Corruption and Social Interaction:
Evidence from China

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Abstract

We explore theoretically and empirically whether social interaction, including local and global interaction, influences the incidence of corruption. We first present an interaction-based model on corruption that predicts that the level of corruption is positively associated with social interaction. Then we empirically verify the theoretical prediction using within-country evidence at the province-level in China during 1998 to 2007. Panel data evidence clearly indicates that social interaction has a statistically significantly positive effect on the corruption rate in China. Our findings, therefore, underscore the relevance of social interaction in understanding corruption.

I. INTRODUCTION

Corruption is a widespread phenomenon affecting human societies throughout time and space. Contemporaneous corruption scandals not only occur in developing countries such as Nigeria, India, and China but also in developed economies such as France, Germany and United States. Even in Scandinavian countries, like Sweden and Norway, supposedly free-from-corruption, managers of state owned companies have been found to be taking bribes (for an overview see Rose-Ackerman, 1999).

Corruption in the public sector is recognised to be the greatest obstacle to development (Kaufmann, 1997). A higher levels of corruption is associated with lower investment and economic growth (Mauro 1995; World Bank, 1997). Corruption weakens the effect of industrial policies and induces private sectors to violate tax and regulatory laws. Foreign direct investment is also depressed by the high level of corruption (Wei, 2000). Anticorruption policies are therefore very important since corruption can induce great harm to countries. Some stress that bribery may increase overall efficiency of an economic system (e.g., Lui, 1985). However, Rose-Ackerman (1999) argues that issues such as tax evasion, violation of environmental rules, certification of unqualified people for public benefit, and grants of immunity to organized crime reduce efficiency. In addition, bureaucrats have an incentive to delay transactions in order to extract higher payments (see Rose-Ackerman, 1997).

Reducing corruption requires a thorough understanding of its causes. A sizable literature has emerged to investigate the determinants of corruption. Current research associates corruption with cultural tradition, economic development, political institutions and government policies. For example, in his comprehensive cross-country study, Treisman (2000) finds that Protestant traditions, history of British rule, long exposure to democracy, higher average income and high levels of imports lead to a decrease of corruption, while decentralization encourages it. Brunetti and Weder (2003) present evidence that press freedom can control corruption. Using a within-country data set, Glaeser and Saks (2006)

document that economic development and education decrease corruption while income inequality and racial fractionalization may increase corruption in America. However, few have explored the impact of social interaction on corruption. A notable exception is Goel and Nelson (2007) who, with state-level U.S. data between 1995 and 2004, show that the effect of neighbouring corruption on local corruption is significantly positive. In other words, corruption is contagious. Contagion effects have been observed in other illegal activities such as assassinations, hijackings, kidnappings, and serial murders as referred to by Bikhchandi, Hirshleifer and Welch (1998). The relevance of social interaction and crime is explored by Glaeser, Sacerdote and Scheinkman (1996) who focus on the United States (across cities and across precincts in New York). The results indicate that social interaction models provide a framework for understanding variances of cross-city crime rates. Individuals are more likely to commit crimes when those around them do. Focusing on corruption, Dong, Dulleck and Torgler (2008) find using cross-sectional micro data that conditional cooperation matters. The willingness to engage in corruption is influenced by the perceived activities of other individuals.

In this paper we explore the effect of social interaction on the incidence of corruption theoretically and empirically in the context of China. China is an interesting country to analyse, not only because it is the largest transitional and developing country, but also because corruption has become more rampant in China since economic reforms were launched in 1978. Even the Chinese government has admitted that corruption "is now worse than during any other period since New China was founded in 1949. It has spread into the Party, into government administration and into every part of society, including politics, economy, ideology and culture" (Liang, 1994, p. 122). Such widespread corruption has caused severe consequences in China, including economic losses estimated to have been between 13.2 and 16.8% of China's GDP in the late 1990s (Hu 2001). Not surprisingly, such rampant corruption has generated much literature, especially in sociology and political science (e.g., White, 1996, and Gong, 2006). From an economic perspective, Yao (2002) argues that corruption in China is generated by the Chinese political system, which grants and protects privileges. With a unique corruption measure, Cai, Fang and Xu (2009) find that corruption has a substantially negative effect on the productivity of Chinese firms. Nevertheless, there is a lack of studies that comprehensively analyse economic underpinnings of corruption in China. We therefore explicitly study the impact of social interaction on the incidence of corruption, and find a statistically significant relationship between social

interaction and corruption. It suggests that like other crimes, the incidence of corruption is significantly affected by social interaction. The rest of this paper is structured as follows: Section II presents a theoretical model. Section III describes our empirical analysis and results. Section IV concludes the paper.

II. THEORETICAL MODEL

In this section we investigate theoretically social interaction in the context of corruption. Following Aidt's survey (2003), we identify three related theoretical articles, which are summarized in Table 1 below. These articles provide stylized facts related to social interaction, but cannot explain thoroughly the effect of social interaction on the incidence of corruption because they do not introduce social interaction explicitly into their models. In terms of social interaction theory, Sah (1988, 2007) and Avdvig and Moene (1990) only study the effect of local interaction, while Lui (1986) simply investigates the effect of global interaction[1].

Table 1   Literature summary

	Crucial point	Approach	Stylized fact
Lui (1986)	It is harder to audit corrupt officials in societies where corruption is more prevalent.	The overlapping-generations model	The different levels of corruption across regions under the same deterrence scheme
Sah (1988, 2007)	An individual's perception of the corruption level is stochastically influenced by the real level that he faced in the past, and this perception affects his current and future corrupt act, which in turn exert stochastic influences on the current and future real corruption level.	The overlapping-generations model	The different levels of corruption across regions
Avdvig and Moene (1990)	The probability of corruption is related to its established frequency.	Simple dynamic model	The different levels of corruption across regions

Nevertheless, a growing body of research considering the role of social interaction in economic outcomes has emerged during the last two decades. According to Zanella (2004, p. 4), social interaction is the "direct interdependences, not mediated by markets and enforceable contracts, between individual decisions and the decisions and characteristics of others within a common sociological group". Economic models that have embedded social interaction "seem particularly adapt to solve a pervasive problem in the social science, namely the observation of large differences in outcomes in the absence of commensurate

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[1] We will discuss these terms later.

differences in fundamentals" (Scheinkman, 2008, p. 2). Sah (1991) states that an individual's environment influences their propensity for crime and explaines the obvious difference between the crime participation rates of societal groups with similar economic fundamentals. With two models of social interaction, Glaeser, Sacerdote and Scheinkman (1996) provide a framework to interpret the cross-city variation in crime rates.

In line with the social interaction research we employ the interactions-based approach (Blume and Durlauf, 2004) to explore bureaucratic corruption. Specifically, we use the binary choice model with social interactions developed by Brock and Durlauf (1995) to model corrupt behaviour.

We consider a population of I homogenous bureaucrats. In the presence of social interactions, each bureaucrat chooses one of two actions: corruption or non-corruption, which is coded by $\omega_i \in \{1, -1\}$. The space of all possible sets of actions by the population is denoted by $\boldsymbol{\omega} = (\omega_1, \cdots, \omega_I)$. Thus $\boldsymbol{\omega_{-i}} = (\omega_1, \cdots, \omega_{i-1}, \omega_{i+1}, \cdots, \omega_I)$ represents the choices of all bureaucrats other than i.

The utility of the bureaucrat i is assumed to be

$$V(\omega_i) = U(\omega_i) + S\big(\omega_i, \mu_i^e(\boldsymbol{\omega_{-i}})\big) + \epsilon_i(\omega_i) \tag{1}$$

Here $U(\omega_i) + \epsilon_i(\omega_i)$ is a private component of the utility. $U(\omega_i)$ is the deterministic private utility decided by the bureaucrat i's choice, which is expressed below, as:

$$U(\omega_i) = \begin{cases} q(w + b), & \omega_i = 1 \\ w, & \omega_i = -1 \end{cases} \tag{2}$$

Here w represents the bureaucrat's wage, b is the bribe a corrupt bureaucrat accepts and q the probability that his corrupt act is not detected. A corrupt bureaucrat will lose his job and hence all his income if his corrupt act is detected. Let $k = \frac{(p+1)w + wb}{2}$ and $h = \frac{(p-1)w + wb}{2}$, we can easily rewrite $U(\omega_i)$ into the form

$$U(\omega_i) = h\omega_i + k \tag{3}$$

$\epsilon_i(\omega_i)$ is the random private utility independently and identically distributed across bureaucrats. In our model it represents the moral shock (moral cost) of taking one of the actions. Following Brock and Durlauf (2001) and Glaeser and Scheinkman (2002), we further assume that $\epsilon_i(\omega_i)$ is extreme-value distributed. Thus the difference between $\epsilon_i(-1)$ and $\epsilon_i(1)$ is logistically distributed,

$$Prob(\epsilon_i(-1) - \epsilon_i(1) \leq x) = {}^1\!/_{1 + exp(-\beta x)}; \quad \beta \geq 0 \tag{4}$$

$S(\omega_i, \mu_i^e(\boldsymbol{\omega_{-i}}))$ in (1), however, is the social component of the utility, namely social utility associated with a bureaucrat's choice. We assume that it captures a pure conformity effect, hence,

$$S(\omega_i, \mu_i^e(\boldsymbol{\omega_{-i}})) = -E_i^s(\sum_{j \neq i} \frac{J_{i,j}}{2}(\omega_i - \omega_j)^2)$$

$$= E_i^s(\sum_{j \neq i} J_{i,j}(\omega_i \omega_j - 1))$$

$$= \sum_{j \neq i} J_{i,j}(\omega_i E_i^s(\omega_j) - 1) \tag{5}$$

Here $J_{i,j} > 0$ are measures of the disutility of nonconformity. $E_i^s(\omega_j)$ denotes the bureaucrat i's subjective expectation of the bureaucrat j's choice. With above assumptions we have,

$$Prob(\omega_i = 1) = Prob(V(1) > V(-1))$$

$$= F(2h + 2\sum_{j \neq i} J_{i,j} E_i^s(\omega_j))$$

$$= \frac{1}{1 + exp(-2\beta(h + \sum_{j \neq i} J_{i,j} E_i{}^s(\omega_j)))} \tag{6}$$

Since the bureaucrats are homogenous, we can assume that $J_{i,j} = \frac{J}{I-1}$ ($J > 0$), and $E_i^s(\omega_j) = E^s(\omega_j)$. Thus,

$$Prob(\omega_i = 1) = \frac{1}{1 + exp(-2\beta(h + JE^s(\omega_j)))} \tag{7}$$

$$E(\omega_i) = 1 \cdot Prob(\omega_i = 1) + (-1) \cdot prob(\omega_i = -1)$$

$$= tanh\beta\left(h + JE^s(\omega_j)\right) \tag{8}$$

The joint set of choices obeys (because ϵ_i is independently distributed),

$$Prob(\boldsymbol{\omega} = \mathbf{1}) = \prod_i \frac{1}{1 + \exp(-2\beta(h + JE^s(\omega_j)))} \tag{9}$$

It is obvious that the corrupt decision of a bureaucrat depends on his expectation of others' decisions. However, there are two different ways in which each bureaucrat interacts with others, namely local interaction and global interaction. According to Brock and Durlauf (2001), local interaction means that each bureaucrat interacts directly only with his neighbourhood in the population, while global interaction implies that each bureaucrat interacts directly with every other bureaucrat of the population. Actually, people often interact with each other in both ways though they assign different weights to these interactions. To reflect this fact, we assume,

$$E^s(\omega_j) = \varphi E_l^s(\omega_j) + (1 - \varphi)E_g^s(\omega_j), \quad 0 \le \varphi \le 1 \tag{10}$$

where the expectation formed from the local interaction can be further expressed as,

$$E_l^s(\omega_j) = \frac{1}{n_i} \sum_{j \neq i} \omega_j, \ j = 1, \dots, n_i < I \tag{11}$$

n_i is the number of bureaucrat i's neighbours. And the expectation formed from the global interaction, on the other hand, can be expressed as,

$$E_g^s(\omega_j) = \frac{1}{I - 1} \sum_{j \neq i} \omega_j, \ j = 1, \dots, I \tag{12}$$

We eventually have following equations

$$Prob(\omega_i = 1) = \frac{1}{1 + \exp(-2\beta(h + J(\varphi E_l^s(\omega_j) + (1 - \varphi)E_g^s(\omega_j))))} \tag{13}$$

$$E(\omega_i) = tanh\beta \left(h + J(\varphi E_l^s(\omega_j) + (1 - \varphi)E_g^s(\omega_j))\right) \tag{14}$$

From above we can deduce,

$$\frac{\partial Prob(\omega_i = 1)}{\partial E_l^s(\omega_j)} > 0; \quad \frac{\partial E(\omega_i)}{\partial E_l^s(\omega_j)} > 0 \tag{15}$$

$$\frac{\partial Prob(\omega_i = 1)}{\partial E_g^s(\omega_j)} > 0; \quad \frac{\partial E(\omega_i)}{\partial E_g^s(\omega_j)} > 0 \tag{16}$$

We therefore conclude that the social interaction, including local interaction and global interaction, does matter in a corrupt act. As can be seen in (15) and (16) the incidence of corruption is positively related to both local interaction and global interaction.

III. EMPIRICAL WORK

The model above generates two testable implications on the relationship between the incidence of corruption and social interaction, presented in equations (15) and (16). We plan to test these implications using within-country panel data of China.

3.1   Data and Methodology

Among related studies, Goel and Nelson (2007) use the cross-sectional within-country data of America, while Attila (2008) and Dong, Dulleck and Torgler (2008) employ cross-country data sets. We prefer within-country panel data in such a context. Studies on corruption could have attributed the different levels of corruption to the cultural and institutional difference across regions, rather than social interactions. In addition, one can stress that social interactions are triggered by the institutional condition within a country. Thus, it is difficult to estimate the importance of social interaction in explaining the different corruption levels across countries. If we use cross-country data,, cultural and institutional variation across countries are hard to proxy and fully control. Using within-country data, especially those of a country homogenous in culture and institutions like China, however, can mitigate this kind of problem. Moreover, we can further control for regional heterogeneity when using within-country panel data since it provides control for the state- and time- invariant variables in the econometric analysis (Hisao, 2003).

   Goel and Nelson (1998), Fisman and Gatti (2002) and Glaeser and Saks (2006) use the corruption convictions of states to measure state-level corruption in America. We use a

similar measure, namely the registered cases of corruption in provincial procurator's offices, to proxy the provincial corruption level in China. Using conviction data[2] has the strength of dealing with a less subjective measure of corruption offering also the opportunity to work with longer time spans. In addition, they are not subject to the problems of sampling error and survey non-response (Glaeser and Saks, 2006). On the other hand, there is the disadvantage that the conviction rate is driven by the quality of the detection process. The weakness, however, will not trouble us in our current study since the quality of local judicial systems in China is basically homogeneous. In addition, we will control local anti-corruption efforts in our regressions.

Following the definition of global interaction, we use the average of corruption levels in the neighbour provinces to measure the global interaction between bureaucrats, which therefore can also be called the neighbouring effect. According to the definition of local interaction, we need to find the average corruption level of closely interacting bureaucrats at the beginning of a period when a bureaucrat makes a corrupt decision. We assume that closely interacting bureaucrats are bureaucrats within the same province. We therefore choose the corruption level of this province in the last period to proxy the local interaction between bureaucrats in the province, which hence can be also referred to as the historical effect. Sah (2005, p. 6), e.g., stresses "(…) if their past experiences have convinced some bureaucrats that cheating is more pervasive in the economy, then they are more likely to choose to be corrupt…Through these dynamic relationships, future levels of cheating and corruption in the economy become explicitly linked to past levels of cheating and corruption in the economy…".

Besides the key variables discussed above we also employ a set of control variables which are commonly used in corruption regressions to minimize omitted variable bias. Treisman (2000) suggested that corruption is associated with historical and cultural traditions, levels of economic development, political institutions and government policies. Since there are no substantial differences in history, culture and institutions between Chinese provinces, we only focus here on the economic and policy controls. Similar to Goel and Nelson (1998),

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[2] Theoretically, conviction rates and the number of registered cases of corruption are different. However in China they are actually the same. In most cases in China suspect officials are first investigated by the discipline inspection commission of the Chinese Communist Party and its local branches. Only after they have obtained enough evidence, the discipline inspection commissions will refer corrupt cases to the procuratorates, and procuratorates then register the cases. Furthermore the courts and the procuratorates are both controlled by the Chinese government. Therefore in few circumstances the courts will reject public prosecutions against corrupt cases.

we use provincial per capita expenditures for police, procuratorate, court and judiciary to proxy anticorruption efforts of each province. This is also important as we are focusing on registered cases of corruption (influenced by regional anticorruption efforts). According to the two comprehensive studies on the causes of corruption, Treisman (2000) and Glaeser and Saks (2005), more educated and richer areas have less corruption. These studies also suggest government regulation and the relative wage of the public sector as potential determinants of corruption. Ades and Di Tella (1999) show the tendency that an increase in rents, due to the discovery of natural resource or a decrease in competition, leads to an increase in corruption. Furthermore, Fisman and Gatti (2002) find, contrary to Treisman (2000), that fiscal decentralization depresses corruption in America. As mentioned in the introduction, Brunetti, and Weder (2003) also show that the media substantially controls corruption. Finally, Swamy, Knack, Lee and Azfar (2001) find that countries with more parliamentary seats held by women tend to have less corruption. We therefore control for such potential determinants of corruption. The detailed description of all the explanatory variables is presented in Table 2. We measure female representation in politics in Chinese provinces with the female representation in the National People's Congress, the only legislative house in China. In line with Zhang and Zou (1998) we use the ratio of per capita provincial government expenditure to per capital central government expenditure to proxy fiscal decentralization among provinces.

Table 2   Variables description (1998—2007)

Variable	Description	Mean	Std. Dev.	Source
Cases	Provincial registered cases on corruption in procurator's office per 100,000 population	3.14	0.96	China Procuratorial Yearbook
Border	Unweighted average of *Cases* in neighbouring provinces	3.04	0.64	
Anticorruption	Per capita expenditure for police, procuratorate, court and judiciary	112.43	103.41	
Income	Logarithm of per capita gross provincial product	9.15	0.63	
Education	Fraction of the population with college completed	5.44	4.31	China Statistical Yearbook
Wage	Ratio of government employee' wage to average wage	1.13	0.13	
Openness	Ratio of export to gross provincial product	14.45	22.62	
Decentralization	Ratio of per capita provincial consolidated spending to per capita central consolidated spending	38.20	19.52	
Resource	The fraction of employment in the mining sector	4.93	3.75	
Regulation	Relationship between the market and the government	6.72	2.04	Fan, Wang, and Zhu (2010)
Media	Annual newspaper circulation per capita	41.38	88.07	China Statistical Yearbook
Female	Female representation in the National People's Congress	0.22	0.041	

Because the definition and thus statistical calibre of the crime of corruption and bribery was changed with a 1997 amendment to China's criminal law, we ensure comparability by collecting data only for 1998 to 2007. Looking at the summary of corruption levels by region, there is a fairly wide degree of regional variation that ranges from 1.77 in Tibet to 5.01 in Tianjin (see Table A1 in the Appendix).

Our basic specification is as follows:

$$Cases_{i,t} = \alpha \, Cases_{i,t-1} + \gamma Border_{i,t} + X'_{i,t-1}\beta + \gamma_i + \epsilon_{i,t} \tag{17}$$

where i and t denote provinces and years respectively and j is the lag value. γ_i indicates unobserved province fixed effects. The vector $X_{i,t-1}$ includes all control variables discussed above. We choose one-year lagged values for explanatory variables because there must be intensive investigations before the corruption cases are registered in the procurator's offices.

We first perform pooled OLS to obtain primary results. However, to identify the causal effect of social interaction on corruption, we need to address the endogeneity problem in our estimation. We first include province fixed effects in our panel regressions to control for unobserved provincial characteristics influencing both corruption and its determinants especially social interaction to deal with potential endogeneity biases. Mo (2001, p. 70) describes a corruption problem as "an institutional problem that lasts for a long period". Thus, since the major source of potential bias in our regressions may be time-invariant historical factors, we choose fixed-effect regressions as the most suitable tool for investigating the relationship between corruption and social interactions.

However, fixed effect regressions do not necessarily estimate the causal effect of social interaction on corruption. First, fixed effects regressions cannot remove endogeneity biases generated by time-varying omitted factors affecting both corruption and its determinants (especially social interaction). Second, the lagged independent variable $Cases_{i,t-1}$ is indeed correlated with $\epsilon_{i,s}$ for $s < t$, which according to Wooldridge (2002), biases our fixed effects OLS estimation. The standard strategy to deal with such potential biases is the instrumental variables method. Anderson and Hsiao (1981) suggest to first-difference the equation like (17) to remove individual effects:

$$\Delta Cases_{i,t} = \alpha \, \Delta Cases_{i,t-1} + \gamma \Delta Border_{i,t} + \Delta X'_{i,t-1}\beta + \Delta \epsilon_{i,t} \tag{18}$$

$Cases_{i,t-2}$ is then used as the instrument for $\Delta Cases_{i,t-1}$ to obtain more consistent estimates since it is uncorrelated with $\Delta\epsilon_{i,t}$ as long as $\epsilon_{i,t}$ are not serially correlated. However, the instrumental variable estimator suggested by Anderson and Hsiao (1981) is not efficient because all further lags of $Cases_{i,t}$ can also be used as additional instruments as they are uncorrelated with $\Delta\epsilon_{i,t}$. Arellano and Bond (1991) therefore derive a GMM estimator with all these instruments to estimate the model more efficiently than the Anderson and Hsiao (1981) estimator. Furthermore, based on Arellano and Bover (1995), Blundell and Bond (1998) develop a system GMM estimator since the above lagged-level instruments in the Arellano and Bond (1991) estimator becomes weak when the autoregressive process is too persistent in the dynamic model. In their system estimator lagged differences are used as instruments for the level equation such as (17) while the lagged levels are used as instruments for an equation such as (18). We therefore estimate our model with this Arellano-Bover/Blundel-Bond system estimator. In our case the lags of $Border_{i,t}$ are used as its instruments since there might be a reverse causality between $Cases_{i,t}$ and $Border_{i,t}$. Using the same method we instrument some other corruption determinants, namely *income, education, openness and regulation* which might potentially be endogenous.

The correlation matrix (Table A2) in the Appendix indicates potential multicollinearity issues. To minimize the consequence of multicollinearity, we first adopt a parsimonious specification including only measures of social interactions and anticorruption efforts. Then some control variables which are not highly correlated with each other are added into the specification. Finally we run regressions with all the discussed control variables. The process allows us also to better check the robustness of the results.

3.2   Results

The findings are presented in Table 3. We start with OLS estimation to obtain primary results (see specification (1), (4), and (7)). Then fixed effects regressions are performed to deal with a potential endogeneity bias (see specification (2), (5) and (8)). Finally, the Arellano-Bover/Blundel-Bond system estimator is used to get the results (see (3), (6), and (9)). In the first three result columns of Table 3 we run regressions with a parsimonious specification where corruption mainly depends on social interaction when anticorruption efforts are controlled. In the following three columns we only include control variables which are not highly correlated with other explanatory variables into our specification to minimize multicollinearity. In the next three columns of Table 3, results of the full specification are

presented. Overall the results presented in Table 3 indicate that there is a positive and highly statistically significant relationship between social interactions and corruption. Both, global and local interactions matter and the findings are quite robust through all the specifications. Furthermore, the effect of social interaction on corruption is sizable. Other things being equal, one standard deviation increase in local interaction ($Cases_{i,t-1}$) raises provincial registered cases of corruption per 100,000 people between 41% and 78% of a standard deviation, while an increment of global interaction $Border_{i,t}$ by one standard deviation is associated with an extra 11% to 23% increase of a standard deviation in provincial registered cases on corruption per 100,000 people. Thus, it looks as if social interaction is a key element in understanding corruption.

Besides social interaction, other explanatory variables are also observed to generally have the expected effects on corruption in our econometric analysis[3]. The results in the regressions indicate that anticorruption efforts and fiscal decentralization significantly decrease corruption, while resource abundance is observed to substantially increase corruption. According to the Arellano-Bover/Blundell-Bond estimation in Column (6) and (9), though insignificant, deregulation, the relative wage of the public sector and female representation in the National People's Congress are negatively correlated with corruption. In Column (9), education reduces corruption, while higher income is weakly correlated with the higher incidence of corruption (not statistically significant), which seems to contradict most previous studies involved. Such a result might be driven by the transitional nature of Chinese society. Actually countries making the transition to a market economy often experience unprecedented corruption (Levin and Satarov 2000; Paldam and Svendsen 2000). China specifically began its transitional process when economic reform loosened up its economy; however, political reform has lagged behind. Therefore, in the absence of institutional and legal constraints, government continues to play an extensive role in China's economic environment. One unavoidable consequence of such involvement is corruption, a type of corruption that becomes more pervasive when government power is widened through increased economic activity. As a result, regions with higher income levels may be more corrupt. Trade openness and media variables in our regression (9) had an unexpected sign, which might be due to multicollinearity. Actually, in Column (10) and (11) when trade openness and media are included without other highly correlated variables, they both have expected signs and are even statistically significant.

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[3] Although some are not statistically significant.

Table 3   Corruption and social interaction

	Annual Cases (1998—2007)										
	Pooled OLS	Fixed effects OLS	Arellano-Bond GMM	Pooled OLS	Fixed effects OLS	Arellano-Bond GMM	Pooled OLS	Fixed effects OLS	Arellano-Bond GMM	Arellano-Bond GMM	Arellano-Bond GMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$Cases_{t-1}$	0.81***	0.43***	0.64***	0.78***	0.41***	0.58***	0.74***	0.41***	0.52***	0.64***	0.64***
	(0.040)	(0.064)	(0.11)	(0.043)	(0.063)	(0.11)	(0.046)	(0.064)	(0.078)	(0.12)	(0.11)
$Border_t$	0.16***	0.35***	0.31***	0.17***	0.23**	0.34***	0.12**	0.22*	0.24**	0.42***	0.34**
	(0.044)	(0.11)	(0.11)	(0.046)	(0.12)	(0.092)	(0.049)	(0.12)	(0.10)	(0.15)	(0.14)
$Anticorruption_{t-1}$	-0.0014***	-0.0021***	-0.0018***	-0.00089***	-0.0016*	-0.00027	-0.0029***	-0.0015	-0.0017		
	(0.00029)	(0.00071)	(0.00043)	(0.00033)	(0.00087)	(0.00077)	(0.00094)	(0.0017)	(0.0020)		
$Resource_{t-1}$				0.011	0.072**	0.075**	0.015	0.072**	0.090***		
				(0.0098)	(0.031)	(0.036)	(0.0100)	(0.032)	(0.029)		
$Decentralization_{t-1}$				-0.014**	-0.025***	-0.020***	-0.018***	-0.025***	-0.020***	-0.020**	-0.021***
				(0.0060)	(0.0035)	(0.0062)	(0.0041)	(0.0039)	(0.0070)	(0.0085)	(0.0074)
$Regulation_{t-1}$				-0.015	-0.063*	-0.043	-0.052**	-0.035	-0.071		
				(0.012)	(0.035)	(0.046)	(0.022)	(0.040)	(0.048)		
$Female_{t-1}$				-0.52	0.57	-0.48	-0.79	0.43	-2.79	-0.75	-0.071
				(0.95)	(1.15)	(2.11)	(1.02)	(1.21)	(1.99)	(2.53)	(1.92)
$Wage_{t-1}$				0.021	0.43	-0.23	-0.077	0.37	-0.32	-0.88	-0.74
				(0.20)	(0.37)	(0.59)	(0.23)	(0.38)	(0.45)	(0.64)	(0.59)
$Income_{t-1}$							0.17	-0.065	0.073		
							(0.11)	(0.22)	(0.26)		
$Education_{t-1}$							0.0100	-0.027	-0.052*		
							(0.018)	(0.031)	(0.031)		
$Openness_{t-1}$							0.0062**	0.0037	0.020**		-0.0046*
							(0.0027)	(0.0051)	(0.0085)		(0.0025)
$Media_{t-1}$							-0.000026	-0.0037	0.000044	-0.0024*	
							(0.00060)	(0.0030)	(0.0012)	(0.0015)	
$Constant$	0.23	0.91**	0.35	0.40	0.82	0.62	-0.36	1.62	1.33	0.81	1.05
	(0.15)	(0.37)	(0.28)	(0.30)	(0.69)	(1.03)	(0.77)	(2.06)	(2.19)	(0.92)	(0.80)
AR(2)Test			[0.21]			[0.18]			[0.20]	[0.17]	[0.16]
R-squared	0.77	0.83		0.78	0.84		0.78	0.85			
Observations	279	279	279	277	277	277	276	276	276	278	

Note: Robust standard errors in parentheses; p-values in brackets; ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

IV. CONCLUSIONS

In this paper, we explore theoretically and empirically whether social interaction influences the incidence of corruption in China. We first present an interaction-based model on corruption that leads to the theoretical prediction that corruption is positively associated with social interaction. We have differentiated in the paper between local interaction (proxied as the lagged corruption values as closely interacting bureaucrats are bureaucrats within the same region), and global interaction (average of corruption levels in neighbour provinces). Then we test the theoretical prediction applying an empirical analysis using province-level data in China over the period 1998 to2007. Empirical evidence clearly indicates that social interactions, both local and global interaction, have a significantly positive effect on the corruption rate in China. Our findings therefore underscore the relevance of social interaction, an aspect that has long been discussed in economics (see, e.g., Smith, 1759/1976, Veblen, 1899 and Duesenberry, 1949). Interestingly, many traditional models have treated cooperation or compliance with rules as an isolated case. However, individuals do not normally act as isolated individuals playing a game against nature. The behaviour of others (individuals or regions) is important to understand compliance. Hence, theories of pro-social behaviour, which take the impact of behaviour or the preferences of others into account, are promising. The concept of pro-social behaviour can be widely applied in daily life. For example, the broken windows theory suggests that "signs of inappropriate behaviour like graffiti or broken windows lead to other inappropriate behaviour (e.g. litter or stealing)" (Keizer et al. 2008, p.1685). The theory has strongly influenced law enforcement strategies in several US cities such as New York, Chicago, Baltimore, Boston and Los Angeles aiming at maintaining order by dealing more aggressively with minor offenses (Harcourt and Ludwig, 2006).

There are important policy implications based on our findings. Regional corruption is affected by neighbourhood corruption. Successful anti-corruption activities in one area have positive spillover effects on reducing corruption in other (contiguous) areas. To efficiently control corruption neighbouring areas should either coordinate their individual anti-corruption efforts with regional agreements or policy makers should take spillover effects into account when allocating resources. This is particularly relevant when corruption is widespread. On the other hand, a critical mass of cooperative behaviour (low level of corruption) can induce a positive dynamic process of conditional cooperation. Moreover, previous corruption levels have a significant effect on the current corruption level. Evolution of corruption is a path-dependent process. Policies should take into account such

path-dependent processes within a society. The closer a region is to the threshold or tipping point, the easier it is to influence the dynamic conditional cooperative processes. However, identifying such a tipping point is not without problems. One possibility is to change underlying institutional conditions at the local level. In general, rigorous anti-corruption measures need to be carried out for a long period to control corruption in areas where corruption is pandemic. As suggested by Aidt (2003), a "big push" like the one that took place in Hong Kong in the 1970s, might be needed to address the corruption levels in areas where previous corruption rates have been high.

APPENDIX

Table A1   Average annual registered cases on corruption per capita across regions in China (1998-2007)

Region	Average annual registered cases per 100,000 Pop.	Region	Average annual registered cases per 100,000 Pop.	Region	Average annual registered cases per 100,000 Pop.
Tianjin	5.01	Shaanxi	3.15	Yunnan	2.61
Heilongjiang	4.77	Qinghai	3.08	Hunan	2.59
Jilin	4.50	Ningxia	3.08	Hainan	2.59
Liaoning	4.12	Hubei	3.05	Beijing	2.59
Shanxi	3.83	Guizhou	2.95	Chongqing	2.49
Hebei	3.67	Zhejiang	2.91	Anhui	2.36
Shandong	3.62	Inner Mongolia	2.77	Sichuan	2.35
Xinjiang	3.41	Shanghai	2.77	Gansu	2.05
Fujian	3.40	Jiangsu	2.71	Guangdong	2.05
Henan	3.35	Guangxi	2.64	Tibet	1.77
Jiangxi	3.29				

Table A2   Pairwise correlation coefficients between variables

	Corruption	Border	Anticorruption	Income	Education	Wage	Openness	Regulation	Media	Resource	Female	Decentralization
Corruption	1.00											
Border	0.32	1.00										
Anticorruption	-0.20	0.25	1.00									
Income	0.04	0.34	0.78	1.00								
Education	0.06	0.44	0.79	0.75	1.00							
Wage	-0.05	0.01	0.23	0.38	0.14	1.00						
Openness	-0.08	0.42	0.76	0.75	0.81	0.27	1.00					
Regulation	-0.15	-0.03	0.25	0.54	0.33	0.31	0.39	1.00				
Media	-0.06	0.40	0.58	0.51	0.78	0.09	0.75	0.15	1.00			
Resource	0.39	0.04	-0.37	-0.30	-0.22	-0.33	-0.43	-0.27	-0.26	1.00		
Female	-0.24	0.23	0.19	0.14	0.24	0.20	0.29	0.08	0.49	-0.15	1.00	
Decentralization	-0.08	0.28	0.52	0.39	0.46	0.01	0.46	-0.08	0.41	-0.18	0.17	1.00

REFERENCES

Ades, A., & Di Tella, R. (1999). Rents, Competition and Corruption. American Economic Review 89, 982-993.

Aidt, T. S. (2003). Economic Analysis of Corruption: A Survey. The Economic Journal 113, 632-652.

Anderson, T., & Hsiao, C. (1981). Estimation of Dynamic Models with Error Components. Journal of the American Statistical Association 76, 598-606.

Andvig, J. C., & Moene, K.O. (1990). How Corruption May Corrupt. Journal of Economic Behaviour and Organization 13, 63-76.

Attila, G. (2008). Is Corruption Contagious? An Econometric Analysis. Norwegian Institute of International Affairs Working Paper, No. 742.

Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. Review of Economic Studies 58, 277-297.

Arellano, M., & Bover, O. (1995). Another Look at the Instrumental-Variable Estimation of Error-Components Models. Journal of Econometrics 68, 29-51.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1998). Learning from the Behaviour of Others: Conformity, Fads, and Informational Cascades. Journal of Economic Perspectives 12, 151-170

Blume, L. E., & Durlauf, S.N. (2004). The Interactions-Based Approach to Socioeconomic Behaviour. In Social Dynamics, Steven N. Durlauf, H. Peyton Young (eds.), The MIT Press.

Blundell, R.W., & Bond, S.R. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. Journal of Econometrics 87, 115-143.

Brock, W. A., & Durlauf, S.N. (1995). Discrete Choice with Social Interactions I: Theory. NBER Working Papers No. 5291.

Brock, W. A. and Durlauf, S.N., 2001. Discrete Choice with Social Interactions. The Review of Economic Studies 68, 235-260.

Brunetti, A., & Weder, B. (2003). A Free Press is Bad News for Corruption. Journal of Public Economics 87, 1801-1824.

Cai, H., Fang, H., & Xu, C.L. (2009). Eat, Drink, Firms and Government: An Investigation of Corruption from Entertainment and Travel Costs of Chinese Firms. Journal of Law and Economics, forthcoming.

Dong, B., Dulleck, U., & Torgler, B. (2008). Conditional Corruption. CREMA Working Paper Series 2008-29.

Duesenberry, J.S. (1949). Income, Saving, and the Theory of Consumer Behaviour. Cambridge, MA: Harvard University Press.

Fisman, R., & Gatti, R. (2002). Decentralization and Corruption: Evidence from U.S. Federal Transfer Programs. Public Choice 113, 25-35.

Glaeser, E.L., Sacerdote, B., & Scheinkman, J.A. (1996). Crime and Social Interactions. The Quarterly Journal of Economics 111, 507-548.

Glaeser, E.L., & Saks, R.E. (2006). Corruption in America. Journal of Public Economics 90, 1053-1072.

Glaeser, E.L., & Scheinkman, J.A. (2002). Non-Market Interactions. in Advances in Economics and Econometrics: Theory and Applications, Eight World Congress, M. Dewatripont, L.P. Hansen, and S. Turnovsky (eds.), Cambridge University Press.

Goel, R.K., & Nelson, M.A. (1998). Corruption and Government Size: A Disaggregated Analysis. Public Choice 97, 107-120.

Goel, R. K., & Nelson, M.A. (2007). Are Corrupt Acts Contagious? Evidence from the United States. Journal of Policy Modelling 29, 839-850.

Gong, T. (2006). Corruption and Local Governance: the Double Identity of Chinese Local Governments in Market Reform. The Pacific Review 19, 85-102.

Harcourt, B.E., & Ludwig, J. (2006). Broken Windows: New Evidence from New York City and a Five-City Social Experiment. University of Chicago Law Review 73, 271-320

Hsiao, C. (2003). Analysis of Panel Data. Cambridge University Press, New York.

Hu, A. (2001). Corruption and Social Inequality. Jiangsu Social Sciences 3, 51-53.

Kaufmann, D. (1997). Corruption: The Facts. Foreign Policy 107, 114-131.

Keizer, K., Lindenberg, S., & Steg, L. (2008). The Spreading of Disorder. Science 322, 1681–1685.

Lambsdorff, J.G. (2005). Consequences and Causes of Corruption—What do We Know from A Cross-Section of Countries? University of Passau discussion paper #V-34-05.

Levin, M., & Satarov, G. (2000). Corruption and institutions in Russia. European Journal of Political Economy 16, 113-132.

Liang, G. (1994). The Practical Encyclopaedia of Anti-Corruption in China and Foreign Countries. Beijing, Xinhua Press.

Lui, F. T. (1985). An Equilibrium Queueing Model of Bribery. Journal of Political Economy 93, 760–781.Lui, F.T. (1986). A Dynamic Model of Corruption Deterrence. Journal of Public Economics 31, 215-236.

Mauro, P. (1995). Corruption and Growth. The Quarterly Journal of Economics 110, 681-712.

Mo, P.H. (2001). Corruption and Economic Growth. Journal of Comparative Economics 29, 66-79.

Paldam, M., & Svendsen, G.T. (2000). Missing Social Capital and the Transition in Eastern Europe. Working Papers 00-5, Aarhus School of Business, Department of Economics.

Rose-Ackerman, S. (1997). The Political Economy of Corruption. in Corruption and the Global Economy, K. A. Elliott (eds.), Washington D.C.: Institute for International Economics 31-60.

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

Sah, R. (1988). Persistence and Pervasiveness of Corruption: New Perspectives. Discussion Paper No. 560, Economic Growth Centre, Yale University.

Sah, R.. (1991). Social Osmosis and Pattern of Crime. Journal of Political Economy 99, 1272-1295.

Sah, R.. (2005). Large and Persistent Differences in Corruption across Countries and Regions. Working Paper No 2003-13.

Sah, R.. (2007). Corruption across Countries and Regions: Some Consequences of Local Osmosis. Journal of Economic Dynamics & Control 31, 2573–2598.

Scheinkman, J. A. (2008). Social Interactions. in The New Palgrave Dictionary of Economics (2nd ed.), S. Durlauf & L. Blume (eds.), Palgrave Macmillan.

Smith, A. (1759/1976). The Theory of Moral Sentiments. Oxford: Clarendon Press.

Swamy, A., Knack, S., Lee, Y., & Azfar, O. (2001). Gender and Corruption. Journal of Development Economics 64, 25-55.

Treisman, D. (2000). The Causes of Corruption: A Cross-National Study. Journal of Public Economics 76, 399-457.

Treisman, D. (2007). What Have We Learned About the Causes of Corruption From Ten Years of Cross-National Empirical Research? Annual Review of Political Science 10, 211-244.

Veblen, T. (1899). The Theory of the Leisure Class. New York: MacMillan.

Wei, S.-J. (2000). How Taxing is Corruption on International Investors. Review of Economics and Statistics 82, 1-11.

White, G. (1996). Corruption and the Transition from Socialism in China. Journal of Law and society 23, 149-169

Wooldridge, J.M. (2002). Econometric Analysis of Cross Section and Panel Data. MIT Press; Cambridge.

World Bank, (1997). Helping Countries Combat Corruption: The Role of the World Bank. Poverty Reduction and Economic Management, World Bank.

Yao, S. (2002). Privilege and Corruption: The Problems of China's Socialist Market Economy. American Journal of Economics and Sociology 61, 279-299.

Zanella, G. (2004). Social Interactions and Economic Behaviour. Working paper No. 411, Department of Economics, University of Siena.

Zhang, T., & Zou, H.-F. (1998). Fiscal Decentralization, Public Spending, and Economic Growth in China. Journal of Public Economics 67, 221-240.