

Asymmetric Effects of the COVID-19 Pandemic on Out-migration Scale: A Study Based on the Nonlinear ARDL Model

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Abstract

In view of the impact of COVID-19 on the scale of migration, a nonlinear autoregressive distributed lag model (NARDL) was constructed to analyze the nonlinear asymmetric relationship and dynamic multiplier effect between the number of new positive COVID-19 cases, the number of new discharges, the proportion of quarantine personnel and the scale of migration in Shanghai. The results showed that the model passed the long-term asymmetric test of the long-term asymmetric relationship between the target variables, indicating that the changes of COVID-19 epidemic had an unequal asymmetric effect on the scale of migration. The results of the dynamic multiplier effect show that, in the long run, the increase of new positive cases will significantly change the scale of migration, and the decrease of the number of new discharges may have a significant asymmetric effect on the scale of migration, while the increase of the number of new discharges is difficult to inhibit the scale of migration. Both the rise and fall of the proportion of isolation control personnel have an asymmetric effect on the emigration scale index.

Keywords

COVID-19; Out-migration Scale; Asymmetric Effects; NARDL Model; Dynamic Multipliers.

1. INTRODUCTION

Since the global outbreak of COVID-19, population mobility has been subject to extensive restrictions, which has also severely affected global economic development. In the early stage of the COVID-19 pandemic, Jithesh P K studied the impacts of lockdown, migration and vaccination on COVID-19 based on a cellular automaton model [1]. Regarding the relationship between pandemic development and population migration, many studies have mainly focused on the influence of population migration on the transmission and spread of COVID-19 [2]. The impact of the pandemic on migration scale is not simply linear. Li et al. found that reduced population mobility in the United States was significantly correlated with a decline in the COVID-19 incidence rate, and this effect varied over time and between urban and rural areas [3].

In recent years, the NARDL model has been widely used in empirical research related to COVID-19 [4,5]. However, empirical studies directly addressing the asymmetric relationships between pandemic variables (the number of new positive cases, the number of new discharges, and the proportion of people under quarantine control) and migration scale remain scarce. Against this background, this paper uses pandemic data of Shanghai from April 13, 2022 to June 23, 2022 as the research object, and applies the NARDL model to analyze the nonlinear asymmetric relationships and dynamic multiplier effects among the number of new positive cases, the number of new discharges, the proportion of people under quarantine control, and Shanghai's out-migration scale index.

2. METHODS

2.1. Variable Description and Data Sources

The data in this article comes from Shanghai's COVID-19 data from April 13 to June 23, 2022. It studies the impact of the COVID-19 pandemic on the migration scale index (Y) based on daily data of new positive cases (X1), new discharges (X2) and the proportion of people under quarantine control (X3). It models the potential long-term relationships and asymmetries in the dynamic adjustment patterns among the four variables, constructs a nonlinear autoregressive distributed lag NARDL model, derives asymmetric cumulative dynamic multipliers, and examines the asymmetric adjustments of the explanatory variables following positive and negative shocks.

2.2. Unit Root Test Methods

Examining the stationarity of time series is essential for time series data analysis. A time series is considered stationary if its mean and variance do not change over time. Stationarity can be tested using various methods, such as the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. The ADF test is frequently employed for unit root testing, with the formula specified as follows:

$$\Delta Y_t = \alpha + \beta_t + \rho Y_{t-1} + \sum_{i=1}^k \gamma_i \Delta Y_t + \varepsilon_t$$

$$\Delta Y_t = (p-1)Y_{t-1} + \varepsilon_t$$

2.3. NARDL Model Specification

The Nonlinear Autoregressive Distributed Lag (NARDL) model, proposed by Shin et al., is an asymmetric nonlinear cointegration approach[6]. The asymmetry and nonlinearity of this method are achieved by decomposing the explanatory variables into partial sum processes of positive and negative changes, thereby enabling the examination of asymmetric transmission in both the long run and the short run. The NARDL model constructed in this paper is specified as follows:

$$\begin{aligned} \Delta \ln Y_{2t} = & \phi_0 + \beta_1 \sum_{i=1}^t \Delta \ln Y_{2t-i} + \beta_{2a} \sum_{i=1}^t \Delta \ln X1_{t-i}^+ + \beta_{2b} \sum_{i=1}^t \Delta \ln X1_{t-i}^- + \beta_{3a} \sum_{i=1}^t \Delta \ln X2_{t-i}^+ \\ & + n\beta_{3b} \sum_{i=1}^t \Delta \ln X2_{t-i}^- + \beta_{4a} \sum_{i=1}^t \Delta \ln X3_{t-i}^+ + \beta_{4b} \sum_{i=1}^t \Delta \ln X3_{t-i}^- + \phi_1 \ln Y_{2t-i} + \phi_{2a} \Delta \ln X1_{t-1}^+ \\ & + \phi_{2b} \Delta \ln X1_{t-1}^- + \phi_{3a} \Delta \ln X2_{t-1}^+ + \phi_{3b} \Delta \ln X2_{t-1}^- + \phi_{4a} \Delta \ln X3_{t-1}^+ + \phi_{4b} \Delta \ln X3_{t-1}^- n + \varepsilon_t \end{aligned}$$

3. RESULTS

3.1. Unit Root Test Results

All manuscripts must be in English, also the table and figure texts, otherwise we cannot publish your paper. Please keep a second copy of your manuscript in your office. 3.1 Unit Root Test Results

The stationarity of the time series data was examined using the ADF and PP tests, and the unit root test results for each variable are presented in Table 1. As shown in Table 1, all variables are integrated of order one, I(1), satisfying the requirements for cointegration testing.

Table 1. Unit root test of variables

Variable	Augmented Dickey-Fuller test			Phillips-Perron test			Stationarity
	Intercept	Intercept and trend	None	Intercept	Intercept and trend	None	
Level series							
lnY	-0.465 (0.891)	-2.040 (0.570)	-0.649 (0.433)	-0.501 (0.884)	-2.199 (0.483)	-0.764 (0.382)	Non-stationary
LnX1	-0.085 (0.947)	-2.467 (0.343)	-2.682 (0.008)	-0.056 (0.950)	-2.541 (0.308)	-2.735 (0.007)	Non-stationary
LnX2	1.849 (0.999)	-2.152 (0.508)	-2.111 (0.034)	2.689 (1.000)	-1.898 (0.645)	-2.183 (0.029)	Non-stationary
LnX3	-1.646 (0.454)	-6.060 (0.000)	-0.037 (0.667)	-5.596 (0.000)	-6.301 (0.000)	0.076 (0.704)	Non-stationary
First difference series							
D.lnY	-8.172 (0.000)	-8.114 (0.000)	-7.814 (0.000)	-8.170 (0.000)	-8.112 (0.000)	-7.844 (0.000)	Stationary
D.lnX1	-8.350 (0.000)	-8.301 (0.000)	-7.446 (0.000)	-8.350 (0.000)	-8.300 (0.000)	-7.598 (0.000)	Stationary
D.lnX2	-12.533 (0.0001)	-13.402 (0.0001)	-11.758 (0.000)	-12.741 (0.0001)	-19.966 (0.0001)	-11.554 (0.000)	Stationary
D.lnX3	-9.115 (0.000)	-9.058 (0.000)	-9.186 (0.000)	-35.379 (0.0001)	-35.203 (0.0001)	-36.26 (0.000)	Stationary

3.2. NARDL Model Estimation Results

Having established the long-run cointegration relationship between Shanghai's out-migration scale index and the COVID-19 pandemic indicators (new confirmed positive cases, new recoveries, and the proportion of quarantined individuals), we proceed to determine the long-run and short-run asymmetries of the main model. The regression results of the NARDL model are presented in Tables 2 and 3, yielding the specification NARDL(1, 3, 1, 2, 1, 1, 0).

Table 2. Model estimation results

Variable	Coefficient	P-value
LN(-1)	0.845	0.000
LN1_POS	0.137	0.282
LN1_POS(-1)	-0.200	0.136
LN1_POS(-2)	0.120	0.317
LN1_POS(-3)	0.142	0.102
LN1_NEG	-0.027	0.600
LN1_NEG(-1)	0.117	0.059
LN2_POS	-0.128	0.067
LN2_POS(-1)	0.292	0.001
LN2_POS(-2)	-0.221	0.002
LN2_NEG	-0.032	0.586
LN2_NEG(-1)	-0.085	0.126
LN3_POS	-0.123	0.460
LN3_POS(-1)	-0.497	0.014
LN3_NEG	-0.343	0.002
C	-0.175	0.069

The estimation results of the asymmetric short-run and long-run coefficients of the NARDL model are presented in Table 3. The error correction term ECt-1 is negative and statistically significant at the 1% level, thereby providing further evidence of cointegration among the variables in the model and representing the speed of adjustment from the short run to the long run.

Table 3. NARDL model effect test results

Long-run estimates				
Variable	Coefficient		P-value	
LNx1_POS	1.284716		0.0751	
LNx1_NEG	0.58127		0.0354	
LNx2_POS	-0.36659		0.3065	
LNx2_NEG	-0.7567		0.0644	
LNx3_POS	-3.99823		0.0221	
LNx3_NEG	-2.2105		0.0452	
C	-1.12764		0.0052	
Short-run estimates				
Variable	Coefficient		P-value	
D(LNx1_POS)	0.136832		0.2819	
D(LNx1_POS(-1))	-0.12013		0.3174	
D(LNx1_POS(-2))	-0.14226		0.1018	
D(LNx1_NEG)	-0.0268		0.6002	
D(LNx2_POS)	-0.12765		0.0674	
D(LNx2_POS(-1))	0.220856		0.0018	
D(LNx2_NEG)	-0.03229		0.5857	
D(LNx3_POS)	-0.12343		0.4602	
D(LNx3_NEG)	-0.34326		0.0016	
CointEq(-1)	-0.15529		0.0078	
Model summary				
Criterion	AIC	SC	Adj-R2	D-W
Value	1.8489	-1.327	0.979	1.938
Bounds test results				
	F-statistic	Lower bound	Upper bound	Conclusion
Cointegration test	2.498	3.15	4.43	Cointegration
Long-run and short-run asymmetry tests				
WLR	4.869(0.0047)			
WSR	1.185(0.3138)			

According to the results of the Bounds test, the F-statistic is lower than the lower critical value at the 1% significance level, so the null hypothesis is rejected, which indicates that there exists a long-run cointegration relationship between the out-migration scale index and various epidemic variables. The long-run asymmetry test is significant at the 1% level, verifying that the epidemic exerts a long-run unequal asymmetric impact on out-migration scale. In terms of long-term estimation results, the coefficient of $LNx1^-$ is significant at the 5% level. A 1% decrease in the number of new positive cases contributes to an average increase of 0.5813% in the out-migration scale index, while the coefficient of $LNx1^+$ is insignificant, suggesting that the

growth of confirmed cases has no significant effect on out-migration scale. The coefficient of $LN\bar{X}2^-$ is significant at the 5% level. Every 1% reduction in newly discharged patients leads to an average drop of 0.7567% in the out-migration scale index, yet the coefficient of $LN\bar{X}2^+$ is insignificant with an unobvious positive effect. Both coefficients of $LN\bar{X}3^+$ and $LN\bar{X}3^-$ are significant at the 5% level. A 1% rise and a 1% fall in the proportion of people under quarantine control cause the out-migration scale index to decline by 3.9982% and 2.2105% on average respectively, showing a two-way inhibitory effect.

3.3. Model Stability Tests

After determining the parameters of the NARDL model, stability tests were conducted using the CUSUM and CUSUMSQ tests. According to these methods, if the model structure is stable, the plots of the recursive residuals cumulative sum and the recursive residuals cumulative sum of squares should remain within the 5% significance bounds, i.e., lying between the two critical lines. The results of the model stability tests are presented in Figure 1.

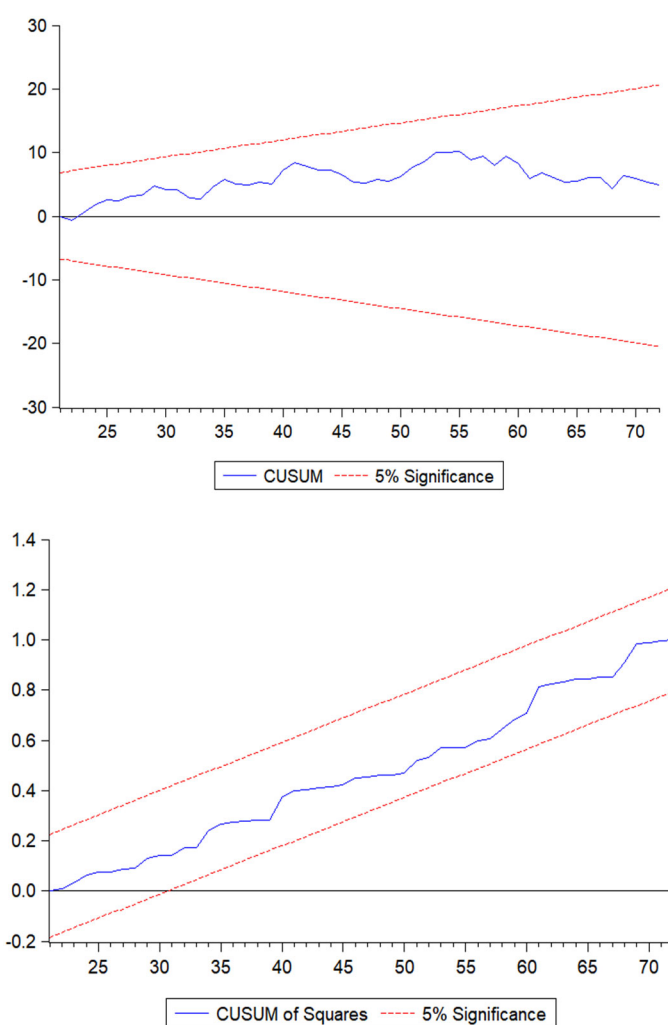


Figure 1. Stability test of NARDL model at 5% significance level

As shown in Figure 1, both the cumulative sum of recursive residuals and the cumulative sum of squared recursive residuals of the NARDL model fall within the critical bounds at the 5% significance level, confirming that the model is stable and reliable for estimating both short-run and long-run coefficients.

3.4. Dynamic Multiplier Effects

Dynamic multiplier analysis is employed to capture the short-run and long-run asymmetric shocks of new confirmed positive cases, new recoveries, and the proportion of quarantined individuals on the out-migration scale index. The dynamic multiplier effect plots for each variable are presented in Figures 2–4, where the solid and dashed black lines represent positive and negative shocks, respectively, and the thick and thin dashed red lines indicate asymmetry and critical bounds, respectively.

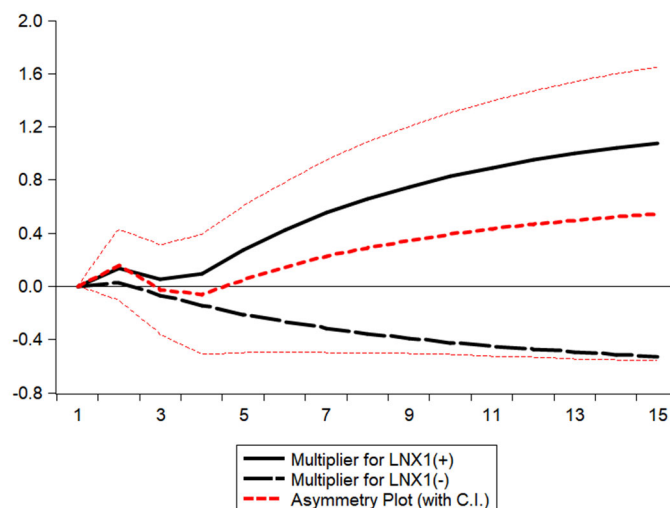


Figure 2. The dynamic multiplier between the scale of emigration index and the number of new positive cases

As shown in Figure 2, new confirmed positive cases exert both short-run and long-run asymmetric effects on the out-migration scale index. Under a positive shock, the adjustment of out-migration exhibits a pattern of initially rising, then falling, and subsequently rising again. Under a negative shock, out-migration first increases briefly, then declines continuously and tends to stabilize. Moreover, the cumulative multiplier effect of an increase in new confirmed positive cases is greater than that of a decrease.

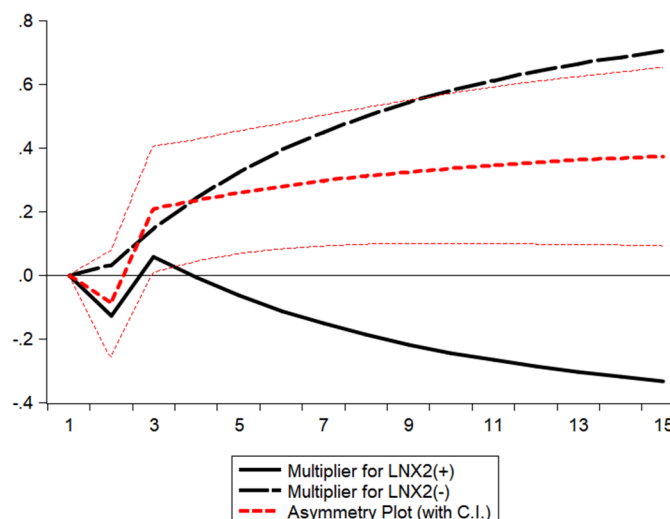


Figure 3. The dynamic multiplier between the scale of migration index and the number of new discharges

As shown in Figure 3, new recoveries exert asymmetric effects on the out-migration scale index. Under a positive shock, the out-migration scale index increases only in the short run (approximately 3 periods) and then declines, failing to generate a sustained restraining effect. Under a negative shock, the out-migration scale index continuously decreases, indicating that a reduction in new recoveries has a more significant long-run impact on migration scale, which may be attributable to measures such as quarantine and traffic restrictions. Moreover, the cumulative multiplier effect of a decrease in new recoveries is greater than that of an increase.

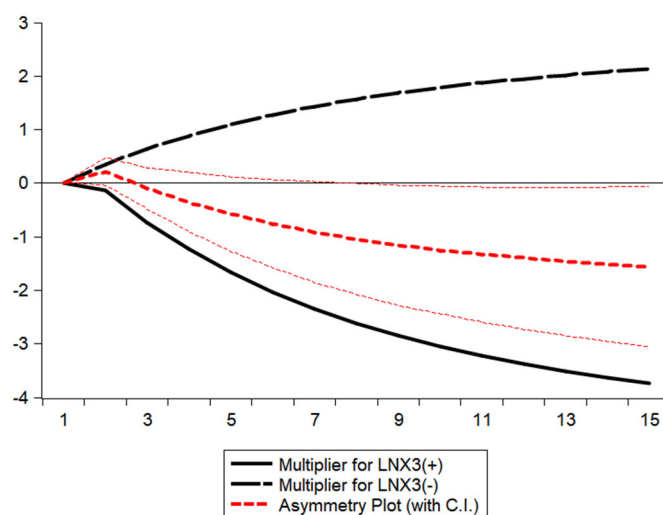


Figure 4. Dynamic multipliers of the scale of emigration index and the proportion of personnel under quarantine control

From Figure 4, it can be seen that the proportion of people under isolation control shows an asymmetric dynamic adjustment for the positive and negative changes in the migration scale index. The negative effect of the proportion of isolation-controlled people is on a continuously increasing trend, while the positive effect is continuously decreasing. This suggests that in the long term, both the increase and decrease in the proportion of people under isolation control have a significant asymmetric effect on the migration scale index, indicating that measures like isolation control had a notable impact on migration scale during the pandemic. At the same time, the cumulative dynamic multiplier effect of an increase in the proportion of isolation-controlled people on the migration scale index is greater than the cumulative multiplier effect of a decrease.

4. CONCLUSION

This paper analyses the nonlinear asymmetric relationship and dynamic multiplier effects between the COVID-19 pandemic and the emigration scale index of Shanghai by constructing a NARDL nonlinear autoregressive distributed lag model. The results show that the NARDL model passes the long-term asymmetry test, indicating that changes in the COVID-19 pandemic have unequal asymmetric effects on emigration scale. Dynamic multiplier analysis shows that the number of new positive cases, the number of new discharges, and the proportion of people under isolation control all present asymmetric dynamic adjustments to positive and negative changes in the emigration scale index. In the long term, an increase in new positive cases significantly affects migration scale, a decrease in new discharges may have a noticeable asymmetric impact on the emigration scale index, while an increase in new discharges hardly suppresses the emigration scale index. Changes in the proportion of people under isolation

control, whether rising or falling, also have significant asymmetric effects on the emigration scale index.

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