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Non-linear Autoregressive Distributed Lag Model Approach and the J-Curve Phenomenon: China and Her Major Trading Partners

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Non-linear Autoregressive Distributed Lag Model Approach and the J-Curve Phenomenon: China and Her Major Trading Partners

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ABSTRACT. Following Bahmani-Oskooee and Fariditavana (2016), I use the non-linear autoregressive distributed lag model approach of Shin et al. (2013) to examine the J-curve phenomenon for the Chinese economy. Most recent studies have used methods such as the linear autoregressive distributed lag model approach of Pesaran et al. (2001) which assumes a linear relationship between the exchange rate and the trade balance. I argue that lack of support for the J-curve effect could be due to assuming that effects of exchange rate changes are symmetric. Using a linear autoregressive distributed lag model approach, I am able to find support for the J-curve effect in two out of four models. When using a non-linear autoregressive distributed lag model approach, however, I am able to find support for the J-curve effect in three out of four models.

I. Introduction

> "When I was a graduate student, estimating and interpreting distributed lags topped the agenda of macroeconomists and other applied economists."
>
> *-Thomas Sargent*

The J-curve effect is the phenomenon that occurs after a devaluation or depreciation of a country's currency; the trade balance worsens in the short-run and then, in the long run, improves to a level higher than where it started. The idea was first introduced by Magee (1973) who found that this phenomenon occurs due to adjustment lags (Bahmani-Oskooee and Fariditavana 2016, 51-70).

The first to test this concept was Bahmani-Oskooee (1985). He tested the J-curve effect using aggregate trade flows of one country with the rest of world. With a VAR model he was able to impose a lag structure on the exchange rate. Using this method, he was able to find evidence that supported the J-curve effect (Bahmani-Oskooee and Fariditavana 2016).

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Rose and Yellen (1989) took a different approach to test this effect by using trade flows between the U.S. and each of her six major trading partners. Using Engle and Granger (1987) cointegration and error-correction modeling methods they concluded there was no evidence to support the J-curve effect. Rose and Yellen (1989) provided an alternative definition of the J-curve effect as a short-run deterioration combined with long-run improvement of the trade balance due to currency devaluation or depreciation (Bahmani-Oskooee and Fariditavana 2016).

Bahmani-Oskooee and Fariditavana (2016) improved on the method used by Rose and Yellen (1989) by considering the effect of purchasing power parity. They used a linear autoregressive distributed lag model following Pesaran et al. (2001) which allows variables to be stationary and non-stationary. They used this method to test the phenomenon between the U.S. and each of her six major trading partners. They found evidence of the J-curve effect in only three out of the six models. Bahmani-Oskooee and Fariditavana (2016) concluded that failure to find more evidence that supported the J-curve effect was due to assuming that the adjustment variables follow a linear path. This assumption implies that the effects of exchange rate changes are symmetric, when in fact effects of exchange rate changes could be asymmetric. Bahmani-Oskooee and Fariditavana (2016) then introduced a non-linear autoregressive distributed lag model following Shin et al. (2013) to test whether exchange rate changes have asymmetric or symmetric effects on the U.S. trade balance with each of her six major trading partners. When using this approach, the J-curve effect was supported in five out of the six models. By introducing a non-linear adjustment process, Bahmani-Oskooee and Fariditavana (2016) were able to provide evidence that in most cases the effects of exchange rate changes are asymmetric and they were able to discover more evidence that supported the J-curve effect (Bahmani-Oskooee and Fariditavana 2016).

II. Background

There have been a limited number of studies that have tested the J-curve effect between China and her trading partners. This is mostly due to the lack of data available since China began her reforms in 1978. Most of the studies that have tested this phenomenon have been unable to provide evidence that support the J-curve effect, even though China has been known to devalue her currency frequently in an attempt to improve her trade balance.

Brada et al. (1993) tested the J-curve effect for China's economy using a simple VAR model and a cointegration model following Johansen (1988). Quarterly data over 1980QI-1989QIV were used to conduct their test. They were unable to find evidence to support the J-curve effect. Similarly, Zhang (1999) was unable to provide evidence that supported the J-curve effect when also using a cointegration model following Johansen (1988). He used monthly data over the period 1986-1997. Weixian (1999) took a different approach in testing the J-curve effect in China's economy by using a cointegration model and following Engle and Granger (1987). Using this method, he was unable to find evidence supporting the J-curve effect. Narayan (2005) tested the J-curve effect using a linear autoregressive distributed lag model. He was unable to find evidence of the J-curve effect using trade flows between China and the U.S. with monthly data over the period November 1979-September 2002. Bahmani-Oskooee and Wang (2006) tested the effect by using trade flows between China and 13 of her major trading partners. They used a linear autoregressive distributed lag model and concluded there was no evidence of the J-curve effect when using quarterly data over the period 1983-2002 (Bahmani-Oskooee and Wang 2006).

All of these previous studies use models that employed aggregate trade data or assume a linear adjustment process between the exchange rate and the trade balance. Could the J-curve effect be recognized using trade data between China and her major trading partners if the models and methods used by Bahmani-Oskooee and Fariditavana (2016) are introduced? Whether the J-curve effect exists is valuable for determining if China's devaluation of her currency has promoted economic growth.

III. Data, Variables, and the Models

DATA

The IMF is governed by and accountable to the 189 countries that make up its membership. It was created in 1945 in order to foster global monetary cooperation, secure financial stability, facilitate international trade, promote high employment and sustainable growth, and reduce poverty around the world. A range of time series data on IMF lending, exchange rates, and other economic and financial indicators is published by the IMF.

I extract the data from the Directions of Trade Statistics from the IMF. I use quarterly data over the period 1986I-2014IV to carry out the empirical analysis.

Variables

Measure of trade balance: the dependent variable

China's trade balance with each of its trading partners, TB_i, is defined as China's imports from partner i divided by her exports to partner i.

Determinants of trade balance: explanatory variables

The explanatory variables used in the model are divided into three categories. The first is a measure of China's income, Y_{CHN}, which is proxied by an index of real GDP. Quarterly GDP data were not available for China; it was calculated from annual GDP figures following the method in Bahmani-Oskooee (1986). The second is China's trading partner's income, Y_i, which is also proxied by an index of real GDP. The third is the real bilateral exchange rate of Chinese renminbi against the currency of partner i, REX_i, which is defined as $REX_i = (P_{CHN} * \frac{NEX_i}{P_i})$. NEX_i is the nominal exchange rate defined as a number of units of partner i's currency per Chinese renminbi. Because of the availability of data, the nominal exchange rate of partner i's currency per U.S. dollar was used to calculate NEX_i. P_{CHN} is the price level in China and P_i is the price level in country i. Both are proxied by an index of a CPI.

Model

I assume the trade balance between China and trading partner i depends directly on the real bilateral exchange rate, China's income, and trading partner i's income. I begin with examining the relationship between the trade balance and exchange rate by following Bahmani-Oskooee and Fariditavana (2016) and employ the following model:

$$LnTB_{i,t} = a + bLnY_{CHN} + cLnY_{i,t} + dLn\,REX_{i,t} + \varepsilon_t \qquad (1)$$

Economic theory suggests that exports to trading partner i will increase when trading partner i's income increases. Theory also suggest that imports from trading partner i will increase when China's income increases. Therefore, I expect the coefficient of China's income to be positive and the coefficient of trading partner i's income to be negative. The way the real exchange rate is defined allows us to evaluate the effect of changes in the exchange rate on the trade balance. If currency devaluation or depreciation improves the trade balance in the long-run, then I expect the coefficient of the real exchange rate to be positive.

The equation above is a long-run model and coefficient estimates only reflect long-run effects of the explanatory variables. By following Bahmani-Oskooee and Fariditavana (2016) and Pesaran et al. (2001) I am able to evaluate the short-run effects of the explanatory variables by introducing a short-run dynamic adjustment process into Equation (1) by using a linear autoregressive distributed lag model approach:

$$\begin{aligned}\Delta LnTB_{i,t} = a' &+ \sum_{k=1}^{n} b'k\Delta LnTB_{i,t-k} + \sum_{k=0}^{n} c'k\Delta LnY_{CHN,K} + \sum_{k=0}^{n} d'k\Delta LnY_{i,t-k} \\ &+ \sum_{k=0}^{n} e'k\Delta LnREX_{i,t-k} + \lambda_1 LnTB_{i,t-1} + \lambda_2 LnY_{CHN,t-1} + \lambda_3 LnY_{i,t-1} \\ &+ \lambda_4 LnREX_{i,t-1} + \mu t\end{aligned} \tag{2}$$

First, I estimate Equation (2) by means of OLS. The short-run effects are given by the sign and significance of the coefficients attached to the first-differenced variables and the long-run effects are given by the size and significance of λ_2 – λ_4 normalized on λ_1. Next, I establish cointegration among the variables. This must be done for long-run effects to be valid. This is achieved using the F-test following Pesaran et al. (2001) to establish the joint significance of lagged level variables as a sign of cointegration. The new critical values account for the stationarity properties of the variables. Therefore, the test does not require pre-unit-root testing. The variables could be integrated of order zero, I(0) or order one, I(1). The J-curve effect provided by Rose and Yellen (1989) is supported if the estimates of e' are negative or insignificant but the estimate of normalized λ_4 is positive and significant (Bahmani-Oskooee and Fariditavana 2015).

To implement the non-linear autoregressive distributed lag model, I first follow Bahmani-Oskooee and Fariditavana (2016) to decompose the movement of the *LnREX* variable into its negative and positive sum, defined as:

$$POS = LnREX_t^+ = \sum_{j=1}^{t} \Delta LnREX_j^+ = \sum_{j=1}^{t} \max(\Delta LnREX_j, 0)$$
$$NEG = LnREX_t^- = \sum_{j=1}^{t} \Delta LnREX_j^- = \sum_{j=1}^{t} \min(\Delta LnREX_j, 0) \quad (3)$$

Following Shin et al. (2013) and Bahmani-Oskooee and Fariditavana (2016) the following non-linear autoregressive distributed lag model can be written by replacing *LnREX* in Equation (2) by POS and NEG variables:

$$\begin{aligned}\Delta LnTB_{i,t} = a' &+ \sum_{k=1}^{n1} b_k' \Delta LnTB_{i,t-k} + \sum_{k=0}^{n2} c_k' \Delta LnY_{t-k}^{CHN} + \sum_{k=0}^{n3} d_k' \Delta LnY_{t-k}^{i} + \sum_{k=0}^{n4} e_k' \Delta POS_{t-k} \\ &+ \sum_{k=0}^{n5} f_k' \Delta NEG_{t-k} + \theta_0 LnTB_{i,t-1} + \theta_1 LnY_{t-1}^{CHN} + \theta_2 LnY_{t-1}^{i} + \theta_3 POS_{t-1} \quad (4) \\ &+ \theta_4 NEG_{t-1} + \varepsilon_t\end{aligned}$$

This non-linear autoregressive distributed lag model allows me to test whether exchange rate changes have asymmetric or symmetric effects on China's trade balance with partner i (Bahmani-Oskooee and Fariditavana 2015, 519-30).

IV. Results

I estimate both error-correction models (2) and (4) using bilateral data between China and four of her major trading partners: The United States, Hong Kong, Japan, and Australia. Following Bahmani-Oskooee and Tanku (2008) I impose a maximum of eight lags on each first-differenced variable and use Akaike's Information Criterion (AIC) to select the optimal lags. Results from each optimum model are reported in Tables 1, 2, 3, and 4. There are two parts to each table. Part I reports the estimates and diagnostics of Equation (2) and Part II does the same for Equation (4). Both parts consist of three panels. Panel A displays short-run coefficient estimates, Panel B displays long-run coefficient estimates, and Panel C reports diagnostic statistics.

First, I concentrate on the China-U.S. models. From Part I and Panel A, it is clear that the real exchange rate has no significant short-run effects. However, from Panel B I gather that at least at the 10% level of significance, it carries a positive and significant coefficient in the long-run, supporting the J-curve-effect. From the long-run results I also gather that the level of income in both China and the U.S. are significant at the 5% significance level. To determine if these long-run estimates are valid I establish joint significance of lagged level variables in Equation (2) as a sign of cointegration. From Panel C I gather that the F test is significant, supporting cointegration. In cases that the F test is not significant, following Bahmani-Oskooee and Tanku (2008) I use normalized long-run coefficient estimates and Equation (1) and calculate the error term. Denoting this new series by *ECM,* I replace the linear combination of lagged variables in (2) by $ECM_{t\text{-}1}$, and estimate the new model after imposing the same optimum lag orders from Panel A. A significantly negative coefficient obtained for $ECM_{t\text{-}1}$ will support convergence toward long-run equilibrium or cointegration (Bahmani-Oskooee and Fariditavana 2016).

A few other diagnostic statistics are also reported in Panel C. The Breusch-Godfrey LM statistic is reported to make sure residuals are autocorrelation free. Ramsey's RESET statistic is reported to check misspecification. To test for stability of all coefficient estimates, I apply CUSUM and CUSUMSQ tests to the residuals of the optimum model. Stable coefficients by either test are indicated by "S" and unstable ones by "US".

From the long-run coefficient estimates in Part II of Table 1, I gather that at least at the 5% significant level the NEG variable carries a positive and significant coefficient. The POS variable does not carry a significant coefficient. This implies that the long-run effects of exchange rate are asymmetric. A real depreciation of the Chinese renminbi has a long-run favorable effects on the China-U.S. trade balance. A real appreciation of the Chinese reminbi has no long-run effects.

Results of China-Hong Kong (Table 2) are similar to those of the China-U.S. case because the J-curve-effect is supported by both models. When I consider the results from the non-linear autoregressive distributed lag model I find that the exchange rate changes have asymmetric effects because both POS and NEG variables carry significantly positive coefficients in the long-run that are not close in size.

TABLE 1: China-U.S. Models

	0	1	2	3	4	5	6	7
	Part I							
	Panel A: A Short-run Estimates							
	Lags							
ΔlnTB		1.067467	.4494521	.7250086	.6442567	.4994607	.2837926	
		(3.62)	(1.63)	(3.06)	(3.34)	(3.99)	(3.15)	
ΔlnY_{CHN}	.1600707	1.107112	.8244445	.8127349				
	(0.66)	(2.69)	(2.96)	(3.42)				
ΔlnY_{US}	-2.816808							
	(2.26)							
ΔlnREX	.3305705	-.9101526	-.710383	.29761	.1079957	.1476638	.1983921	-.5061156
	(1.14)	(1.54)	(1.44)	(0.66)	(0.27)	(0.40)	(0.70)	(2.00)
	Part B: Long-run Estimates							
Constant	.0275947							
	(1.28)							
lnY_{CHN}	-.544218							
	(1.99)							
lnY_{US}	-1.540753							
	(2.09)							
lnREX	.6949189							
	(1.93)							
	Panel C: Diagnostic Statistics							
	F	ECM_{t-1}	LM	RESET	CUSUM	$CUSUM^2$	$\overline{R}^2$	
	10.106	-1.828202	1.128	1.24	S	S	0.8515	
		(5.81)						
	Part II							
	Panel A: Short-run Estimates							
	Lags							
ΔlnTB		.7409837	.1819258	.4906529	.457155	.3746759	.2015577	
		(2.91)	(0.78)	(2.40)	(2.74)	(3.37)	(2.43)	
ΔlnY_{CHN}	.0102495	1.345242	.8816235	.8637024				
	(0.04)	(3.20)	(3.17)	(3.81)				
ΔlnY_{US}	-2.844147							
	(2.40)							
ΔPOS	1.780344							
	(3.02)							
ΔNEG	-6560321	-.0366904	-.7529336	1.225384	.208237	.3248617	.3543776	-.7416608
	(1.76)	(0.06)	(1.40)	(2.45)	(0.43)	(0.73)	(1.01)	(2.23)
	Panel B: Long-run Estimates							
Constant	.0295649							
	(1.48)							
lnY_{CHN}	-.9601004							
	(2.37)							
lnY_{US}	-1.945977							
	(2.20)							
POS	1.218118							
	(0.29)							
NEG	.1365266							
	(2.71)							
	Panel C: Diagnostic Statics							
	F	ECM_{t-1}	LM	RESET	CUSUM	$CUSUM^2$	$\overline{R}^2$	
	8.765	-1.461552	1.303	1.80	S	S	0.8328	
		(5.37)						

Numbers inside the parenthesis are the absolute value of the t-ratio

TABLE 2: China-Hong Kong Models

	0	1	2	3	4	5	6	7
	Part I							
	Panel A: A Short-run Estimates							
	Lags							
ΔlnTB		.5923073	.2747588	.5286422	.1887338	.3549378	.107691	.2495296
		(2.33)	(1.21)	(2.61)	(1.07)	(2.34)	(0.94)	(2.65)
ΔlnY$_{CHN}$	-.0311511	1.748798	1.06141	1.266985	.2903636	.5019244	-.080519	.658511
	(0.11)	(2.74)	(1.73)	(2.15)	(0.54)	(1.07)	(0.24)	(2.27)
ΔlnY$_{HK}$	.1481577							
	(0.73)							
ΔlnREX	.2062555	.5892554	.7385698	.4995901	1.100792	.7701388	.7701388	
	(.078)	(1.29)	(1.64)	(1.24)	(2.94)	(2.68)	(1.83)	
	Part B: Long-run Estimates							
Constant	.0189986							
	(0.74)							
lnY$_{CHN}$	-.964297							
	(2.18)							
lnY$_{HK}$	-.3206438							
	(1.57)							
lnREX	.090095							
	(1.80)							
	Panel C: Diagnostic Statistics							
	F	ECM$_{t-1}$	LM	RESET	CUSUM	CUSUM^2	$\bar{R}^2$	
	7.957	-1.460008	1.297	3.27	S	S	0.7386	
		(5.20)						
	Part II							
	Panel A: Short-run Estimates							
	Lags							
ΔlnTB		.6867603	.3169116	.5947729	.2612028	.4357477	.1782191	.3288506
		(2.70)	(1.38)	(2.85)	(1.42)	(2.72)	(1.48)	(3.39)
ΔlnY$_{CHN}$	-.1747768	3.117428	2.117699	2.095198	.78741	.7314278	-.0198357	.7153486
	(0.58)	(3.91)	(3.07)	(3.33)	(1.44)	(1.55)	(0.06)	(2.53)
ΔlnY$_{HK}$	-.4571036	-1.728966	-.9728493	-1.4617				
	(0.70)	(1.47)	(1.22)	(2.03)				
ΔPOS	2.197622							
	(2.70)							
ΔNEG	-.5172471	1.021803	1.301547	.8064669	1.651745	1.006003	.5969067	
	(1.30)	(1.96)	(2.42)	(1.70)	(3.44)	(2.84)	(1.70)	
	Panel B: Long-run Estimates							
Constant	.032788							
	(1.27)							
lnY$_{CHN}$	-1.867193							
	(3.26)							
lnY$_{HK}$	.0506318							
	(0.06)							
POS	1.393555							
	(2.64)							
NEG	.565118							
	(2.50)							
	Panel C: Diagnostic Statics							
	F	ECM$_{t-1}$	LM	RESET	CUSUM	CUSUM^2	$\bar{R}^2$	
	7.291	-1.57699	1.733	2.66	S	S	0.6688	
		(5.65)						

Numbers inside the parenthesis are the absolute value of the t-ratio

TABLE 3: China-Japan Models

	0	1	2	3	4	5	6	7
	Part I							
	Panel A: A Short-run Estimates							
	Lags							
ΔlnTB		.2795758	-.2025988					
		(2.31)	(1.96)					
ΔlnY$_{CHN}$	.8084741	.976625	1.444375	1.215276	.8950152	.6236518	.2827116	
	(4.20)	(2.26)	(3.26)	(2.87)	(2.47)	(2.63)	(1.41)	
ΔlnY$_{JPN}$	-.3490455	-.2973765	-.5172389	-.1882204	-1.869171			
	(0.42)	(0.28)	(0.49)	(0.22)	(2.51)			
ΔlnREX	.1030318							
	(0.91)							
	Part B: Long-run Estimates							
Constant	.0240956							
	(1.41)							
lnY$_{CHN}$	-.6323813							
	(1.37)							
lnY$_{JPN}$	-.958469							
	(0.74)							
lnREX	.1067939							
	(0.91)							
	Panel C: Diagnostic Statistics							
	F	ECM$_{t-1}$	LM	RESET	CUSUM	CUSUM^2	$\overline{R}^2$	
	8.764	-.9647727	1.026	1.51	S	S	0.7083	
		(5.46)						
	Part II							
	Panel A: Short-run Estimates							
	Lags							
ΔlnTB		1.024768	.5798649	.7914478	.6331628	.5823105	.3851147	.1999338
		(4.62)	(2.78)	(4.44)	(3.78)	(4.24)	(3.66)	(2.59)
ΔlnY$_{CHN}$	.7478215	-.2817801						
	(4.58)	(1.59)						
ΔlnY$_{JPN}$	-.3768747	2.404531	2.486377	1.447777				
	(0.49)	(2.41)	(2.93)	(1.87)				
ΔPOS	-.2312644	1.071239	.6209442					
	(1.09)	(3.86)	(2.79)					
ΔNEG	.0659171	-.3855748	-.5600856					
	(0.32)	(1.68)	(2.86)					
	Panel B: Long-run Estimates							
Constant	.0257895							
	(1.53)							
lnY$_{CHN}$	.4095042							
	(2.52)							
lnY$_{JPN}$	-1.983891							
	(3.30)							
POS	-.8140803							
	(4.00)							
NEG	.288323							
	(2.77)							
	Panel C: Diagnostic Statics							
	F	ECM$_{t-1}$	LM	RESET	CUSUM	CUSUM^2	$\overline{R}^2$	
	10.233	-1.798129	0.260	0.06	S	S	0.6840	
		(6.97)						

Numbers inside the parenthesis are the absolute value of the t-ratio

TABLE 4: China-Australia Models

	0	1	2	3	4	5	6	7
	Part I							
	Panel A: A Short-run Estimates							
	Lags							
ΔlnTB		.3404901 (1.37)	-.2605978 (1.24)	-.0977668 (0.69)	-.238531 (2.41)			
$\Delta \ln Y_{CHN}$	.006456 (0.02)							
$\Delta \ln Y_{AUS}$	-1.369198 (2.79)							
ΔlnREX	-.0606567 (0.25)							
	Part B: Long-run Estimates							
Constant	.0077016 (0.43)							
$\ln Y_{CHN}$	.0049855 (0.02)							
$\ln Y_{AUS}$	-1.695897 (2.70)							
lnREX	-.0468408 (0.25)							
	Panel C: Diagnostic Statistics							
	F 7.626	ECM_{t-1} -1.294956 (4.43)	LM 1.210	RESET 1.25	CUSUM S	$CUSUM^2$ S	$\overline{R}^2$ 0.7436	
	Part II							
	Panel A: Short-run Estimates							
	Lags							
ΔlnTB		.3618217 (1.44)	-.2389511 (1.12)	-.0844479 (0.59)	-.2297393 (2.29)			
$\Delta \ln Y_{CHN}$	-.0294823 (0.09)							
$\Delta \ln Y_{AUS}$	-1.360953 (2.76)							
ΔPOS	-.2981261 (0.69)							
ΔNEG	.1048562 (0.30)							
	Panel B: Long-run Estimates							
Constant	.0175276 (0.76)							
$\ln Y_{CHN}$	-.0223133 (0.09)							
$\ln Y_{AUS}$	-1.666131 (2.71)							
POS	-.225633 (0.70)							
NEG	.0793591 (0.30)							
	Panel C: Diagnostic Statics							
	F 6.158	ECM_{t-1} -1.321288 (4.47)	LM 1.057	RESET 1.13	CUSUM S	$CUSUM^2$ S	$\overline{R}^2$ 0.7422	

Numbers inside the parenthesis are the absolute value of the t-ratio

Results of China-Japan (Table 3) do not support the J-curve-effect by the linear autoregressive distributed lag model. When I consider the results from the non-linear autoregressive distributed lag model I find that the J-curve effect is supported. This is because the NEG variable carriers a significantly positive coefficient in the long-run.

The J-curve effect is not supported by the linear autoregressive distributed lag model or the non-linear autoregressive distributed lag model in the China-Australia case (Table 4).

V. Conclusion

The J-curve effect exists when a country's trade balance worsens in the short-run and then improves to a level higher than where it started in the long run, following a devaluation or depreciation of its currency. Earlier studies tested the phenomenon in the Chinese economy by using aggregate and disaggregate trade flows along with standard VAR models and autoregressive distributed lag models. The previous studies found no evidence of the J-curve effect.

In this paper I introduce the linear autoregressive distributed lag model and the non-linear autoregressive distributed lag model approach used by Bahmani-Oskooee and Fariditavana (2016) to test the phenomenon for the Chinese economy. When the linear autoregressive distributed lag model was used, the J-curve effect was supported in two out of the four models. When the non-linear autoregressive distributed lag model was used, the J-curve effect was supported in three out of the four models. The non-linear autoregressive distributed lag model helps to discover more evidence of the J-curve effect and also shows that in most cases the effects of exchange rate changes are asymmetric.

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