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Can the internet reduce corruption? A cross-country study based on dynamic panel data models

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ABSTRACT

This study attempts to estimate the effects of internet adoption on reducing corruption by using a panel consisting of 70 countries covering the period from 1998 to 2005. The results of Granger causality tests reveal that, while causality running from internet adoption to corruption reduction can be established, the causality between internet adoption and corruption is bi-directional. To deal with the problem of endogeneity, the dynamic panel data (DPD) models are employed. The estimation results show that the effects of internet adoption on corruption reduction are statistically significant but not too substantial. Our findings suggest that the internet has shown a capacity for reducing corruption, but its potential has yet to be fully realized.

1. Introduction

The rapid development and diffusion of new information and communication technology (ICT) have led to the notion of e-government that has been quickly embraced by many governments. Using new ICT, especially the internet, governments can not only link databases in different departments to streamline the back-end of public administration processes, but can also improve the interface through which governments interact with their citizens (Mahmood, 2004). Having largely evolved from the e-business framework, the services provided through e-government have now evolved from websites offering everything from basic government information to more value-added transactional-level services that offer convenience, efficiency, and transparency (Dwivedi, Weerakkody, & Williams, 2009).

In addition to making the government more efficient and cost-effective, many scholars and policy-makers believe that e-government can play a substantial role in combating corruption by improving the enforcement of rules, lessening the discretion of officials, and increasing transparency (Bhatnagar, 2003a; Sturges, 2004; UNDP, United Nations Development Programme, 2008; Vinod, 1999). It is argued that one of the potential benefits that ICT can bring to developing countries is to address corruption and thus help to remove one of the systemic barriers to pro-poor growth (OECD, 2005; Piatkowski, 2006).

Although there are some illuminating case studies regarding e-government and anti-corruption, for example the study of Kim, Kim, and Lee (2009) on Seoul Metropolitan Government's development of an anti-corruption system called OPEN (Online Procedures ENhancement for civil application), so far in the literature there are few studies attempting to estimate the effects of internet adoption on corruption reduction. The purpose of this paper is to empirically test whether the internet can lead to corruption reduction by using a cross-country sample consisting of 70 countries covering the period from the year 1998 to 2005. This study has two important features. First, we test the possibility of two-way causality between internet adoption and corruption reduction by applying Granger causality tests. Second, to deal with the potential endogeneity problem caused by the reverse causality running from corruption to internet adoption, we employ the dynamic panel data (DPD) models to estimate the effects of internet adoption on corruption reduction. In addition to the endogeneity problem, this approach can take into account the persistence of corruption, which is an important issue in the literature on corruption (Mauro, 2004; Mishra, 2006; Tirole, 1996).

The remainder of this paper is organized as follows. In The theoretical ground section, the theoretical relationship between corruption reduction and internet adoption is investigated. In the Methodology and data section, the methodology is discussed. Data sources and variable definitions are also presented in this section. The empirical findings are reported and discussed in the Empirical results section. The last section concludes this paper.

2. The theoretical ground

Corruption is commonly defined as the "misuse of entrusted power for private gains" (UNDP, United Nations Development Programme, 2008, p. 18). The acts of corruption can take many forms, including bribery, embezzlement, theft, extortion, abuse of

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discretion, favoritism, exploiting conflicting interests, and improper political contributions (UNODC, United Nations Office on Drugs and Crime, 2004). It is widely recognized that corruption can severely impede development by weakening national institutions, raising business costs, discouraging domestic investments and FDI, eroding trust, and generating a perverse incentive system. A country in which corruption is endemic is usually plagued with widespread economic inefficiency and unchecked environmental exploitation, and the poor are usually hit the hardest (UNDP, United Nations Development Programme, 2008).

Klitgaard (1988) argues that corruption is a problem of asymmetric information and incentives, which can be explained by a simple *principal–agent–client* model. In this model, the principals are elected officials within a government representing the state and its citizens to employ a wide range of public servants (the agents), such as tax officials, labor inspectors and teachers, to deliver public services to citizens (the clients). It is assumed that the principals (the elected officials) want to ensure that public services are adequately delivered to the clients (the citizens), but since they are unable to deliver most of the services themselves, they have to employ agents (the public servants) to work on their behalf. However, a typical situation is that there exists the problem of asymmetric information in which the agents know far more about the administration than either the principals or the clients, and the problem of corruption arises when the agents exploit their position as go-betweens and take advantage of the power entrusted to them to act more in their own interest, commonly through bribery, extortion, fraud, nepotism, or embezzlement (UNDP, United Nations Development Programme, 2008).

The *principal–agent–client* model predicts that corruption is more likely to occur when a public official possesses access to a monopoly, has discretion in administering it, and operates with a lack of accountability. An important implication of this model is that, in order to reduce corruption, it is crucial to restructure the principal–agent–client relationship to alter the amount of monopoly, discretion, and accountability with which the agent is endowed (Klitgaard, 1988). From this theoretical point of view, the internet can lead to a reduction in corruption if it is adequately used to alter the principal–agent–client relationship in the public sector–citizen interface through e-government (Mahmood, 2004). E-government applications can enhance transparency and mitigate the asymmetric information problem by increasing access to information; e-government can curb the agent's opportunities for arbitrary action by reducing discretion; and e-government can promote accountability as it enhances the ability of citizens to track the decisions and actions of individual officials and emboldens citizens and businesses to question unreasonable procedures and their arbitrary application by making rules simpler and more transparent (Bhatnagar, 2003a).

Bhatnagar (2003b) presents a variety of types of information which can be made transparent, including rules and procedures governing services, outcomes of government decisions, data about individual entities in government records, actions/decisions of government functionaries, performance indicators for government departments, names of civil servants under investigation or convicted, and disclosure of assets and income of election candidates, elected representatives, ministers or civil servants. Bhatnagar (2003b) argues that for each of them greater transparency can be enabled though e-government applications, which in turn can create disincentives for corrupt officials by increasing the chances of exposure. UNDP (United Nations Development Programme) (2008) uses several cases to illustrate how governments can utilize ICT to enhance transparency and accountability. For example, the Indian Government has formulated plans to computerize all 2500 court complexes, create a database of new and pending cases, and digitalize the law libraries and court archives, all of which can help combat corruption in the judiciary. India's Central Vigilance Commission has published on its website the names of officers against whom corruption investigations have been ordered or on whom penalties have been imposed, and on this website any citizen can lodge a complaint.

Another well-known case is, since 1999, the Seoul Metropolitan Government has used ICT to minimize corruption in applications for licenses and other permits by launching an Online Procedure Enhancement for Civil Applications (OPEN) system covering 54 common procedures, which enables citizens to monitor the progress of their applications as those responsible officials have to upload reports and documents (Kim et al., 2009; UNDP, United Nations Development Programme, 2008). In short, there are strong theoretical grounds to believe that e-government can promote transparency and accountability, and evidence from case studies indicates that the internet can be used to effectively combat corruption.

However, as Kim et al. (2009) have pointed out, there are doubts whether ICT can effectively reduce corruption in reality. For example, based on a study of five cases regarding ICT and corruption, Heeks (1998) finds that sometimes ICT has no significant effects on reducing corruption, and even creates new opportunities for corruption. Wescott (2001) suggests that ICT can lead to an "upskilling" of corruption and reduce competition for upskilled corrupt civil servants. Mahmood (2004) argues that most reported cases of using ICT to effectively reduce corruption happen in developed countries, and whether developing countries can produce such successful cases is doubtful. Therefore, in this empirical study we will try to answer if the introduction of new ICT can significantly reduce corruption by utilizing a broad sample consisting of both developed and developing countries.

3. Methodology and data

3.1. Granger causality tests

This study intends to estimate the effects of internet adoption on the reduction in corruption. However, as several previous studies have suggested, corruption may also hinder the introduction of ICT (Oruame, 2008; Quibria, Ahmed, Tschang, & Reyes-Macasaquit, 2003; Yoon & Chae, 2009). In other words, the problem of reverse causality may exist.

In this study we first employ panel Granger causality tests to investigate the possible directions of causality between internet adoption and corruption. Recent years have seen a continuous increase in the application of the panel Granger causality test as this approach can significantly improve the estimation efficiency by increasing the degrees of freedom (Justesen, 2008; Kónya, 2006). To perform panel Granger causality tests, we specify the following autoregressive models for country i and period t:

$$CPI_{it} = \alpha_0 + \sum_{j=1}^{p_1} \alpha_j CPI_{i,t-j} + \sum_{k=1}^{q_1} \delta_k Internet_{i,t-k} + f_i + u_{it} \tag{1}$$

$$Internet_{it} = \beta_0 + \sum_{j=1}^{p_2} \beta_j Internet_{i,t-j} + \sum_{k=1}^{q_2} \gamma_k CPI_{i,t-k} + \theta_i + \varepsilon_{it} \tag{2}$$

where CPI is the Corruption Perception Index which measures a country's level of corruption with 0 representing the highest level of corruption and 10 representing the lowest level of corruption (Transparency International, 1998–2005); $Internet$ is the level of internet adoption; f_i and θ_i are country-specific (fixed) effects; and u_{it} and ε_{it} are disturbances assumed to be distributed across countries with a zero mean.

The starting point of the Granger causality test is that the future cannot cause the past or the present, whereas the past may cause the present or the future (Granger, 1969; Justesen, 2008). That is, past values of a given variable, X, may be a cause of the present value of another variable, Y, but future values of X cannot be a cause of present values of Y. However, just because X occurs before Y does not mean that X is a cause of Y, and we need to control for other factors relevant to the explanation of Y. The standard Granger causality test presumes that this information is contained in the past values of Y, and in the panel data set-up in the presence of unit-specific dummy variables (Justesen, 2008).

Therefore, the basic concept behind Eq. (1) is that, if the information contained in the past values of *Internet* is significantly able to explain *CPI* with the past values of *CPI* and the country-specific effect being controlled, then we can say that *Internet* Granger-causes *CPI*. That is, a change in the level of internet adoption can lead to a change in the level of corruption. Similarly, the basic concept behind Eq. (2) is that, if the information contained in the past values of *CPI* is significantly able to explain *Internet* with the past values of *Internet* and the country-specific effect being controlled, then we can say that *CPI* Granger-causes *Internet*.

The research problem, then, is to find out whether the coefficients δ_k in Eq. (1) and γ_k in Eq. (2) are significantly different from zero at the chosen significance level. There are four possible scenarios. If neither δ_k nor γ_k are significantly different from zero, we can suggest that *Internet* and *CPI* are not causally related. If δ_k is statistically different from zero and γ_k is not, then *Internet* may be said to cause *CPI*, but the reverse causality does not exist. If γ_k is statistically different from zero and δ_k is not, then *CPI* may be said to cause *Internet*, but the reverse causality does not exist. Finally, if both δ_k and γ_k are statistically different from zero, then we can suggest that there is bi-directional causality between *Internet* and *CPI*. In this case, corruption and internet adoption endogenously cause each other.

This study employs two types of tests to investigate whether the Granger causality relationship between *Internet* and *CPI* is bi-directional. The first is the standard Granger causality test for joint significance. In econometric practice, the causality from *Internet* (*CPI*) to *CPI* (*Internet*) can be established if the Wald tests show that the coefficients of lagged *Internet* (*CPI*), namely δ_k (γ_k), are jointly statistically different from zero.

The main disadvantage with the test of joint significance lies in its inability to distinguish between temporary and permanent Granger causality. That is, it is possible for the test of joint significance to suggest that X causes Y but the sum of coefficients is zero. Such a result would suggest that a permanent change in X generates a temporary fluctuation in Y, but X exerts no permanent influence on Y (Drobny, 1988, p. 163).

Therefore, in addition to the test for joint significance, a neutrality test for the sum of coefficients is performed to ascertain the statistical significance of the accumulated effect of lagged independent variables (Justesen, 2008; Maier, Sturm, & de Haan, 2002). If in this test the sum of coefficients of lagged *Internet* in Eq. (1), namely $\sum \delta_k$, is significantly different from zero, we can argue that causality from *Internet* to *CPI* exists. Similarly, the reverse causality from *CPI* to *Internet* in Eq. (2) can be established if $\sum \gamma_k$ is found to be significantly different from zero.

The Granger causality test may be sensitive to the selection of the lag-length. Regarding the determination of the appropriate lag-length, Holtz-Eakin, Newey, and Rosen (1988) suggest that the lag-length should be less than 1/3 of the total time period, or else the covariance matrix will not be correctly estimated due to over-identification problem. Due to the short time period of our sample, in order to retain sufficient degrees of freedom, we follow Justesen (2008) and only include lag-lengths of up to two for the independent and dependent variables in the estimated equations. As a result, four possible scenarios are considered for each equation. We then employ the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) to determine the optimal lag-length.

The models specified in Eqs. (1) and (2) include lagged dependent variables and unobserved individual-specific effects. Using pooled OLS to estimate the parameters in these two equations would yield biased and inconsistent estimates, owing to the correlation between the error terms and the lagged dependent variables. A standard procedure to overcome this problem in dynamic panels is to wipe out the individual effects by means of a first difference transformation. As the differenced errors are correlated with some of the differenced values of the lagged dependent variables, consistent estimation of the parameters requires instrumental variables methods. Both the difference GMM estimator (Arellano & Bond, 1991) and the system GMM estimator (Arellano & Bover, 1995; Blundell & Bond, 1998), which use lagged values as instruments, are suggested in the literature to estimate this kind of model. In this study, we employ the system GMM estimator, which uses more instruments than the difference GMM estimator and can achieve higher estimation efficiency.

3.2. Estimating the effects of the internet on corruption

In order to estimate the effects of internet adoption on corruption, we specify the following dynamic panel data model which includes the lagged dependent variable as an explanatory variable:

$$CPI_{it} = \beta_0 + \beta_1 CPI_{i,t-1} + \beta_2 Internet_{it} + \beta_3 GDPpc_{it} + \beta_4 Edu_{it} + \theta_i + \varepsilon_{it} \quad (3)$$

where *GDPpc* is GDP per capita; *Edu* is the level of education; θ_i refers to the country-specific effects; and the ε_{it} are disturbances assumed to be distributed across countries with a zero mean. Both *GDPpc* and *Edu* are control variables. *GDPpc* is included as many studies (Brunetti & Weder, 2003; Fisman & Gatti, 2002; Serra, 2006; Treisman, 2000) find that countries with higher levels of economic development in general have lower levels of corruption. *Edu* is included as previous studies (Ades & Di Tella, 1999; Persson, Tabellini, & Trebbi, 2003; Serra, 2006) suggest that countries with a better-educated population usually have less corruption because education can effectively reduce the tolerance for observing and participating in corruption.

We employ the dynamic panel data model specified in Eq. (3) for the following reasons. First, as previously mentioned, corruption appears to be persistent. The persistence of corruption is noted in the literature. For example, Tirole (1996) argues that once agents are corrupt, they remain so due to reputation effects. Mauro (2004) suggests that in countries where corruption is pervasive, there are no incentives for individuals to fight corruption, even though they would be better off if corruption were eradicated. Mishra (2006) indicates that when there are many corrupt individuals, it is optimal to be corrupt; thus once corruption is widespread, it will be persistent. To account for the persistence of corruption, we need to work with a dynamic, lagged dependent econometric model as shown in Eq. (3).

Second, the possibility of reverse causality running from corruption to internet adoption suggests the existence of the endogeneity problem, and failure to correct for this problem may lead to inconsistent coefficients. We address the endogeneity problem by employing an instrumental variable procedure applied to the dynamic panel data model, which is referred to as the GMM estimator and uses the dynamic properties of the data to generate proper instrumental variables.

Several econometric problems may arise from estimating Eq. (3). The first problem is that the explanatory variable *Internet* is assumed to be endogenous. The second is that time-invariant country characteristics (fixed effects) may be correlated with the explanatory variables. The third is that the presence of the lagged dependent variable $CPI_{i,t-1}$ in the regressor gives rise to autocorrelation. Furthermore, in this study the panel has a short time dimension (T) and a large country dimension (N).

Using pooled OLS to estimate Eq. (3) may yield biased and inconsistent estimates. The GMM estimator proposed by Holtz-Eakin et al. (1988) and developed by Arellano and Bond (1991) is used to solve the above problems. The Arellano and Bond (1991) GMM estimator has several characteristics. First, to solve the problem of endogeneity, it employs the lagged values of the endogenous regressors as instruments. Second, it uses first-differences to remove the fixed effects. Third, to solve the problem of autocorrelation, the lagged dependent variable is instrumented with its past values. Finally, the Arellano–Bond estimator is designed for small-*T* large-*N* panels.

In this study we use the augmented version of the Arellano–Bond estimator, the system GMM estimator, to estimate Eq. (3). The Arellano–Bond system GMM estimator uses the levels equation to obtain a system of two equations: one differenced and one in levels. By adding the equation in levels, additional instruments can be obtained, which usually increases efficiency (Arellano & Bover, 1995; Blundell & Bond, 1998). The proprietary *Stata* program, called xtabond2 and written by Roodman (2006), is employed in this study.

3.3. Data sources and variable definitions

For the definitions and sources of variables employed in this study, a country's internet adoption (*Internet*) is measured by internet users per 100 inhabitants, which is taken from The *World Telecommunication/ICT Indicators Database* provided by ITU (2008). The level of corruption is measured by the *Corruption Perception Index* (*CPI*) provided by Transparency International (1998–2005). Higher values of *CPI* represent lower levels of corruption. The data for the control variables are obtained from *World Development Indicators* provided by the World Bank (2008), including GDP per capita (*GDPpc*) and the level of education (*Edu*) measured by the gross enrolment ratio in secondary education. The definitions and sources of variables are given in Table 1. The summary statistics of the variables are given in Table 2.

3.4. Sample countries

We use a sample of 70 countries with data covering the years from 1998 and 2005. Table 3 provides the list of sample countries, which are grouped by levels of internet implementation and corruption. In this sample, Sweden has the highest level of internet adoption ($Internet = 76.35$) and Malawi has the lowest level of internet adoption ($Internet = 0.40$) in the year 2005. Therefore, we divide the 70 countries into three groups according to their values of *Internet* in the year 2005: countries with higher levels of internet adoption ($Internet \geq 50$), countries with medium levels of internet adoption ($25 \leq Internet < 50$), and countries with lower levels of internet adoption ($Internet < 25$).

For the 17 countries with higher levels of internet corruption, all have lower levels of corruption ($CPI \geq 5$). For the 16 countries with medium levels of internet adoption, 12 countries have lower levels of corruption. The other four countries in this group, including Czech Republic, Latvia, Poland and Slovak Republic, have higher levels of corruption ($CPI < 5$). For the 37 countries with lower levels of internet adoption, 34 countries have higher levels of corruption, and only three countries in this group, including Botswana, Israel and Jordan, have lower levels of corruption.

It can be found that there is a clear correlation between levels of internet adoption and corruption. The estimation of correlation shows that, for the year 2005, the correlation coefficient between *Internet* and *CPI* is 0.85. In this study we will try to clarify if there are causal relationships underlying this high correlation. Furthermore, the fact that most of the countries with higher levels of corruption have lower levels of internet adoption implies that, if causality from internet adoption to corruption reduction can be established, the control of corruption in the countries with higher levels of corruption may benefit significantly by greatly enhancing their levels of internet adoption.

Table 1
Definitions and sources of variables.

Variables	Definitions	Sources
Internet	Internet users per 100 inhabitants	ITU (2008)
CPI	Corruption Perception Index, bounded between 0 and 10, with 0 being the highest corruption rating and 10 being the lowest corruption rating	Transparency International (1998–2005)
GDPpc	GDP per capita, in thousands of constant 2000 US dollars	World Bank (2008)
Edu	Gross enrolment ratio in secondary education (%)	World Bank (2008)

Note. The missing value for *CPI* in the year 2002 for Poland is replaced by the average of the 2001 and 2003 values.

Table 2
Summary statistics of main variables.

	Mean	Std. Dev.	Min	Max	# of countries	# of observations
Internet	18.65	18.93	0.01	76.35	70	560
CPI	5.26	2.43	1.40	10.00	70	560
GDPpc	11.10	12.20	0.13	51.59	70	560
Edu	84.95	28.68	9.55	161.66	70	497

4. Empirical results

We first perform Granger causality tests for Eqs. (1) and (2) with four specifications for each equation. The dynamic panel data model

Table 3
List of 70 sample countries, grouped by different levels of *Internet* and *CPI*.

$Internet_{2005} < 25$		$25 \leq Internet_{2005} < 50$		$Internet_{2005} \geq 50$	
Country	CPI_{2005}	Country	CPI_{2005}	Country	CPI_{2005}
Kenya	2.1	Poland	3.4	Korea, Rep.	5.0
Indonesia	2.2	Latvia	4.2	Estonia	6.4
Cameroon	2.2	Slovak Republic	4.3	Japan	7.3
Venezuela, RB	2.3	Czech Republic	4.3	U.S.	7.6
Ecuador	2.5	Italy	5.0	Hong Kong, China	8.3
Philippines	2.5	Hungary	5.0	Canada	8.4
Bolivia	2.5	Malaysia	5.1	Luxembourg	8.5
Uganda	2.5	Portugal	6.5	Netherlands	8.6
Vietnam	2.6	Spain	7.0	United Kingdom	8.6
Ukraine	2.6	Chile	7.3	Australia	8.8
Zimbabwe	2.6	Belgium	7.4	Norway	8.9
Zambia	2.6	Ireland	7.4	Switzerland	9.1
Argentina	2.8	France	7.5	Sweden	9.2
Malawi	2.8	Germany	8.2	Denmark	9.5
India	2.9	Austria	8.7	New Zealand	9.6
Romania	3.0	Singapore	9.4	Finland	9.6
China	3.2			Iceland	9.7
Senegal	3.2				
Egypt, Arab Rep.	3.4				
Mexico	3.5				
Peru	3.5				
Turkey	3.5				
Ghana	3.5				
Brazil	3.7				
Thailand	3.8				
Bulgaria	4.0				
Colombia	4.0				
Mauritius	4.2				
Costa Rica	4.2				
El Salvador	4.2				
Greece	4.3				
Namibia	4.3				
South Africa	4.5				
Tunisia	4.9				
Jordan	5.7				
Botswana	5.9				
Israel	6.3				

Note. $Internet_{2005}$ is the value of internet users per 100 inhabitants in 2005. CPI_{2005} is the value of Corruption Perception Index in 2005.

specified in Eq. (3) is further employed to estimate the effects of internet adoption on corruption reduction. Five specifications for Eq. (3) are estimated. Tables 4 and 5 summarize the empirical results.

4.1. Results of the Granger causality tests

The empirical results of the Granger causality tests for Eqs. (1) and (2) are shown in Table 4. The estimation method employs the Arellano–Bond system GMM estimator. For each equation, we test four specifications. For each of them the lag-lengths of *CPI* and *Internet* are either one or two. The effective sample size is 420.

To deal with endogeneity and autocorrelation, the second and available deeper lags are used as the instruments. The rule of thumb suggests that, in order to mitigate the problem of too many instruments, the number of instruments should not exceed the number of groups — 70 in this study. The numbers of instruments used in estimating the eight specifications of Eqs. (1) and (2) range from 53 to 55, and do not exceed 70, suggesting that the potential problem of too many instruments is not serious (Roodman, 2006).

Regarding the problem of endogeneity, in all eight specifications the results of the Hansen test show that we cannot reject the null hypothesis that the instruments as a group are exogenous, indicating that there is no serious problem of invalid instruments in the models. Regarding the problem of autocorrelation, the results of the AR(2) test show that the null hypothesis of no autocorrelation cannot be rejected, indicating that there is no serious problem of second-order serial correlation in the models.

The empirical results of the Granger causality tests for Eq. (1) are shown in the upper part of Table 4. The main research problem here is to test whether the coefficients of lagged *Internet*, namely δ_k, are significantly different from zero. The standard Granger causality test for joint significance (the null hypothesis is that the coefficients δ_k are jointly equal to zero) and the test for the sum of the coefficients (the null hypothesis is $\sum \delta_k = 0$) are employed. If the empirical results reject the null hypotheses in both tests, we can say that *Internet* Granger-causes *CPI*.

As shown in the upper part of Table 4, for the four specifications testing causality running from *Internet* to *CPI*, the tests for joint significance and for the sum of coefficients are all significant at the 1% significance level, rejecting the null hypothesis of non-causality. Therefore, the Granger causality running from *Internet* to *CPI* can be established. The coefficients of lagged *Internet* are positive, ranging from 0.004 to 0.006. As higher values of *CPI* represent lower levels of corruption, these results indicate that internet adoption can reduce corruption. The statistics of AIC and BIC suggest that the optimal specification is the model with lag-lengths of one for *Internet* and of two for *CPI*.

The empirical results of the Granger causality tests for Eq. (2) are shown in the lower part of Table 4. Similarly, the standard Granger causality test for joint significance (the null hypothesis is that the coefficients γ_k are jointly equal to zero) and the test for the sum of the coefficients (the null hypothesis is $\sum \gamma_k = 0$) are employed to test whether the Granger causality running from *CPI* to *Internet* exists.

As shown in the lower part of Table 4, for the four specifications testing causality running from *CPI* to *Internet*, the tests for joint significance and for the sum of coefficients are all significant at the 1% significance level, thus rejecting the null hypothesis of non-causality. In other words, the reverse causality running from *CPI* to *Internet* can be established. The coefficients of lagged *CPI* are positive, ranging from 1.242 to 1.429. These results indicate that higher levels of corruption can Granger-cause lower levels of internet adoption. The statistics for AIC and BIC suggest that the optimal specification is the model with lag-lengths of two for *CPI* and of one for *Internet*.

In sum, the empirical results of the Granger causality tests indicate that the causality between internet adoption and corruption is bi-directional. Therefore, the problem of two-way causality should be considered when analyzing the effects of internet adoption on corruption.

4.2. Estimation results of the dynamic panel data model

The dynamic panel data model specified in Eq. (3), which takes into account the two-way Granger causality between corruption and internet adoption and controls GDP per capita and the education level, is employed to estimate the effects of internet adoption on corruption reduction. The estimation results are shown in Table 5.

There are five models in Table 5. In all of them the dependent variable is *CPI*. In order to compare the results obtained from the GMM estimator with that obtained from the frequently-used OLS method, in model (1) we employ pooled OLS to estimate Eq. (3) with the lagged

Table 4
Results of Granger causality tests.

Direction	*Internet* → *CPI*			
Lag terms	[1/1]	[1/2]	[2/1]	[2/2]
Joint significance	$\chi^2(1)=9.19^{**}$	$\chi^2(2)=25.73^{**}$	$\chi^2(1)=8.77^{**}$	$\chi^2(2)=24.50^{**}$
Sum of coefficients	$Z=3.03^{**}$	$\chi^2(1)=7.13^{**}$	$Z=2.96^{**}$	$\chi^2(1)=6.68^{**}$
Hansen test	$\chi^2(52)=60.79$	$\chi^2(49)=56.01$	$\chi^2(49)=56.02$	$\chi^2(48)=52.33$
AR(2) test	Z = 1.55	Z = 1.19	Z = 1.03	Z = 1.19
AIC	−1067.95	−1077.15	−1071.09	−1075.82
BIC	−1055.83	−1060.99	−1054.93	−1055.62
Direction	*CPI* → *Internet*			
Lag terms	[1/1]	[1/2]	[2/1]	[2/2]
Joint significance	$\chi^2(1)=19.00^{**}$	$\chi^2(2)=12.64^{**}$	$\chi^2(1)=11.93^{**}$	$\chi^2(2)=11.52^{**}$
Sum of coefficients	$Z=4.36^{**}$	$\chi^2(1)=12.62^{**}$	$Z=3.45^{**}$	$\chi^2(1)=11.51^{**}$
Hansen test	$\chi^2(52)=62.87$	$\chi^2(49)=48.95$	$\chi^2(49)=49.17$	$\chi^2(48)=47.44$
AR(2) test	Z = −0.40	Z = −0.17	Z = 0.14	Z = 0.20
AIC	1104.28	1104.26	1064.00	1069.50
BIC	1116.40	1120.42	1080.16	1089.70
# of countries	70			
# of obs.	420			

Note. (a) * and ** indicate statistical significance at the 5% and 1% levels, respectively. (b) The first number in bracket [p/q] refers to the lag-length of the dependent variable (p), and the second number refers to the lag-length of the independent variable (q). (c) The test statistics for the test of joint significance follow the Chi-square distribution. (d) The test statistics for the test of the sum of coefficients follow the z distribution (Z) if the lag-length is one, and in the other cases the test statistics follow the Chi-square distribution. (e) The test statistics for the AR(2) test follow the z distribution (Z).

Table 5
Estimation results of dynamic panel data models.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	OLS	DPD	DPD	DPD	DPD
Lagged CPI (*lag* = 1)		0.879** (0.035)	0.881** (0.034)	0.862** (0.035)	0.868** (0.035)
Internet	0.029** (0.005)	0.004** (0.001)	0.004** (0.001)	0.006* (0.002)	0.005* (0.002)
GDPpc	0.109** (0.007)	0.013* (0.006)	0.012** (0.005)	0.013* (0.006)	0.012** (0.005)
Edu	0.015** (0.002)	0.004 (0.002)	0.004** (0.001)	0.004 (0.002)	0.004** (0.001)
Year dummy 1999				0.071 (0.058)	0.062 (0.057)
Year dummy 2000				0.019 (0.058)	0.012 (0.056)
Year dummy 2001				−0.013 (0.054)	−0.018 (0.053)
Year dummy 2002				−0.036 (0.043)	−0.040 (0.043)
Year dummy 2003				−0.067 (0.043)	−0.070 (0.040)
Year dummy 2004				−0.002 (0.038)	−0.003 (0.038)
Constant	2.222** (0.179)	0.125 (0.150)	0.092 (0.087)	0.174 (0.158)	0.125 (0.088)
Adj. R^2	0.761				
Hansen test		$\chi^2(58)=$ 62.98	$\chi^2(59)=$ 63.23	$\chi^2(58)=$ 62.32	$\chi^2(59)=$ 62.69
AR(2) test		Z = 1.69	Z = 1.69	Z = 1.75	Z = 1.74
# of countries	70	70	70	70	70
# of obs.	497	462	462	462	462

Note. (a) * and ** indicate statistical significance at the 5% and 1% levels, respectively. (b) Figures in parentheses are robust standard errors. (c) Models (3) and (5) include the urban population ratio in the instrumental variables.

dependent variable and the fixed-effect variable dropped. The effective sample size for model (1) is 497. In models (2) to (5), we use the Arellano–Bond system GMM estimator to estimate the dynamic panel data models. The effective sample size for these models is 462.

The estimation results of model (1) using pooled OLS are shown in the first column of Table 5. The adjusted R^2 is 0.76, suggesting that the three explanatory variables can explain a substantial level of cross-country variation in corruption. As expected, both the coefficients of *GDPpc* and *Edu* are positive and statistically significant, indicating that countries with higher levels of income and better-educated people have lower levels of corruption. The coefficient of *Internet* is 0.029 with a level of statistical significance of 1%, indicating that internet adoption can reduce corruption. However, as the results in Table 4 suggest that an increase in *CPI* can reversely cause an increase in *Internet*, the OLS method is likely to over-estimate the effects of *Internet* on *CPI*.

In models (2) to (5), the explanatory variable *Internet* is assumed to be endogenous. The persistence of corruption is considered by including a lagged dependent variable in the regressor. We assume that the two control variables, *GDPpc* and *Edu*, are predetermined but not strongly exogenous, i.e., they are independent of current disturbances but may be influenced by past ones (Roodman, 2006). In addition to the lags of endogenous variables, the GMM estimator allows the use of additional instrumental variables in estimation. In models (3) and (5), we use the level of urbanization, measured by the urban population ratio (%) and obtained from World Bank (2008), as an additional instrumental variable. We select this variable because it is frequently found in previous studies (for example, Liu & San, 2006) that urbanization is positively associated with internet adoption, and it is not found in the literature that urbanization is a significant driving force behind corruption. Following Roodman's (2006) suggestion, we include time dummies in models (4) and (5).

In order to deal with endogeneity and autocorrelation, for *CPI* and *Internet*, we use their second lags as instruments. For *GDPpc* and *Edu* (the predetermined variables), we use their first and second lags as instruments. The numbers of instruments for models (2), (3), (4), and (5) are 63, 64, 69, and 70, respectively. Because the numbers of instruments do not exceed the number of groups, we can reasonably assume that there is no serious problem of too many instruments.

Regarding the problem of endogeneity, the Hansen test is performed to test the validity of the instruments. The null hypothesis is that the instruments are not correlated with the residuals. As shown in Table 5, for models (2) to (5), the results of the Hansen test are all statistically insignificant, indicating that we cannot reject the exogeneity of the instruments as a group, i.e., there is no serious problem of invalid instruments in the models. Regarding the problem of autocorrelation, the standard Arellano–Bond test is used to check for autocorrelation in errors. As presented in Table 5, the results of the AR(2) test show that the null hypothesis of no autocorrelation cannot be rejected, indicating that there is no serious problem of second-order serial correlation in the models.

For models (2) to (5), as expected, the coefficients of *GDPpc* are positive and statistically significant. The coefficients of *Edu* are positive in models (2) to (5) and statistically significant in models (3) and (5). These results indicate that richer countries with better-educated people have lower levels of corruption. The coefficients of *Lagged CPI* (lag = 1) are statistically significant with values ranging from 0.862 to 0.881, showing that the persistence of corruption is an issue of concern.

The empirical results of models (2)–(5) support the hypothesis that the internet can reduce corruption. The estimation results of models (2) and (3) show that the coefficients of *Internet* are around 0.004 and statistically significant at the 1% level. The estimation results of models (4) and (5) show that the coefficients of *Internet* lie between 0.005 and 0.006 and are statistically significant at the 5% level. Nevertheless, the empirical results also indicate that, without taking into account the endogeneity problem, pooled OLS can over-estimate the effects of the internet on corruption reduction. According to the estimation results of the pooled OLS model, if the internet users per 100 inhabitants increase by 10 persons, the Corruption Perception Index, which ranges from 0 to 10, will on average increase by 0.29. However, according to the estimation results of the dynamic panel data models, if the internet users per 100 inhabitants increase by 10 persons, the Corruption Perception Index will on average increase by only about 0.05.

5. Conclusions

Scholars and policy-makers have argued that the internet can play a substantial role in combating corruption by improving the enforcement of rules, lessening the discretion of officials, and increasing transparency. From a theoretical point of view, the internet can lead to corruption reduction if it is adequately used to alter the principal–agent–client relationship in the public sector through e-government.

In this study we estimate the effects of internet adoption on corruption reduction by utilizing a panel consisting of 70 countries from the year 1998 to 2005. We first test the possibility of two-way causality between internet adoption and corruption. The results of Granger causality tests show that, while causality running from internet adoption to corruption reduction can be established, the reverse causality running from corruption to internet adoption is also found to exist. Therefore, the estimated effects of internet adoption on corruption reduction may be over-estimated if the problem of endogeneity is not appropriately addressed.

To deal with the problem of endogeneity, we employ the dynamic panel data models to estimate the effects of internet adoption on corruption. This approach can also take into account the persistence of corruption which is an important issue in the literature. The empirical results support the hypothesis that the internet has significant effects on corruption reduction. However, we find that on average an increase of 10 in the number of internet users per 100 inhabitants raises the Corruption Perception Index by about 0.05 points, which is not a substantial amount for a 10-point scale. It is also found that the persistence of corruption is significant.

In sum, our results indicate that the internet can lead to corruption reduction, but during the sample period, the effects of internet adoption on corruption reduction are not too substantial. A possible explanation of this result is that, for a country to be able to effectively use the new ICT to reform bureaucracy and combat corruption, some important conditions should be met, e.g., minimal democracy, a sense of crisis, a renewed ideology, and the political will (Mahmood, 2004). But during the sample period one or more of these conditions are not sufficiently met in quite a few countries.

Based on the empirical findings of this study, we believe that the internet has shown its ability in reducing corruption, but its potential has yet to be fully realized. Many countries can still improve the effectiveness of e-government on controlling corruption. As Kim et al. (2009) suggest, these countries should embed effective strategies for fighting corruption in the design of the e-government anti-corruption system, and stronger leadership is needed in implementing such systems. These countries can also benefit from adopting what Heeks (1998) calls "a more holistic vision" that takes into account not only the information system but also organizational and environmental factors when implementing a system for corruption control.

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