Journal of Institutional Economics (2023), **19**, 564–578
doi:10.1017/S1744137423000061

RESEARCH ARTICLE

The effect of corruption control on efficiency spillovers

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(Received 30 August 2022; revised 8 February 2023; accepted 11 February 2023; first published online 20 March 2023)

Abstract

We examine the effect of corruption control on efficiency and its implications for efficiency spillovers by a stochastic frontier model. Our dataset covers 102 countries from 1996 to 2014. We find a positive relationship between corruption control and efficiency. If neighboring countries have difficulty in handling corruption, the country would be negatively affected by its neighbors' corruption through efficiency spillovers. We then compare the efficiency differences across countries for three time periods: 1996–2002, 2002–2008, and 2008–2014. On average, technical efficiencies slightly increased in the second period compared to the first period. In the third period, the efficiencies declined, particularly in China.

Key words: Corruption; Efficiency; Spatial autoregressive model

JEL Classification: C13; C23; D24; D73

1. Introduction

Social scientists have been discussing the two sides of corruption. Several studies argued that corruption could grease the wheel of development by enhancing efficiency (Huntington, 1968; Leff, 1964; Saha and Sen, 2021) and reducing business transaction costs (Jiang and Nie, 2014). However, many others evidenced that corruption is a sand in the wheel of development. Corruption can hamper economic growth in many ways (Aidt, 2009; Mauro, 1995), such as by distorting governmental expenditures (Mauro,1998; Tanzi, 1998; Tanzi and Davoodi, 1998; Zergawu *et al*., 2020), hindering investment (Hodgson and Jiang, 2007; Zakharov, 2019), reducing the effectiveness of foreign aid (Princeton Survey Research Associates, 2003), disturbing the efficiency in fiscal policies (Fjeldstad, 2003; Runde and Metzger, 2020), lowering the quality of bureaucracy (Runde and Metzger, 2020; Tanzi, 1998), aggravating poverty and inequality (Gupta *et al*., 2002), reducing competitiveness, and finally lowering the productivity (Ogun, 2019).

Organizational corruption in public institutions and private corporations transform into many formations including bribery, kickbacks from public procurement, lobbying, extortive and evasive bribes,[1] cronyism, nepotism, patronage, graft, embezzlement of public funds, etc. (Bardhan, 2006; Kaymak and Bektas, 2015). These forms of corruption spread quite easily within and across public and private sectors while impeding economic development directly and indirectly through many channels, such as increasing cost and level of private investment (Kaymak and Bektas, 2015; Liu and Feng, 2015; Mauro, 1995, 1998; Tanzi, 1998). To expand international business, companies would pay a large amount of bribes to obtain local government contracts, permission to access the market, or government subsidies. Thus, corruption is not only an issue that exists within a single country or region but also a contagion that is spatially spreading between foreign governments and domestic private

[1]A bribe that is given to officials to do what they are supposed to do is said to be an extortive bribe. A bribe that is given to officials to avoid regulations is said to be an evasive bribe.

sectors through international business transactions (Attila, 2008; Becker *et al.*, 2009; Hodgson and Jiang, 2007). In addition, Adomako *et al.* (2021) find that institutional networking positively mediates the relationship between perceived corruption and small–medium enterprise growth.

Many countries jointly combat corruption in international business transactions by implementing laws and regulations. In a recent scandal, Walmart was fined $282 million according to the US Foreign Corrupt Practices Act (FCPA) after exercising corruption activities in Brazil, India, and Mexico. However, the anticorruption actions have not effectively alleviated the coexistence of global corruption and development. According to the World Bank estimates, businesses and individuals worldwide pay $1.5 trillion in bribes each year, making up 2% of global GDP and 10 times the total official development assistance (Runde and Metzger, 2020). Two-thirds of countries faced severe corruption issues, and most countries had minimal or no progress in tackling corruption over time (CPI 2019 Report, 2019).

While we have argued that corruption may traverse borders, we are more interested in the mechanism in which efficiency spreads between nations and the part that corruption control plays in this mechanism. To link the spatial interactions of countries' technical efficiencies and control of corruption, we estimate the efficiencies via a spatial autoregressive (SAR) stochastic frontier model using 102 countries' data from 1996 to 2014. In particular, technical efficiency measures the managerial effectiveness in terms of maximizing outputs conditional on a country's production technology, which describes the production possibilities of a country, and inputs (i.e. labor, capital, and energy). Since our measure of technical efficiency is conditional on the level of technology, a country with advanced production technology in production may still be inefficient if it does not use its technological advantage effectively. To our knowledge, our work fills the gap in the economic literature that captures the effect of corruption control on technical efficiency spillovers using the stochastic frontier model. Particularly, the model includes the distribution of the inefficiency as a function of the control of corruption variable. Our results show that control of corruption in a country would improve the efficiency of the country, which in turn helps reduce inefficiencies of neighbors through efficiency spillovers. In line with this idea, we obtain both country-specific average efficiency estimates and efficiency losses due to other countries not being fully efficient. Moreover, we estimate the averages of direct and indirect marginal effects of corruption control on efficiency. Here, the direct marginal effect refers to the counterfactual effect of corruption control on the efficiency of a country if there were no spillovers. The indirect marginal effect refers to the counterfactual effect of corruption control on the efficiency of a country only through spillovers (excluding the direct effect). Our findings indicate that control of corruption has a significant effect on a country's efficiency as well as other neighboring countries.

We then visualize the efficiency spillover effects by transferring the data into maps. The maps indicate that many countries in Southeast Asia and Europe have the highest average efficiency in the period of 1996–2014. In order to study dynamic changes of efficiencies, we split our sample into three periods following the business cycle expansions and contractions: 1994–2002, 2002–2008, and 2008–2014. The results show that global efficiency slightly increased in the second period compared to the first period. Only eight countries' efficiencies declined in the second period compared to 10 countries in the first period. However, we find that 57 countries' efficiencies decreased in the third period compared to the first period.

2. Background

Corruption not only distorts the market, but it also reduces capital and efficiencies in both public and private sectors. Corruption in the privatization of firms could intensify public capital loss (Tanzi, 1998). Many government-controlled firms were highly likely to file for bankruptcy with the inefficient allocation of resources (Kaufmann and Siegelbaum, 1997). Hence, if corruption control is a determinant of efficiency, it may help reduce the probability of bankruptcy. Corruption also negatively associates with government revenue (Kaymak and Bektas, 2015) by reducing the efficiency of government

https://doi.org/10.1017/S1744137423000061 Published online by Cambridge University Press

projects, distorting tax structure (Liu and Feng, 2015), and increasing uncertainty while reducing the expected returns of the investment outcome (Mauro, 1995). In addition, corruption increases income inequality by reducing the progressivity of the tax system while intensifying evasive and extortive tax (Gupta *et al*., 2002). Corruption also leads to trade-taxing extortion that increases the magnitude of bribes and reduces foreign producers' incentives for exports (Dutt and Traca, 2010).[2] Aside from direct economic effects, many conflicts have manifested by corruption, which further indirectly impedes economic growth. The uncertainty associated with corruption can possibly escalate to political violence, including revolutions, coups, and assassinations (Clammer, 2012).

Corruption can be traced to a more granular level, which discourages employees from improving their skills while reducing productivity (Acemoglu and Verdier, 1998; Ogun, 2019). Employees follow their colleagues after they observe the acquiescence and ignorance of corruption from managers. In the long run, it generates a culture of corruption in the firm, then further spreads it to firms in their supply chains and the entire industry.[3] To control the spillover effect of corruption through foreign business transactions, multinational corporations (MNCs) chose a collaboration structure with their local partners in highly corrupt countries that consequently minimize the uncertainty and inefficiency generated by corruption (Sartor and Beamish, 2020). In particular, MNCs are more likely to invest through a joint venture rather than a wholly owned subsidiary in highly corrupt countries.

The global battle against corruption started in the late 90's. In 1997, OECD countries held Anti-Bribery Convention to prohibit private-sector bribery (Levine, 2019). To continue with the convention, in 2003, the United Nations General Assembly adopted the 'UN Convention Against Corruption', which is a landmark of the international anticorruption treaty. Individual countries and regions also recognize the importance of anticorruption programs and legislation, such as the UK Bribery Act of 2010, and China's Anticorruption and Build a Clean Government program (Alonso *et al*., 2022; Fayissa and Nsiah, 2013; Runde and Metzger, 2020). However, these anticorruption actions have not effectively alleviated the coexistence of global corruption and development.

Besides the existing studies that examine the interplay between corruption and efficiency, many others investigate the pattern of corruption spillover effect. Tanzi (1998) highlights that corruption cumulates in individual institutions and then resembles the spreading of a contagious disease. The contagion of corruption would not only spread within the country but also spread to other countries (Hodgson and Jiang, 2007). Using the data from low- and middle-income countries, Ugur and Dasgupta (2011) show that corruption is a problem that exists in both developing and developed countries. Becker *et al*. (2009) apply a spatial econometric model to capture the regional dependency of corruption. The average level of corruption in one country's neighbor would positively affect the level of national corruption. Thus, low-corrupt countries are more likely to be in a lower-level corruption region. However, the link between spatial interactions of countries' technical efficiencies and control of corruption is missing. We will address this issue from a SAR stochastic frontier model in the next section.

3. Model and estimation

3.1. Data

In this study, we are interested in the mechanism in which efficiency spreads between nations and the role of corruption control plays in this mechanism. To conduct the study, we utilize the control of corruption variable in 'Worldwide Governance Indicators' from The World Bank. The control of

[2]A corrupt environment could aggravate customs officials' incentives to permit tariff evasion and appropriate a higher share of the ensuing rise in import rents and reduce social welfare obtain from free trade. Meanwhile, corruption also causes a trade-enhancing evasion effect. A more serious corrupt environment could aggravate customs officials' incentives to permit tariff evasion and appropriate a higher share of the ensuing rise in import rents. The evasion effect positively associates with the level of nominal tariffs and vanishes with free trade (Dutt and Traca, 2010).

[3]UNODC, Causes of private sector corruption (Retrieved date: 23 May 2021): https://www.unodc.org/e4j/en/anti-corruption/module-5/key-issues/causes-of-private-sector-corruption.html.

Table 1. Descriptive statistics

Variable	Unit	Mean	Std. Dev.	5th Perc.	Median	95th Perc.
GDP (Q)	$ Billion	655.69	1885.93	14.90	114.04	2509.51
Labor (L)	Million	26.12	87.34	0.74	5.30	75.94
Capital (K)	$ Billion	1372.46	4056.88	22.98	190.96	5888.72
Energy (E)	kt	94.12 M	314.30 M	2.05 M	14.85 M	294.88 M
Population (POP)	Person	57.31 M	174.70 M	1.95 M	12.88 M	179.42 M
Corruption control (CC)	–	−0.13	0.98	−1.29	−0.41	1.97
# Obs.	1,632					

corruption captures how much public power affects private gain, as well as the elites and private interests (WGI 2020 Data Source, 2020). The variable was generated by many resources, including corruption among public officials, the public trust of politicians, and the corruption index, etc. Our SAR stochastic frontier model links technical efficiencies and control of corruption by considering the spatial spillover effect. To build the model, we first retrieved the country and year-specific production input and output variables from the International Monetary Fund (IMF) and the World Bank (WB) websites. We consider balanced panel data for 102 countries between 1996 and 2014 (excluding 1997, 1999, 2001).[4] There are three input variables in the dataset: labor (L), capital (K), and energy (E). The labor input is the labor force variable that is obtained from the World Bank website; the capital input is the capital stock in billions of constant 2011 international dollars, which is obtained from the IMF website. Both energy consumption per capita and population variables are obtained from the World Bank website.[5] We then conduct the country's energy input in kilotonnes of oil equivalent (Ktoe) by multiplying energy consumption per capita and population. Following Kutlu (2020), we calculate the capital stock by summing the government, private, and public–private capital stocks; and we assume that the output is the real GDP in billions of constant 2011 international dollars.[6]

We obtain the geographical distances between two countries from CEPII dataset (Mayer and Zignago, 2011).[7] The geographic distance is calculated based on bilateral distances of most important cities of two countries using the great circle formula. For most countries in our dataset, the most important city of a country is taken as its capital.[8] Several previous firm-level productivity spillover studies assume that the spillover effect is a function of distance. For example, Halpern and Muraközy (2007) identify the effect of distance on horizontal and vertical productivity spillovers via labor channel by using Hungarian manufacturing firms' data. Distance limits labor mobility and further retards the effectiveness of knowledge transfer. The study suggests that knowledge transfers more effectively through face-to-face communication. Similarly, using US firm-level data, Lychagin *et al.* (2016) explain that geographic location is important for both intra- and inter-country productivity spillover. High-skilled workers are more likely to change jobs in the same geographic region, which causes knowledge flows within regional labor networks. Geographic distance weights specify that productivity spillovers decay gradually as distance becomes farther. Thus, distance is an appropriate candidate to measure productivity spillovers. In Table 1, we present the descriptive statistics for our dataset.

[4]Corruption control does not have data for these years.

[5]As of May 2022, the most recent record of national energy consumption per capita from the World Bank is the 2015 data. But most of the observations for 2015 are missing. Therefore, to obtain the balanced panel, the latest year in our sample is 2014.

[6]We consider missing values in public–private capital stocks are zeros because some countries do not have this item.

[7]www.cepii.fr/CEPII/en/

[8]Exceptions: Brazil (São Paulo), Germany (Essen), Kazakhstan (Almaty), South Africa (Cape Town), Turkey (Istanbul), and United States (New York).

https://doi.org/10.1017/S1744137423000061 Published online by Cambridge University Press

3.2. Productivity and efficiency spillover model for countries

We assume that the output and technical efficiency of a country are affected by spillovers from other countries. Following Glass *et al.* (2016), we assume that the production process of a country is determined by the following SAR production function:[9]

$$\begin{aligned} y_{it} &= \alpha_i + \rho \sum\nolimits_j w_{ij} y_{jt} + x_{it}^{'}\beta - u_{it} + v_{it} \\ u_{it} &= \sqrt{\exp(r_{it}^{'}\gamma)} u_{it}^{*}, \end{aligned} \tag{1}$$

where y_{it} is the logarithm of real GDP (output) of country i at time t; $\rho \in [0, \ 1)$ represents the SAR parameter, which is capturing the spatial spillovers; $w_{ij} \geq 0$ is the spatial weight for the effect of jth country's real GDP on the real GDP of ith country and $w_{ii} = 0$, which rules out self-spillover; x_{it} is the vector of frontier variables, which are exogenous; $u_{it} \geq 0$ is a term that captures technical inefficiency; and r_{it} is a vector of variables that affect efficiency. For example, in the 'Empirical model and results' section, we assume that r_{it} includes a variable representing the control of corruption control. Hence, the distribution of inefficiency is a function of control of corruption. We assume that $v_{it} \sim N(0, \ \sigma_v^2)$ and $u_{it}^{*} \sim N + (0, \ 1)$ are independently distributed random variables. Hence, $u_{it} \sim N^{+}(0, \ \sigma_{u,it}^2)$ where $\sigma_{u,it}^2 = \exp(r_{it}^{'}\gamma) \geq 0$. Similar to the variance of u_{it}, we reparameterize the variance of v_{it} as follows $\sigma_v^2 = \exp(c_v)$ where c_v is a parameter. We assume that the weighting matrix is row-normalized, i.e. $\sum_j w_{ij} = 1$. This weighting matrix assures that the efficiency estimates lie in the unit interval (Kutlu, 2018b). We assume that the ijth component of weighting matrix is:

$$w_{ij} \begin{cases} \exp(-d_{ij}) / \sum\limits_{i \neq j} \exp(-d_{ij}) & if \quad i \neq j \\ 0 & if \quad i = j, \end{cases} \tag{2}$$

where d_{ij} is the distance between country i and j. When $\rho = 0$, we would not have productivity and efficiency spillovers. However, when $\rho \neq 0$, we would have productivity and efficiency spillovers. The estimations are done via maximum likelihood estimation method.

3.3. The effect of spillovers on technical efficiencies of countries

The conventional stochastic frontier models calculate the efficiency by $\exp(-u_{it})$. However, since this formula ignores spatial spillovers, we need to rearrange our model to obtain spillover-corrected efficiency scores. In matrix notation, we have:

$$y_t = \tilde{x}_t \beta - \tilde{u}_t + \tilde{v}_t, \tag{3}$$

where $y_t(y_{1t}, \ y_{2t}, y_{Nt})$, $x_t(x_{1t}, \ x_{2t}, x_{Nt})$, $u_t(u_{1t}, \ u_{2t}, u_{Nt})$, $v_t(v_{1t}, \ v_{2t}, v_{Nt})$, $S(\rho;q_t) = (I_N - \rho W(q_t))^{-1}$, w is the weighting matrix, $\tilde{x}_t = S(p; q_t)x_t$, $\tilde{u}_t = S(p; q_t)u_t$, and $\tilde{v}_t = S(p; q_t)v_t$. Then, the spatial-spillover-corrected efficiency is given by Kutlu (2018b, 2022):

$$E_{it} = \exp(-\tilde{u}_{it}) \tag{4}$$

4. Empirical model and results

We provide the estimation results of three models in Table 2. The first set of parameters represent the stochastic frontier parameters. In line with the conventional stochastic frontier models, we model the

[9] Kutlu (2012, 2018a) argues that efficiency calculations may not be robust to outliers in distribution-free models. Moreover, these models do not disentangle efficiency and technological heterogeneity (Greene, 2005; Kutlu *et al.*, 2019). Hence, we prefer distribution-based stochastic frontier models, which are more robust to outliers and can disentangle heterogeneity and efficiency.

https://doi.org/10.1017/S1744137423000061 Published online by Cambridge University Press

Table 2. Estimation results for SAR stochastic frontier production models

	No heterogeneity			No spatial spillovers			Spatial spillovers and heterogeneity		
ln(GDP)	Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.	
ln(L)	0.63608	0.18086	***	−1.36966	0.00012	***	0.08110	0.00016	***
ln(K)	0.38152	0.27668		−0.71989	0.00007	***	−0.29443	0.00040	***
ln(E)	−0.14481	0.37109		0.78598	0.00011	***	0.37859	0.00011	***
T	−0.03729	0.02276		−0.10630	0.00006	***	−0.06893	0.00312	***
$0.5 \times \ln(L)^2$	−0.17107	0.01481	***	0.10598	0.00004	***	0.01283	0.00001	***
$0.5 \times \ln(K)^2$	−0.01265	0.02419		−0.05964	0.00027	***	−0.06418	0.00046	***
$0.5 \times \ln(E)^2$	−0.07139	0.04680		−0.05620	0.00003	***	−0.03290	0.00001	***
$0.5 \times T^2$	−0.00051	0.00047		0.00133	0.00012	***	0.00159	0.00020	***
ln(L) × ln(K)	0.03206	0.01514	*	0.00215	0.00006	***	0.00011	0.00002	***
ln(L) × ln(E)	0.10955	0.02370	***	0.00001	0.00001		0.00000	0.00001	
ln(L) × T	−0.00113	0.00146		0.00717	0.00001	***	0.00059	0.00005	***
ln(K) × ln(E)	−0.01954	0.03102		0.07283	0.00006	***	0.05707	0.00002	***
ln(K) × T	−0.00418	0.00198	*	−0.00448	0.00010	***	−0.00549	0.00024	***
ln(E) × T	0.00543	0.00243	*	−0.00015	0.00000	***	0.00456	0.00004	***
ln(POP)	0.28175	0.03209	***	0.26115	0.00008	***	−0.14426	0.00026	***
Constant	−8.08153	1.87895	***	–	–		–	–	
Fixed effects	No			Yes			Yes		
σ_v^2									
Constant	−4.16754	0.09441	***	−5.81214	0.00290	***	−8.07174	0.07370	***
σ_u^2									
CC	−1.36266	0.07751	***	−0.26858	0.07535	***	−1.17400	0.05902	***
T	−0.07671	0.03876	*	−0.02626	0.02631	***	−0.51744	0.04093	***
$0.5 \times T^2$	0.00482	0.00363		−0.03598	0.00565		0.03890	0.00404	***
Constant	−1.85784	0.19108	***	−1.12911	0.14691	***	−1.73066	0.17974	***
P	0.09914	0.01189	***	–	–	–	0.38124	0.00538	***
Average efficiency	72.16			85.40			71.16		
Median efficiency	71.12			90.69			74.72		
Log-likelihood	−48.54			2199.10			2136.24		

Note: Standard errors are given in parenthesis. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

production frontier via the translog functional form where the technological changes are captured by the time trend, *T*, and its interaction with other variables. Then, the table presents the parameter estimates for σ_v^2 and $\sigma_{u,it}^2$. The inefficiency estimates are positively related to the parameter estimates in $\sigma_{u,it}^2$. Hence, a negative coefficient for corruption control would indicate a positive relationship between efficiency and corruption control. The table also announces the spatial spillover parameter, ρ, along with mean and median efficiency estimates.[10]

The first model ignores heterogeneity; the second model ignores spatial spillovers; and the third model controls for both heterogeneity and spatial spillovers. In these models, the country-specific heterogeneity is controlled via country-fixed effects and spatial spillovers are controlled by the SAR stochastic frontier model that we described earlier. Among others, Greene (2005), Kutlu and McCarthy (2016), and Kutlu *et al.* (2019, 2020) point out the importance of controlling heterogeneity in a stochastic frontier model.[11] When heterogeneity is present and ignored, inefficiency would be confused with heterogeneity, which may bias the parameter estimates. Heterogeneity includes technological and other differences between countries. Hence, a developed country may end up being less efficient if it is not utilizing the existing resources and technology entirely, even if its output is more than a developing country. Similarly, if there are spatial spillovers and these spillovers are not controlled, the parameter and efficiency estimates would be biased. We test for homogeneity (i.e. equality of coefficients of country-specific dummy variables) and then reject the homogeneity at any conventional statistical significance level. The SAR coefficient is statistically significant at any conventional statistical significance level. Moreover, the estimated model satisfies the input monotonicity assumption at the mean. In particular, the mean (median) elasticity of output with respect to labor, capital, and energy inputs are 0.46 (0.46), 0.39 (0.38), and 0.31 (0.31), respectively. Hence, we will use the third model that controls for heterogeneity and spatial spillovers as our benchmark model.[12]

In what follows, unless otherwise is stated the estimation results would be based on our benchmark model. The estimates show that the average and median efficiencies are 71.16% and 74.72%, respectively.[13] The coefficient of corruption control variable is negative and statistically significant at any conventional levels. Hence, we predict that the higher controlling for corruption would improve efficiency in a country. Some studies explain part of our results from different perspectives. For example, Dal Bó and Rossi (2007) and Gamberoni *et al.* (2016) use firm-level data to probe corruption that can lead input misallocation and distort firm's productivity. Dal Bó and Rossi (2007) elaborate that firms in more corrupt countries are more likely to misallocate their resources by using electricity firms' efficiency data in 13 Latin American countries. Corruption leads firms to move their managerial effort away from the supervision and coordination of the production process. Thus, firms will hire more workers to produce a given level of output. Moreover, Gamberoni *et al.* (2016) argue that corruption negatively influences the input allocation as well as total factor productivity (TFP) growth in Central

[10]In Table 2, σ_v is the variance of the two-sided error term, which is modeled as the exponential of a parameter (constant); σ_u is the variance term, which captures the mean of inefficiency, for the half-normal distribution. σ_u is modeled as the exponential of the constant as well.

[11]See Kutlu and Tran (2019) for a brief summary of heterogeneity models in stochastic frontier analysis.

[12]In order to check the robustness of our results, we interpolated the missing values for the corruption control variable (years 1997, 1999, and 2001). Then, we estimated our benchmark model using these interpolated values. The parameter and efficiency estimates were reasonably close ($\rho = 0.42$, median efficiency = 68.3, mean efficiency = 73.2). We also estimated our benchmark model with countries more than \$20 billion and \$100 billion GDP (on average). The sign for corruption control variable was robust to these changes. Similarly, in these scenarios, we conclude that there are heterogeneity and spillovers.

[13]As a robustness check, we included corruption control, regulation quality, rule of law, time trend, and its square when modeling the distribution of inefficiency in the spatial spillover stochastic frontier model where the heterogeneity is controlled. The mean and median efficiencies estimated by this extended model were close to the ones that we obtained in our benchmark model (69.67% and 71.16%, respectively). Moreover, both Pearson and Spearman correlations of efficiencies based one of these models exceeded 0.99. Also, the coefficient of corruption control was statistically significant at any conventional significance level, i.e. p-value = 0.00000.

https://doi.org/10.1017/S1744137423000061 Published online by Cambridge University Press

and Eastern European (CEE) firms.[14] They then highlight that controlling of corruption, especially improving the effectiveness of the regulatory environment, would be beneficial to weak institutions in improving the production process and aggravating TFP growth.[15]

In Table 3, we present country-specific technical efficiency and related estimates by considering the spillover effect of corruption control. The first column presents the averages of efficiency estimates; the second column presents the averages of efficiency losses due to spillovers (there is efficiency loss because other countries are not fully efficient); the third column presents the average change in efficiency when the corruption control variable increases by one standard deviation for all countries; and the fourth column presents the average change in efficiency when the corruption control variable increases only for the relevant country. According to the estimates in the first two columns, we find many countries in Southeast Asia are most technically efficient in the production process while they minimize efficiency loss. Reversely, many highly corrupt African countries performed the worst with the lowest efficiency and highest efficiency loss. From 1996 to 2014, Southeast Asian countries such as Indonesia, Malaysia, and Cambodia are the most efficient countries with efficiencies 96.58%, 96.44%, and 96.1%, respectively. This result is similar to Kao (2013)'s national productivity study by measuring TFP. He highlights that Indonesia and Malaysia have the highest combination of labor and capital productivity among 10 Southeast Asian countries in the study.[16] This finding also indicates that both countries performed well in allocating their production resources. At this point, we want to state that although the technical efficiency of Cambodia is high, the country does not perform very well in terms of overall production due to its intrinsic technological disadvantages. That is, while the management is relatively good, the production technology/environment dampens the overall production levels for given inputs. In particular, Cambodia is ranked 100th out of 102 countries in terms of the dummy variable that captures heterogeneity. In contrast to Cambodia, Indonesia performed better than the median country in terms of its available production technology.[17]

Regarding the results shown in Table 3, note that technical efficiency refers to how well the country maximizes the outputs giving the available inputs conditional on the technology available to the country. Hence, it is a concept that is related to how well the resources of a country are managed relative to its potential. Thus, a country with advanced production technology may still show technical inefficiency if it does not use its technological advantage effectively. The way that we capture country heterogeneity allows us to compare the technical efficiencies of countries based on their own potentials. Our results suggest that while some countries (e.g. Algeria, Morocco, etc.) have some technological disadvantages, they manage their production process relatively well.

Despite the financial crisis in 1997, countries in this region recovered very soon with high economic growth. For most Southeast Asian countries, the average real GDP has steadily grown approximately 5% or more every year, which is higher than the world GDP growth rate.[18] During this time period, 'Factory Asia' has placed in Southeast Asian countries. This region becomes one of the most important producers in manufacturing global value chains.[19] In addition, we find that lower corruption-controlled African countries' efficiencies are generally lower than other regions. Zimbabwe (30.3%),

[14]Central and Eastern European includes Czech Republic, Estonia, Hungary, Lithuania, Poland, Slovakia, Slovenia, Romania, and Croatia.

[15]Technical efficiency is one of the components of TFP.

[16]Ten countries are: Malaysia, Indonesia, Philippines, Singapore, Brunei, Myanmar, Cambodia, Thailand, Laos, and Vietnam.

[17]A referee suggested that Indonesia's efficiency levels are unrealistically high. Moreover, based on our estimates, the country did not do poorly in terms of its production technology level as well. Although these results are in line with that of Kao (2013), the referee's doubt still seems to be reasonable. Therefore, we must warn the readers about the precision of the efficiency estimates for Indonesia. Recall that our study has 102 countries, and the efficiency estimators are random. Therefore, among 102 draws from such a random variable, it is possible to get outlier draws. This potential issue is not specific to our study, and such dangers exist in any study that estimates many different numbers.

[18]World GDP growth rate: https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?end=2014&start=1996

[19]OECD Agriculture outlook (2017): https://www.oecd-ilibrary.org/docserver/agr_outlook-2017-5-en.pdf?expires=1621021974&id=id&accname=guest&checksum=38ACF1758A9733C005D2B33A5D832B3C

https://doi.org/10.1017/S1744137423000061 Published online by Cambridge University Press

Table 3. Efficiency estimates and effects of spillovers and corruption control

Country	Efficiency	Efficiency loss	Total CC effect	Direct CC effect	Country	Efficiency	Efficiency loss	Total CC effect	Direct CC effect
Albania	87.98	7.83	9.52	6.98	Kenya	66.74	25.68	9.14	6.23
Algeria	81.88	6.08	7.84	5.79	Kyrgyz Rep.	82.91	16.43	11.83	7.93
Angola	36.78	12.69	5.26	3.72	Latvia	90.82	6.90	6.75	4.27
Argentina	82.99	7.09	7.66	5.34	Lebanon	85.33	13.30	9.81	6.68
Armenia	74.41	10.47	7.69	5.04	Lithuania	92.31	7.39	6.51	3.87
Austria	90.76	6.50	4.04	1.61	Luxembourg	93.90	6.04	3.82	1.53
Azerbaijan	68.46	9.55	8.41	6.02	Malaysia	96.44	3.39	9.16	4.37
Bangladesh	91.44	7.90	13.31	8.95	Mauritius	64.69	22.12	5.16	2.47
Belarus	89.15	7.24	8.59	6.11	Mexico	67.95	16.37	7.04	4.21
Belgium	94.02	5.86	4.28	2.08	Moldova	84.67	7.82	8.55	6.08
Benin	64.02	18.28	7.35	4.54	Mongolia	86.41	13.43	9.50	5.50
Bolivia	82.47	14.63	9.40	6.24	Morocco	92.20	7.32	7.85	5.40
Bosnia & Herz.	91.13	7.52	8.25	5.66	Mozambique	53.45	21.79	5.52	3.56
Botswana	39.92	14.11	2.79	1.17	Myanmar	91.50	4.45	14.80	10.83
Brazil	70.23	5.93	6.26	3.66	Namibia	61.82	25.73	4.92	2.43
Bulgaria	90.81	8.70	7.97	5.18	Nepal	84.37	9.21	10.31	6.28
Cambodia	96.10	3.87	14.04	9.79	Netherlands	92.79	5.73	3.60	1.40
Cameroon	41.94	12.81	6.03	4.14	Nicaragua	74.42	19.81	8.74	5.78
Chile	82.05	8.25	4.86	1.82	Nigeria	56.67	14.94	7.57	5.33
China	61.94	3.97	6.70	3.96	Pakistan	68.99	10.29	9.34	6.12
Colombia	52.21	12.42	4.97	2.94	Panama	45.96	10.21	4.45	2.63
Congo, Rep.	37.94	13.07	5.29	3.56	Paraguay	85.96	9.72	11.37	8.84
Costa Rica	53.02	11.68	3.84	1.71	Peru	57.34	10.23	5.66	3.42
Croatia	89.82	6.81	7.35	4.90	Philippines	86.51	3.51	9.74	5.85
Cyprus	72.51	9.73	4.53	1.88	Poland	84.34	5.89	5.26	3.03
Czech Rep.	85.90	5.70	5.57	3.39	Portugal	93.26	6.61	4.91	2.45

https://doi.org/10.1017/S1744137423000061 Published online by Cambridge University Press

Denmark	90.75	5.82	3.38	1.14	Russian Fed.	77.54	6.74	8.91	6.67
Dominican Rep.	46.62	11.16	5.66	3.57	Senegal	70.36	12.66	6.65	4.00
Ecuador	52.19	12.22	5.95	3.94	Slovak Rep.	81.43	5.30	5.43	3.39
Egypt	57.36	7.80	6.13	4.07	Slovenia	92.50	6.99	5.27	2.71
El Salvador	58.00	12.94	6.14	3.83	South Africa	39.40	13.31	3.04	1.60
Ethiopia	43.90	9.15	4.84	3.02	Spain	86.41	5.76	4.44	2.20
Finland	81.57	5.55	3.26	1.04	Sri Lanka	91.62	8.30	9.87	5.35
France	87.46	5.00	3.88	1.92	Sweden	90.55	6.17	3.59	1.24
Gabon	35.71	11.12	4.93	3.16	Syrian Arab Rep.	77.14	11.82	9.98	7.16
Georgia	66.00	8.55	6.39	4.01	Tajikistan	76.47	12.41	10.54	7.25
Germany	91.56	5.51	3.66	1.53	Tanzania	32.14	9.06	3.59	2.23
Ghana	38.88	8.48	3.85	2.11	Thailand	93.08	3.71	10.57	5.90
Greece	70.54	6.90	5.19	2.98	Togo	66.34	20.10	9.03	6.02
Guatemala	56.31	12.39	6.48	4.26	Tunisia	75.90	6.68	6.86	4.56
Haiti	53.85	15.00	8.59	6.26	Turkey	62.29	6.07	5.12	3.17
Honduras	54.33	11.43	6.53	4.51	Ukraine	55.93	4.02	6.39	4.82
Hungary	84.53	6.19	5.38	3.06	United Kingdom	89.98	5.24	3.53	1.51
India	68.49	8.88	7.76	4.38	United States	53.36	12.27	3.29	1.06
Indonesia	96.58	3.03	12.66	8.43	Uruguay	81.46	6.75	5.03	2.18
Iran	48.55	7.39	5.32	3.31	Uzbekistan	58.85	7.50	7.83	5.36
Iraq	47.28	6.68	6.82	5.10	Venezuela	59.20	15.65	7.88	5.45
Ireland	81.65	4.27	3.32	1.57	Vietnam	92.64	4.99	11.32	6.79
Italy	68.37	4.75	4.66	2.79	Yemen	69.01	15.37	9.04	6.20
Jordan	51.52	6.62	4.21	2.31	Zambia	34.17	12.29	3.63	2.26
Kazakhstan	44.10	4.51	5.50	3.60	Zimbabwe	30.30	10.60	4.27	3.07

Note: Total CC effect: the total marginal effect of corruption control variable when increased by one standard deviation. Direct CC effect: the direct marginal effect of corruption control variable when increased by one standard deviation.

Tanzania (32.14%), and Zambia (34.17%) are the most inefficient countries in managing the production process (in the sense of technical efficiency). Meanwhile, most of the countries in Southeast Asia minimize their efficiency loss (e.g. Indonesia (3.03pp), Malaysia, (3.39pp) and Philippines (3.51pp) have best performance in efficiency).[20] However, Africa, Namibia (25.73pp), Kenya (25.68pp), and Mauritius (22.12pp) have largest efficiency losses due to spillovers (i.e. the efficiency loss due to other countries not being fully efficient) in their production. The high-efficiency losses in these countries are partially caused by deficiency of corruption control efforts by their neighboring countries. We then displayed the estimated countries corruption control effort in the last two columns. The average and median change in the efficiency when the corruption control variable increases by one standard deviation (0.9828) for all countries are 6.75pp and 5.82pp, respectively.[21] Similarly, the average and median change in the efficiency when the corruption variable increases by one standard deviation for the country of interest (i.e. direct efficiency change) are 4.22pp and 3.64pp, respectively.

In order to visualize the spillover effect, we facilitate the average spatial efficiency (column 1) in Figure 1. We observe that Southeast Asian and European countries have the highest technical efficiency. The most efficient Southeast Asian countries, Indonesia, Malaysia, and Cambodia, intensified their clampdown on corruption more than others, while bringing positive efficiency spillovers to their neighbors, Thailand, Vietnam, and Myanmar. Consequently, the high anti-corruption efforts enhance their neighbors' technical efficiency that Thailand, Vietnam, and Myanmar estimated average technical efficiency is 93.08%, 92.64%, and 91.50%, respectively. Similarly, Western European countries with relatively high-level corruption control (Belgium, Netherlands, Luxembourg, and Portugal) have high technical efficiency that spillovers to their neighboring countries (United Kingdom, Germany, and Spain).

Overall, we observe efficiency spillovers across countries (regions) that high-corruption-control and high-efficiency countries are more likely to have relatively high corruption-control and high-efficiency neighbors. That is, high-corruption-control and high-efficiency counties would boost their neighbors' efforts in combating corruption, as well as technical efficiency through spillovers. Hence, corruption control is not only important in the origin country but also other countries surrounding it. On the other hand, a country surrounded by countries that are having difficulty in handling corruption would also be negatively affected through efficiency spillovers. This suggests that countries have incentives to handle their own corruption problems, meanwhile, they may benefit if the surrounding countries do not have corruption-related problems. Of course, in practice, there may exist political reasons that dominate efficiency-related benefits. However, this study only concentrates on economic benefits that are related to efficiency gains.

To uncover how country-level technical efficiency has changed over time, we divide countries into subgroups according to their changes in efficiency between time periods. We use the ending year efficiency minus the beginning year efficiency to calculate the efficiency difference and present them in Figure 2. In Figure 2, according to the National Bureau of Economic Research (NBER) business cycle peak year data,[22] we divide our 19-year sample into three periods, where period 1 is between 1996 and 2002, period 2 is between 2002 and 2008, and period 3 is between 2008 and 2014.

Figure 2(a) shows changes in spatial technical efficiency in the first period. In this period, the majority of Southeast Asian countries suffered a loss in efficiency, potentially reducing the effort on corruption control. That is, the financial crisis reduced government spending on clamping down on corruption. The East and Southeast Asian financial crisis in 1997 devalued Asian countries' currencies and defaulted on their domestic debt. Therefore, it consequently caused inflation and other financial losses as well as reduced the effort of corruption control. As the center of the financial crisis,

[20]pp denotes percentage points.

[21]We abbreviate percentage points by pp.

[22]NBER highlighted that March 2001 and December 2007 are two peak months and November 2001 and June 2009 are two through months. Since the 2001 corruption control is missing in our sample, we use 2002 instead as one of the thresholds. We then apply 2008 as another threshold because the second peak month was at the end of 2007. For more details, please see: https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions.

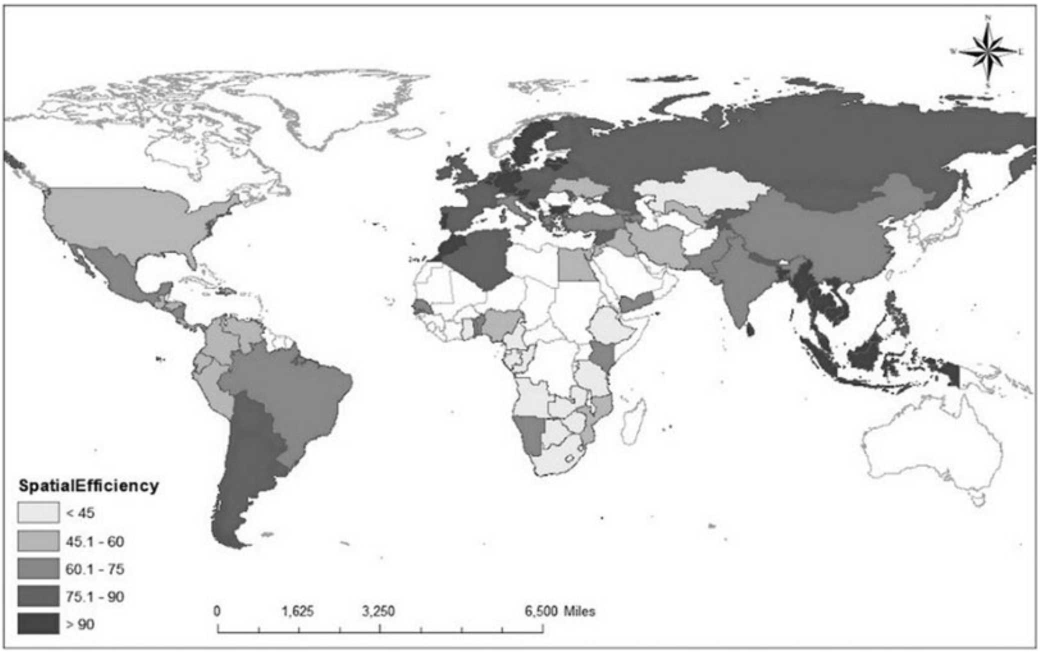

Figure 1. Estimated average technical efficiency (1996–2014).
(*Source*: World Map shapefile, 2021, ArcGIS)

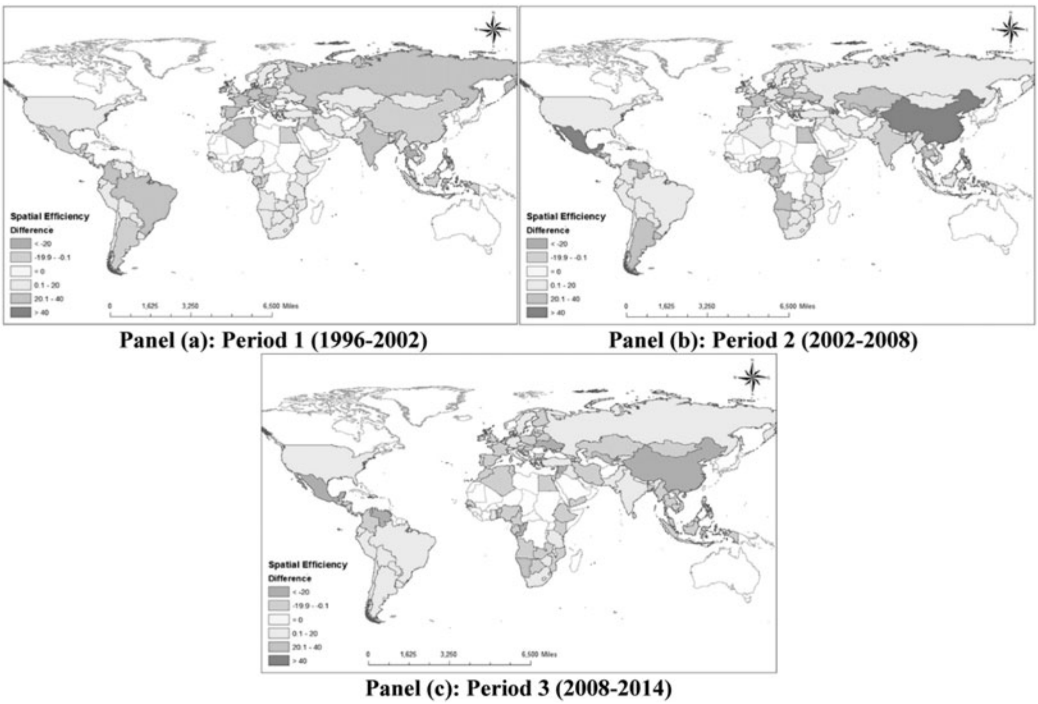

Figure 2. Dynamic estimated spatial efficiency difference (1996–2014).
(*Source*: World Map shapefile, 2021, ArcGIS)

https://doi.org/10.1017/S1744137423000061 Published online by Cambridge University Press

Thailand lost the most efficiency (26.46pp) and corruption control (31.6%) during the first period. Their neighbors, China and Indonesia suffered efficiency losses while their enforcement of corruption control decreased in varying degrees. China and Indonesia suffered an efficiency loss of 15.64pp and 1.66pp. At the same time, their control of corruption decreased by 10.3% and 86.9%, respectively.

In the second period (see Figure 2(b)), many Asian countries achieved rapid efficiency growth and jointly enhanced efforts to combat corruption. For example, China's efficiency increased by 55.74pp and its corruption control effort raised by 51.5%. China's neighboring countries' technical efficiency and the effort of corruption control increased. Thailand's efficiency improved the most by 26.48pp and its corruption control increased by 7.3% during the second period. At the same time, Malaysia and Indonesia's efficiency and corruption control improved marginally as well. Malaysia and Indonesia's efficiency increased by 0.59pp and 2.01pp, and corruption control was enhanced by 2.9% and 26.3%, respectively.

According to Figure 2(c), we observe that both efficiency and the enforcement of corruption control weakened, that most European, African, and Southeast Asian countries suffered losses in technical efficiency and the reduction in corruption control efforts in the third period. This period began with the global financial crisis from 2007 to 2009 due to an unsustainable asset bubble in the US and ended with the great oil crisis in 2014. The worldwide financial crises weakened corruption control efforts, raised fraud, and deteriorated technical efficiencies through spillovers. Accordingly, China, El Salvador, and Congo, the countries most affected in this period, experienced efficiency losses of 32.7pp, 34.29pp, and 35.54pp, respectively, and their neighboring countries' efficiency was reduced at the same time due to the spillover effect. In particular, China's efficiency decreased by 32.7pp in 2014, and its corruption control effort was reduced by 54.2%. Another potential reason was the promotion of new anticorruption policies by the Chinese government that had to break the old pattern. The promotion process might cause a temporary disruption in technical efficiency. While these new anticorruption policies brought a temporary distortion of efficiency, they may enhance efficiency better than old policies in the long run.

5. Concluding remarks

Our study applies a SAR stochastic frontier model to estimate the effect of corruption control on efficiency from 1996 to 2014 for 102 countries. The study fills the gap in the economic literature on corruption control, technical efficiency, and spatial spillovers. It is notably novel in several respects. First, the SAR model controls heterogeneity to eliminate biases in parameter estimates. The model also considers the spillover effect of technical efficiency and the control of corruption. The estimates show that the lack of corruption controls reduces efficiency more with spillovers. Control of corruption in a country not only significantly reduces the country's inefficiency but also its negative spillovers influence their neighboring countries. Similarly, if the neighboring countries enhance their control of corruption, then the country is likely to be relatively efficient compared to a country with more corrupt neighbors.

We then present the averages of efficiency estimates, the averages of efficiency losses due to spillovers from corrupt neighbors, and the efficiency changes are partially affected by the change of corruption control. The results indicate that Southeast Asian and European countries were the most efficient countries on average from 1996 to 2014. We observe that technical efficiencies are significantly distorted during the oil crisis in 2014. To study the dynamic change of country-level technical efficiency, we divide countries into three subgroups according to the changes in efficiency between time periods: 1996 and 2002, 2002 and 2008, and 2008 and 2014. We obtain efficiency changes by calculating the difference between ending year efficiency and the beginning year efficiency. The results show that 85 out of 102 countries' technical efficiencies continually increased in the second period compared to the first period. However, in the third period, 67 (out of 102) of countries' efficiencies dramatically declined, particularly in China. We suspect the deterioration of efficiencies in China was caused in part by financial crises as well as the temporary disruption by implementing new anticorruption policies. It is worth investigating whether the episode of financial crises is an important mechanism in the causal relationship between corruption control and technical efficiency in a future study.

In order to improve technical efficiency spillovers, we suggest that countries should jointly take actions to enhance the control of corruption. While collaborating with other countries, governments need to investigate corruption from different perspectives, and then formulate corresponding anticorruption regulations and policies based on their actual situations. In addition, we suggest that governments encourage market competition by enhancing property rights, creating tax incentives, and propagating procurement transparency. To maximize technical efficiency and stimulate economic growth, promoting anticorruption policies and enforcing market competitiveness associated with local and regional conditions at an appropriate time will be a valuable research topic in the future.

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Cite this article: Kutlu L, Mao X (2023). The effect of corruption control on efficiency spillovers. *Journal of Institutional Economics* **19**, 564–578. https://doi.org/10.1017/S1744137423000061