection policy in health and illness, a social security policy and its monitoring, and a customer protection policy with its quarterly assessment. However, the implementation of those policies was seen to be effective and efficient since 1990 until recent times. As of the present (2018), the social growth rate had a positive development in the same way that the economic development has [2]. Nevertheless, boosting economic and social development had changed the environment at the same. There was evidence that from 1990 to 2018, greenhouse gases increased steadily [3]. In particular, CO_2 emissions had risen across all sectors, but especially in the electronic, transportation, and industrial sectors, producing a 92.5% increase in greenhouse gases (2018) since 1990 [4,5]. Therefore, public policies and plans become the most important elements for Thailand to realize national sustainability. In order to strive for great policies, there had to the right tools to support the planning process. One such tool was to establish a model constructed on the causal factors relationship between the economic, social, and environmental aspects as these effect the future implementation of sustainable policy in Thailand. Since the paper applied the path analysis-GMM model, it helped support the long-term planning, and becomes applicable to different contexts in various sectors. In fact, the used model in this research was deemed to be different in its application and process, and this caned be observed from other relevant studies. Based on a review of the previous research, a number of studies differed in the used models for the analysis, research process, and duration. In this paper, we adapted the path analysis-GMM model to produce the best result, yet was applicable for optimization in strategy planning to achieve sustainability. The research process would be demonstrated as follows.

1. Determine a variable framework based on the path analysis [6], which contains both latent variables and observed variables.

2. Perform a unit root test of the observed variables according to the concept of the augmented Dickey–Fuller [7], and analyze a long-term causal relationship by using the theory of Johansen Juselius [8-10].

3. Take the co-integrated variables at the same level to build a path analysis-GMM model, which features both short- and long-term causal relationships, adding to the presentation of direct and indirect effects [10].

4. Assess a BLUE feature of the path analysis-GMM model, and test its goodness of fit [11,12]. The flowchart of the path analysis-GMM model is shown in Figure 1.

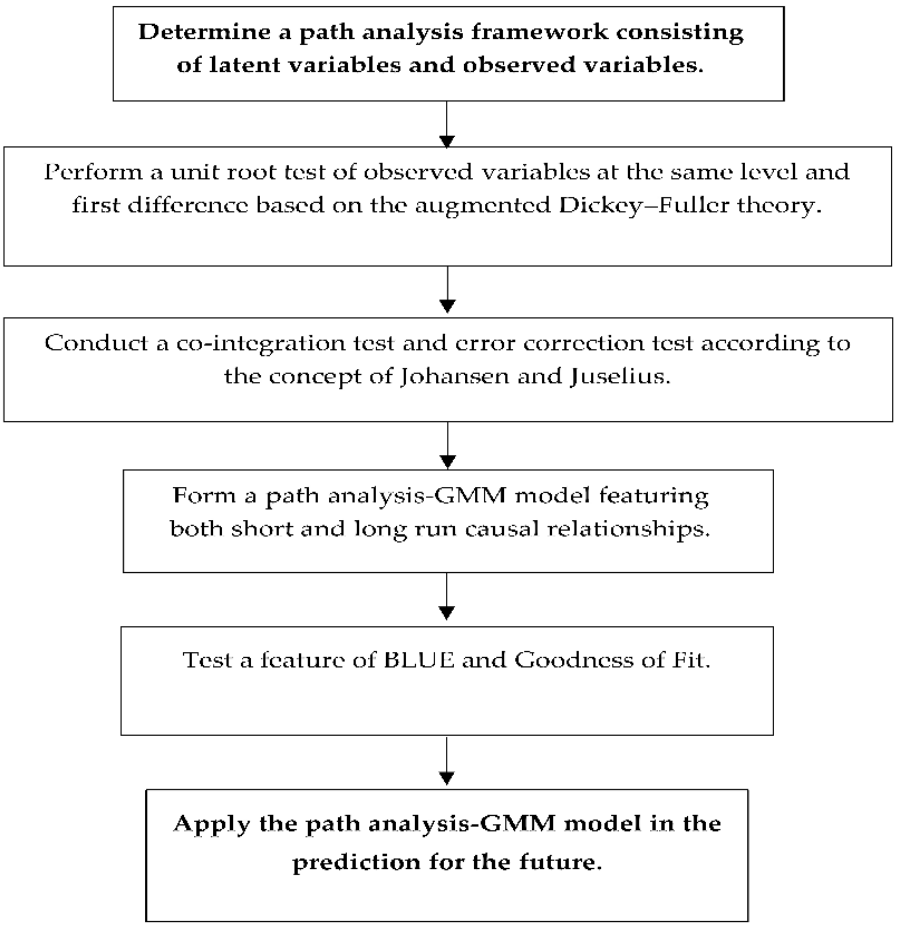

Figure 1. The flowchart of the path analysis-GMM model.

Material and Method

Path Analysis-GMM Model

The path analysis-GMM model is a specific analysis of regression analysis with the purpose of analyzing variables (both independent variables and dependent variables) to find out the direct or indirect correlation of which the impact may be passing to each other or be both. Additionally, it analyzes if there are any external factors that promote the relationship on variables as per the reason in theory. The reason for studying the path analysis-GMM model is to study the causal relationships between variables. Although correlation analysis, either simple correlation, partial correlation, multiple correlation, canonical correlation, or regression analysis can answer this question, it can deal with some limitations in some issues, especially in the correlation between variables, which is the objective of the path analysis-GMM model.

The process of the path analysis-GMM model is as follows:

1. To draw path diagram or causal model

The path diagram is the most important part, and should be drawn first because the path diagram describes the correlation among the variables. However, drawing the path analysis-GMM model is not something we could do easily by ourselves. The path diagram is a model from a theory. As such, the path diagram must done according to theory. Once done, it is both a problem or hypothesis to be proven and is the objective at the same time. To prove the path, it must be done one at a time as well as eliminate any unnecessary paths. To do so, it does not mean that the theory behind such paths is not realistic, but it means that there are sampling errors which contain unappropriated data to support such theory.

There are two types of variables in the path diagram which are endogenous variables and exogenous variables. To understand the difference between these variables will result in drawing the path equation system correctly.

Exogenous variables are variables that can be varied because of external variables or variable which impact other variables within the path directly or indirectly where the exogenous variable itself has been impacted from another external influence. Endogenous variables are the variables within the path diagram and vary from the influence of exogenous variables or from the influence of the variables in the same path.

Assume that the theories confirm that variables nos. 1, 2, 3, and 4 are related in the path as follows:

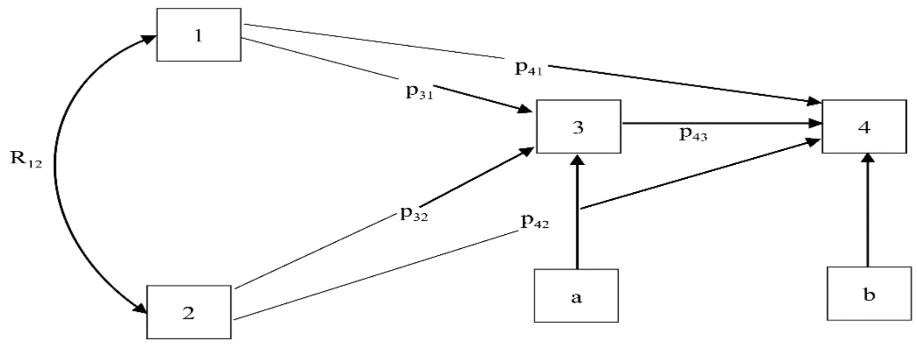

Figure 2. Path analysis-GMM model.

From Figure 2, variables 1 and 2 are exogenous variables because the variation of both variables are from external factors of the path or because variable no. 1 and no. 2 impact other variables, which are variable no. 3 and no. 4. Variable no. 3 and no. 4 are endogenous variables because variable no. 3 is impacted from exogenous variables (variable no. 1 and no. 2). Variable no. 4 is also an endogenous variable because it is impacted from exogenous variables (variable no. 1 and no. 2) and an endogenous variable in the same path (variable no. 3) and from both exogenous variable no. 1 and no. 2. Variable no. 1 and no. 2 are correlated and not separated as independent variables (so-called correlated causes). Please notice the arrow with two ends.

In addition, we can further analyze Figure 2 by looking at the path (arrow) to see:

- Variable no. 3 is directly impacted by variable no. 3 and no. 2.
- Variable no. 3 is indirectly impacted from variable no. 2 through variable no. 1 and is indirectly impacted from variable no. 1 through variable no. 2.
- Variable no. 4 is directly impacted from variable nos. 1, 2, and 3.
- Variable no. 4 is indirectly impacted from variable no. 1 through variable no. 2 and no. 3 and is indirectly impacted from variable no. 2 through variable no. 1 and no. 3.
- a and b are residual.

Remark:

- p_{ij} is the path coefficient to represent level (percentage). The influence of variable j's impact on variable i such as p_{31} shows the level of influence of variable no. 1, which impacts variable no. 3.
- r_{ij} is the correlation of variable j and variable i.
- In fact, p_{ij} is the population corre-

lation of variable j and variable i where $p_{ij} = \rho_{ij}$, which can be easily proven.

For analyzing the path and to draw the path diagram, it is assumed as follows:

- The correlation of the path is unidirectional or one way causal flow. Any variable at any time cannot be both the cause and effect of other variables at the same time. The arrow should run in the same direction which is from left to right. It cannot be reversed from right to left (except for the exogenous variable which can be a correlated cause of the endogenous variable).

- The correlation between variables is a causal linear additive model. It cannot be curvilinear, multiplicative, interactive, or others.

- The residual is free from the independent variable and dependent variable.

- The value of the variable is measured to be at the interval scale.

2. Path equation and calculation of path coefficient

Normally, the path equation can be drawn using the basis of the path diagram, and then the equation can gradually draw to other paths, one path at a time until all paths are completed. The variable which is pointed by the arrow is a dependent variable and all variables on the same path can be either exogenous variables or endogenous variables or both as independent variables. The equation will be arranged the same as the regression analysis by trying to reduce the quantity of equations to be as low as possible by combining the equations showing the correlation of independent variables and the same dependent variable into the same equation. Any equation that needs to stay alone will be another equation. In general, the overall equations should not be more than all variables (variables in path diagram).

When all equations are done and cover the relation in the path diagram, an analysis is performed to estimate the coefficient in each path (or each equation) by regression analysis. The result will be the path coefficient and estimated equation of the path equation. After that, if we want to know the quantity of the indirect influence of any variable, we substitute the estimated equation to the other equation to get the answer. Testing the truth as indicated in the theory of whether such a path is necessary or not by proceeded in the same way as above, but only changed some path diagrams as appropriate.

Path Equation [39]

Assume that all variables in the system $r+1$ are $X_1, X_2, \ldots X_{r+1}$ where $\mathrm{E}(X_j) = \mu_j$ and $V(X_j) = \sigma_j^2; j = 1(1)(r+1)$. Therefore, the path equation k; $k = 1(1)(r+1)$ will be as follows:

$$X_{ki} = \beta_0 + \beta_1 X_{ij} + \beta_2 X_{2i} + \ldots + \beta_r X_{ri} + u_i \tag{1}$$

Combining all values of i and divide by N will derive the average value equation

$$\mu_k = \beta_0 + \beta_1 \mu_1 + \beta_2 \mu_2 + \ldots + \beta_r \mu_r + \mu_u \tag{2}$$

Equations (1) and (2) will form a new equation as follows:

$$X_{ki} - \mu_{\mathrm{k}} = \beta_1 (X_{1i} - \mu_1) + \beta_2 (X_{2i} - \mu_2) + \ldots + \beta_r (X_{ri} - \mu_r) + u_i - u_u \tag{3}$$

To format Equation (3), divide all with σ_k and multiply $\beta_j (X_{ji} - \mu_j)$ by $\frac{\sigma_j}{\sigma_j}; j = 1(1)r$, the equation of the standardized variable is as follows:

$$\begin{aligned} \frac{X_{ki} - \mu_k}{\sigma_k} = \beta_1 \frac{\sigma_1}{\sigma_k} \left(\frac{X_{1i} - \mu_1}{\sigma_1}\right) + \beta_2 \frac{\sigma_2}{\sigma_k} \left(\frac{X_{2i} - \mu_2}{\sigma_2}\right) + \ldots \beta_r \frac{\sigma_r}{\sigma_k} \left(\frac{X_{ri} - \mu_r}{\sigma_r}\right) \\ + \frac{\sigma_u}{\sigma_k} \left(\frac{u_i - \mu_u}{\sigma_u}\right) \end{aligned} \tag{4}$$

Or

$$Z_{ki} = \left(\beta_1 \frac{\sigma_1}{\sigma_k}\right) z_{1i} + \left(\beta_2 \frac{\sigma_2}{\sigma_k}\right) z_{2i} + \ldots + \left(\beta_r \frac{\sigma_i}{\sigma_k}\right) z_{ri} + \left(\frac{\sigma_u}{\sigma_k}\right) e_i \tag{5}$$

However, $\rho_{ki} = \beta_j \frac{\sigma_i}{\sigma_k}; j = 1(1)r$ and $\rho_{ki} = p_{kj}$ as the path coefficient. To substitute the value in Equation (5), it will appear in the path equation at k as follows. Such an equation will be in a general form or specific form which is composed of less independent variables than r.

$$Z_{ki} = \mathrm{p}_{\mathrm{ki}} z_{1i} + p_{k2} z_{2i} + \ldots + p_{kr} z_{ri} + p_{ku} e_i : k = 1(1)r \tag{6}$$

It depends on why z_k is varied or what are the cause factors (see equation sample of path diagram).

From Equation (6), it can be noted that although e (e is residual) has coefficient p_{ku}, which is shown that in addition to the exogenous variable and endogenous variable influence on z_k it is residual, which is the un-indicated factor in the path diagram which also co-influences to impact on z_k. However, in theory, it is allowed that $(p_{ku} e_i)$ is the random variable and the value of p_{ku} can be estimated in Equation (7) as follows:

From Equation (6), it is found that

$$V(z_{ki}) = V(p_{\mathrm{k}1} z_{1i} + p_{k2} z_{2i} + \ldots + p_{kr} z_{r1} + p_{ku} e_i)$$

$$1 = \sum_{j=1}^{r} V(p_{kj} z_{ji}) + \sum_{s \neq t}^{r} p_{ks} p_{kt} \operatorname{cov}(z_s z_t) + V(p_{ku} e_i)$$

$$1 = \sum_{j=1}^{r} p_{kj}^2 + \sum_{s \neq t}^{r} r_{st} p_{ks} p_{kt} + p_{ku}^2 \quad (7)$$

The covariance = $\sum_{j}^{r}$ (direct influence of z_j to z_k) + $\sum_{s \neq t}^{r}$ (indirect influence of independent variable) + other influence of z_k.

Please consider the following path diagram and draw an equation:

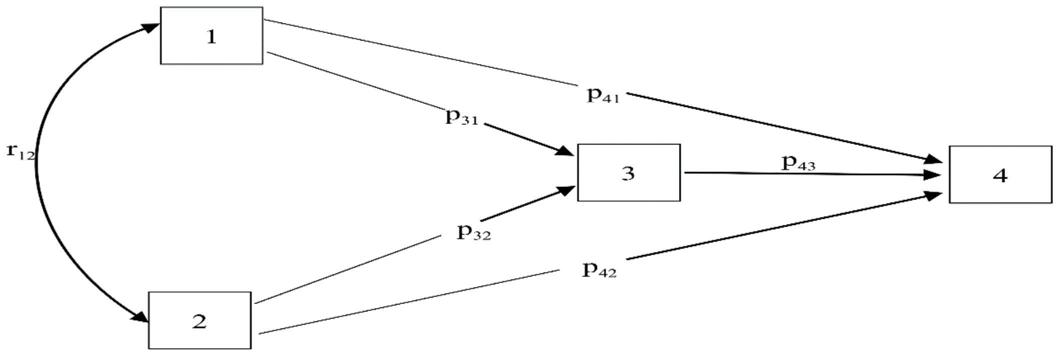

Figure 3. Path analysis-GMM model 1.

From Figure 3, it was found that in case z_1 and z_2 are correlated causes of z_3, we will not separate z_1 and z_2 from each other but gather them in the form of co-variables which impact on z_3 (see the variable that the arrow run into), which means that z_3 is impacted by z_1 and z_2 both directly and indirectly. z_4 is impacted directly by z_3 and is impacted both directly and indirectly by z_1 and z_2.

The equation of path diagram 1 is shown as follows:

$$Z_3 = p_{31} z_1 + p_{32} z_2 + p_{3u} z_e$$

$$Z_4 = p_{41} z_1 + p_{42} z_2 + p_{43} z_3 + p_{4u} z_e$$

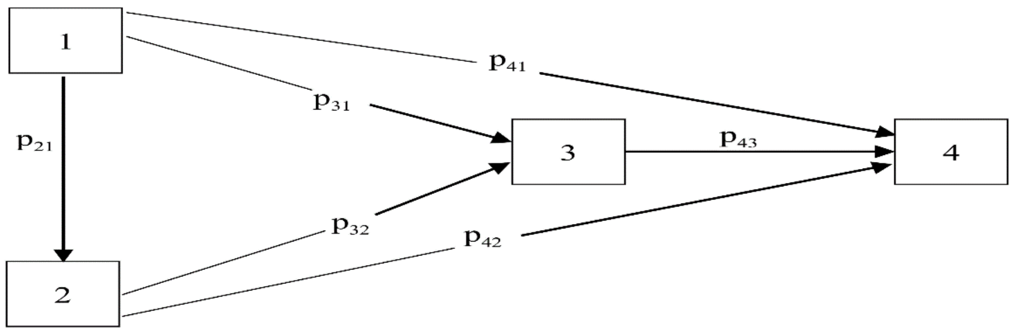

Figure 4. Path analysis-GMM model 2.

From Figure 4, it case z_1 is an exogenous variable while z_2, z_3, and z_4 are endogenous variables, therefore, the equation will be as follows (indicate the variable at the end of arrow as the dependent variable, the variable at the front of arrow is the independent variable at any time of drawing an equation):

$$Z_1 = p_{1u}e$$
$$Z_2 = p_{21}z_1 + p_{2u}e$$
$$Z_3 = p_{31}z_1 + p_{32}z_2 + p_{3u}e$$
$$Z_4 = p_{41}z_1 + p_{42}z_2 + p_{43}z_3 + p_{4u}e$$

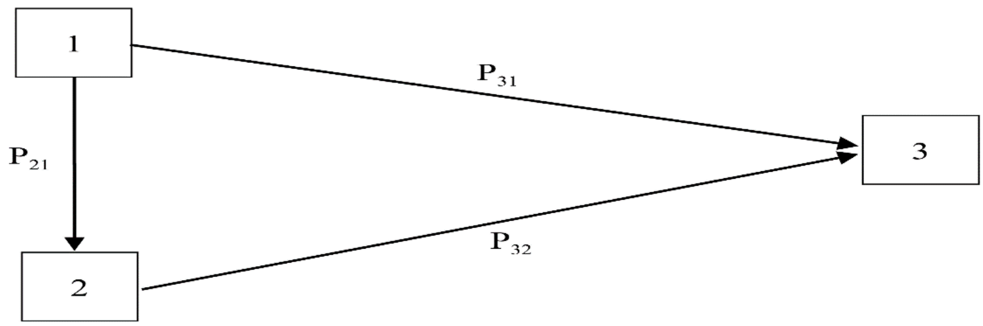

Figure 5. Path analysis-GMM model 3.

From Figure 5, it case z_1 is an exogenous variable, therefore, the path equation system is shown as follows:

$$Z_1 = p_{1u}e$$
$$Z_2 = p_{21}z_1 + p_{2u}e$$
$$Z_3 = p_{31}z_1 + p_{32}z_2 + p_{3u}e$$

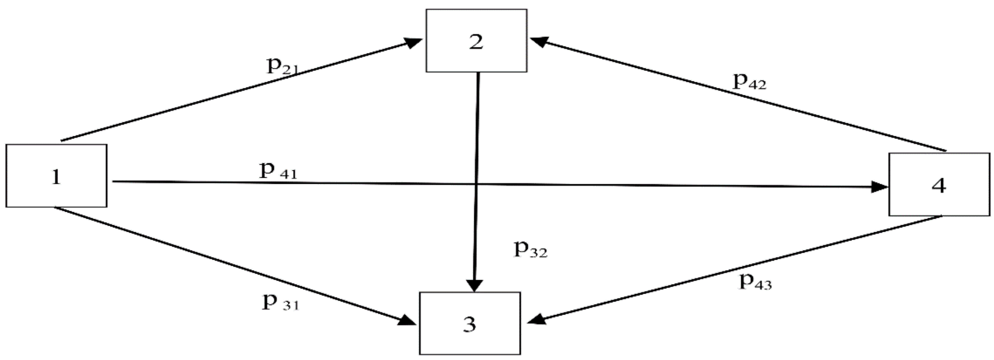

Figure 6. Path analysis-GMM model 4.

From Figure 6, it case z_1 is an exogenous variable which impacts indirectly on z_4 through z_2 and z_3, therefore, the path equation system is shown as follows:

$$Z_1 = p_{1u}e$$
$$Z_2 = p_{21}z_1 + p_{2u}e$$
$$Z_3 = p_{31}z_1 + p_{32}z_2 + p_{3u}e$$
$$Z_4 = p_{41}z_1 + p_{42}z_2 + p_{43}z_3 + p_{4u}e$$

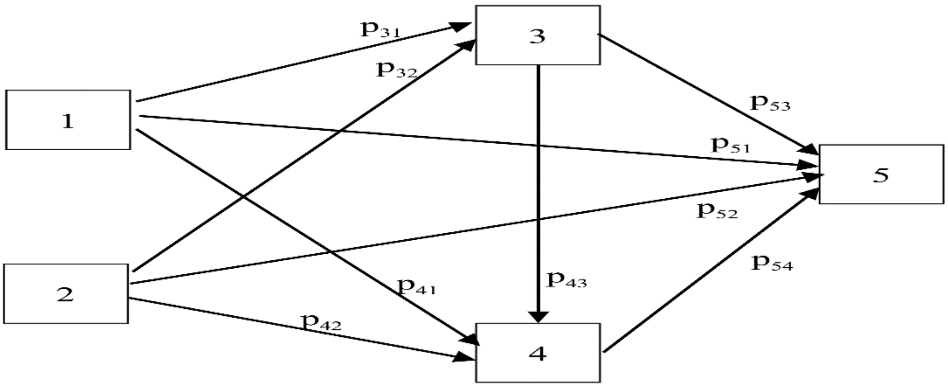

Figure 7. Path analysis-GMM model 5.

From Figure 7, it case z_1 and z_2 are exogenous variables, the path equation is shown as follows:

$$Z_1 = p_{1u}e$$
$$Z_2 = p_{2u}e$$
$$Z_3 = p_{31}z_1 + p_{32}z_2 + p_{3u}e$$
$$Z_4 = p_{41}z_1 + p_{42}z_2 + p_{43}z_3 + p_{4u}e$$
$$Z_5 = p_{51}z_1 + p_{52}z_2 + p_{53}z_3 + p_{54}z_4 + p_{5u}e$$

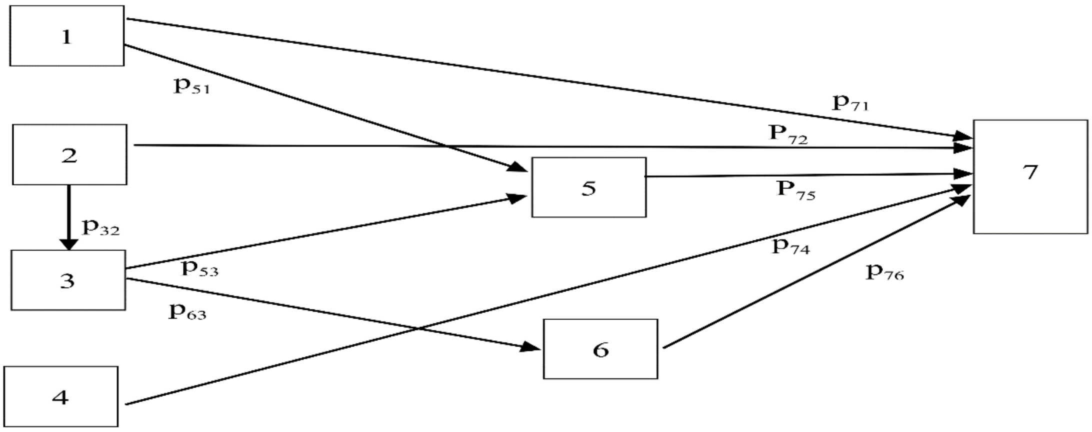

Figure 8. Path analysis-GMM model 6.

From Figure 8, it case z_1, z_2, and z_4 are exogenous variables, the path equation is shown as follows:

$$Z_1 = p_{1u}e$$
$$Z_2 = p_{2u}e$$
$$Z_3 = p_{32}z_2 + p_{3u}e$$
$$Z_4 = p_{4u}e$$
$$Z_5 = p_{51}z_1 + p_{53}z_3 + p_{5u}e$$
$$Z_6 = p_{63}z_3 + p_{6u}e$$
$$Z_7 = p_{71}z_1 + p_{72}z_2 + p_{74}z_4 + p_{75}z_5 + p_{76}z_6 + p_{7u}e$$

For parameter estimation, the researcher applied the GMM model, which can be described as follows:

The generalized method of moments (GMM) is the direct estimation of parameter value from moment conditions which are put into the model. These moment conditions can be linear attributes in the parameter, however, they often become nonlinear. In order to find out the parameter, the number of moment conditions should be at least equal to the number of unknown parameters.

In case the moment conditions are nonlinear, the instrument used to estimate the variables is called the instrumental variables estimator.

The generalized method of moments (GMM) [51,52] is the model which is a set of *R*, where the moment conditions will be as follows:

$$E\{f(w_t, z_t, \theta)\} \quad = \quad 0 \qquad (8)$$

where f = the vector function which is composed of elements R.

0 = the dimension vector which is equal to K and is the vector of all unknown parameters.

W_1 = the vector of variables, which is the observable variable and can be either endogenous variables or exogenous variables.

Z_1 = is the vector of instruments

From the example above $w_t^{'} = \left(C_{t+1}/C_t.r_{t+1}\right)$

In the estimation of θ, the same method as above by using the equivalent sample with Equation (8) is defined by

$$g_r(\theta) = \frac{1}{T}\sum_{t=1}^{r} f(w_t, z_t.\theta) \qquad (9)$$

If the moment conditions that are equal to R are equivalent to unknown parameter K, we can have elements in Equation (9) that are equal to 0 and find out θ, which will obtain unique consistent estimator as follows:

If f is nonlinear in θ, a solution may not exist.

If the moment conditions are less than the parameters, uniquely unknown parameters cannot be found by using Equation (9), which is equal to 0.

Selection of the estimator for θ in the form where the vector of sample moments have a value which is close to 0, meaning that quadratic form in $g_r(\theta)$ has the lowest value as follows:

$$\min_{\theta} \mathrm{Q_r}\ (\theta) = \min_{\theta} \mathrm{g_r}\ (\theta)^{'}\ W_r\ \mathrm{g_r}\ (\theta) \qquad (10)$$

Where W_r is the positive definite matrix with p lim $W_r = W$. The solution of this problem is the generalized method of moments or GMM estimator θ. It can be presented that the GMM estimator has consistent and normal linear distribution under weak regularity conditions.

In practice, the GMM estimator is derived from minimizing Equation (10).

It is known that different matrix to weight W_r will also have different consistent estimators by linear co-variance. The appropriately weighted matrix will derive the least variation for the GMM estimator, which is the inverse of the covariance of sample moments. In case there is no autocorrelation, the appropriated weighted matrix can be written as follows:

$$W^{OPT} = \left(\mathrm{E}\left\{\mathrm{f}\left(\mathrm{w}_t, z_t, \theta\right) f\left(w_t, z_1, \theta\right)^{'}\right\}\right)^{-1}$$

In general, the matrix will depend on the vector of unknown parameter θ, which cannot be found in the linear model. The solution is many estimation processes, starting from the first one using the suboptimal choice of W_r, which is not dependent on θ, such as the identity matrix to find the first consistent estimator. Assuming that $\hat{\theta}_{[1]}$, after that we will estimate the appropriated weighted matrix by:

$$W_r^{OPT} = \left(\frac{1}{n} \sum_{t=1}^{T} f\left(\mathrm{w}_t, z_t\ \hat{\theta}_{[1]}\right) \mathrm{f}\left(\mathrm{w}_t, z_t, \hat{\theta}_{[1]}\right)' \right)^{-1} \tag{11}$$

The second process is to find an efficient asymptotic GMM estimator, $\hat{\theta}_{GMM}$ by the asymptotic distribution as follows:

$$\sqrt{T}\left(\hat{\theta}_{GMM} - \theta\right) \rightarrow N(o, v) \tag{12}$$

where asymptotic covariance matrix V is

$$V = \left(\mathrm{D}\,\mathrm{W}^{\mathrm{OPT}}\,\mathrm{D}'\right)^{-1} \tag{13}$$

where $D = K \times$ derivative matrix *R*

$$D = \mathrm{E}\left\{ \frac{\partial \mathrm{f}\ (\mathrm{w}_t, z_t, \theta)}{\partial \theta'} \right\} \tag{14}$$

For the over identifying restrictions test of nonlinear models, if moment conditions have been correctly defined, the test statistic will be:

$$\zeta = \mathrm{T}\mathrm{g}_{\mathrm{T}}\left(\hat{\theta}_{GMM}\right)'\ \mathrm{W}_{\mathrm{T}}^{\mathrm{OPT}}\ \mathrm{g}_{\mathrm{t}}\left(\hat{\theta}_{GMM}\right) \tag{15}$$

Where $\hat{\theta}_{GMM}$ is the appropriated GMM estimator and W_T^{OPT} is the appropriated weighted matrix in Equation (11); ζ has a chi square asymptotic distribution by *R–K* degrees of freedom. In the case that it is exactly identified, the degrees of freedom will be 0, then there is nothing to test.

3. Empirical Analysis

Screening of Influencing Factors for Model Input

In this paper, the path analysis framework was determined. There were three factors of the latent variables, namely, economic $(Econ)$, social $(Socia)$, and environmental $(Envir)$, while the observed variables contained 12 factors including per capita GDP (GDP), urbanization rate (URE), industrial structure (ISE), net exports $(X-E)$, indirect foreign investment (IFI), employment (EMS), health and illness (HIS), social security (SSS), consumer protection (CPS), energy consumption (ECE), energy intensity (EIE), and carbon dioxide emissions (CO_2).

In structuring a framework of the path analysis model, the stationary observed variables at level I (0) or first level I (1) must be identified and selected. This caned be done with the application of the unit root test based on the augmented Dickey–Fuller theory. In this paper, only the stationary observed variables at the same level were taken. Here, the study found that the 12 causal factors were stationary at the first difference I (1), as illustrated in Table 1.

Table 1. Unit root test at first difference I (1).

Tau Test		MacKinnon Critical Value		
Variables	Value	1%	5%	10%
$\Delta\ln(GDP)$	−5.99***	−4.25	−3.05	−2.70
$\Delta\ln(URE)$	−5.51***	−4.25	−3.05	−2.70
$\Delta\ln(ISE)$	−4.95***	−4.25	−3.05	−2.70
$\Delta\ln(X-E)$	−4.05***	−4.25	−3.05	−2.70
$\Delta\ln(IFI)$	−5.21***	−4.25	−3.05	−2.70
$\Delta\ln(EMS)$	−4.75***	−4.25	−3.05	−2.70
$\Delta\ln(HIS)$	−4.31***	−4.25	−3.05	−2.70
$\Delta\ln(SSS)$	−4.29***	−4.25	−3.05	−2.70
$\Delta\ln(CPS)$	−4.67***	−4.25	−3.05	−2.70
$\Delta\ln(ECE)$	−6.55***	−4.25	−3.05	−2.70
$\Delta\ln(EIE)$	−4.90***	−4.25	−3.05	−2.70
$\Delta\ln(CO_2)$	−6.07***	−4.25	−3.05	−2.70

Note: GDP is the per capita GDP, URE is the urbanization rate, ISE is the industrial structure, $X-E$ is the net exports, IFI is the indirect foreign investment, is the employment, is the health and illness, is the social security, is the consumer protection, ECE is the energy consumption, EIE is the energy intensity, CO_2 is the carbon dioxide emissions. *** denotes a significance, α = 0.01, compared to the Tau test with the MacKinnon critical value, Δ is the first difference, and $\ln$ is the natural logarithm.

Table 1 showed that all factors were non-stationary at Level I (0). Therefore, the first difference was required, and all factors were found to be stationary at Level I (1). This indicated that the value of the Tau test was greater than the MacKinnon critical value, signifying that every factor was significant at 1%, 5%, and 10%. Thus, it was suitable to use them for the co-integration test proposed by Johansen and Juselius, as shown in Table 2.

Analysis of Co-Integration

According to Table 2, the outcomes showed that all observed variables had a significant level at 1% and 5% because the trace values were 210.50 and 75.95, which were higher than the MacKinnon critical values. In addition, the maximum eigenvalue test results were 235.05 and 94.60, which were higher than the MacKinnon critical values. Hence, this indicated that all variables were suitable for the modeling of a path analysis-GMM model.

Formation of Analysis Modeling with the Path Analysis-GMM Model

The path analysis-GMM model was built upon a short- and long-term causal relationship, where the study showed that such a relationship of latent variables had a direct causal, and indirect effect. This caned be illustrated further in Figure 9. In fact, the path analysis-GMM model was tested and qualified for a BLUE feature.

Figure 9 demonstrated the analysis of the casual relationship in the path analysis-GMM model, where the latent variables were economic $(Econ)$, social $(Socia)$, and environmental $(Envir)$, while the observed variables consist of per capita GDP (GDP), urbanization rate (URE), industrial structure (ISE), net exports $(X-E)$, indirect foreign investment (IFI), employment (EMS), health and illness (HIS), social security (SSS), consumer protection (CPS), energy consumption (ECE), energy intensity (EIE), carbon dioxide emissions (CO_2), and ECM_{t-1}. From the study, it provided a finding of which factor had a direct effect, causal effect, and indirect effect, where the results could be seen in Table 3.

Table 2. Co-integration test by Johansen and Juselius.

Variables	Hypothesized No of CE(S)	Trace Statistic Test	Max-Eigen Statistic Test	MacKinnon Critical Value	
				1%	5%
	None**	210.50**	235.05**	15.75	12.50

$\Delta\ln(GDP)$, $\Delta\ln(URE)$, $\Delta\ln(ISE)$, $\Delta\ln(X-E)$, $\Delta\ln(IFI)$, $\Delta\ln(EMS)$, $\Delta\ln(HIS)$, $\Delta\ln(SSS)$, $\Delta\ln(CPS)$, $\Delta\ln(ECE)$, $\Delta\ln(EIE)$, $\Delta\ln(CO_2)$	At Most 1**	75.95**	94.60**	7.50	5.55

*** denotes significance α = 0.01.

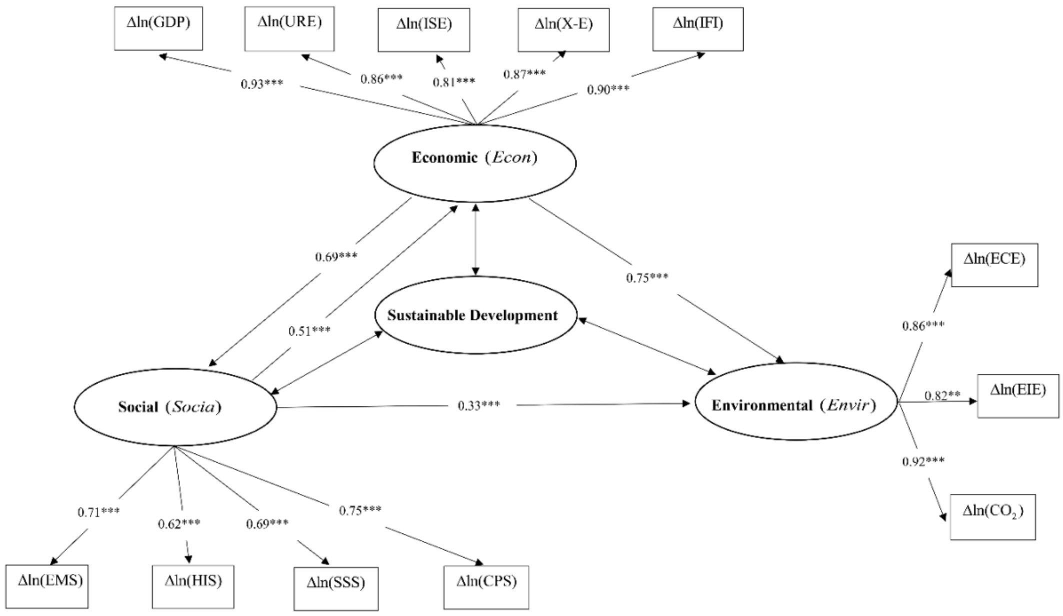

Figure 9. The casual relationship in the path analysis-GMM model.

Table 3. Results of relationship size analysis of the path analysis-GMM model.

Dependent Variables	Type of effect	**Independent Variables** Economic $(Econ)$	Social $(Socia)$	Environmental $(Envir)$	Error Correction Mechanism (ECM_{t-1})
	DE	-	0.51***	-	-0.62***

Economic $(Econ)$	IE	-	-	-	-
Social $(Socia)$	DE	0.69***	-	-	-0.55***
	IE	-	-	-	-
Environmental $(Envir)$	DE	0.75***	0.33***	-	-0.04**
	IE	0.21***	0.27***	-	-

Note: In the above, *** denotes significance α = 0.01, ** denotes significance α = 0.05, χ^2/df is 1.10, root mean square of error approximation ($RMSEA$) is 0.03, root mean squared residual (RMR) is 0.005, goodness of fit index (GFI) is 0.97, adjusted goodness of fit index ($AGFI$) is 0.95, R-squared is 0.95, the F-statistic is 121.00 (probability is 0.00), the Autoregressive Condition Heteroscedastic test (ARCH test) is 25.75 (probability is 0.1), the Lagrange multiplier test (LM test) is 1.27 (probability is 0.10), DE is the direct effect, and IE is the indirect effect.

Table 3 illustrates the parameters of the path analysis-GMM model at the statistically significant levels of 1% and 5%. With the analyzed findings, the path analysis-GMM model was deemed to be ideal due to its qualification of goodness of fit, where the values of RMSEA and RMR reached 0, while the GFI and AGFI values approached 1. Furthermore, when the model was tested for a BLUE feature, the result was positive, indicating that the path analysis-GMM model was an appropriate model to analyze the magnitude of the relationship. In addition, the problems of heteroskedasticity, multicollinearity, and autocorrelation were not found. Furthermore, the R-square value was equal to 95%, and the F-test value was greater than the F-critical value at a significance level of 1%. Therefore, the path analysis-GMM model could be used to analyze the magnitude of the relationship to the sustainable development policy. In detail, $(Econ)$ had a direct effect on, which was equivalent to 69% at a significance level of 1%. This indicates that when $(Econ)$ changed about 1%, it affected $(Socia)$ to 69%. Meanwhile, the change in

$(Socia)$ had a direct effect on $(Econ)$, equivalent to 51% at a significance level of 1%. This implies that when $(Socia)$ changed about 1%, the variable $(Econ)$ will change about 51%. Furthermore, the study showed that the relationship between $(Econ)$ and $(Socia)$ was a causal relationship. This type of relationship between $(Econ)$ and $(Socia)$ could also be called a cause and effect relationship.

In addition to this, $(Econ)$ was found to have a direct effect on $(Envir)$, equivalent to 75% at a significance level of 1%, implying that when $(Econ)$ changed about 1%, it would affect $(Envir)$, which changed up to 75%. In terms of $(Econ)$, it had an indirect effect on $(Envir)$, equivalent to 21% at a significance level of 1%. This explains that when $(Econ)$ changed about 1%, it influenced $(Envir)$ to change up to 21%, which was made transferable through $(Socia)$.

As for $(Socia)$, it had a direct effect on $(Envir)$ of about 33% at a significance level of 1%, which tells us that when $(Socia)$ made a change of about 1%, it would make a change in $(Envir)$ of about 33%. Whereas $(Socia)$ was observed to have an indirect effect on $(Envir)$ of about 27% at a significance level of 1%, implying that when $(Socia)$ changed by about 1%, it would change $(Envir)$ up to 27%, which was made transferable through $(Econ)$.

In the case of ECM_{t-1}, it had a direct effect on $(Econ)$, where the parameter value was −0.62 at a significance level of 1%. This indicated that the adjustment rate of $(Econ)$ in the path analysis-GMM model toward equilibrium was 62%. In another case, ECM_{t-1} had a direct effect on $(Socia)$, whose parameter value was −0.55 at a significance level of 1%. This implies that the adjustment rate of $(Socia)$ in the path analysis-GMM model toward equilibrium was 55%. In addition to ECM_{t-1}, it also had a direct effect on $(Envir)$, whose parameter value was −0.04 at a significance level of 5%. This explained that the adjustment rate of $(Envir)$ in the path analysis-GMM model toward equilibrium was 4%.

5. Conclusions and Discussion

With all of the research processes in place, this paper achieved tremendous outcomes; developing the path analysis-GMM model was one of the research results. The above model presents the relationship of latent variables in three aspects: economic, social, and environmental. Each aspect had its own observed variables. The observed variables in economy include per capita GDP urbanization (GDP), rate (URE), industrial structure (ISE), net exports (IFI), and indirect foreign investment (X-E), while the observed variables in society were employment (EMS), health and illness (HIS), social security (SSS), and customer protection (CPS). In the environmental aspect, energy consumption (EIE), and energy intensity (ECE) carbon dioxide emissions were the observed variables. From this study, it indicated that the economic, social, and environmental factors were directly and indirectly related, yet were causal. Here, the latent variables in each factor were correlated and influential over one another, enabling it to support national policy formulation in order to achieve future sustainable development. The path analysis model-GMM model had a feature of goodness of fit fulfilling all criteria. Additionally, it was identified to be a BLUE, which indicated its appropriated future application for long-term forecasting. To this particular research, the path analysis-GMM model was adapted to facilitate in the estimation of future values in order to examine the policy formation and planning in Thailand. With the above analysis, its finding reflected that the future implementation of several policies of Thailand did not truly contribute in the sustainability. The reason of this conclusion was that although Thailand had made national management strategies, it still failed to develop simultaneous growths in these three aspects altogether; economic, social and environment. Therefore, those in charge of policies and governance had to emphasize this challenge in the policy planning, and revised current policies to achieve national sustainability. In fact, such action was urgent because of the environmental recovery was slowing. This was supported by this study where the results produced a parameter of $\mathbf{ECM}_{t-1}$ of only about 4%, which showed a slow environmental adjustment toward the equilibrium. Such a percentage was lower than the adjustment rate of the economic and social balance, respectively. If the Thai government did not prioritize this and made it urgent, it would worsen the environmental damage more than ever and make the issue more complex. In the meantime, a sustainability plan would not be materialized in the future.

Based on previous relevant studies, we distinguished this research with other past researches. In this paper, we established the path analysis-GMM model by adapting the concept and theory of path analysis in the causality analysis. At the same time, the estimation of the parameter was done by using a GMM model. In fact, the software of LISREL was deployed along with EVIEWS. Thus, such a model became a suitable and effective model for long-term forecasting when compared to other models. In addition, the model was a BLUE model by ensuring that there were no problems of heteroscedasticity, multicollinearity, and autocorrelation. This made the model useful to expend in academic research and implement future development planning in Thailand.

As for recommendations for future applications of this research, researchers were encouraged to give full attention to the analysis process and determination of the observed variables because each factor would have an impact on the causal relationship of the latent variables as well as the estimation of the parameter. Additionally, there was a requirement of advanced statistics to maximize the effectiveness and fulfill past research gaps. The estimation of the parameter by using a method of ordinary least square was found to be highly inaccurate and failed to qualify a feature of BLUE. In addition, the method of error correction mechanism was needed to explore how each factor adjusts toward equilibrium, which would facilitate future planning.

The limitation of this research lied in the old-fashioned sustainable development policy. This means that there were no new scenarios have been put into the planning. By having new scenarios, it would allow the country to make better decisions, while the influential magnitude over changes was better determined. Moreover, long-term prediction became challenging because of the changes in scenarios. Therefore, in further research or study on the path-GMM model, different scenarios should be taken into consideration and depth analysis.

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