# Stabilizing Error Correction Mechanism in the Presence of Explosiveness 

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Authors' contributions
This work was carried out in collaboration among all authors. Author AMO designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript, Authors IA, YY and ARA modified the derivatives and corrected the draft of the manuscript. All authors read and approved the final manuscript.

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#### Abstract

In the presence of explosiveness of the adjustment term in the error correction model, the adjustment of the dependent variable Y was too large and overshoots the equilibrium, creating a divergent pattern. The error correction model fails to capture the deviation from equilibrium appropriately, thereby resulting in overshooting of the model. In this paper, a new model to stabilize the explosiveness in an Error Correction model called the stabilizing Error Correction Mechanism was proposed. Mathematical methodology for obtaining the estimate of the model using the Ordinal Least Square method was derived. Error Correction model was used to model the relationship among the variables and the result was compared with the Stabilizing Error Correction Mechanism using root mean square error. A Monte-Carlo simulation was performed, and the stimulation results showed that the error correction model exhibited some explosiveness, and the damping coefficient of the stabilizing model exerted a stabilizing effect on the error correction mechanism, thereby reducing the overshooting in the error correction model. The proposed model contributed to a smoother and more stable response to deviations from the long-run equilibrium. The root mean square


[^0]error of the stabilizing Error Correction model was observed to be $1.30663,1.04533,12.55786,10.49876$, 10.0034 , and 19.41545 as compared to the adjustment model in the Error Correction model ( 60.6888 , $35.5929,315238,24.31958,10.1485$ and 19.7687$)$ when the persistence is high and $\left(\boldsymbol{\beta}_{\mathbf{0}}, \boldsymbol{\beta}_{\mathbf{1}}, \boldsymbol{\phi}\right)=(\mathbf{1}, \mathbf{0}, \mathbf{0})$. Therefore, the Stabilizing Error Correction model performs better than the Error Correction model.

Keywords: Autoregressive distributed lag; error correction model; long-run model and stabilizing error correction model.

## 1 Introduction

Econometrics analysis of long-run relationship has been the focus of much theoretical and empirical research in economics, Pesaran and Shin [1]. The Autoregressive Distributed lag (ARDL) model is adopted when the dynamics of a single equation regression is involved, when the variables are non-stationary, the ARDL model is reparameterized into an error correction form to study the short-run fluctuation around the equilibrium. Attempt to uncover the long-run/equilibrium relationship is equivalent to separating it from its short-term dynamics which shows evidence for/against the equilibrium relationship Kripfganz and Schneider [2]. The ARDL model can be applied to study the relationship between different economic indicators such as gross domestic product, exchange rate, money supply, inflation, and interest rate over time, Pesaran et al. [3], Adamu and Usman [4], Aronu et al. [5], Ibrahim [6], Charles et al. [7], Elem-Uche et al. [8]; to examine the relationship between financial variables such as stock prices and economic indicators, Adeleye et al. [9], Narayan and Smyth [10], Catau and Asmah [11], Mustafa [12], Celina, U.C. [13], Enisan and Olufisayo [14], Rostin et al. [15], Liaqat et al. [16]; to investigate the impact of exchange rate on trade balance; Bahmani and Narayan [17], Belloumi [18]; to examine the effect of environmental factors, policies, or regulations on economic variables, Ozturk and Acaravci [19], Hamid et al. [20], Saida and Kais [21]; to study the long-run and short-term effect of healthcare policies, expenditures, and other health-related variables, Mamun and Sohag [22]; to examine the relationship between energy prices, consumption, and economic growth over time, Zhigang and Huang [23].The idea of differencing of integrated time series before modelization was advocated by Box and Jenkins [24] while Engle and Granger [25] formalized the idea of cointegration, which is used in a variety of economic models (Iyeli et al.,[26], Nkoro and Uko [27]. In recent years, the cointegration method has been developed to address the issue of non-stationarity in time-series data. Over the past forty years, it has established itself as a standard tool in econometrics and provides evidence for the presence of a real long-term economic relationship. Applying the real economic data to the cointegration test gives a formal and practical foundation for evaluating the short-run and long-term models. When two or more economic variables are cointegrated, short-term deviations from equilibrium have an effect on the other variables, which in turn influences a shift in the direction of the long-run equilibrium. The cointegration of the two variables suggests that an adjustment mechanism is in place to keep the long-run relationship's errors from increasing. The Error Correction model is used to measure the correction from the disequilibrium of the previous period, which has a very good economic implication; it eliminates trends from the variables involved and thereby resolves the problem of spurious regressions. Muritala et al. [28], Albdulaziz and Basmah [29], and Wasanthi [30] observed some explosiveness in the adjustment term creating a divergent pattern where the error correction model fails to capture the deviation from equilibrium appropriately, thereby resulting in overshooting of the model.
The objective of this paper is to investigate the explosiveness in the Error correction model and to propose a model to adjust for the explosiveness in the model. The paper is limited to the short-run error correction model. The plan of the paper is as follows: Section 2 provides the methods to be applied, which include the ARDL, cointegration, and the Error Correction Mechanism. Section 3 adjusts for explosiveness in the model. Section 4 presents the Monte-Carlo simulation results for the model, and Section 5 is on some concluding remarks

## 2 Materials and Methods

### 2.1 The Autoregressive Distributed Lag (ARDL) model

The Autoregressive Distributed Lag (ARDL) model by Pesaran and Shin [1] is given as:

$$
\begin{equation*}
\alpha(L) Y_{t}=\mu+\beta(L) X_{t}+\mu_{t} \tag{1}
\end{equation*}
$$

Where,
$X_{t}$ is explanatory variable, $Y_{t}$ is the dependent variable, and $\mu_{t}$ is the stationary error term,
$\beta(\mathrm{L})$ and $\alpha(\mathrm{L})$ are the lag polynomials such that;
$\alpha(\mathrm{L})=1-\alpha_{1} \mathrm{~L}-\alpha_{2} \mathrm{~L}^{2}-\ldots-\alpha_{p} \mathrm{~L}^{\mathrm{p}}$
$\beta(\mathrm{L})=1-\beta_{1} \mathrm{~L}-\beta_{2} \mathrm{~L}^{2}-\ldots-\beta_{q} \mathrm{~L}^{\mathrm{q}}$
We assume that $X_{t}$ is vector of a random variable and
$\mathrm{X}_{\mathrm{t}}=\mathrm{X}_{\mathrm{t}-1}+\mathrm{e}_{\mathrm{t}}$
Where $X_{t-1}$ is the lag of $X t$, $e_{t}$ is stationary and equation (2.2) implies that $X_{t}$ is integrated of $I(1)$ or $1(0)$ and $Y_{t}$ is also of Order $I(1), \quad Y_{t}$ and $X_{t}$ are cointegrated, allowing for the $\operatorname{Cov}\left(u_{t}, e_{t}\right) \neq 0$ in which $X_{t}$ is said to be endogenous

### 2.2 Cointegration model

Equation (1) can be rewritten as

$$
\begin{align*}
& \alpha(1) Y_{t}=\mu+\left[\beta(1)+\beta^{\prime}(L)-\beta(1)\right] X_{t}+[\alpha(1)-\alpha(L)] Y_{t}+\mu_{t} \\
& Y_{t}=\frac{\mu}{\alpha(1)}+\frac{\beta(1)^{\prime}}{\alpha(1)} X_{t}+\frac{[\beta(L)-\beta(1)]^{\prime}(1-L)}{\alpha(1)(1-L)} X_{t}+\frac{[\alpha(1)-\alpha(L)](1-L)}{\alpha(1)(1-L)} Y_{t}+\frac{\mu_{t}}{\alpha(1)} \\
& Y_{t}=\lambda_{1}+\lambda_{2}^{\prime} X_{t}+\gamma_{2}^{\prime}(L) \Delta X_{t}+\gamma_{1}(L) \Delta Y_{t}+v_{t} \tag{3}
\end{align*}
$$

Where

$$
\begin{aligned}
& \lambda_{1}=\frac{\mu}{\alpha(1)}, \lambda_{2}=\frac{\beta(1)^{\prime}}{\alpha(1)} \\
& \gamma_{2}^{\prime}=\frac{[\beta(L)-\beta(1)]^{\prime}}{\alpha(1)(1-L)}, \gamma_{1}=\frac{[\alpha(1)-\alpha(L)]}{\alpha(1)(1-L)} \text { and } v_{t}=\frac{\mu_{t}}{\alpha(1)}
\end{aligned}
$$

Equation (3) is the cointegration model and $\lambda_{2}$ measures the long-run impact of X on Y .
Stock [31], and Engle and Granger [25] estimated equation (3) using OLS estimator since $Y_{t}$ and $X_{t}$ are of order $\mathrm{I}(1)$ and $\Delta \mathrm{Y}_{\mathrm{t}}$ and $\Delta \mathrm{X}_{\mathrm{t}}$ are of order $\mathrm{I}(0)$.

### 2.3 Error correction model

Using (ARDL (1,1)), we have:

$$
\begin{align*}
& Y_{t}=\alpha_{o}+\alpha_{1} Y_{t-1}+\beta_{0} x_{t}+\beta_{1} x_{t-1}+\varepsilon_{t}  \tag{4}\\
& Y_{t}-\alpha_{1} Y_{t-1}=\alpha_{o}+\beta_{0} x_{t}+\beta_{1} x_{t-1}+\varepsilon_{t}  \tag{5}\\
& Y_{t}\left(1-\alpha_{1}\right)=\alpha_{o}+\left(\beta_{0}+\beta_{1}\right) x_{t}+\varepsilon_{t}  \tag{6}\\
& Y_{t}=\frac{\alpha_{o}}{\left(1-\alpha_{1}\right)}+\frac{\left(\beta_{0}+\beta_{1}\right) x_{t}}{\left(1-\alpha_{1}\right)}+\frac{\varepsilon_{t}}{\left(1-\alpha_{1}\right)}  \tag{7}\\
& Y_{t}=\alpha_{0}^{*}+\beta^{*} x_{t}+\varepsilon_{t} \tag{8}
\end{align*}
$$

Equation (8) is the long-run multiplier.
Re-parameterizing the ARDL model using the technique of Perasan and Shin [32], is done by adding and subtracting $Y_{t-1}$ and $\beta_{0} x_{t-1}$ into equation 4, we have

$$
\begin{equation*}
Y_{t}=\alpha_{o}+\alpha_{1} Y_{t-1}+Y_{t-1}-Y_{t-1}+\beta_{0} x_{t}+\beta_{0} x_{t-1}-\beta_{0} x_{t-1}+\beta_{1} x_{t-1}+\varepsilon_{t} \tag{9}
\end{equation*}
$$

Rearranging we have,

$$
\begin{align*}
& Y_{t}-Y_{t-1}=\alpha_{o}+\alpha_{1} Y_{t-1}-Y_{t-1}+\beta_{0} x_{t}-\beta_{0} x_{t-1}+\beta_{0} x_{t-1}+\beta_{1} x_{t-1}+\varepsilon_{t}  \tag{10}\\
& \Delta Y_{t}=\alpha_{o}+Y_{t-1}\left(\alpha_{1}-1\right)+\beta_{0} \Delta x_{t}+\left(\beta_{0}+\beta_{1}\right) x_{t-1}+\varepsilon_{t}  \tag{11}\\
& \Delta Y_{t}=-\left(1-\alpha_{1}\right)\left[Y_{t-1}-\frac{\alpha_{o}}{\left(1-\alpha_{1}\right)}-\frac{\left(\beta_{0}+\beta_{1}\right)}{\left(1-\alpha_{1}\right)} x_{t-1}\right]+\beta_{0} \Delta x_{t}+\varepsilon_{t} \tag{12}
\end{align*}
$$

The interpretation of the error correction model relies on a long run equilibrium relationship $y=\beta^{\prime} x$.
The error correction mechanism is the adjustment of $y_{t}$ through $a(1)$ to equilibrium deviation in the previous period, in equation (8). The equation is rewritten as follows.

$$
\begin{equation*}
\Delta y_{t}=\lambda E C M_{t-1}+\beta_{0} \Delta x_{t}+\varepsilon_{t} \tag{13}
\end{equation*}
$$

Where $E C M_{t-1}=\left[Y_{t-1}-\frac{\alpha_{o}}{\left(1-\alpha_{1}\right)}-\frac{\left(\beta_{0}+\beta_{1}\right)}{\left(1-\alpha_{1}\right)} x_{t-1}\right]$ and $\lambda=-\left(1-\alpha_{1}\right)$
Where $-1<\lambda<0$

$$
\lambda=\left(\begin{array}{c}
>0, \text { the disequilibrium expands } \\
=0, \text { there is no error correction } \\
-1<\lambda<0, \text { a quick equilibrium } \\
=-1, \text { Full error correction in one point } \\
<-1, \text { over shooting: oscillatory adjustment }
\end{array}\right)
$$

## 3 Explosiveness in the Error Correction Model

In the figure below, the blue line represents the long-run equilibrium relationship between Y and X , and the red line represents the actual values of Y. The green horizontal line show the direction of adjustment of Y in each period. When $\lambda$ is the coefficient of the error correction term (ECT) which is expected to be between -1 and 0 . The negative indicate the degree of correction. The magnitude of the correction suggests a fairly high speed of adjustment in the aftermath of a shock. When $\lambda$ is less than -1 , the adjustment of $Y$ is too large and overshoots the equilibrium, creating a divergent pattern. This is in contrast to the case when $\lambda$ is between -1 and 0 , where the adjustment of $Y$ is gradual and convergent, and the red line eventually approaches the blue line. To correct the problem of explosiveness in the short run model a stabilizing error correction mechanism is proposed which is given as:

Stabilizing Error Correction Mechanism.

$$
\begin{equation*}
\Delta Y_{t}=\sum_{i=1}^{p} \beta_{i} \Delta Y_{t-i}+\sum_{j=0}^{q} \beta_{j} \Delta X_{t-j}+\lambda E C T_{t-1}+\theta S E C M+e_{t} \tag{14}
\end{equation*}
$$

SECM is called the Stabilization error correction mechanism by damping the speed of correction. It measures the change in the error correction term from one period to the next. It helps to slow down the correction process. By introducing SECM, we allow the model to adjust the speed of correction dynamically based on past adjustments.

In Matrix form equation (14) can be represented as:

$$
\begin{align*}
& y_{t}=h d_{t}+\theta \text { SECM }_{t}+e_{t}  \tag{15}\\
& y_{t}=\left[y_{1}, y_{2}, \ldots, y_{n}\right]^{\prime} \\
& y_{t-1}=\left[y_{0}, y_{1}, \ldots, y_{n-1}\right]^{\prime}
\end{align*}
$$

$$
\begin{aligned}
& e_{t}=\left[e_{1}, e_{2}, \ldots, e_{n}\right] \\
& d_{t}=\left[\Delta Y_{t} \Delta X_{t} E C M_{t}\right] \\
& g=[\beta, \theta]
\end{aligned}
$$

set
$H_{d t}=\left[d_{T}, S E C M_{t}\right]$
$G=[g, \lambda]$
Using OLS, the estimator G is denoted by $G_{t}$

$$
\begin{align*}
& G_{t}=\left[H_{d t}{ }^{\prime} H_{d t}\right]^{-1}\left[H_{d t}{ }^{\prime} y_{t}\right]  \tag{16}\\
& V(d)=\sigma_{u}^{2}\left[H_{d t}^{\prime} H_{d t}\right]^{-1}  \tag{17}\\
& \text { And } \sigma_{u}^{2}=N^{-1}\left(y-H_{d t}{ }^{\prime} \widehat{G_{t}}\right)^{\prime}\left(y-H_{d t}^{\prime} \widehat{G_{t}}\right) \tag{18}
\end{align*}
$$

The t - statistic for the parameter estimate is given as

$$
\begin{align*}
& t=\frac{G_{t}-\widehat{G_{t}}}{S . E\left(\widehat{G_{t}}\right)}  \tag{19}\\
& S . E\left(\widehat{G_{t}}\right)=\sqrt{\operatorname{var}\left(G_{t}\right)} \tag{20}
\end{align*}
$$



Fig. 1. Illustration of explosiveness

## 4 Monte-Carlo Simulation

In this section, Monte-Carlo analysis used to illustrate the impact of the shock. The sample size considered is 50.

### 4.1 Data generating process

The parameters are selected arbitrarily.

$$
\begin{equation*}
y_{t}=\alpha+\beta_{0} x_{t}+\beta_{1} x_{t-1}+\phi y_{t-1}+u_{t} \tag{21}
\end{equation*}
$$

Where,

$$
\begin{equation*}
x_{t}=\rho_{1} x_{t-1}+v_{t} \tag{22}
\end{equation*}
$$

$$
\eta_{1 t} \sim N(0,1)
$$

$u_{t}$ and $v_{t}$ are generated by the processes;

$$
\begin{align*}
& u_{1 t}=p_{11} \eta_{1 t}  \tag{23}\\
& v_{1 t}=p_{21} \eta_{1 t}+p_{22} \eta_{2 t}+p_{23} \eta_{1 t-1} \tag{24}
\end{align*}
$$

The initial values are: $x_{0}=1, y_{0}=1, \alpha=0$

$$
\begin{aligned}
& \left(\beta_{0}, \beta_{1}, \phi\right)=B_{1}=(1,0,0), B_{2}=(0.6,0,0.4), B_{3}=(0.6,0.4,0), B_{4}=(0.6,0.4,0.4) \\
& p_{11}=0.95,1.0 \\
& \left(p_{21}, p_{22}, p_{23}\right)=P_{1}=(0,1,0), P_{2}=(0.5,0.866,0), \quad P_{3}=(0.5,0.866,0.5), P_{4}=(0.5,0.9,0.9), \\
& \quad P_{5}=(0.9,0.5,0.5), P_{6}=(0.9,0.9,0.9)
\end{aligned}
$$

$\eta_{1 t}$ and $\eta_{2 t}$ are independently and identically distributed standard normal variables.
The various combinations of $P_{2 i}$ allow for correlation between the $u_{t}$ and $v_{t}$ and hence the endogeneity of $X_{t}$ and for some serial correlation in $\mathrm{v}_{\mathrm{t}}$.

## 5 Results

Tables 1 and 2 present results of the persistence of the estimation of the short-run model at $\mathrm{P}_{11}=0.95$ and 1.0. We observed the following:
i. The short-run model yielded an explosive behaviour when $\phi=0$, it seems that the adjustment of Y is too large and overshoots the equilibrium, creating a divergent pattern.
ii. When $\mathrm{P}_{22}, \mathrm{P}_{23}=0.9$ and $\phi=0.4$ we observed that the adjustment of Y is too large and overshoots the equilibrium, creating a divergent pattern.
iii. When $\phi \neq 0$, the adjustment of Y is gradual and convergent, and long-run will eventually approaches the equilibrium point.
iv. The influence of the lag of the independent variable on the current value of the dependent variable continues to decrease across all $\beta_{0}, \beta_{1}, \phi$,
v. For all $\beta_{0}, \beta_{1}, \phi$, the influence of the current independent variable on the current dependent variable increases for a while and then decreases.
vi. For all the adjustment value $(\lambda)$ less than -1 , it shows that the adjustment of the dependent variable $Y$ is too large and overshoots the equilibrium, creating a divergent pattern. The error correction model fails to capture the deviation from equilibrium appropriately, thereby resulting in overshooting of the model.

Tables 3 and 4 present results of the stabilizing error correction model, we observed the following:
i. The adjustment term was within $-1<\lambda<0$ which implies that there was a gradual and convergent and the long run will eventually approach the equilibrium.
ii. The values of the coefficient of the stabilizing model was observed to be very high which implies that stabilising model is exerting a stabilizing effect on the error correction mechanism in our model, thereby reducing the overshooting in the error correction model.
iii. The coefficient of the stabilizing model was observed to be consistently positive which implies that it contributes to a smoother and more stable response to deviations from the long run equilibrium.
iv. The standard error of the coefficient of the adjustment term in the stabilizing error correction mechanism was observed to be smaller compared to the error correction model.
v. There is an increase in the effect of the independent variable $\left(x_{t}\right)$ on the dependent variable $\left(y_{t}\right)$ in the stabilizing error correction mechanism with a smaller standard error as compared to the error correction model.

Table 1. Persistence at $\mathbf{P 1 1 = 1 . 0}$ when the sample size is 50


Table 2. Persistence at $\mathbf{P 1 1}=\mathbf{0 . 9 5}$ when the sample size is 50


Table 3. Persistence at $\mathbf{P 1 1 = 1 . 0}$ when the sample size is $\mathbf{5 0}$

| - | $\mathrm{N}=50, \mathrm{P} 11=1.0$ |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | $\left(\boldsymbol{\beta}_{0}, \boldsymbol{\beta}_{1}, \phi\right)=(1,0,0)$ |  |  | $\left(\boldsymbol{\beta}_{0}, \boldsymbol{\beta}_{1}, \phi\right)=(0.6,0,0.4)$ |  |  | $\left(\boldsymbol{\beta}_{0}, \boldsymbol{\beta}_{1}, \phi\right)=(0.6,0.4,0)$ |  |  | $\left(\beta_{0}, \beta_{1}, \phi\right)=(0.6,0.4,0.4)$ |  |  |
|  | ESTIMATOR | COEFF | ST.ERR | PVALUE | COEFF | ST.ERR | PVALUE | COEFF | ST.ERR | PVALUE | COEFF | ST.ERR | PVALUE |
| P21,P22,P23 | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | , | - | - |  |  |  | - | - | - |  |  |  |
| $(0,1,0)$ | $D\left(X_{t}\right)$ | 1.0804 | $0.0251$ | $0.000$ |  |  |  | 0.7134 | $0.0240$ | $0.000$ |  |  |  |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | - | - | - |  |  |  | 0.3019 | 0.0239 | 0.000 |  |  |  |
|  | $\lambda$ | -0.124 | 0.0313 | 0.000 |  |  |  | -0.136 | 0.030 | 0.000 |  |  |  |
|  | $\Theta$ | 0.9814 | 0.0219 | 0.000 |  |  |  | 0.9861 | 0.021 | 0.000 |  |  |  |
| P21,P22,P23 | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | , | - | - |  |  |  | -0.036 | 0.0182 | 0.058 |  |  |  |
| (0.5, 0.866, | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.0581 | 0.0219 | 0.000 |  |  |  | 0.6715 | 0.0219 | 0.000 |  |  |  |
| 0) | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | 0.6493 | 0.0214 | 0.000 |  |  |  | 1.0651 | 0.0237 | 0.000 |  |  |  |
|  | $\lambda$ | -0.117 | 0.0373 | 0.003 |  |  |  | -0.118 | 0.0414 | 0.007 |  |  |  |
|  | $\Theta$ | 1.0234 | 0.0265 | 0.000 |  |  |  | 1.0169 | 0.0266 | 0.000 |  |  |  |
| P21,P22,P23 | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | - | - | - | - | - | - | -0.293 | 0.0547 | 0.000 | - | - | - |
| (0.5, 0.866, | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.3418 | 0.070 | 0.000 | 1.0652 | 0.0768 | 0.000 | 1.0600 | 0.064 | 0.000 | 0.9493 | 0.011 | 0.000 |
| 0.5) | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | 0.0322 | 0.0717 | 0.666 | 0.2249 | 0.0755 | 0.005 | 0.5457 | 0.0916 | 0.000 | 0.7942 | 0.011 | 0.000 |
|  | $\lambda$ | -0.481 | 0.1425 | 0.002 | -0.399 | 0.1503 | 0.011 | -0.181 | 0.1336 | 0.182 | -0.058 | 0.023 | 0.015 |
|  | $\Theta$ | 0.906 | 0.0980 | 0.000 | 1.063 | 0.1083 | 0.000 | 0.986 | 0.0913 | 0.000 | 1.008 | 0.016 | 0.000 |
| P21,P22,P23 | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | - | - | - | - | - | - | - | - | - | - | - | - |
| (0.5, 0.9, | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.454 | 0.0538 | 0.000 | 1.099 | 0.0077 | 0.00 | 1.112 | 0.0509 | 0.000 | 1.023 | 0.014 | 0.000 |
| 0.9) | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | -0.332 | 0.0536 | 0.000 | - | - | - | -0.002 | 0.0486 | 0.9614 | 0.5764 | 0.013 | 0.000 |
|  | $\lambda$ | -0.486 | 0.1513 | 0.003 | 0.0522 | 0.0244 | 0.038 | -0.431 | 0.1443 | 0.005 | -0.154 | 0.0379 | 0.000 |
|  | $\Theta$ | 0.924 | 0.1019 | 0.000 | 1.007 | 0.0158 | 0.000 | 0.996 | 0.0998 | 0.000 | 0.983 | 0.0268 | 0.000 |
| P21,P22,P23 | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | - | - | - | - | - | - | - | - | - | - | - | - |
| (0.9, 0.5, | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.117 | 0.0631 | 0.000 | 0.711 | 0.020 | 0.000 | 0.738 | 0.0949 | 0.000 | 0.680 | 0.0130 | 0.000 |
| 0.5) | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | 0.682 | 0.0663 | 0.000 | 0.956 | 0.0214 | 0.000 | 1.013 | 0.0977 | 0.000 | 1.411 | 0.0138 | 0.000 |
|  | $\lambda$ | -0.615 | 0.2287 | 0.010 | -0.101 | 0.0705 | 0.160 | -0.690 | 0.3441 | 0.051 | -0.173 | 0.0473 | 0.001 |
|  | $\Theta$ | 0.761 | 0.1592 | 0.000 | 1.069 | 0.0525 | 0.000 | 0.768 | 0.2417 | 0.003 | 0.985 | 0.0343 | 0.000 |
|  | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | - | - | - | - | - | - | -0.532 | 0.0615 | 0.000 |  |  |  |
| $(0.9,0.9$ | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.258 | 0.0684 | 0.000 | 0.838 | 0.0243 | 0.000 | 0.878 | 0.0539 | 0.000 | 0.811 | 0.0208 | 0.000 |
| 0.9) | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | 0.090 | 0.0710 | 0.211 | 0.455 | 0.0254 | 0.000 | 0.894 | 0.0913 | 0.000 | 0.918 | 0.0219 | 0.000 |
|  | $\lambda$ | -0.689 | 0.2331 | 0.005 | -0.232 | 0.0814 | 0.007 | -0.101 | 0.1825 | 0.583 | -0.245 | 0.0737 | 0.002 |
|  | $\Theta$ | 0.774 | 0.1599 | 0.000 | 1.020 | 0.0591 | 0.000 | 0.992 | 0.1287 | 0.000 | 0.976 | 0.0516 | 0.000 |

Table 4. Persistence at $\mathbf{P 1 1}=\mathbf{0 . 9 5}$ when the sample size is $\mathbf{5 0}$

| - | $\mathrm{N}=50, \mathrm{P} 11=0.95$ |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | $\left(\beta_{0}, \beta_{1}, \phi\right)=(1,0,0)$ |  |  | $\left(\boldsymbol{\beta}_{0}, \boldsymbol{\beta}_{1}, \phi\right)=(0.6,0,0.4)$ |  |  | $\left(\boldsymbol{\beta}_{0}, \boldsymbol{\beta}_{1}, \phi\right)=(0.6,0.4,0)$ |  |  | $\left(\beta_{0}, \beta_{1}, \phi\right)=(0.6,0.4,0.4)$ |  |  |
|  | ESTIMATOR | COEFF | ST.ERR | PVALUE | COEFF | ST.ERR | PVALUE | COEFF | ST.ERR | PVALUE | COEFF | ST.ERR | PVALUE |
| $\begin{aligned} & \text { P21,P22,P23 } \\ & (0,1,0) \end{aligned}$ | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | - | - | - |  |  |  | - | - | - |  |  |  |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.171 | 0.0202 | 0.000 |  |  |  | 0.762 | 0.0230 | 0.000 |  |  |  |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | - | - | - |  |  |  | 0.368 | 0.0228 | 0.000 |  |  |  |
|  | $\lambda$ | -0.101 | 0.0277 | 0.0007 |  |  |  | -0.138 | 0.0312 | 0.0001 |  |  |  |
|  | $\Theta$ | 0.987 | 0.0191 | 0.000 |  |  |  | 0.986 | 0.0218 | 0.000 |  |  |  |
| $\begin{aligned} & \text { P21,P22,P23 } \\ & (0.5,0.866, \\ & 0) \end{aligned}$ | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | - | - | - |  |  |  | - | - | - | - | - | - |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.071 | 0.0237 | 0.000 |  |  |  | 0.757 | 0.069 | 0.000 | 0.703 | 0.0004 | 0.000 |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | 0.614 | 0.0231 | 0.000 |  |  |  | 0.864 | 0.0068 | 0.000 | 1.138 | 0.0004 | 0.000 |
|  | $\lambda$ | -0.142 | 0.0436 | 0.0023 |  |  |  | -0.255 | 0.115 | 0.0324 | -0.002 | 0.0007 | 0.006 |
|  | $\Theta$ | 1.022 | 0.0312 | 0.000 |  |  |  | 1.083 | 0.0883 | 0.000 | 0.999 | 0.0005 | 0.000 |
| $\begin{aligned} & \text { P21,P22,P23 } \\ & (0.5,0.866, \\ & 0.5) \end{aligned}$ | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | - | - | - | - | - | - | - | - | - | - | - | - |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.369 | 0.0568 | 0.000 | 0.942 | 0.0102 | 0.000 | 1.036 | 0.0764 | 0.000 | 0.934 | 0.0103 | 0.000 |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | 0.044 | 0.0582 | 0.451 | 0.434 | 0.0105 | 0.000 | 0.286 | 0.0748 | 0.0004 | 0.881 | 0.0102 | 0.000 |
|  | $\lambda$ | -0.402 | 0.125 | 0.003 | -0.09 | 0.0222 | 0.000 | -0.428 | 0.1641 | 0.013 | -0.103 | 0.0222 | 0.000 |
|  | $\Theta$ | 1.007 | 0.0879 | 0.000 | 0.996 | 0.0158 | 0.000 | 1.042 | 0.1172 | 0.000 | 0.985 | 0.0158 | 0.000 |
| $\begin{aligned} & \text { P21,P22,P23 } \\ & (0.5,0.9, \\ & 0.9) \end{aligned}$ | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | - | - | - |  |  |  | -0.054 | 0.0319 | 0.0965 | - | - | - |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.527 | 0.0425 | 0.000 |  |  |  | 1.119 | 0.0466 | 0.00 | 1.005 | 0.0132 | 0.000 |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | -0.406 | 0.0409 | 0.000 |  |  |  | - | - | - | 0.603 | 0.0131 | 0.000 |
|  | $\lambda$ | -0.326 | 0.134 | 0.019 |  |  |  | -0.377 | 0.1536 | 0.0182 | -0.159 | 0.0405 | 0.000 |
|  | $\Theta$ | 1.014 | 0.0902 | 0.000 |  |  |  | 0.983 | 0.1025 | 0.000 | 0.982 | 0.0284 | 0.000 |
| $\begin{aligned} & \mathrm{P} 21, \mathrm{P} 22, \mathrm{P} 23 \\ & (0.9,0.5,0.5) \end{aligned}$ | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | -0.445 | 0.0096 | 0.000 | - | - | - | -0.443 | 0.0097 | 0.000 | - | - | - |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.076 | 0.0114 | 0.000 | 0.718 | 0.0244 | 0.000 | 0.681 | 0.0114 | 0.000 | 0.677 | 0.0116 | 0.000 |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | 1.196 | 0.0175 | 0.000 | 0.916 | 0.0249 | 0.000 | 1.411 | 0.0149 | 0.000 | 1.381 | 0.0122 | 0.000 |
|  | $\lambda$ | -0.039 | 0.0449 | 0.394 | -0.16 | 0.0903 | 0.082 | -0.095 | 0.0444 | 0.039 | -0.163 | 0.0467 | 0.001 |
|  | $\Theta$ | 1.016 | 0.0031 | 0.000 | 1.054 | 0.0677 | 0.000 | 1.006 | 0.0316 | 0.000 | 0.986 | 0.0332 | 0.000 |
| $\begin{aligned} & \mathrm{P} 21, \mathrm{P} 22, \mathrm{P} 23 \\ & (0.9,0.9,0.9) \end{aligned}$ | $\mathrm{D}\left(\mathrm{Y}_{\mathrm{t}-1}\right)$ | - | - | - | - | - | - | -0.574 | 0.0509 | 0.000 | - | - | - |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}}\right)$ | 1.327 | 0.0523 | 0.000 | 0.837 | 0.0256 | 0.000 | 0.844 | 0.0426 | 0.000 | 0.801 | 0.0184 | 0.000 |
|  | $\mathrm{D}\left(\mathrm{X}_{\mathrm{t}-1}\right)$ | -0.639 | 0.1009 | 0.000 | 0.441 | 0.0267 | 0.000 | 0.972 | 0.0732 | 0.000 | 0.918 | 0.0192 | 0.000 |
|  | $\lambda$ | -0.466 | 0.2155 | 0.0362 | -0.29 | 0.0936 | 0.0032 | -0.019 | 0.1583 | 0.9054 | -0.225 | 0.0715 | 0.0031 |
|  | $\Theta$ | 1.029 | 0.1509 | 0.000 | 0.995 | 0.0684 | 0.000 | 1.036 | 0.1096 | 0.000 | 0.980 | 0.0493 | 0.000 |

### 5.1 Comparison between error correction model and adjustment for explosives

Table 5 shows the comparison between error correction model and the adjustment for explosiveness. It was discovered that the adjustment value from the error correction model was explosive but it became stabilized and ranges from -0.7 to 0.5 in the stabilizing error correction model. Furthermore, the Sum of Square of regression for the stabilizing error correction model was observed to be smaller than the Sum of square of regression of the error correction model.

Table 5. Comparison between error correction model and stabilizing error correction model

| $\mathrm{P} 11=1.0, \mathrm{~N}=50$ |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Adjustment term ( $\lambda$ ) of ECM | SSR of ECM | Adjustment term ( $\lambda$ ) of SECM | $\boldsymbol{\theta}$ of SECM | $P$-Value of $\lambda$ of SECM | $P$-value of $\boldsymbol{\theta}$ of SECM | SSR of $\boldsymbol{\theta}$ of SECM |
| B1P1 | -1.10655 | 60.6888 | -0.12440 | 0.98137 | 0.000 | 0.000 | 1.30663 |
| B1P2 | -1.26337 | 35.5929 | -0.11647 | 1.02339 | 0.003 | 0.000 | 1.04553 |
| B1P3 | -1.3908 | 31.5238 | -0.48134 | 0.90574 | 0.002 | 0.000 | 12.55786 |
| B1P4 | -1.437906 | 24.31958 | -0.48642 | 0.92381 | 0.003 | 0.000 | 10.49876 |
| B1P5 | -1.490685 | 10.14827 | -0.615326 | 0.476059 | 0.010 | 0.000 | 10.0034 |
| B1P6 | -1.56265 | 19.76874 | -0.68851 | 0.774112 | 0.005 | 0.000 | 19.41545 |
| B2P3 | -1.054627 | 30.55614 | -0.05275 | 1.000434 | 0.000 | 0.000 | 0.116955 |
| B2P4 | -1.040132 | 24.24044 | 0.052218 | 1.00697 | 0.038 | 0.000 | 0.255406 |
| B2P5 | -1.16411 | 10.32825 | -0.100937 | 1.06846 | 0.159 | 0.000 | 1.172805 |
| B2P6 | -1.271669 | 19.0875 | -0.231787 | 1.02035 | 0.007 | 0.000 | 2.76766 |
| B3P1 | -1.12293 | 60.0683 | -0.135836 | 0.986107 | 0.000 | 0.000 | 1.1716 |
| B3P2 | -1.295019 | 36.51251 | -0.118448 | 1.016958 | 0.007 | 0.000 | 1.02564 |
| B3P3 | -1.72957 | 31.37935 | -0.39903 | 1.062714 | 0.011 | 0.000 | 15.12816 |
| B3P4 | -1.64704 | 23.79466 | -0.431338 | 0.99639 | 0.005 | 0.000 | 10.18373 |
| B3P5 | -1.490685 | 10.14827 | -0.690228 | 0.76807 | 0.051 | 0.003 | 24.27447 |
| B3P6 | -1.8940 | 19.4337 | -0.10106 | 0.99155 | 0.583 | 0.000 | 13.29955 |
| B4P3 | -1.068969 | 30.86852 | -0.05828 | 1.00814 | 0.015 | 0.000 | 0.3488 |
| B4P4 | -1.149705 | 21.95608 | -0.15423 | 0.983161 | 0.000 | 0.000 | 0.61719 |
| B4P5 | -1.16268 | 9.29939 | -0.17327 | 0.98506 | 0.001 | 0.000 | 0.43112 |
| B4P6 | -1.240767 | 17.48065 | -0.24517 | 0.97566 | 0.002 | 0.000 | 1.851388 |
| $\mathbf{P} 11=0.95$ and $\mathrm{N}=50$ |  |  |  |  |  |  |  |
|  | Adjustment term ( $\lambda$ ) of ECM | SSR of <br> ECM | Adjustment term ( $\lambda$ ) of SECM | $\theta$ of SECM | $P$-Value of $\lambda$ of SECM | $P$-value of $\theta$ of SECM | SSR of $\boldsymbol{\theta}$ of SECM |
| B1P1 | -1.08815 | 54.14689 | -0.10133 | 0.98666 | 0.001 | 0.000 | 0.87679 |
| B1P2 | -1.30745 | 32.56275 | -0.14165 | 1.02145 | 0.002 | 0.000 | 1.27827 |
| B1P3 | -1.5663 | 27.25855 | -0.40192 | 1.006948 | 0.003 | 0.000 | 8.72927 |
| B1P4 | -1.60915 | 21.91993 | -0.32638 | 1.013603 | 0.019 | 0.000 | 7.50795 |
| B1P5 | -1.58782 | 8.79073 | -0.0387 | 1.01632 | 0.394 | 0.000 | 0.3462 |
| B1P6 | -1.7079 | 16.99948 | -0.46628 | 1.028523 | 0.036 | 0.000 | 16.05396 |
| B2P3 | -1.08961 | 27.00202 | -0.09139 | 0.99576 | 0.000 | 0.000 | 0.28104 |
| B2P5 | -1.20909 | 8.9427 | -0.16071 | 1.053848 | 0.082 | 0.000 | 1.67437 |
| B2P6 | -1.31123 | 16.86052 | -0.29248 | 0.99493 | 0.003 | 0.000 | 3.21218 |
| B3P1 | -1.12398 | 53.77957 | -0.137669 | 0.985928 | 0.000 | 0.000 | 1.108223 |
| B3P2 | -1.59286 | 34.5018 | -0.2550 | 1.08251 | 0.032 | 0.000 | 10.42417 |
| B3P3 | -1.70537 | 27.43358 | -0.4275 | 1.042278 | 0.013 | 0.000 | 15.6464 |
| B3P4 | -1.61517 | 21.17412 | -0.37719 | 0.98297 | 0.018 | 0.000 | 9.54722 |
| B3P5 | -1.65556 | 8.79209 | 0.09494 | 1.006336 | 0.004 | 0.000 | 0.35042 |
| B3P6 | -1.84399 | 17.14969 | -0.01894 | 1.03599 | 0.905 | 0.000 | 8.571186 |
| B4P2 | -1.001949 | 34.5340 | -0.001997 | 0.99999 | 0.006 | 0.000 | 0.00041 |
| B4P3 | -1.09065 | 25.52617 | -0.10264 | 0.98456 | 0.000 | 0.000 | 0.24994 |
| B4P4 | -1.15423 | 19.3038 | -0.15957 | 0.98158 | 0.000 | 0.000 | 0.61537 |
| B4P5 | -1.15222 | 8.12881 | -0.16291 | 0.98564 | 0.001 | 0.000 | 0.355688 |
| B4P6 | -1.22386 | 15.51496 | -0.22498 | 0.980316 | 0.003 | 0.000 | 1.4984 |

## 6 Conclusion

In modeling the short-run relationship, we observed that most of the adjustment terms were less than -1 , which implies that the adjustment term is explosive, thereby creating an over-correction, and it also implies an oscillatory convergence. To correct the problem of explosiveness in the short-run model, a stabilizing error correction mechanism was proposed. The coefficient of the stabilizing error correction model was observed to be consistently positive, with values greater than 0 in all cases, which means that the damping coefficient exerted a stabilizing effect on the error correction mechanism in the model, thereby reducing the overshooting in the error correction model. It also implies that the adjustment mechanism responds to deviations from the longrun equilibrium in a way that prevents rapid and excessive corrections. It contributes to a smoother and more stable response to deviations from the long-run equilibrium. There is an increase in the effect of the independent variable $\left(\mathrm{x}_{\mathrm{t}}\right)$ on the dependent variable $\left(\mathrm{y}_{\mathrm{t}}\right)$ in the stabilizing error correction mechanism with a smaller standard error as compared to the error correction model.

The root mean square error of the stabilizing Error Correction model is observed to be smaller than the adjustment model in the Error correction model. The stabilizing error correction model performs better than the Error correction model.

## Competing Interests

Authors have declared that no competing interests exist.

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