12. Corruption and Income Inequality in Asian Countries: Bootstrap Panel Granger Causality Test[1]

Chiung-Ju HUANG[2]

Abstract

The purpose of this study is to investigate the causal relationship between corruption and income inequality experienced in ten Asian economies over the period 1995 to 2010. This study utilizes the bootstrap panel Granger causality approach, which allows both cross-sectional dependence and heterogeneity across countries, and is based on seemingly unrelated regressions (SUR) systems and Wald tests with country-specific bootstrap critical values. The empirical results show that there is a unidirectional causality from corruption to income inequality in China and the Philippines. Meanwhile, a one-way causal relationship running from income inequality to corruption exists in Indonesia, Japan, Korea, and Thailand.

Keywords: corruption, income inequality, cross-sectional dependence, heterogeneity, panel Granger causality test

JEL Classification: C23, C33, H80

1. Introduction

Corruption represents a common issue globally. The Corruption Perception Index, published annually by Transparency International (TI) since 1995, has been widely credited for raising the issue of corruption to the international policy agenda. The Corruption Perception Index ranks approximately 200 countries/territories based on how corrupt their public sector is perceived, allotting scores between 0 and 100, where 0 means that a country is perceived as highly corrupt, while 100 means it is perceived as very clean. According to the Corruption Perception Index 2012, Taiwan ranks 37th, with a score of 61; being perceived as more corrupt than other Asian countries such as Singapore (ranking 5th, with a score of 87) and Japan (ranking 17th, with a score of 74), but less corrupt than South Korea, Malaysia, China, Thailand, Indonesia, Vietnam, and the Philippines. While no country has received a perfect score (100), two-thirds of countries score below 50, indicating a serious corruption problem.

---

[1] This study was presented at 2013 Global Business, Economics, and Finance Conference, Wuhan University, China, 9-11 May 2013.

[2] Department of Public Finance, Feng Chia University, Taiwan, E-mail:cjhuang@fcu.edu.tw.

Corruption might decrease a country's competitiveness, cause a decrease in economic growth, and lead to a decrease in government spending on education and health, while causing an increase in income inequality and distorting a countries' market mechanism and resource allocation (Tanzi, 1997; Rose-Ackerman, 1999). In recent years, the relationship between corruption and income inequality has been an ongoing topic of debate and has been examined in several empirical studies. While a large number of empirical studies have attempted to explore the relationship between corruption and economic growth, there are only a few empirical studies that analyze the causality between corruption and income inequality. In their respective studies, Johnston (1989), Jain (2001), Hendriks and Muthoo (1998), Li *et al*. (2000), Gupta *et al*. (2002), Gyimah-Brempong (2006), and Dincer and Gunalp (2011) suggest that corruption directly causes an increase in the level of income inequality. Similarly, other studies also suggest that corruption has changed the distribution of social welfare spending and will benefit the rich people (Gupta *et al*., 2000; Tanzi and Davoodi, 1997). However, Dobson and Ramlogan-Dobson (2010) suggest that the impact of corruption on income inequality is actually negative.

In recent years, economic growth in Asia has rapidly expanded, but several countries have also experienced increase in corruption and income inequality. Therefore, the question that is often raised is whether there is a causality relationship between corruption and income inequality. While most existing studies on this topic explore how the OECD countries, the European countries, the Americas, the Latin America, or the African countries have experienced serious corruption accompanied with increasing income inequality, there are few studies that focus on the Asian countries. This study examines the causality between corruption and income inequality experienced in ten Asian countries. The ASEAN+3 (excluding Brunei, Cambodia, Laos, and Myanmar) and Taiwan are selected as the main countries of interest for this empirical study.[3] We use panel data from ten Asian economies over the period 1995-2010 and adopt the panel Granger causality test to examine whether corruption causes income inequality or income inequality causes corruption.

2. Data

Annual data involving ten Asian countries (including China, Indonesia, Japan, South Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, and Vietnam) from 1995 to 2010 was used in the analysis. Variables *CPI* and *Gini* indicate Corruption Perception Index and Gini Index, respectively.[4] *CPI* denotes the level of corruption and is based on the Corruption Perception Index and data on *CPI* was obtained from the Transparency International. Countries with a higher Corruption Perception Index

[3] The Association of Southeast Asian Nations (ASEAN), established in 1967, comprises ten countries: Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar (Burma), Philippines, Singapore, Thailand, and Vietnam. ASEAN+3 is a forum that functions as a coordinator of cooperation between the ASEAN and the three East Asia nations of China, Japan, and South Korea.

[4] Gini Index equals to the Gini coefficient times 100.

score are perceived as having less corruption.[5] We adopt the SPSS procedures to handle missing data (e.g. Vietnam's Corruption Perception Index in 1995 and 1996 is not available) and obtain the predicted data in SPSS data transformations. *Gini* standards for income inequality, which is measured by Gini Index, and data on *Gini* is obtained from World Development Indicators (WDI) databank, the Standardize World Income Inequality Database (SWIID), Human Development Report (HDI), and each country's Bureau of Statistics.

3. Methdology

The method used in this study to detect potential causal linkages between corruption and income inequality is the bootstrap panel Granger causality testing approach developed by Kónya (2006). This approach has three main advantages. First, it does not require pretesting for unit roots and cointegration. Traditional causality tests proceed with the the unit root and cointegration tests, which are generally characterized as having lower power and inconsistent test results. Instead, the approach used in this study extends the framework of Phillips (1995) by generating country specific bootstrap critical values and, therefore, does not require pretesting for unit roots and cointegration.[6] Second, the approach allows for contemporaneous correlation across countries and cross-country heterogeneity. Approaches based on a traditional panel vector autoregressions or panel vector error-correction model do not take into account cross-country interrelations and country-specific heterogeneity, and thus provide biased results when testing causal relationships between two time series. Last, the approach used in this study detects the frequency and specific members of the panel for which one-way, two-way, or no Granger casuality exists. Before proceeding with the bootstrap panel causality test, three issues should be addressed, as follows.

3.1. Cross-sectional Dependence Tests

One important issue to be considered in a panel data analysis is to test for cross-sectional dependence across countries. Before estimating empirical models, we first test for cross-sectional dependence. Breusch and Pagan (1980) propose the Lagrange Multiplier (LM) test to detect cross-sectional dependence. To compute the LM test requires the estimation of the following panel data model:

$$Gini_{it} = \alpha_i + \beta_i' CPI_{it} + \varepsilon_{it} \text{ for } i = 1,\dots,N \text{ ; } t = 1,\dots,T \quad (1)$$

where: *Gini* and *CPI* represent the Gini index and the corruption perception index; *i* is the cross-sectional dimension, *t* is the time dimension; α_i and β_i are the individual

[5] Over the 1995 to 2011 period, the Corruption Perception Index ranks countries/territories on a scale of 0 to 10, with 0 indicating highly corrupt and 10 indicating very clean. In 2012, the Corruption Perception Index scores countries on a scale from 0 to 100 instead of a scale of 0 to 10.

[6] The result of Phillips (1995) shows that "optimal estimation of the cointegration space is attainted in fully modified vector autoregression without prior knowledge of the number of unit roots in the system, without pretesting to determine the dimension of the cointegration space and without the use of restricted regression technigues like reduced rank regression.

intercepts and slope coefficients, respectively. In the LM test, the null hypothesis of no cross-sectional dependence is $H_0 : Cov(\varepsilon_{it}, \varepsilon_{jt}) = 0$ for all *t* and $i \neq j$. The LM statistics is

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2 \quad (2)$$

where: $\hat{\rho}_{ij}$ is the sample estimate of pairwise correlation of the residuals from OLS estimation of equation (1) for each *i*. The test is valid for *N* relatively small and *T* sufficiently large. Pesaran (2004) proposes the following statistics and applicable for *N* and *T* large.

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}(T\hat{\rho}_{ij}^2 - 1) \quad (3)$$

Under the null hypothesis of no cross-sectional dependence with the first $T \rightarrow \infty$ and then $N \rightarrow \infty$, this test statistic is asymptotically distributed as standard normal.

Pesaran *et al*. (2008) propose a bias-adjusted test, which is a modified LM test that uses the exact mean and variance of the LM tests. The bias-adjusted LM test is

$$LM_{adj} = \sqrt{\frac{2T}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{\nu_{Tij}^2}} \quad (4)$$

where: μ_{Tij} and ν_{Tij}^2 are the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$ that are provided in Pesaran *et al*. (2008).

3.2. Slope Homogeneity Tests

Another important point in the bootstrap panel causality approach is cross-country heterogeneity. Therefore, we need to determine whether slope coefficients are homogeneous or not. In order to test slope homogeneity, the familiar approach is to apply the Wald principle. The null hypothesis is $H_0 : \beta_1 = \cdots = \beta_N$ where the Wald statistic is asymptotically distributed as Chi-square with *N*-1 degree of freedom (Mark *et al*., 2005). The Wald principle is valid for cases where the cross section dimension (*N*) is relatively small and the time dimension (*T*) of panel is large. The explanatory variables are strictly exogenous and the error variances are homoscedastic (Pesaran and Yamagata, 2008). Similar to the Wald principle, Swamy (1970) develops the slope homogeneity test that allows for cross-section heteroskedasticity. Meanwhile, the Wald and Swamy's test are applicable for panel data models where *N* is small relatively to *T*.

Pesaran and Yamagata (2008) propose a standardized version of Sway's test (the so called $\tilde{\Delta}$ test) for testing slope homogeneity in large panels. In the $\tilde{\Delta}$ test approach, the first step is to compute the modified version as follows:

$$\tilde{S} = \sum_{i=1}^{N}(\hat{\beta}_i - \tilde{\beta}_{WEF})'\frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2}(\hat{\beta}_i - \tilde{\beta}_{WEF}) \quad (5)$$

where: $\hat{\beta}_i$ is the pooled OLS estimator, $\tilde{\beta}_{WEF}$ is the weighted fixed effect pooled estimator; M_τ is an identity matrix; $\tilde{\sigma}_i^2$ is the estimator of σ_i^2. Then, the standardized dispersion statistic is developed as

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \tag{6}$$

Under the null hypothesis with the condition of (*N*, *T)*→ ∞ as long as $\sqrt{N}/T \to \infty$ and the error terms are normally distribution. The small sample properties of $\tilde{\Delta}$ test can be improved under the normally distributed errors by using the following bias-adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{\mathrm{var}(\tilde{z}_{it})}}\right) \tag{7}$$

where: the mean $E(\tilde{z}_{it}) = k$ and the variance $\mathrm{var}(\tilde{z}_{it}) = 2k(T-k-1)/(T+1)$.[7]

3.3. Panel Granger Causality Analysis

Three common approaches have been employed to examine the direction of causality in a panel data. The first approach is based on estimating a panel vector error-correction model by means of a generalized method of moments (GMM) estimator. However, this approach is not able to take into account either the cross-sectional dependence or the heterogeneity. The second is Hurlin’s (2008) approach which controls for the heterogeneity, but it is not able to take into account the cross-sectional dependence. Finally, Kónya’s (2006) approach is good enough to take into account both the cross-sectional dependence and the heterogeneity and does not require any pre-testing for panel unit root and cointegration. In this study, we adopt the panel causality approach of Kónya (2006) that is appropriate to capture the features of cross-sectional dependence and heterogeneity across countries.

The system to be estimated in the bootstrap panel approach can be written as

$$\begin{cases} Gini_{1,t} = \alpha_{1,1} + \sum_{l=1}^{mly_1} \beta_{1,1,l} Gini_{1,t-l} + \sum_{l=1}^{mlx_1} \gamma_{1,1,l} CPI_{1,t-l} + \varepsilon_{1,1,t} \\ Gini_{2,t} = \alpha_{1,2} + \sum_{l=1}^{mly_1} \beta_{1,2,l} Gini_{2,t-l} + \sum_{l=1}^{mlx_1} \gamma_{1,2,l} CPI_{2,t-l} + \varepsilon_{1,2,t} \\ \vdots \\ Gini_{N,t} = \alpha_{1,N} + \sum_{l=1}^{mly_1} \beta_{1,N,l} Gini_{N,t-l} + \sum_{l=1}^{mlx_1} \gamma_{1,N,l} CPI_{N,t-l} + \varepsilon_{1,N,t} \end{cases} \tag{8}$$

[7] See Pesaran and Yamagata (2008), p. 57.

$$\begin{cases} CPI_{1,t} = \alpha_{2,1} + \sum_{l=1}^{mly_2} \beta_{2,1,l} Gini_{1,t-l} + \sum_{l=1}^{mlx_2} \gamma_{2,1,l} CPI_{1,t-l} + \varepsilon_{2,1,t} \\ CPI_{2,t} = \alpha_{2,2} + \sum_{l=1}^{mly_2} \beta_{2,2,l} Gini_{2,t-l} + \sum_{l=1}^{mlx_2} \gamma_{2,2,l} CPI_{2,t-l} + \varepsilon_{2,2,t} \\ \vdots \\ CPI_{N,t} = \alpha_{2,N} + \sum_{l=1}^{mly_2} \beta_{2,N,l} Gini_{N,t-l} + \sum_{l=1}^{mlx_2} \gamma_{2,N,l} CPI_{N,t-l} + \varepsilon_{2,N,t} \end{cases} \quad (9)$$

where: *CPI* is the corruption perception index and *Gini* is the Gini index; *N* is the number of countries (*i*=1,…,*N*); *t* is the time period (*t*=1,…,*T*); *l* is lag length; mly_1, mlx_1, mly_2, and mlx_2 are the maximal lags for *Gini* and *CPI* in systems (8) and (9). We allow different maximal lags for *Gini* and *CPI,* but do not allow them to vary across countries. We estimate the system (8) and (9) for each possible pair of mly_1, mlx_1, mly_2, and mlx_2, respectively by assuming from 1 to 4 lags and then choose the combinations which minimize the Schwarz Bayesian Criterion (SBC). *i* is the cross-sectional dimension and *t* is the time dimension; α_i and β_i are the individual intercepts and slope coefficients, respectively.

In this system, each equation has different predetermined variables and the error terms are assumed to be cross-sectional dependence. Thus, these set of equations are the seemingly unrelated regressions (SUR) system.

In the two set of equations (8) and (9), the Granger causality for country *i* is determined as follows:

(i) if γ_{1i} =0 for all *i* , *CPI* does not Granger cause *Gini*.

(ii) if β_{2i} =0 for all *i* , *Gini* does not Granger cause *CPI*.

(iii) if (i) and (ii) hold, there is no Granger causality between *CPI* and *Gini*.

(iv) if (i) holds but (ii) does not, there is a one-way causality from *Gini* to *CPI*.

(v) if (i) does not hold but (ii) does, there is a one-way causality from *CPI* to *Gini*.

(vi) if (i) and (ii) do not hold, there is a two-way causality between *CPI* and *Gini*.

4. Empirical Results

This study takes into account both cross-sectional dependence and slope homogeneity. Before conducting the panel Granger causality analysis, we test whether there is cross-sectional dependence and slope homogeneity across countries.

Cross-sectional dependence tests were conducted using three techniques: LM , CD_{LM} , and LM_{adj} . The results are reported in Table 1. The null hypothesis of no cross-sectional dependence across countries is rejected according to these three tests. This outcome implies that a shock occurred in one of the ten Asian countries has been transmitted to other countries.

Table 1

Cross-sectional Dependence Tests

LM	85.621***
CD_{LM}	4.282***
LM_{adj}	214.8929***

Note: *** indicates significance at the 1% level.

Furthermore, we also examine whether slope homogeneity exists using the recently developed methodology proposed by Pesaran and Yamagata (2008). According to the results of slope homogeneity tests in Table 2, all tests results ($\tilde{S}$, $\tilde{\Delta}$, and $\tilde{\Delta}_{adj}$) reject the null hypothesis of slope homogeneity. The rejection of slope homogeneity implies that the direction of the causal linkages between corruption and income inequality may differ across the ten Asian countries.

Table 2

Slope Homogeneity Tests

$\tilde{S}$	49.843***
$\tilde{\Delta}$	8.909***
$\tilde{\Delta}_{adj}$	9.818***

Note: *** indicates significance at the 1% level.

The application of the bootstrap panel causality approach is appropriate for this study due to the existence of the cross-sectional dependence and heterogeneity across countries. The results of the bootstrap panel Granger causality analysis are reported in Table 3 and Table 4. Table 3 shows that the null hypothesis of Granger non-causality from *CPI* to *Gini* cannot be rejected for all ten countries, with the exception of China and the Philippines. This suggests that there is a positive causality from *CPI* to *Gini* in China and the Philippines. *CPI* represents corruption as measured by the corruption perception index, the greater the *CPI*, the lower the corruption, indicating that an increase in corruption leads to a decrease in income inequality in China and the Philippines. Subsequently, this suggests that there is a negative causality from corruption to income inequality in China and the Philippines. As for the remaining eight countries, corruption does not appear to lead directly to income inequality. Meanwhile, Table 4 indicates that the null hypothesis of Granger non-causality from *Gini* to *CPI* cannot be rejected for all ten countries, with the exception of Indonesia, Japan, Korea, and Thailand. The results show that there is a positive causality from *Gini* to *CPI* in Indonesia, Japan, and Korea, a negative causality from *Gini* to *CPI* in Thailand, and no significant Granger causality from *Gini* to *CPI* in China, Malaysia, Philippines, Singapore, Taiwan, and Vietnam. Thus, for Indonesia, Japan, and Korea, an increase in income inequality leads to a decrease in corruption, but for Thailand an increase in income inequality leads to an increase in corruption. Overall, the causal relationship from income inequality to corruption is negative in Indonesia, Japan, and Korea, positive in Thailand, and nonexistent for China, Malaysia, Philippines, Singapore, Taiwan, and Vietnam.

Table 3

CPI Does not Granger Cause Gini

Country	Estimated Coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
China	1.280	31.393*	28.579	40.721	105.887
Indonesia	-.719	2.511	16.270	28.300	67.728
Japan	-1.09	6.522	19.168	34.184	72.505
Korea	-0.228	1.983	17.352	29.788	72.327
Malaysia	-3.456	8.043	22.325	35.763	93.246
Philippines	1.509	91.407***	18.733	29.053	88.433
Singapore	2.407	10.459	19.380	31.529	71.446
Taiwan	0.747	1.517	19.872	35.338	71.542
Thailand	1.413	7.990	23.440	35.938	97.178
Vietnam	-0.397	0.389	17.555	27.912	54.453

*Notes: *** and * indicate significance at the 1% and 10% levels, respectively. Bootstrap critical values are obtained from 10,000 replications.*

Table 4

Gini Does not Granger Cause CPI

Country	Estimated Coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
China	0.011	0.419	14.914	22.220	155.893
Indonesia	0.135	53.979*	35.881	54.522	294.916
Japan	0.182	37.075*	33.834	51.172	202.543
Korea	0.238	29.756*	28.947	44.678	359.834
Malaysia	0.017	0.813	20.783	35.178	285.242
Philippines	0.167	9.192	27.373	38.479	76.891
Singapore	0.024	6.981	29.740	41.439	105.664
Taiwan	0.005	0.027	21.298	32.887	65.019
Thailand	-0.080	38.422**	22.827	32.273	88.713
Vietnam	0.040	10.524	17.902	28.264	81.223

*Notes: ** and * indicate significance at the 5% and 10% levels, respectively.*

Bootstrap critical values are obtained from 10,000 replications.

5. Conclusions

This study uses the bootstrap panel causality approach, which takes into account cross-sectional dependence and heterogeneity across countries, in order to investigate the causal relationship between corruption and income inequality experienced in ten Asian countries over the period 1995 to 2010. The empirical results indicate that there is a one-way Granger causality from corruption to income inequality for China and the Philippines, and a one-way Granger causality from income inequality to corruption for Indonesia, Japan, Korea, and Thailand.

Meanwhile, for the remaining four countries (Malaysia, Singapore, Taiwan, and Vietnam), there appears to be no Granger causality between corruption and income inequality.

These findings suggest that China and the Philippines could leverage changes in corruption level to influence income inequality. More specifically, for China and the Philippines, implementing policies to change their existing corruption levels may serve as an alternative way for the countries to improve their income inequality. Meanwhile, Indonesia, Japan, Korea, and Thailand, may potentially decrease their corruption levels by administering changes to income inequality. These findings provide important policy implications that may improve several countries seeking to address corruption and income inequality.

References

Breusch, T. S. and Pagan, A. R., 1980. The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *Review of Economic Studies*, 47(1), pp. 239-253.

Dincer, O. C. and Gunalp, B., 2011. Corruption and Income Inequality in the United States. *Contemporary Economic Policy*, 30(2), pp. 283-292.

Dobson, S. and Ramlogan-Dobson, C., 2010. Is There a Trade-off between Income Inequality and Corruption? Evidence from Latin America. *Economic Letters*, 107(2), pp. 102–104.

Colombatto, E., 2003. Why is Corruption Tolerated? *Review of Austrian Economics*, 16 (4), pp. 363-379.

Gupta, S., Davoodi, H., and Alnso-Terme, R., 2002. Does Corruprion Affect Income Distribution? *Economic Governance*, 3(1), pp. 23-45.

Gyimah-Brempong, K., and de Camacho, S. M., 2006. Corruption, Growth, and Income Distribution: Are There Regional Differences? *Economics of Governance*, 7, pp. 245-269.

Hendriks, J. M. K. and Muthoo, A., 1998. Corruption Extortion and Evasion. *University of Exeter Department of Economics Discussion Paper* No. 98/09.

Jain, A. K., 2001. Corruption: A Review. *Journal of Economic Surveys*, 15, pp. 71-121.

Johnston, M., 1989. Corruption, Inequality, and Change. In Peter M. Ward (ed.), *Corruption, Development and Inequality: Soft Touch or Hard Graf*, Routledge, London.

Kónya, L., 2006. Exports and Growth: Granger Causality Analysis on OECD Countries with a Panel Data Approach. *Economic Modelling*, 23, pp. 978–992.

Li, H. L., Xu, C., and Zou, H., 2000. Corruption, Income Distribution and Growth. *Economic Political*, 12(2), pp.155-185.

Mark, N. C., Ogaki, M., and Sul, D., 2005. Dynamic Seemingly Unrelated Cointegratin Regression. *Review of Economic Studies*, 72, pp. 797-820.

Pesaran, M. H., 2004. General Diagnostic Tests for Cross Section Dependence in Panels. *Cambridge Working Papers in Economics* No. 0435, Faculty of Economics, University of Cambridge.

Pesaran, M. H., Ullah, A., and Yamagata, T., 2008. A Bias-Adjusted LM Test of Error Cross-Section Independence. *Econometrics Journal*, 11, pp. 105-127.

Pesaran, M. H. and Yamagata, T., 2008. Testing Slope Homogeneity in Large Panels. *Journal of Econometrics*, 142, pp. 50-93.

Phillips, P. C. B., 1995. Fully Modified Least Squares and Vector Autoregression. *Econometrica*, 63, pp. 1023-1078.

Rose-Ackerman, S., 1999. *Corruption and Government. Causes, Consequences, and Reform*, Cambridge University Press.

Tanzi, V. and Davoodi, H., 1997. Corruption, Public Investment and Growth, *IMF Working Paper* No. WP/97/139.

Swamy, P. A. V. B., 1970. Efficient Inference in a Random Coefficient Regression Model. *Econometrica*, 38, pp. 311-323.