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Panel cointegration analysis of export facilitation and comparative advantages: The case of Chinese low-technology manufactures

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ABSTRACT

This paper attempts to investigate the nexus between the comparative advantages and the net export capability by employing panel Granger non-causality analysis technique on a dataset of the Chinese low-technology manufactures for the period of 1987-2011. The results show that the net export capabilities significantly surpass the comparative advantages. However, there is no sign that the enhanced net export capabilities as the results of export facilitation have any statistically significant effect on the improvement of the Chinese comparative advantages in the low-technology manufactures. On the opposite, the comparative advantages Granger cause the net exports in both short-run and long-run. Further examination indicates that the short-run effect is negative while the long-run effect is positive, implying that in the short-run, the export facilitation targets at saving the deteriorating comparative advantages, and the long-run net export capabilities are essentially based upon the comparative advantages. At least for the low-technology manufactures, the Chinese export facilitation aims at employment and economic growth instead of the improvement of comparative advantages.

KEYWORDS

Comparative advantage; Export facilitation; Trade policy; Panel cointegration analysis; Granger non-causality test.

INTRODUCTION

It is controversial whether export facilitation can improve the comparative advantages of industries[1,2]. Dynamic comparative advantage theories and strategic trade theories state the answer should be yes, because developing countries may be locked in a "comparative advantage trap" without being able to update their low-technological labor-intensive industries[3,4]. On the other hand, the free-trade proponents believe that policy intervention in trade will only distort the factor markets, arguing that export facilitation is one of the manifestations of trade protectionism, which is not confined to the form of import limitation[5,6]. Behind these academic controversies, there is still an even more fundamental question left to be answered: is it really advantageous for a country to improve the comparative advantage of a specific industry? Even according to the former strand of literatures, the export facilitation of a developing country should target at improving the international competitiveness of higher technology or strategically potential domestic industries by taking advantage of the effects of increasing returns[7,8]. However, a country may also have plenty of incentives to develop labor-intensive industries with a mere purpose of employment enhancement. In this case, deteriorating comparative advantages may adversely encourage the government of a developing country to facilitate exports in these labor-intensive industries to generate more working opportunities. This is especially true when the country is in transition of an urban-rural dual economy, which is in face of the problems of absorbing the comparatively excessive rural labor forces.

Chinese experiences in the recent years add evidences that government can play a crucial role in trade development and economic growth[9]. There are three main causes for China's heavy dependence on exports. Firstly, the domestic demand has been limited in relation to the supply side, driving China to seek external demand from the world market. Secondly, the need to absorb the redundant rural labor force has made structural changes in industries. The relatively cheap labor cost has guaranteed the development of Chinese exports in labor-intensive manufactures. Thirdly, Chinese government has taken active measures to facilitate exports to dynamic comparative advantage. In short words, China may have facilitated its exports in both higher-technology and low-technology labor-intensive industries with essentially different policy targets.

Does the Chinese government aggressively facilitate her export in low-technology products? What is the policy target of the Chinese export facilitation in low-technology products? How is the performance of the trade policy? This study addresses these questions by empirically testing for the Granger causal relation between the indices of net export ratio and revealed symmetric comparative advantage. Our findings from panel data shed a new light on the understanding of the performance of Chinese strategic trade policy.

MEASUREMENTS AND DATA

Our basic idea is to measure the degree of a country's export facilitation, or the propensity for divergence of trade pattern, by deducting the comparative advantage from the net export capability of a specific product.

Net export ratio

Net exports capability in a product is measured by

$$y_k = NX_k = (X_k - M_k)/(X_k + M_k) \quad \textbf{(1)}$$

where y_k (or NX_k) stands for the net exports ratio of product k; X and M represent exports and imports. This indicator consequently captures the percentage of the trade balance in the total exports and imports. The value interval of y_k is [-1, 1] with a mean of zero. y_k>0 indicates trade surplus in product k, and the extreme of y_k=1 implies there are only exports. Similarly, y_k<0 indicates trade deficit in product k.

Revealed symmetric comparative advantage

Comparative advantage is measured by the Balassa index of

$$RCA_{ik} = (X_{ik} / X_i)/(X_{wk} / X_w) \quad \textbf{(2)}$$

where RCA_k is the revealed comparative advantage of product k exports[10]; X_i is the total exports of the concerned country i; X_{wk} is the world exports of product k and X_w is the total world exports. The value interval of RCA_k is [0, ∞], with a median of 1. In order to compare with y_k, this study follows Dalum (1998) transformation technique[11] to normalize the RCA_k index by

$$x_k = RSCA_k = (RCA_k - 1)/(RCA_k + 1) \quad \textbf{(3)}$$

where x_k is the revealed symmetric comparative advantage.

The value interval of x_k is [-1, 1] with a mean of zero, which is exactly identical to the distribution of y_k. Note that when RCA_k=1, we have x_k =0, implying that the specialization of country i in product k is identical to the world average. Similarly, x_k>0 reflects to RCA_k>1 and x_k<0 is equivalent to RCA_k<1.

Propensity for divergence of trade pattern

This study defines divergence of trade patterns as the relative difference between the net export capability and the current comparative advantage. Heckscher-Ohlin-Ricardo approach predicts that a country tends to specialize in and to export the comparative advantage products. The higher the comparative advantage, the more product k exports by the country. Assuming in equilibrium, y_k is strictly in accordance with x_k, the condition of trade pattern equilibrium is thus given by y_k=x_k. Define

$$h_k = y_k - x_k \quad \textbf{(4)}$$

as the propensity for trade pattern divergence. The h-index measures the difference between y_k and x_k. It has a symmetric distribution with a mean of zero. h_k=0 indicates a trade pattern equilibrium, while h_k>0 reveals a propensity for "positive divergence" which is featured by excessive net exports in relation to the temporary comparative advantage. This form of trade pattern divergence may reflect a mercantilist tendency inherent in the possible strategic trade policy which targets at the comparative advantage improvement of a specific industry, by means of export promotion or/and import protection. When it involves a category of n products, we use

$$H = \sum_{k=1}^{n} (h_k \cdot w_k) \text{ , } w_k = (X_k + M_k) / \sum_{k=1}^{n} (X_k + M_k) \quad \textbf{(5)}$$

to measure the weighted divergence propensity for trade pattern. w_k is the weight of product k in the total value of exports and imports of the category.

Data

We follow Lall (2000)[12] to classify the Standard International Trade Classification Revision 2 (SITC Rev.2) three-digit products. As shown in TABLE 1, there are two sub-categories of low-technology manufactures: the category of “textile, garment and footwear” (LT1) includes 20 products while the category of “other low-technology products” contains 24 products. All of the trade data are compiled from UN Comtrade database. We eliminate “Iron, steel hoop, strip” (code 675) from our samples because China has involved no trade of this product since 1992. TABLE 1 reports the classification scheme.

TABLE 1 : Product codes of low-technology manufactures

Category	SITC Rev. 2 three-digit product codes
LT1	611, 612, 613, 651, 652, 654, 655, 656, 657, 658, 659, 831, 842, 843, 844, 845, 846, 847, 848, 851
LT2	642, 665, 666, 673, 674, 675, 676, 677, 679, 691, 692, 693, 694, 695, 696, 697, 699, 821, 893, 894, 895, 897, 898, 899

A preliminary observation of the weight averaged trade patterns of the low-technology category shows that the Chinese comparative advantage in low-technology products has been stable while the net export ratio has exhibited an apparently increasing trend. As a result, the H index has been positive since 1990 and records 0.363 in the year of 2011, implying a strong propensity for trade pattern divergence.

PANEL COINTEGRATION ANALYSIS

Panel unit root test

In order to avoid spurious regression which arises from the using non-stationary panel data, we conduct panel unit root tests to examine the stationarity of y_k and x_k series. Five alternative methods are available, among which LLC and Breitung assume common unit root process, while IPS, ADF-Fisher and PP-Fisher assume individual unit root process. We carry out lag selection via Schwarz criterion (SC).

TABLE 2 presents the summary of the results for y_k and x_k. For both y_k and x_k level series, the method of Breitung can not reject the null of common unit root, implying that neither is stationary. Both are stationary upon taking first-difference, making it possible and necessary for panel cointegration tests.

TABLE 2 : Panel unit root test for net export ratio and revealed symmetric comparative advantage

	y_k			x_k			Δy_{kt}			Δx_{kt}		
	CT	***C***	***CT***	***C***	***N***	***N***	***C***	***N***	***CT***	***CT***	***C***	***N***
LLC	-13.50 (0.00)	-4.06 (0.00)	-18.38 (0.00)	-24.37 (0.00)	-28.12 (0.00)	-1.32 (0.09)	-4.96 (0.00)	-4.68 (0.00)	-17.56 (0.00)	-13.81 (0.00)	-16.56 (0.00)	-22.25 (0.00)
Breitung	1.61 (0.95)	2.79 (1.00)	2.58 (1.00)	-9.77 (0.00)	-16.96 (0.00)	0.45 (0.67)	1.38 (0.92)	-0.05 (0.48)	-11.09 (0.00)	-8.89 (0.00)	-9.14 (0.00)	-16.28 (0.00)
IPS	-8.74 (0.00)	-2.38 (0.01)	-8.95 (0.00)	-20.53 (0.00)			-4.56 (0.00)		-17.42 (0.00)	-14.86 (0.00)	-16.59 (0.00)	
ADF	460.2 (0.00)	367.0 (0.00)	432.2 (0.00)	625.9 (0.00)	623.2 (0.00)	151.6 (0.00)	192.0 (0.00)	171.5 (0.00)	417.6 (0.00)	364.1 (0.00)	429.9 (0.00)	575.9 (0.00)
PP	93.41 (0.27)	104.3 (0.09)	149.7 (0.00)	545.2 (0.00)	738.2 (0.00)	131.4 (0.00)	166.4 (0.00)	189.6 (0.00)	537.0 (0.00)	551.7 (0.00)	483.8 (0.00)	669.4 (0.00)

Note: C stands for individual intercept, T for trend and N for no exogenous variable; probabilities are in parentheses.

Pedroni panel cointegration test

Considering the heterogeneity across individual of the panel members, this study uses Pedroni’s method to test for the cointegration relationship between y_k and x_k. Among the seven available statistics, Panel v, Panel rho, Panel PP and Panel ADF are based on pooling the residuals of the regression along the within-dimension, while Group rho, Group PP, Group ADF are based on pooling the residuals of the regression along the between-dimension. TABLE 3 shows the results of three possible model specifications.

TABLE 3 : Panel cointegration test results

	Panel v	Panel rho	Panel PP	Panel ADF	Group rho	Group PP	Group ADF
CT	0.72 (0.23)	-0.88 (0.19)	-3.63 (0.00)	-4.60 (0.00)	2.05 (0.98)	-1.81 (0.04)	-7.51 (0.00)
C	1.92 (0.03)	-2.03 (0.02)	-3.03 (0.00)	-3.39 (0.00)	1.12 (0.87)	-0.94 (0.17)	-0.75 (0.23)
N	-1.58 (0.94)	0.07 (0.53)	-1.68 (0.05)	-1.26 (0.10)	2.68 (1.00)	-3.01 (0.00)	-1.69 (0.05)

Note : C stands for individual intercept, T for trend and N for no exogenous variable; Automatic selection of maximum lags is based on Schwarz information criterion.

When the model specification allows for individual intercept and deterministic time trend, panel PP, Panel ADF, Group PP, Group ADF reject the null of no cointegration at 0.05 confidence level. We thus can come to the conclusion that there is a cointegration relationship between y_k and x_k.

MODEL SPECIFICATIONS FOR PANEL VECM

We intend to employ vector error correction model (VECM) to conduct panel Granger non-causality tests. A crucial step is to specify the VECM as well as the cointegrating equation.

Panel cointegrating equation

We assume there are three possible types of panel models for the cointegrating equation. Let y_{kt} be the dependent variables, the unrestricted panel model is given by

$$y_{kt} = \alpha_k + \beta_k \cdot x_{kt} + e_{kt} \tag{6}$$

where α_k stands for intercepts, β_k represents the parameters for estimation, and e_k is the residuals. By allowing individual intercepts and parameters, this is a variable-coefficient model with fixed effect. If we impose the restriction of $\beta_1=\beta_2=\ldots=\beta_k=\beta$, where β is a common coefficient, we can therefore have a variable-intercept panel regressional model

$$y_{kt} = \alpha_k + \beta \cdot x_{kt} + e_{kt} \tag{7}$$

By further imposing the restriction on the intercepts of $\alpha_1=\alpha_2=\ldots=\alpha_k=\alpha$, we can obtain a mixed-pool model in the form of

$$y_{kt} = \alpha + \beta \cdot x_{kt} + e_{kt} \tag{8}$$

which requires a common intercept as well as a common coefficient for all cross-sections of the pooled panel model. The multiple possibilities imply that any pre-assumption of the specification of the optimal model would be imprecise or even dangerous. We therefore employ F-tests to determine which is the optimal model

Model specification tests

Let S_1 be the sum of squared residuals of variable-coefficient model (6), S_2 be that of variable-intercept model (7), and S_3 be that of mixed-pool model (8). Using S_1, S_2 and S_3, we can obtain F_1 and F_2 statistics. F_1 statistic is

$$F_1 = \frac{(S_2 - S_1)/[(n-1)K]}{S_1/[nT - n(K+1)]}$$

which is asymptotically distributed as an F-statistic with $(n-1)K$ and $n(T-K-1)$ degrees of freedom, where n is the number of cross-sections, T is the number of sample periods and K is the number of independent variables. The F_1 statistic compares the (6) and (7), with a null hypothesis of $\beta_1=\beta_2=\ldots=\beta_k=\beta$. A significant F_1 statistic rejects the null of variable-intercept model.
In step three, we obtain F_2 statistic by

$$F_2 = \frac{(S_3 - S_1)/[(n-1)(K+1)]}{S_1/[nT - n(K+1)]}$$

which is asymptotically distributed as an F-statistic with $(n-1)(K+1)$ and $n(T-K-1)$ degrees of freedom. The F_2 statistic compares the (6) and (8), with a null hypothesis of $\alpha_1=\alpha_2=\ldots=\alpha_k=\alpha$ and $\beta_1=\beta_2=\ldots=\beta_k=\beta$. A significant F_2 statistic rejects the null of mixed-pool model, implying that the optimal model should allow for individual fixed-effects.

Moreover, the optimum model may either contain deterministic time trend(s) or not. TABLE 4 reports the F-test results for both occasions.

TABLE 4 : Specification Test for the Panel Cointegrating Equation

	S_1	S_2	S_3	F_1	F_2	SC
No trend	14.13	40.49	123.08	21.02 (0.00)	57.90 (0.00)	-0.362
Trend	25.08	44.54	126.39	18.28 (0.00)	47.57 (0.00)	-0.656

F_1 and F_2 statistics are both significant, suggesting that the variable-coefficient model is optimal. When comparing the SC statistics for the two variable-coefficient models (one has individual time trends and one has no trend), we conclude that the optimal model have deterministic time trend as shown in

$$y_{kt} = C_{kt} + \tau_k \cdot Trend + \beta_k \cdot x_{kt} + \varepsilon_k \tag{9}$$

where τ_k is the individual parameter of time trend (Trend). We estimate the model in this form and make the residuals for further use.

Panel vector error correction model

There are also three possible basic specifications for the panel VECM, each has or has no individual time trend. TABLE 5 reports the F-test results separately, by allowing the maximum lags to be up to four.

TABLE 5 : Specification test for panel VECM

Lag	No trend						Deterministic Trend					
	S_1	S_2	S_3	F_1	F_2	SC	S_1	S_2	S_3	F_1	F_2	SC
1	11.06	12.97	13.38	0.88 (0.84)	0.86 (0.82)	-1.43	11.78	12.97	13.38	0.69(0.99)	0.69(0.99)	-1.44
2	8.26	12.05	12.45	1.41 (0.00)	1.34 (0.00)	0.28	9.03	12.05	12.46	1.16(0.07)	1.10(0.17)	-1.45
3	6.06	11.00	11.35	1.67 (0.00)	1.59 (0.00)	0.75	6.92	11.02	11.37	1.22(0.02)	1.16(0.06)	0.56
4	3.10	9.67	9.99	3.04 (0.00)	2.90 (0.00)	0.93	4.11	9.73	10.06	1.71(0.00)	1.63(0.00)	0.87

If no trend involves, mixed-pool model is optimal for one lag while a variable-coefficient model is suitable for 2, 3 and 4 lags. When assuming the presence of deterministic time trend, a mixed-pool model is optimal for 1 and 2 lags, while a variable-coefficient model is adequate when the lag is 3 or 4. We estimate all of the eight possible models and obtain the SC statistics. SC statistics indicate that

$$\Delta y_{kt} = \rho \cdot e_{kt-1} + \sum_{p=1}^{2}\left(\psi_p \cdot \Delta y_{kt-p} + \xi_p \cdot \Delta x_{kt-p}\right) + \theta \cdot Trend + c_k + \mu_k \quad \textbf{(10)}$$

$$\Delta x_{kt} = \rho^* \cdot e_{kt-1} + \sum_{p=1}^{2}\left(\psi_p^* \cdot \Delta y_{kt-p} + \xi_p^* \cdot \Delta x_{kt-p}\right) + \theta^* \cdot Trend + c_k^* + \mu_k^* \quad \textbf{(11)}$$

are the optimal panel VECMs with dependent variables to be Δy_{kt}. and Δx_{kt} respectively. The symbol of $\Delta(\cdot)$ stands for first difference; the subscript p stands for lags; e_{kt-1} is the error correcting term or the residuals of (9); c is a common intercept; ρ, ψ_p, ξ_p and θ are parameters for estimation and μ_k is the residual term. The asterisks in (11) distinguish the related parameters in (10).

PANEL GRANGER NON-CAUSALITY TESTS

Methods of short-run and long-run Tests

e_{kt-1} in (10) and (11) reflects the long-run relationship between y_{kt} and x_{kt} and the lags of the first differences ($\Delta(\cdot)$) contain the short-run information. Following previous literatures, we argue that the key to identify short-run and long-run effects is the assumption of "other conditions keeping unchanged"[13]. We test for the Wald restrictions of the null of $\xi_1=\xi_2=0$ for (10) and $\psi^*_1=\psi^*_2=0$ for (11) to examine the short-run Granger non-causality because the tests involve no error correcting term.

We examine the long-run effects by two approaches. First, we test ρ =0 for (10) and ρ^*=0 for (11) to see whether the long-run equilibrium relation improves the explanatory power of the models. Second, we test for the null of $\rho^*_k=\xi_1=\xi_2=0$ for (10) and $\rho^*=\psi^*_1=\psi^*_2=0$ for (11) to check whether the lagged differences of the independent variable exert significant effects upon the dependent variables via e_{kt-1}.

Test results

Granger non-causality test results are shown in TABLE 6. We identify a uni-directional Granger causal relationship running from Δx_{kt} to Δy_{kt}. In other words, revealed symmetric comparative advantage is the short-run determinant of net export capability. When examining the estimation in (10), we find ξ_1= –0.157 and ξ_2= –0.143, implying that NX_k has negative short-run effects upon $RSCA_k$.

In the long-run, the error correcting term (e_{kt-1}) as well as its combination with Δx_{kt-1} and Δx_{kt-1} Granger causes Δy_{kt} uni-directionally. Because the cointegrating equations are the residual series of the variable-coefficient models, we aggregate the coefficients (β_k) in (9), which is the long-run equilibrium cointegrating equation, to generate a sum of 35.13, with a mean of 0.817. This indicates that the long-run effect of comparative advantage upon net export capability is positive.

TABLE 6 : Panel Granger non-causality test results

	Short-run Effects		Long-run Effects		
	Δy_{kt-1}, Δy_{kt-2}	Δx_{kt-1}, Δx_{kt-1}	e_{kt-1}	e_{kt-1}, Δy_{kt-1}, Δy_{kt-2}	e_{kt-1}, Δx_{kt-1}, Δx_{kt-2}
Δy_{kt}		8.03 (0.00)	129.7 (0.00)		43.32 (0.00)
Δx_{kt}	1.45 (0.24)		2.06 (0.15)	1.84 (0.14)	

Note: The first column indicates dependent variables of the panel VECMs and the values presented are F-statistics.

CONCLUSION

The Chinese industrialization and urbanization has attracted a large number of rural labor forces to move to the non-agricultural industries. On one hand, this process has generated abundant supply in the labor market, enabling China to gain comparative advantages in the labor-intensive low-technology manufactures. On the other hand, it has also brought tight pressure of employment, which has prompted the Chinese government to seek for even stronger comparative advantages by means of export facilitation. Using panel data of 1987-2011, this paper empirically studies the dynamic relation between Chinese net export ratio and revealed symmetric comparative advantage.

Firstly, we find that the net export ratio of the Chinese low-technology manufactures as a category has kept increasing since 1987, while the revealed symmetric comparative advantage has exhibited no obvious trend. The inconsistent time paths have given rise to a positive propensity for trade pattern divergence, where the net export ratio keeps upwardly diverged from the revealed symmetric comparative advantage. This phenomenon may be much a result of governmental export facilitation.

Secondly, Granger causality runs form revealed symmetric comparative advantage to net export ratio in both short-run and long-run. However, revealed symmetric comparative advantage exerts positive effect upon net export ratio only in the long-run, while the short-run effect is negative. In other words, a drop in the comparative advantage will encourage export facilitation in short-run.

Last but not least, we can not ignore the fact that net export ratio has no significant effect on comparative advantage. This implies that the performance of government export facilitation is very poor in terms of improving the comparative advantage of Chinese low-technology manufactures.

These evidences suggest a story that Chinese government does take measures to facilitate the exports of the low-technology manufacturing industries with a policy target of improving the domestic employment. The net export capabilities of these industries are based upon the comparative advantages, although there are indications that the Chinese government has an expectation that the export facilitation efforts can level up the comparative advantages at the expense of market distortion. The facilitation efforts, however, are virtually in vain.

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REFERENCES

[1] T.Iwanow, C.Kirkpatrick; Trade facilitation and manufactured exports: Is Africa different? World Development, **37(6)**, 1039-1050 **(2009)**.

[2] D.Lederman, M.Olarreaga, L.Payton; Export promotion agencies: Do they work? Journal of Development Economics, **91(2)**, 257-265 **(2010)**.

[3] M.Cimoli; Lock-in specialization (Dis)advantages in a structuralist growth model, in J.Fagerberg, B.Verspagen, Von N.Tunzelmann (Eds), "The dynamics of technology trade and growth, Aldershot: Edward Elgar, **(1994)**.

[4] A.P.D'Costa; Export growth and path dependence: The locking-in of innovations in the software industry. Science Technology and Society, **7(1)**, 51-89, 2002 **(2002)**.

[5] D.Pang, Y.Hong; Measuring distortions of trade patterns: An application to China. IEEE International Conference on Service Operations and Logistics and Informatics, 424-429 **(2010)**.

[6] Y.Hong, H.Su; A test of dynamic comparative advantage hypothesis using panel data of the Chinese trade in medium-technology products. 2010 International Conference on Management Science and Engineering (ICMSE), 1600-1605 **(2010)**.

[7] E.Helpman, P.R.Krugman, Market structure and foreign trade: Increasing returns, imperfect competition, and the international economy. Cambridge, MA: MIT Press, **(1985)**.

[8] P.R.Krugman; Rethinking international trade, Cambridge, MA: MIT Press, (**1994)**.

[9] B.Hoekman, A.Nicita; Trade policy, trade costs, and developing country trade. World Development, **39(12)**, 2069-2079 **(2011)**.

[10] B.Balassa; The purchasing-power parity doctrine: A reappraisal. The Journal of Political Economy, **72(6)**, 584-596 **(1964)**.

[11] B.Dalum, K.Laursen, G.Villumsen; Structural change in OECD export specialisation patterns: De-specialisation and 'stickiness'. International Review of Applied Economics, **12(3)**, 423-443 **(1998)**.

[12] S.Lall; The technological structure and performance of developing country manufactured exports, 1985-98. Oxford Development Studies, **28(3)**, 337-369 **(2000)**.

[13] Y.Hong; A study of changes and distortions of Chinese commodity trade pattern. Ph.D. dissertation of Jilin University, (in Chinese), **(2009)**.

[14] Y.Hong, Z.Song, J.Wang, H.Su; Comparative advantage of food exports, rural-urban income disparity and agricultural employment: Empirical evidence from China. Journal of Chemical and Pharmaceutical Research, **6(1)**, 439-445 **(2014)**.