Social Capital and Corruption: Theory, and Evidence from India*

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Abstract

Potential bribe-payers often face a collective action problem: they would all be better off if they could enforce an agreement not to pay bribes. This paper uses a linked-games model to show how social capital, viewed as trust generated through repeated interactions in other games, can help them to overcome this collective action problem and enforce agreements (or norms) against bribery. We also carry out an empirical test which explores variations in the frequency with which officials are transferred between posts in Indian states. Consistent with our model, we find that social capital in Indian states is positively correlated with transfer frequency. We argue that plausible alternative theories would have predicted a negative relationship.
1 Introduction

The empirical literature on corruption is substantial and growing rapidly (see Lambsdorff 2005 for a survey). A variety of cultural and historical variables, such as social capital, ethnic heterogeneity, and colonial heritage are generally found to be significant in explaining differences in the level of corruption across countries.\(^1\)

However, the existing literature is overwhelmingly based on cross-country regressions using subjective corruption indices.\(^2\) This is problematic for several reasons. First, the meaning of the indices is unclear because of the important differences between the kinds of corruption which occur in different countries. For example, India, Russia and Tanzania all received the same score on the Transparency International’s 2004 corruption perceptions index, but they clearly face qualitatively very different problems. Furthermore, the subjective perceptions on which the survey data are based might be misleading. For example, a few high-profile prosecutions might raise people’s perceptions of the level of corruption while actually reducing the true level of corruption by serving as an example to others.

But even if we could be confident that the corruption indices were measuring a meaningful variable, cross-country regressions would still tell us little about how the explanatory variables affect the level of corruption, and are therefore of limited use in generating policy prescriptions (other than vague entreaties to “build social capital”). In the words of an eminent authority,

Cross-country empirical work... is of little use in designing anti-corruption strategies...

In fact, it is not even clear what it means for a country to rank highly on a corrup-
tion index... The surveys give no information that would help one understand their underlying meaning. (Rose-Ackerman 1999:3-4)

This paper explores the relationship between social capital and corruption while attempting to avoid these deficiencies. First we use a simple linked-games model to show how social capital can reduce corruption. The basic idea of the model is that paying bribes often creates a negative externality among the potential bribe-payers: by paying a bribe in exchange for preferential treatment, an individual reduces the benefits available to everyone else. As a result, bribe-payers face a collective action problem: they would all be better off if they could all mutually commit not to pay bribes. “Social capital” (which we view as trust generated through repeated interaction in other games) can enable them to enforce agreements not to pay bribes (or informal “norms” against bribery) and thereby reduce the level of corruption.

We then carry out an empirical test based on Indian data. Focusing on India has the advantage that in the states of India, a relatively uniform formal system interacts with diverse cultural and social environments, enabling us to avoid some of the problems associated with cross-country comparisons. Also, rather than relying on subjective corruption survey indices to measure corruption, our variable of interest will be the frequency with which government officials are transferred between posts. Clearly, this will give us some explaining to do, but it has the important advantage that the data are objective.

Furthermore, we argue that the effect of social capital on transfer frequency may differ depending on how social capital affects corruption. Frequent transfers of government officials
in India are often regarded as a symptom of corruption and political instability, so one might predict that social capital would reduce transfer frequency. However, our model reveals the surprising possibility that social capital might increase transfer frequency. The intuition, roughly, is that social capital indeed reduces the level of corruption, but does so by enabling collective action against corrupt officials, and this can sometimes lead to corrupt officials being transferred.

Measuring social capital (or related variables like “trust” or “civicness”) presents many of the same problems as measuring corruption. For one thing, there are probably several different kinds of social capital, and they might have different effects; also, direct measures are hard to come by. We employ two kinds of proxies for (a lack of) social capital in Indian states: an index of ethnic diversity, and two measures of the frequency of riots. The diversity index is based on an anthropological survey and is broadly similar to the ethnolinguistic fractionalization index used in several cross-country studies. The riots variable, however, is a context-specific innovation. We justify its use by drawing on studies which indicate that riots are likely to be less frequent when there is a significant amount of social capital linking members of the relevant groups.

We also consider the role of literacy, but we argue that it is a better proxy for human capital than for social capital in the Indian context. One of our interesting empirical results is that literacy significantly affects transfer frequency, but it has the opposite effect of our measures of social capital. Our model helps to explain these findings by differentiating the effects of human capital and social capital.
The paper proceeds as follows. Section 2 presents the model. Section 3 discusses public administration in India, highlighting the importance of transfer frequency. Section 4 motivates the use of the riots variable. Section 5 carries out the empirical test. Section 6 concludes.

2 Model

This model uses an infinitely-repeated game to show how relationships among the clients of a bureaucracy can affect officials’ incentives to engage in corruption. We employ the concept of strategic linkage: when the same individuals encounter each other in several different games, they can pool the incentive constraints across games (Bernheim and Whinston 1990). First we describe a “social exchange” game which generates social capital. Next we describe a “rent-seeking” game in which corruption can occur. Then we link the two games to see how the level of social capital can affect the level of corruption.

Consider a large population of players, who discount future payoffs at a rate $\delta$. Associated with each player there is a subset of the other players who are that players “acquaintances”. In every period, each pair of acquaintances play a “social exchange” game. The players move simultaneously, and each player can either do a favor for her acquaintance (“cooperate”) or defect. Doing a favor costs $u$ and generates a benefit $u + z$ for the recipient. The game is therefore a prisoner’s dilemma, with the following payoffs:
Social exchange might represent a variety of self-enforcing social or economic interactions. The key feature of social exchange is that enforcement is informal, in the sense that opportunism is constrained by the “trust” generated through repeated interaction, rather than by a third party. We will interpret the trust generated within social exchange relationships as a form of social capital.

We will focus throughout on grim trigger strategies. These are not renegotiation-proof, but they are optimal penal codes in the games we will consider, and have the advantage of simplicity.

Lemma 2.1. Cooperation can be sustained as a subgame-perfect equilibrium within a social exchange relationship if and only if

\[
S(u, z, \delta) := \frac{\delta z}{1 - \delta} - u \geq 0
\]  

(1)

Proof. Consider a grim trigger strategy. This is subgame perfect. With this enforcement regime, defection yields a one-shot gain of \(u\); the net loss in each future period is \(z\). Therefore, cooperation can be sustained if and only if (1) holds. \(\square\)

Next we describe the rent-seeking game. Each period, a government official is born and lives for one period. Two players (“clients”) are randomly chosen from the population, and
the official must allocate a valuable rent worth \( R > 0 \) between them. Government policy specifies rules according to which the official is supposed to allocate the rent. The official knows these rules and therefore the clients true entitlements. With probability \( \alpha \), the clients are also aware of their entitlements and able to assert their rights (in court, for example). \( \alpha \) can be regarded as a measure of how well-informed and sophisticated the clients are as well as the transparency of the regulations. If the clients can assert their rights, the official has no discretion in the award of the rent, and therefore no opportunity to act corruptly. If the clients are not able to assert their rights, the official has an opportunity to act corruptly (though he may still choose to act honestly).

For reasons we will discuss below, one of the factors which may influence an official’s decision of whether to act corruptly is whether the clients with whom he is dealing are acquaintances. However, an official may not know the nature of the relationship between the clients. To capture this, we assume that at the start of the period, the official observes a signal which indicates whether the two clients with whom he will deal in that period are acquaintances, and that this signal is incorrect with probability \( \mu > 0 \).

After observing the signal, the official can choose to be honest \( (h) \) or make it known that he is willing to accept bribes \( (d) \). If he acts honestly (ie., allocates the rent according to government policy), each client obtains an (expected) payoff of \( \frac{1}{2}R \), and the official’s payoff is 0. If he acts dishonestly, we assume for simplicity that he awards the rent to whichever client offers the highest bribe (if both clients offer the same bribe amount, the official chooses one at random). Then the clients move simultaneously. Each can either offer the official a
bribe (of any positive amount), or complain to the official’s superiors at a cost \( c \). The idea here is that they must choose whether to resist or accommodate the official’s demand for bribes, but they cannot do both. We also make the natural assumption that they cannot observe each other’s actions.

Most of the theoretical literature treats corruption as a principal-agent problem between “the state” and government officials, focusing primarily on the state’s optimal choice of monitoring intensity, incentives and sanctions to constrain officials’ behavior. A key difference here is that we assume instead that monitoring of officials is carried out by the clients (perhaps through complaints to their political representatives), rather than by the state itself directly.

**Assumption 1.** *If both clients complain, the official suffers a punishment \( P > 0 \). However, isolated complaints are ignored. All players observe whether the official is punished.*

The punishment inflicted on an official following coordinated complaints might be interpreted as a fine, demotion, or dismissal, depending on the circumstances.

**Lemma 2.2.** *A one-shot rent-seeking game has a unique subgame-perfect equilibrium, in which the official chooses \( d \) if he has an opportunity to act corruptly, and both clients offer to pay bribes of \( R \) if the official chooses \( d \).*

*Proof.* If an official has chosen \( d \), and one client complains or offers a bribe \( b \), then unless \( b = R \), the other client’s best response is to pay a bribe slightly higher than \( b \) and obtain the whole of the rent. The unique Nash equilibrium in this subgame is for both clients to
offer bribes of $R$. The official’s resulting payoff is $R$ and the clients have a net payoff of zero. If instead the official chooses $h$, both clients have a dominant strategy of offering no bribe and not complaining. The official’s payoff is zero. Thus, by backward induction, there is a unique subgame-perfect equilibrium in the one-shot rent-seeking game, in which the official chooses $d$ and both clients offer bribes of $R$.

The rent-seeking game is a “dilemma” for the clients because if they could both credibly commit to complain rather than pay bribes after an official chooses $d$, the official would be induced to act honestly and they could each obtain an expected payoff of $\frac{1}{2}R$ rather than their equilibrium payoff of zero. One possible means of enforcing such a commitment would be if the game was repeated. In this case, the following argument still goes through. Here, for simplicity, we will assume that the population is large enough that the clients treat the probability that they will play another rent-seeking game in the future as zero. This will allow us to focus on how enforcement can occur through strategic linkage.

Suppose now that the two clients who must play a rent-seeking game are also acquaintances (i.e., they also play a social exchange game), and that the two games are played simultaneously, according to the timeline depicted in Figure 1.

**Proposition 1.** If the two clients in a rent-seeking game are acquaintances, a subgame-perfect equilibrium in which no bribes are paid exists if and only if

$$\frac{R}{2} + c \leq S(u, z, \delta) \quad (2)$$

**Proof.** Consider a grim trigger strategy according to which the players agree to complain about any official who plays $d$, and defection in either game is punished by Nash reversion in
Clients choose to cooperate or defect in social exchange game. Official observes whether clients are acquaintances (error w/prob $\mu$). Nature decides whether official can act corruptly (yes w/prob $1 - \alpha$). Clients can either bribe or complain. Official chooses $h$ or $d$. Clients choose to cooperate or defect in social exchange game. Official punished if both clients complain.

Figure 1: Time line, linked games

the social exchange game (since the official’s punishment is publicly observable, the clients can infer that one of them defected if an official who plays $d$ is not punished). With this enforcement regime, an individual would prefer to defect in both games simultaneously than in either alone. A player would therefore defect unless

$$R + (u + z) + \frac{\delta}{1 - \delta}(0) \leq \frac{R}{2} - c + z + \frac{\delta}{1 - \delta}(z)$$

The left-hand side shows the one-shot payoffs from defection in both games, plus the stream of payoffs from the social exchange game following Nash reversion. The right-hand side shows the value of the expected payoff stream from cooperation in both games after an official has chosen $d$, assuming the other player also cooperates. This inequality simplifies to (2). $\square$

Proposition 1 shows that strategic linkage can enable two acquaintances to overcome
corruption if the “slack” from the social exchange game, $S(u, z, \delta)$, is sufficiently large, by staking their reputations in the social exchange game on their commitment to resist corruption. If the two clients are not acquaintances, however, they cannot avoid having to pay bribes. In fact, this conclusion is probably too pessimistic. As Kandori (1992) has shown, even if a particular pair of players only interact occasionally, they may be able to trust each other if information about their actions circulates within the community. Therefore, one reasonable interpretation of social capital is the information-sharing networks which enable “community enforcement” to work. The argument below can be extended to this situation (Kingston 2004). For simplicity, however, we will focus on direct bilateral enforcement.

To see how social capital will affect the level of corruption, we define the following.

**Definition.** The *level of social capital*, $\sigma$, is the probability that two randomly-selected individuals are acquaintances.

**Definition.** The *level of corruption*, $\gamma$, is the probability that bribery occurs in a rent-seeking game.

**Definition.** *Punishment frequency*, $\lambda$, is the expected probability that an official is punished in a rent-seeking game.

Consider the following “linked” strategy for the clients:

- Cooperate in social exchange games as long as neither player has ever defected in the social exchange game or failed to complain about an official who played $d$ in the rent-
seeking game. When playing the rent-seeking game against an acquaintance, if the
official chooses \( d \), and if neither player has ever cheated in the social exchange game,
complain. Otherwise, offer a bribe of \( R \). When playing the rent-seeking game against
someone who is not an acquaintance, if the official chooses \( d \), offer a bribe of \( R \).

**Proposition 2.** Suppose that (2) holds. There exists \( \mu^* > 0 \) such that, for all \( \mu < \mu^* \), there
exists a Perfect Bayesian equilibrium in which the clients all play the “linked” strategy. In
this equilibrium,

\[
\frac{\partial \gamma}{\partial \sigma} < 0 \quad \frac{\partial \lambda}{\partial \sigma} > 0 \quad \frac{\partial \gamma}{\partial \alpha} < 0 \quad \frac{\partial \lambda}{\partial \alpha} < 0
\]

*Proof.* Suppose the clients adopt the “linked strategy”. The expected payoff to an official
who chooses \( h \) is zero, whatever the identity of the clients. If an official chooses \( d \), and
the two clients are acquaintances, the official will face coordinated complaints and will be
punished (payoff \( -P \)). If they are not acquaintances, the payoff to choosing \( d \) will be
\( R \). Therefore, having observed a signal that indicates that the clients are acquaintances,
the official’s expected payoff to choosing \( d \) is \( \mu R - (1 - \mu)P \). If \( \mu \) is sufficiently small,
this is negative, so the official will prefer to choose \( h \) for a payoff of zero. Similarly, the
expected payoff to choosing \( d \) in the case of a signal which indicates that the clients are not
acquaintances is \( (1 - \mu)R - \mu P \). If \( \mu \) is sufficiently small, this is positive, so the official will
choose \( d \). We have shown that the following strategy is optimal for the official for sufficiently
small \( \mu \):
• If the signal indicates that the clients are acquaintances, choose $h$; otherwise, choose $d$.

Now suppose officials follow this strategy. Since (2) holds, the “linked” strategy is an equilibrium for the clients if they are acquaintances (Proposition 1) and also if they are not (Lemma 2.2). Therefore, these strategies constitute an equilibrium strategy profile.

Given these strategies, payment of bribes will occur when three things happen: an official has an opportunity to act corruptly (probability $1 - \alpha$), faces a pair of clients who are not acquaintances $(1 - \sigma)$, and receives a correct signal $(1 - \mu)$. Therefore, $\gamma = (1 - \alpha)(1 - \sigma)(1 - \mu)$. Officials will be punished when they have an opportunity to act corruptly, face a pair of clients who are acquaintances, and receive an incorrect signal, so they demand bribes and, (to their surprise), trigger coordinated complaints. Therefore, $\lambda = (1 - \alpha)\sigma\mu$.

The proposition follows. $\square$

Proposition 2 shows that as long as “mistakes” (arising from incorrect signals) are rare, then, even though some officials are punished as a result of attempted corruption, and the level of corruption is decreasing in the level of social capital, the frequency of punishment is increasing in the level of social capital. The intuition is that as long as mistakes are infrequent, officials will seek bribes if they believe that the clients with whom they are currently dealing do not trust each other. Officials can make two kinds of errors in this situation. If the clients cannot trust each other, but the official “mistakenly” does not demand bribes, he loses an opportunity to make money, but is not punished. However, officials who misread the situation and demand bribes when the clients do trust each other
trigger complaints which result in their punishment.

3 Public Administration in India

Propositions 1 and 2 showed one way in which social capital may help to reduce corruption. One possible approach to testing the theory would be to see if a proxy for corruption were negatively correlated with a proxy for social capital. However, even if satisfactory proxies could be found, it would hardly be surprising if they were negatively correlated. A variety of possible theories might explain such a correlation.

This paper therefore adopts a different approach. In accounts of public administration in India, the frequency with which government officials are transferred between posts is often identified as a variable closely linked to corruption. However, as discussed below, depending on how social capital reduces corruption, it might be either positively or negatively related to transfer frequency. Thus, focusing on transfer frequency will enable us to investigate not just whether, but also how, social capital reduces corruption.

3.1 Corruption and Transfer Frequency

Indian government officials are frequently transferred between posts. While official rules specify that officials should be transferred every 3 to 5 years, in fact they “can always and at any moment be transferred” (de Zwart 1994:53), and are often transferred several times in a single year. Transfers are generally considered to be closely related to corruption; indeed, “A conversation about transfers is more or less equal to a conversation about corruption”
The most commonly identified cause of transfers is political interference. Wade (1982:319) calls transfers “the politician’s basic weapon of control over the bureaucracy.” Indian politicians have extensive influence over transfers of officials and routinely employ this influence to obtain favors for their supporters and to extract bribes from officials vying for particular jobs.

In Wade’s (1982, 1989) detailed study of an Indian irrigation department, for example, irrigation officials obtained bribes from farmers by manipulating their water supply, and from contractors in exchange for the award of construction and maintenance contracts. Junior officials paid bribes to obtain transfers to especially lucrative posts, the price for each post being dependent on the projected earnings. In this way, bribe money was aggregated and channelled up the hierarchy to senior officials and, ultimately, politicians. The sums involved far exceeded the official’s salaries. de Zwart (1994) calls this system the “leasing of offices”: officials effectively “lease” posts from the politicians who can control their transfers, providing the politicians with a flow of administrative favors and a share of the bribes received, in exchange for transfers to desirable posts and protection from complaints.

Because transfers play such a key role in the system of administrative corruption in India, we might expect transfer frequency to be lower in well-governed states. Accordingly, we might hypothesize that

**Hypothesis 1.** If social capital helps to reduce corruption, and transfers are a symptom of corruption, social capital will reduce transfer frequency.
Another symptom of political interference in transfers is that wholesale transfers frequently occur following changes of government, as politicians reward their supporters and tighten their control over administrative decisions by transferring cooperative officials into important posts while removing officials loyal to their opponents. As a result, transfer frequency tends to be higher at times of political instability, such as in election years. Therefore,

**Hypothesis 2.** *If social capital reduces political instability, and political instability increases transfer frequency, social capital will reduce transfer frequency.*

### 3.2 Transfers: the role of complaints

Another reason politicians may try to have an official transferred is in response to complaints from constituents. “Complaints” can range from informal lobbying or anonymous letters to *gheraos*, demonstrations, and so on.

The most common situation that produces [transfers] is a flow of complaints about individual civil servants, offices, or departments, especially complaints concerning corruption. The first administrative reaction is usually to order a number of transfers. (de Zwart 1994:8)

However, although transfers often result from complaints, Indian bureaucracy is generally viewed as unresponsive to complaints. According to Wade (1989:95), “denunciations are so common that, to exaggerate only a little, no one takes any notice”. How can complaints be so important and yet so ineffective?
The explanation is that formal accountability procedures are extremely weak. Officials enjoy substantial legal protections against dismissal, and investigations can easily be obstructed, making officials relatively immune to isolated formal complaints. But if many constituents complain about a particular official, then politicians have an incentive to get them transferred. For the politician, a transfer is far easier to achieve than a formal prosecution, and just as effective at “keeping the peace”. So, in practice, irrespective of the merits of the case, officials who face a large volume of complaints are usually transferred. The upshot is that an official’s objective is to

maximize revenue subject to the constraint of maintaining complaints about his performance at a low level; a ‘low’ level being that which is insufficient to set off the transfer mechanism (Wade 1989:77).

How will the role of complaints affect the relationship between social capital and transfer frequency? One might argue that if social capital reduces corruption, there will be fewer complaints and therefore a lower transfer frequency (this is another version of Hypothesis 1). However, Proposition 2 shows that while reducing corruption, social capital may increase the frequency of punishment (in this case, transfer frequency) because it facilitates collective action against corrupt officials. Proposition 2’s therefore suggests the possibility of a positive relationship between social capital and transfer frequency, in contrast with the negative relationship predicted by Hypotheses 1 and 2 (all these arguments agree, however, that social capital ought to reduce the level of corruption).
These hypotheses do not exhaust all the reasonable possibilities. For example, one rationale for transferring officials is to prevent corruption by breaking up corrupt networks of officials and bribe-payers. If social capital helps to reduce the level of corruption, it may reduce the need for such transfers, and thereby reduce transfer frequency. Or, we might consider a principal-agent model in which the government randomly monitors officials and punishes those caught taking bribes by transferring them to less desirable posts. In this case, again, social capital might reduce both corruption and transfer frequency. The point is simply that a variety of reasonable theories might predict that social capital would reduce transfer frequency, but that our model suggests a different possibility. Based on this discrepancy, we will investigate the relationship between social capital and transfer frequency in section 5.

Official figures on transfer frequency do not exist (de Zwart 1994:54), but one source of data is available. Potter (1987) traced movements of officials over a ten-year period (1976 to 1985) by directly comparing records of each individual’s position on 1 January each year, and from this obtained annual transfer frequency data for each state.\(^9\)

These data are for the Indian Administrative Service (IAS), an elite group whose members occupy most top posts in the civil service. IAS personnel are allocated to a particular state, and transferred only within that state.\(^10\) Like other government officials, they are exposed to substantial political pressure.

Any Collector [the senior IAS official in a district] was continually being pushed by politicians from different groupings to allocate scarce resources in one particular direction or another. (Potter 1986:224)
Inevitably, “some Collectors were more easily pushed than others” (ibid). According to Godbole (a former IAS officer), IAS officials “are faced with the prospect of making difficult choices involving personal honesty, integrity and moral rectitude early in life” (1997:66), while Gill (also former IAS) states that IAS officers “are exposed to the same temptations, and succumb to them the same way as others do” (1998:139). Brass (1994:56) believes that “extensive, massive corruption at the middle and higher levels up to and including some IAS officials is endemic and pervasive.”

Perhaps not surprisingly, candid anecdotal accounts of corrupt activity are not plentiful. Stories of how an official was transferred for being “too honest” are much more common (though presumably, if people can use complaints to have excessively honest officials transferred, they can complain about corrupt ones too). For example, Chatterjee (1994:117-20) describes how he overruled a subordinate’s (corrupt) decision to disburse a grant to a group which was not eligible to receive it. The group complained about him to some local politicians, who quickly managed to get him transferred.

Transfers of IAS officials are extremely rapid. When surveyed, IAS officers identified short tenure as the greatest perceived problem they faced (Singh and Bhandarkar 1994). In Rajasthan between 1956-65, a 3-year minimum incumbency rule for IAS Collectors was broken in 98.5% of cases (Bhatnagar and Sharma 1973). On average in the data used below, less than half the officials lasted even a year in their posts.
4 Social Capital and Riots

Measuring social capital poses formidable problems. No single definition has become widely accepted, and it has been argued that there are in reality several different kinds of social capital, such as “bonding” social capital within groups and “bridging” social capital which links members of different groups (e.g., Lederman et al. 2002).

Scholars have used two main approaches to measuring social capital and related variables. Some have used survey responses to questions about the perceived trustworthiness of strangers (Knack and Keefer 1997). Others have used proxies. For example, Putnam (1993) uses membership in formal associations, newspaper readership, and voter turnout in referenda to compare “civic-ness” in Italian regions.

Indian society is particularly diverse, with many divisions based on caste, religion, language and other traits. In some respects, these divisions are often very rigid; yet traditionally, members of different social groups were often highly economically interdependent as a result of a caste-based division of labor. In modern India, the nature of social groups and the patterns of social and economic interaction between members of different groups varies greatly, making meaningful measures of social capital highly elusive. Serra (1999) discusses these problems and concludes that Putnam’s indices are not suitable for measuring social capital in Indian states. She also stresses the role of literacy in improving citizen’s access to public services.

Clearly, no measure of social capital will be entirely satisfactory. This paper uses several variables to get at the extent of social capital in Indian states. We consider the effect
of literacy and that of ethnic diversity (see Table I for descriptions and sources). What we really want to capture, however, is a particular aspect of social capital, namely people’s ability to generate the trust necessary to overcome collective action problems. We will now argue that in the Indian context, social conflict (as measured by the frequency of riots) can serve a proxy for (the absence of) this form of social capital.

Although many different kinds of sparks can ignite riots,\(^{12}\) they often reflect an accumulation of underlying tensions. “Two communities start a slow pirouette of confrontation which gradually builds up to the moment when the tension must explode into violence” (Akbar 1988:151). Yet in some places, riots are common whereas in others, they are rare. What explains the difference? Fearon and Laitin (1996) argue that if some members of each group have a strong interest in preserving the peace (for example, because they are involved in valuable intergroup trade), then when trouble is brewing, those individuals often step in to defuse the situation peacefully.

Varshney (2002) compares three pairs of demographically similar cities in India. One city in each pair is comparatively peaceful, whilst the other experiences frequent communal (Hindu-Muslim) violence. Varshney finds that in each case, for various historical or economic reasons the populace in the peaceful cities is relatively integrated compared to the violence-prone cities. In the more integrated cities, formal and informal “networks of civic engagement”, frequently built on an economic symbiosis between groups, facilitate communication and constrain polarizing behavior, thereby helping to prevent riots.

For example, Varshney contrasts Hyderabad, which has a history of Hindu-Muslim
violence, with Lucknow, which is relatively peaceful. In Lucknow, an economic symbiosis between Muslim embroiderers and Hindu textile merchants is the key factor in maintaining peace. The textile industry operates informally: “lacking explicit and formal contracts, the entire system works on trust” (ibid:178). In the process, a large reservoir of trust, and a mutual interest in peace, is formed out of everyday economic interactions. As a result, when tensions begin to rise, members of both communities come together to “build bridges”, and defuse them before they lead to violence. In contrast, there is little social or economic interaction between Hindus and Muslims in Hyderabad, and communal tensions frequently escalate into violence.

Varshney’s thesis is that social and economic interaction can create trust and thereby reduce the frequency of riots. Our contention is that exactly this kind of trust might also help to reduce corruption. Therefore, we will use a low level of riots as a proxy for this particular form of social capital in Indian states.

5 Empirical Analysis

Because we are looking at Indian states, the number of observations (19 states observed over a 10-year period) is smaller than is typical in cross-country regressions. Given the small sample size, the potential for omitted variables, and the difficulty in finding good measures for the variables we are interested in, the regression analysis below must be considered merely suggestive. Our main purpose in this section is merely to document an intriguing pattern: social capital seems to be positively correlated with transfer frequency. Our model provides
one possible explanation.

5.1 Measures of Social Capital

We use three measures of social capital. The first is a measure of ethnic diversity constructed by Mitra and Verma (1997), based on a comprehensive anthropological survey of India which identified 2753 distinct “communities” in the country. We also use two separate sources of riots data, which we will call Riots\textsuperscript{A} and Riots\textsuperscript{B}.

\textit{Riots}\textsuperscript{A}: Our main source of riots data is the annual Government of India publication \textit{Crime in India}, which provides yearly data on the number of riots\textsuperscript{13} in each Indian state. During the years covered by Potter’s transfer frequency data (1976-85), the total number of riots recorded in India varied from a low of 63,675 in 1976 to a high of 110,361 in 1981. Given the large numbers of riots reported, this data probably does not primarily measure large-scale Hindu-Muslim or inter-caste riots. Instead, most of these “riots” are probably fairly minor incidents involving small groups. This makes the data quite suitable as a general measure of social and political conflict, and it has been used for this purpose by Kohli (1990), among others.

\textit{Riots}\textsuperscript{B}: Krishna (1985) reports the proportion of districts in each state affected by Hindu-Muslim riots between 1961 and 1970. While this data does not cover the same time period as Potter’s transfer data, it is useful because it will not be distorted by the presence of “hotspots” in several states (it measures the proportion of districts in which riots occurred, but not the intensity or frequency of the violence).
The Diversity index is correlated with Riots$^{A}$, significant at the 5% level, and with Riots$^{B}$, significant at the 1% level. The two riots variables are correlated at the 5% level.

5.2 Control Variables

The variable most robustly associated with corruption in cross-country regressions is per-capita income. Literacy can also help to reduce corruption, since more literate citizens are probably more aware of their rights and more able to ensure that they receive the benefits due to them. Inequality may also increase the level of corruption, for example, by making local governments more prone to “capture” by elites. La Porta et al. (1999) found in a cross-country study that the percentage of muslims in the population was correlated with corruption. Finally, the level of urbanization might affect the kinds of administrative functions undertaken and thus the opportunities for corruption. See Table I for descriptions of the variables and sources.

5.3 Results

Table II investigates the OLS cross-sectional relationship between social capital (proxied by a low level of ethnic diversity and riots) and transfer frequency. For each measure of social capital, we report three regressions: one with all the controls included, a second with the two least significant controls removed, and a third controlling only for literacy (which appears to be the most statistically significant control variable). All of the results show social capital to be positively correlated with transfer frequency. What makes this interesting is
that, as argued above, a variety of reasonable alternative arguments would predict that the correlation might have gone the other way.

Literacy is significantly negatively correlated with transfer frequency in most specifications. This fits with Proposition 2’s prediction that $\alpha$ reduces transfer frequency,\textsuperscript{15} where $\alpha$ is a measure of the constraints on an official’s discretion. Since a well-informed citizenry will reduce the proportion of situations in which officials can demand bribes, literacy can serve as a proxy for $\alpha$.

Note that this suggests that literacy is a flawed proxy for social capital in the Indian context. There is no obvious reason to suppose that education makes people better at cooperating, and as the model makes clear, there is a fundamental difference between an ability to assert one’s own rights (human capital) and a willingness to defend the rights of others (social capital). At the least, if literacy does indeed reflect some kind of “social capital”, then it must be a qualitatively different kind of social capital from that reflected in a low level of riots or low ethnic diversity.

The remaining control variables are not significantly correlated with transfer frequency (though this does not imply that they do not affect the level of corruption).\textsuperscript{16}

5.4 Instrumental Variables

One possible concern is that the level of social capital may be endogenous. Suppose, for example, that contrary to the implications of Proposition 2, transfer frequency is actually positively correlated with corruption, and suppose that when the formal system is corrupt,
people tend to rely more heavily on informal (self-enforced) contracts. Then corruption might lead to an increase in social capital, and this might account for our observed positive correlation between social capital and transfer frequency. This seems less of a problem for the ethnic diversity index, since it is based on relatively fixed cultural identities, but it might affect the riots variables, particularly \( Riots^A \), which is contemporaneous with the transfers data. To try to ensure that this is not driving the observed correlation between social capital and transfer frequency, we employ several instruments for the riots variables. First, we use \( Muslim \), which is highly correlated with \( Riots^A \) \((r=0.69, t=3.96)\), but which the OLS regressions suggest has little impact on transfer frequency once we control for \( Riots^A \). Second, we use the average value of \( Riots^A \) from 1970-75 (in effect, a lagged value of \( Riots^A \)), which is correlated with \( Riots^A \) during the period being studied (1976-85) at the 1% level. Finally, as is common in the literature, we use regional dummies, on the basis that Indian states can be grouped into several distinct regions, which share cultural and historical attributes that may affect the level of social capital.

The results of the two-stage least squares estimation is reported in Table III. The coefficients do not change much, but the significance of both riots variables drops slightly below the 5% level. Except for the first equation, the instruments pass a Hausman test for weak exogeneity at the 10% level.
5.5 Panel Estimations

Another possible concern with the use of the \( Riots^A \) variable is that there may be a direct causal relationship between riots and transfers; for example, that officials are transferred for failing to prevent a riot, or for causing a riot, or that people riot in protest against the transfer of an official, or to force the transfer of an official, or any one of endless other possibilities. As shown in Figure 3, in some states (notably Punjab), riots and transfers appear to be positively related; in other states, such as Kerala, no such relationship is apparent.

The most likely explanation for the positive short-run correlation between riots and transfer frequency within some states is that political instability can lead to increases in both riots and transfer frequency. In particular, election years seem important; in Punjab, for example, the effects of federal elections in 1977, 1980 and 1984 are readily apparent in Figure 3, as is the impact of violence associated with a state assembly election in Assam in 1983. In the case of Gujarat, Kohli (1990) describes the political violence which followed the elections of 1980 and 1985,\(^{17}\) and Figure 3 shows that transfer frequency also increased substantially in these years.

Table IV reports pooled regressions investigating the contemporaneous relationship between riots and transfer frequency. Because the dynamics of transfer frequency appear to work differently in different states, we include cross-section specific AR(1) terms. The coefficients are not reported; they vary widely, but in most cases they turn out to be negative, reflecting the idea that transfer frequency is lower in a year following an unusually high number of transfers, perhaps because so many officials are new in their jobs. Regression
(4.1) finds that within states, the level of Riots^A is not significantly correlated with transfer frequency. However, changes in the level of riots may be a better indicator of political stability. Regression (4.2) finds that, without controls, changes in Riots^A are positively correlated with transfer frequency, significant at the 5% level. As Figure 3 suggests, however, this may be largely driven by elections. In regression (4.3) we include dummies for state and general (federal) election years, and the strength and statistical significance of the △Riots^A variable diminishes. In regression (4.4) we include time fixed effects to pick up the influence of nationwide political events (including general elections), and the strength and significance of △Riots^A falls still further.

Overall, it appears that the correlation between riots and transfers is not causal, but instead largely driven by political events such as elections. This lends some support to Hypothesis 2. However, the cross-section regressions suggest that if social capital decreases political instability and thereby reduces transfer frequency, this effect is more than outweighed by the increase in transfer frequency due to the increased potential for collective action predicted by Proposition 2.

The estimated fixed effects from the pooled regressions can be viewed as a measure of the underlying cross-sectional variation in transfer frequency after controlling for some of the influence of short-run political events, so it might make sense to re-run our cross-section regressions using these fixed effects as a dependent variable instead of transfer frequency. Table V does this; it is identical to Table II except for the change in the dependent variable. Compared to Table II, several things happen. In the regressions which employ several
controls, the $R^2$ increases substantially, the social capital variables generally become more significant, and the coefficients on income and inequality become more significant. However, in the regressions which control only for literacy, the $R^2$ and the significance of both the explanatory variables decrease. Overall, these results confirm that, after accounting for short-run factors, states with higher levels of social capital experience a higher transfer frequency.

5.6 Further Evidence: Corruption Cases and Arrests

We have argued that the high transfer frequency observed in the states with high social capital reflects a capacity for collective action which can lead to corrupt officials being transferred. Is this consistent with the qualitative evidence?

Consider Punjab and Haryana, the two least riotous and least ethnically diverse states. The anthropological evidence supports the view that social capital is relatively high in these states. In Punjab, the egalitarian doctrines of the dominant Sikh religion (which in theory admits no caste system), and the historically cordial Hindu-Sikh ties help to blur group boundaries. In her study of the Sikh Jats (most Punjabis are Sikh, and most Sikhs are Jats), Pettigrew described a “network of links that seemed to connect all Jats if not on one basis, then on another, and if not at one time, then at another” while “social groups include multiple ties with men of different types” (1975:xvi,45), and “It is indeed a basic feature of Jat society, if not its most important feature, that everyone is contactable to everyone else, for all purposes” (ibid:20).
According to Proposition 2, this kind of social capital ought to reduce corruption by facilitating collective action against corrupt officials. Can we find evidence that this occurs?

Each year, *Crime in India* records the number of cases reported and the number of arrests made under the Prevention of Corruption Act. These data are somewhat erratic, but one fact which stands out is that between 1976 and 1985, over a third of the cases reported and *more than half* of all the arrests made under the Prevention of Corruption Act occurred in Haryana and Punjab, although together they contained less than 5% of the Indian population.

Does the fact that many prosecutions for corruption took place in these two states mean that they are unusually corrupt? That seems unlikely; according to a survey published in *India Today* (11/24/97), the least corrupt state government, as perceived by inhabitants of the state, was Punjab. This paper’s argument suggests an alternative explanation: that in states with high levels of social capital, such as Punjab and Haryana, corrupt behavior by officials is more likely to result in concerted pressure leading to their transfer (Haryana had the highest transfer frequency of any state during 1976-85), or in extreme cases, to prosecution. Thus, paradoxically, the high number of corruption cases and arrests and the relatively high transfer frequency in Punjab and Haryana probably reflects a *lower* level of corruption than elsewhere.
6 Conclusion

This paper has argued that social capital can enable citizens to engage in collective action against corruption. As a result, in states with high levels of social capital, officials are less likely to act corruptly, and more likely to be punished if they do so. This hypothesis is supported by evidence that social capital in Indian states is positively correlated with the frequency with which government officials are transferred between posts.

Compared to the existing literature, this test has the advantage of using objective data and comparing the operation of a relatively uniform administrative system in varying social environments. The main disadvantage is the small sample size; there is reason to doubt whether measures of social capital make sense at the state level in India (Serra 1999). Unfortunately no data on transfers is yet available at the district level (though data on riots is available). As such this paper is really only a first step in investigating the determinants of transfer frequency.

Because social capital is exogenous at least in the short run, the policy implications may at first glance appear discouraging. However, if we can understand how social capital affects the level of corruption, it should be possible to take this into account when designing formal rules. For example, India has recently undertaken decentralizing reforms. Our model suggests that besides the usual tradeoffs, it may be desirable to decentralize to a level at which an official’s clients share social or economic ties, so that they can more easily enforce agreements (or norms) against paying bribes.

The value of “transparency” in making clients aware of their rights and helping them
to monitor *officials* (promoting “accountability”) has of course been noted before, and is confirmed by our finding that literacy is an important determinant of transfer frequency. An additional and largely overlooked benefit of transparency is that it may help clients to monitor *each other* more closely, increasing the range of situations in which they can sustain anti-bribery norms.
Notes


2Putnam (1993) and Svensson (2003) are exceptions to the cross-country approach.

3This is only one of many possible ways in which the official can “build the game” in order to capture the whole of the rent.

4Strategic linkage still relaxes the incentive compatibility constraints. See Kingston (2004) for details.

5Nominally, transfers are decided by senior officials rather than local politicians. However, in practice, Chief Ministers in the states, who appoint the most senior officials routinely delegate influence over transfers to local politicians in exchange for their support. As a result, the transfer system in practice is subject to political interference at all levels.

6de Zwart (1994:92) even found that there were specialists who charged fixed prices for drafting and sending complaints.

7“(D)epartments take advantage of every procedure to delay inquiries, investigations, and prosecutions . . . [officials have] two codes of conduct, two allegiances if you will, one to the group of departmental colleagues, the other to the administration as a whole.” (Palmier
8Wade (1982:311; 1989:77.95); de Zwart (1994:8,71,130)

9Potter records the proportion of officials who moved at least once during the year. This data is transformed to obtain the average transfer frequency assuming a Poisson process. With a Poisson distribution, $P(0) = e^{-\lambda}$, so $\lambda = -\ln(P(0)) = -\ln(1 - P(\geq 1))$, where $P(\geq 1)$ is the data reported by Potter.

10Except for a small number on deputation to the Government of India.

11She also presents some survey data, but these are somewhat hard to interpret as they are based on exit polls of voters rather than a representative population sample.

12In Krishna’s (1985) data, proximate causes of communal violence included festivals, quarrels over the honor of women, desecration of religious places, cow slaughter, etc.

13A “riot” is defined as five or more people who use violence or the threat of violence against others.

14For the muslim population percentage, we take logs to avoid placing undue weight on an outlier, Jammu and Kashmir. Otherwise, this in effect becomes akin to a dummy variable for Jammu and Kashmir, which is not what we want.

15Recall that the probability that an official has an opportunity to act corruptly is $1 - \alpha$.

16The sample size is small. Also, the correlation between inequality and transfer frequency,
for example, might be either positive or negative, depending on why it matters; for example, inequality might impede collective action, thereby increasing corruption but reducing transfer frequency. Or, inequality might increase political instability, thereby increasing both corruption and transfer frequency.

17 The reasons for the connections between elections and riots in India are not our concern here; there is a substantial literature on the topic. See Wilkinson (2004) for a recent contribution.

18 Although an armed insurrection began during the 1980s in Punjab, this was directed primarily against the federal government. Indeed one could argue that the rebellion itself was an extreme form of collective action against transgressions by government officials.

19 See also, for example, Brass (1994:152); Mandelbaum (1970:539ff).

20 For example, local flexibility and the benefits of interjurisdictional competition versus economies of scale and interjurisdictional coordination.
References


Figure 2: Social Capital and Transfer Frequency

*Riots-A*: Average Log Riots per 100,000 pop. (1976-85)

*Riots-B*: Fraction of districts experiencing riots (1961-70)
Figure 3: Transfer frequency and Riots in Selected Indian States, 1976-1985
Table I: Variable Descriptions and Sources

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<tr>
<th>Variable</th>
<th>Description</th>
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<td><strong>Dependent Variables:</strong></td>
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<td>Log of the number of riots per 100,000 people per year.</td>
<td>Gov't of India, <em>Crime in India</em>, 1976-1985.</td>
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<td>$Diversity$</td>
<td>A “diversity index” based on anthropological survey data distinguishing individuals based on kinship, caste, language and other traits.</td>
<td>Mitra and Verma (1997).</td>
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<td><strong>Control Variables and Instruments:</strong></td>
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<td>$Inequality$</td>
<td>Sum of the rural and urban gini coefficients of per-capita consumer expenditure in 1987-88, weighted by rural/urban population.</td>
<td>Derived from Dreze and Sen (1995), table A3.</td>
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<td>$Riots_{7075}$</td>
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<td>$Gelec$</td>
<td>General election year dummy.</td>
<td>Election Commission of India.</td>
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<tr>
<td>$Selec$</td>
<td>State Assembly election year dummy.</td>
<td>Election Commission of India.</td>
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Notes: Some data for Manipur-Tripura and Assam-Meghalaya are calculated from disaggregated data. For Jammu and Kashmir, data for *Muslim* is for 1981. Source Brass (1994:231). For Assam, data on literacy is unavailable for 1981. We use a figure extrapolated from the 1991 figure. For regressions involving $Riots^A$, the sample is Assam-Meghalaya, Andhra Pradesh, Bihar, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur-Tripura, Nagaland, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal. Union territories are omitted. This sample of 19 corresponds to those states with populations over 750,000 in 1981. For regressions involving $Riots^B$, Himachal Pradesh, Manipur-Tripura, and Nagaland are omitted because of missing data. The resulting sample of 16 corresponds to states with populations over 5 million in 1981. For *Diversity*, Jammu and Kashmir, Manipur-Tripura, and Nagaland are omitted. For *Inequality*, Manipur-Tripura and Nagaland are omitted.
Table II: Determinants of Average Transfer Frequency ($\bar{\lambda}$)
Cross-section OLS, constants not shown

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Absolute White heteroskedasticity-consistent t-statistics are in parentheses. See Table I for sources and descriptions of variables.
Table III: Determinants of Average Transfer Frequency ($\bar{\lambda}$)  
Two-stage least squares, constants not shown

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Absolute White heteroskedasticity-consistent t-statistics are in parentheses. See Table I for descriptions and sources. Instruments: $Muslim$, regional dummies, and $Riots_{7075}$. The “regions” are: (Assam, Bihar, Manipur-Tripura, Nagaland, Orissa, West Bengal); (Haryana, Punjab, Himachal Pradesh, Jammu and Kashmir); (Maharashtra and Gujarat); (Andhra Pradesh, Karnataka, Kerala and Tamil Nadu); and (Rajasthan, Madhya Pradesh and Uttar Pradesh).
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White heteroskedasticity-consistent t-statistics are in parentheses. See Table I for variable descriptions and sources.
Table V: Determinants of the Fixed Effects in (4.4)
Cross-section OLS, constants not shown

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Absolute White heteroskedasticity-consistent t-statistics are in parentheses. See Table I for sources and descriptions of variables.