# REDISTRIBUTION AND CIVIL UNREST*

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***Abstract***

*Recurrent episodes of civil unrest significantly reduce the potential for economic growth and poverty reduction. Yet the economics literature offers little understanding on what triggers social unrest and how to prevent it. We analyse theoretically the merits of redistributive policies in the onset and reduction of civil unrest and compare it with more direct policies such as the use of police. We present empirical evidence for a panel of Indian states, where conflict, redistributive policies and policing are treated as endogenous variables. Our empirical results show, in the medium-term, redistributive policies are an effective means to reduce civil unrest, as they affect directly important causes of social conflict, notably poverty. Policing is at best a short-term strategy. In the long-term, it may trigger further social discontent.*

**JEL codes:** C23, C33, D74, I38, O53.

**Keywords:** Redistribution, policing, conflict, inequality, India, panel data.

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## 1. Introduction

The magnitude of private and social costs of recent social and political instability across many developing countries has brought social conflict into the forefront of modern development economics. Conflicts across the world, ranging from civil wars to riots, civil protests and industrial disputes, have affected millions of people and have resulted in lost opportunities in terms of economic growth and human development [Collier, 1999; Stewart et. al., 2001; Fearon and Laitin, 2003].

Persistent poverty and inequality amongst certain population groups have been shown to increase society's propensity for engaging in forms of civil conflict.[1] Rises in economic and social disparities between the poor and the rich, systematic social exclusion and other forms of perceived unfairness in social relations often result in the accumulation of discontent to a sufficiently high level to break social cohesion [Becker, 1967; Sigelman and Simpson, 1977; Muller, 1985; Muller and Seligson, 1987; Midlarsky, 1988; Schock, 1996; Easterly and Levine, 1997; Gurr and Moore, 1997; Elbadawi, 1999], and increase the probability of some population groups engaging in rent-seeking or predatory activities [Benhabib and Rustichini, 1991; Fay; 1993; Sala-i-Martin, 1996; Fajnzylber, Lederman and Loayza, 1998]. In addition, research has drawn attention to the negative impact of inequality on economic growth when societies are characterised by political instability and civil unrest [Venieris and Gupta, 1986; Alesina and Perotti, 1996 and Alesina et al., 1996].

It is thus important that we understand what determines this potentially important constraint to development and what can be done to prevent it. There is, however, little research exists that deals with these issues. This gap in the development literature is at odds with the current political need to understand what factors elicit instability and violence, in order to prevent the onset of large-scale conflicts, develop more sustainable approaches to human security and promote stable environments for economic growth and poverty reduction.

[1] Civil unrest, civil conflict, social conflict and socio-political instability are terms used interchangeably in this paper. They comprise all forms of organised collective actions designed to express discontent from individuals and population groups. They include political demonstrations, violent protests, rioting, industrial disputes, etc, but exclude extreme violence in the form of revolutions, political assassinations and civil wars, which are analysed elsewhere [Elbadawi, 1999; Collier and Hoeffler, 2000]. See Gupta [1990] for a systematic classification of forms of conflict. Boix [2004] analyses empirical the determinants of various forms of violent and non-violent conflict included above.

The general tendency of governments in economies prone to violent civil unrest is to resort to the use of police and military forces to offset civil and political upheavals. This can be a counterproductive measure since it does not address direct causes of conflict. Moreover, most populations living in democratic or semi-democratic regimes will be subject to a repression threshold beyond which the continued use of coercive force may result in resentment and, therefore, increase the risk of further civil unrest in the longer run [Gurr, 1970; Hirschman, 1981; Bourguignon, 1999; Boix, 2004].

Policies that address directly the causes of social discontent are likely to be more effectual at reducing conflict. However, to the best of our knowledge, little is known about the impact of social redistributive policies on conflict, whether different types of conflict will respond in different ways to the implementation of pro-poor policies and how effective redistributive policies are in relation to other policy options. This paper investigates the use of pro-poor redistributive policies as an alternative way of preventing the onset of civil unrest and reducing existing conflicts, and assesses their effectiveness in relation to the use of police force.

The implementation of redistributive policies is usually not a popular policy recommendation in developing countries. Income transfer policies and tax reforms are often constrained by budgetary and administrative limitations and the opposition of political and social elites [Radian, 1980; Newbery and Stern, 1987]. They are thus disliked by governments involved in the pursuit of electoral advantages and support coalitions. Fiscal redistribution is also believed to result in implicit taxes on investment and distort market forces.[2]

There are forms of redistribution that benefit those in need without necessarily distorting private investment decisions and harming economic growth [Chenery et al., 1974; Bénabou, 1996; Killick, 2002]. These include programmes of public employment, investment in basic education and primary health care, food security programmes and so forth. These social redistributive policies decrease inequality by shifting incomes from the rich, or the whole population, into the accumulation of wealth and human capital amongst the poor [Bourguignon, 2002]. As such, they should not be viewed as a pure form of income redistribution and are, therefore, less likely to cause political and social opposition. In addition, social redistributive policies will increase of the potential costs of the poor engaging in conflicts [Boix, 2004], and are also likely to raise the welfare of higher income groups that get negatively affected by conflict (but that may nonetheless oppose redistribution) [Sala-i-Martin, 1996].[3]

This paper takes a first step towards the systematic understanding of the role of social redistributive policies in the reduction and prevention of civil conflict. A theoretical framework for the analysis of the relationship between redistribution, policing and civil unrest is developed. Within this framework, redistribution is treated as endogenous to conflict, as redistributive policies may simultaneously be cause and consequence of socio-political conflicts when they affect the welfare characteristics of those involved. The model predicts that in societies with a high propensity for civil unrest, instability will only decrease when the marginal impact of redistribution on conflict is higher than the marginal impact of policing. In the absence of redistributive systems, these societies will only be able to avoid the escalation of conflict if they can afford indefinitely higher levels of policing. Societies with a lower propensity to conflict will be able to avoid the escalation of civil unrest if a system of minimum redistribution is in place.

These insights are supported by empirical evidence based on data for a panel of fourteen Indian states for the period between 1973 and 1999. Indeed, we find that, in the medium term, social redistributive policies have been a more effective policy to avoid the onset of civil unrest and reduce existing instability in India. This is because these policies reduce affect directly important causes of conflict, notably poverty. Although policing is an effective short-term option, in the longer-term it may trigger further conflicts. This result is robust to different model specifications and the use of other proxies for civil unrest. The result is particularly significant when the relationship between redistribution, policing and conflict is analysed within an endogenous framework. Failure to consider the endogenous nature of this relationship may result in mis-judgements.

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[2] See Lindert and Williamson [1985] for a review. See also Persson and Tabellini [1994].

[3] This latter impact results from an externality effect caused by the interdependency that necessarily arises between the utility functions of the perpetrators of conflict and their targets, when conflict is introduced as a constraint to the maximisation of the utility functions of both groups [Zeckhauser, 1971; Sala-i-Martin, 1994].

The paper focuses on the analysis of local episodes of civil unrest represented by the incidence of riots. We provide therefore a new contribution to the recent literature on the causes and consequences of conflict in developing countries, pioneered by Collier [1999] and Collier and Hoeffler [2000]. This literature has focused thus far on the analysis of large-scale civil wars based on evidence from cross-sections of countries across several years. Although civil wars have represented a serious constraint to development in recent decades, many developing countries have also been badly affected by local conflicts and social upheavals [Barron, Kaiser and Pradhan, 2004; Boix, 2004]. These forms of internal civil unrest may not necessarily result in large-scale wars. Nevertheless, they have been responsible for the destruction of livelihoods and markets, increases in the risk of investment, loss of trust between economic agents and the waste of significant human and economic resources [Barron, Kaiser and Pradhan, 2004]. Persistent forms of civil unrest have also often constituted the preliminary stages of more violent conflicts, including civil wars.[4]

A further contribution of this paper is that our empirical analysis is based on panel data for one country, India. India is a particularly good example to study the relationship between redistribution and civil unrest. Its religious, social and political diversity has often given rise to clashes between different population groups. Yet social conflicts have not resulted into full scale civil wars, as in other parts of the world, despite their violence at times. India has a strong police force but also a fully functioning democratic system that responds quite effectively to demands from various social groups. These features have allowed us to analyse in detail several facets of civil unrest in the context of a developing economy. The size of each Indian state has, in addition, allowed us to incorporate in our analysis important variations across very different economies, while avoiding concerns regarding data comparability across countries, since all Indian states share similar data collection methods.

The paper is organised as follows. In section 2, we develop a theoretical framework for the analysis of the determinants of civil unrest using a two-period recursive model. The model theorises key impending trade-offs between the use of police and redistributive policies to reduce the level and intensity of civil conflicts. Sections 3 and 4 assess the validity of the theoretical model using empirical evidence from India. In section 3, we discuss briefly

[4] Rwanda and Haiti, amongst others, constitute recent examples of countries where civil wars were preceded by civil protests and widespread rioting [The Economist, various issues].

relevant aspects of civil unrest in India, while in section 4 we replicate empirically the main theoretical results for a real economy affected by socio-political instability. We first analyse the relationship between redistribution, policing and civil unrest using standard dynamic panel models. We then introduce key endogenous constraints to the analysis. Finally, we test the sensitivity of our results to alternative specifications of the dependent variable. Section 5 concludes the paper.

## 2. Theoretical framework

We assume a society formed by two groups (the *rich* and the *poor*), where inequalities between social groups ($I_t$) cause social discontent and, consequently, conflict. Choices regarding conflict management (i.e. choices about the use of police or the implementation of redistributive programmes) are taken by the *rich* in a two-period ($t$ and $t-1$) decision process.

In a situation of conflict, the *rich* face the usual 'stick or carrot' dilemma. The general tendency of policymakers in economies prone to civil unrest is to resort to the use of police or military force to offset conflict. An alternative way to prevent civil unrest or offset existing conflicts is to address directly the causes of social discontent. If these result from feelings of deprivation, exclusion and other forms of inequality, social policies that allow the transfer of resources to relevant population groups would prevent the onset of many forms of civil unrest.

We start from an initial setting where society is subject to a repression threshold, whereby the excessive use of force causes discontent amongst the population. $P_t$ represents the immediate or short-term effect of the use of police on conflict. This effect is negative, indicating that the immediate use of police will reduce the onset of civil unrest in period $t$. $P_{t-1}$ represents the long-term effect of continuous use of police on conflict. The existence of a repression threshold is incorporated in the positive coefficient of $P_{t-1}$.

The interplay between inequality, use of police and civil unrest can be represented in a difference equation:

(1) $$C_t = C_{t-1} - \sigma P_t + \lambda P_{t-1} + \theta I_{t-1},$$

where the initial level of conflict ($C_t$) depends on the use of police, as described above, the level of conflict in the previous period ($C_{t-1}$) and on inequality. It is therefore assumed that, in the absence of factors that either contain or encourage conflict, the level of conflict in period $t$ will be the same as in the previous period.[5] This may result in the emergence of 'conflict traps' as found in Azam, Collier and Hoeffler [2001] and Collier [2000]. Conflict is also determined by the level of inequality in society. In particular, it depends on past levels of inequality, assuming that it will take a while before feelings of unfairness result in the breach of social cohesion [Hirschman, 1981].

$\sigma$, $\lambda$ and $\theta$ are coefficients that represent the marginal impacts of each variable on conflict. They are normalised to take values between 0 and 1, inclusive. $\theta$ represents the inverse of the level of inequality aversion in society [Atkinson, 1970; Hirschman, 1981]. Values of $1/\theta$ close to zero indicate a society with a high tolerance for inequality, whilst values close to one indicate high levels of inequality aversion. $\sigma$ and $\lambda$ are fixed coefficients that represent the intertemporal impact of the use of police and military forces on conflict. If $\lambda < \sigma$, the steady state impact of policing on conflict will be negative and there will be a decrease in the potential for conflict from one period to the next. $\lambda > \sigma$ represents a society with a high potential for conflict, where $\lambda$ is in effect a measure for people's 'memory' on the effects of repression.

Each variable in equation (1) represents a choice process. The decision on the amount of police depends on the amount of conflict the *rich* face and is given by $P_t = \alpha C_t$, where $\alpha$, with $0 \leq \alpha \leq 1$, measures the elasticity of the use of police in response to conflict.

In order to simplify the model, we assume that only relative income inequality matters. More specifically, conflict in this model is affected by intertemporal differences between changes in the income of the *rich* ($\Delta Y^R$) and changes the income of the *poor* over time. If we make the reasonable assumption that the poor do not save from their earned income, and normalise the income of the poor by the poverty line, any changes in their income over time will equal the

[5] This is a simplifying assumption. It will be relaxed in section 4, where current levels of conflict will be allowed to decrease/increase at various rates.

amount of transfers ($T_t$) in society.[6] In other words, $I_t = \Delta Y^R - T_t$. This expression defines inequality as the difference between maximum and minimum incomes accrued to population groups agglomerated, respectively, at the top and bottom of the distribution. This is a crude measure of inequality but is useful as an indication of effectively observed level of inequality in society.[7]

This definition also establishes implicitly that, by resorting to conflict, the *poor* do not incur in any costs, but only in benefits in the form of $T_t$. Costs can be incorporated into the analysis by removing the assumption that changes in the income of the poor between two time periods depend only on the amount of transfers. This will, however, complicate unnecessarily the intuitive aspects of the analysis without changing the final outcome, other than adding further constants to the solution of the difference equation.[8]

As with policing, transfers from the rich to the poorer members of the population depend on the level of conflict observed in society, i.e. $T_t = \beta C_t$, where $\beta$, with $0 \leq \beta \leq 1$, measures the elasticity of the use of redistributive transfers in response to conflict.

The propositions discussed above provide a solution for the difference equation (1). This solution is given by the general form $C_t = J(K)^t + L$, where $J$ can be fixed by some initial condition $C_0$, $K = \dfrac{1+\alpha\lambda-\theta\beta}{1+\sigma\alpha}$ and $L = \dfrac{\theta}{\alpha(\lambda-\sigma)-\theta\beta} Y^R$. $J + L$ represent the initial level of conflict, whilst $L$ represents the amount of conflict that will always persist, even when $(K)^t \to 0$ and $\sigma$, $\lambda$, $\theta$ and $\delta$ are fixed. It constitutes thus a dynamic equilibrium or stationary state for $C_t$. $J(K)^t$ specifies, for every period of time, the deviation of $C_t$ from its dynamic equilibrium. The equation has three regions in its moduli space, corresponding to $K > 1$, $K = 1$, and $K < 1$. In the first region, conflict increases. The second region corresponds to a discontinuity point. In the third region, conflict decreases (i. e., converges towards its dynamic stable equilibrium, $L$).

[6] The transfer can be a result of both fiscal redistribution or social redistributive policies, as discussed in the introduction.
[7] Boix [2004] uses a similar measure of inequality in an independent study. The empirical analysis in section 4 will use more sophisticated measures of inequality.

In order to be in region 3, we must have

(2) $$\frac{1}{\theta}(\lambda-\sigma)<\frac{\beta}{\alpha}.$$

Condition (2) has important policy implications. The right-hand side of (2) represents the ratio between policing and transfer elasticities, whereas the left-hand side of (2) includes the expression for the repression threshold $(\lambda-\sigma)$, calibrated by the inequality aversion coefficient.

When faced with a situation of conflict, the *rich* must decide whether to have a system of economic transfers to those worse-off (assumed to be the conflict perpetrators). $\beta/\alpha$ represents the choice mechanisms within the model. In reality, this ratio depends on various factors and is affected by political and social institutions, including voting mechanisms and the relative bargaining power of the two groups. We will first consider the case in which the *rich* decide to transfer income to the *poor* or implement systems of social redistribution (i. e. $\beta>0$). The impact of the use of transfers on conflict depends in turn on the level of the repression threshold in society $(\lambda-\sigma)$.

*Scenario 1: Positive transfers when $\lambda\leq\sigma$.*[9] In this scenario, condition (2) is always true, since all coefficients take values between 0 and 1, inclusive. In this region, it does not matter whether new episodes of conflict are tackled by using redistribution or policing. This is a situation likely to take place in either a perfect democracy or a perfect dictatorship regime. In a perfect democracy, everyone votes over the optimal level of taxation (i. e. $\beta$). Therefore, the higher the level of inequality, the higher the preference of the median-voter for taxation and redistribution will always be at the optimal level [Persson and Tabellini, 1994; Alesina and Rodrik, 1994]. In a perfect dictatorship, the wealthy are powerful enough to exclude the *poor* from any decision-making process. Since the poor do not participate in the decision-making

[8] Boix [2004] incorporates possible costs of conflict for the perpetrators of conflict in his game theory analysis but his results do not differ significantly from ours. See also Becker [1967].

[9] The case $\lambda=\sigma$ is included in this scenario because we assume $\beta\neq 0$. Condition (2) is automatically satisfied for $\lambda=\sigma$ and $\beta\neq 0$.

process, only a minimum level of redistribution will take place. This is similar to previous findings in the interest group theories [Buchanan and Tullock, 1962; Buchanan, 1967].

*Scenario 2: Positive transfers when* $\lambda > \sigma$. Societies in this scenario are generally neither perfect democracies nor perfect dictatorship regimes. In this case, the onset of new conflict depends on whether transfers are used or not. When $\lambda > \sigma$, the use of police is inefficient. The only way to decrease conflict in the long term is to decrease inequality. Because this society responds strongly to repression, the rich must take into consideration the fact that the poor have the capacity to engage in conflicts and have therefore some bargaining power in the decision-making process. There is hence an interdependency between the welfare functions of the *rich* and the *poor*. This results from the fact that by instigating unrest, the poor can influence the income and welfare of the rich (because property is destroyed, the risk of investment increases or conflict affects the lives of the *rich* and their families'). This interdependency will result in redistribution as demonstrated in Zeckhauser [1971], Sala-i-Martin [1994] and Sen [1997]. The *poor* will demand a certain level of redistribution and the *rich* must decide on the level of those transfers.

Condition (2) allows the calculation of the optimal ratio between the use of transfers and police that leads to a decrease of conflict in a society characterised by $\lambda > \sigma$. This ratio takes into account the relationship between $(\lambda - \sigma)$ and $\theta$. The optimal ratio will depend on the aversion to inequality coefficient $1/\theta$. The closer this coefficient is to one, the larger the reduction in inequality must be for conflict to decrease. In order to guarantee decreases in conflict, we must have $(\lambda - \sigma) > \theta$. This implies the following condition: $\frac{1}{\theta}(\lambda - \sigma) > 1 \Rightarrow \frac{\beta}{\alpha} > 1 \Leftrightarrow \beta > \alpha$. In other words, conflict will be reduced iff the transfer elasticity coefficient is larger than the police elasticity coefficient. In those circumstances, the *poor* will realise that their income and well-being is increasing, inequality is decreasing, and thus have no incentive to resort to further conflict. This result is in line with the theoretical conditions derived by Ghate, Le and Zak [2003] in a general growth model with instability.[10]

[10] In an independent study, these authors show, using a theoretical growth model, that the marginal efficiency of the police at reducing socio-political instability and the marginal sensitivity of socio-political instability to changes in the income distribution determine the economy's growth trajectory in a country characterised by high inequality and political instability.

*Scenario 3: No redistributive transfers*. In this scenario, conflict will decrease iff $\frac{1}{\theta}(\lambda - \sigma) < 0$, i.e. iff $\lambda < \sigma$. In other words, in the absence of systems of redistribution, the immediate use of police has to be either very large or very efficient. If not, conflict will always increase away from its equilibrium state. Here we return to the case of dictatorship regimes. Whether any given society will be in scenario 1 or 3 will depend on how much repression the *rich* can afford. If the *rich* have a lot to loose, they will vote for a little redistribution (scenario 1). If the *rich* do not have a lot to loose and can sustain indefinitely high levels of repression, scenario 3 will prevail.[11]

Sustainable increases in policing may thus depend on the economy's capacity to attract national and international investment and their endowment in natural resources [Collier and Hoeffler, 2000; Ghate, Le and Zak, 2003], as well as on how mobile capital is (thus allowing the rich to send capital abroad and avoid costs of conflict) [Boix, 2004]. In the next section, we test empirically the framework developed here using data for India.

## 3. India case study

India is an important case study for testing the relationship between redistributive policies and civil unrest. India is a very diverse country both in religious and cultural terms. Hindus constitute the majority of its population (around 83%), whereas Muslims, India's largest religious minority, represent 11% of the country's total population. Other minorities are the Sikhs, concentrated in Punjab (2% of the total population), Christians, Buddhists, Jains, Parsees and Jews [Hardgrave, 1993]. Hindus are, in turn, divided in thousands of castes and sub-castes, different languages and across different states.[12] This enormous diversity poses serious pressures on India's social and political cohesion and the extent of deprivation and hardship in the country.[13]

[11] Ghate, Le and Zak [2003] also demonstrate theoretically that sustainable increases in policing can only be maintained when police is extremely efficient and their actions result in net positive effects on economic growth. If the cost of police becomes too high, the equilibrium will be broken.

[12] There are more than a dozen major languages in India and Hindi, the official language, is spoken by a mere 30% of the population [Hardgrave, 1993].

[13] In 1999-2000, around 27 percent of India's rural population and 24 per cent of its urban population lived below the national poverty line, based on poverty lines of 327.56 rupees per capita per month for the rural sector and 454.11 rupees per capita per month for the urban sector [Deaton, 2001].

Episodes of civil unrest are relatively common in India. Some have resulted from separatist movements, whereas others have been caused by clashes between ethnic and religious groups and different castes, as a response to disparities in the distribution of employment conditions, access to land and other assets, use of and access to social services and access to institutional power and legal institutions [Hardgrave, 1993; Oberoi, 1997; Justino, 2003a].

Two of the most serious separatist conflicts have taken place in the northern states of Punjab and Kashmir. The ethnic conflict between the minority of Sikhs and Hindus in Punjab have led to the death of more than 20000 people since 1981 [Hardgrave, 1993; Jodhka, 2001]. The conflict in Kashmir has resulted in two wars between India and Pakistan and has led to the death of around 12000 people since 1989. Other violent separatist conflicts have taken place in West Bengal, Assam and Bihar [EPW, 2001]. Conflicts between ethnic and religious groups have resulted in riots across various states between Hindus and Muslims, following the destruction of the Ayodhya mosque in 1992.[14] Violent riots have taken place in rural and urban areas in Gujarat and Maharashtra, since the late 1990s, and in Bihar since 1994. In addition, violence against Dalits (former 'untouchables') has been widespread across various states both in rural and urban areas [Banerjee and Knight, 1985; Human Rights Watch, 1999, 2000, 2001], while increasing linguistic and cultural identities have led to conflicts against outsiders in Maharashtra, Assam, Gujarat, Karnataka, Madhya Pradesh, Orissa, Maharashtra and Uttar Pradesh [Human Rights Watch, 2000, 2001].

These conflicts are reflected in the upward trend of civil unrest in India, measured by the number of riots recorded by the various state police bureaus,[15] between 1973 and 1999 (figure 1).[16] Despite its seriousness at times, episodes of rioting in India have not, however, resulted in major civil wars as in other countries in Africa and South and Central America.

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[14] See Wilkinson [2004] for a discussion of religious mobilisation in India.

[15] Riots are typically defined as collective acts of spontaneous violence that include five or more people [Gurr, 1970]. Riots are classified as violent crimes by the Indian Penal Code, under the category of cognisable crime. The data on riots is provided by the National Crime Records Bureau (NCRB), part of the Indian Ministry of Home Affairs.

[16] Figure 1 in reality may represent an underestimation of the extent of riots in India since the data is likely to underreport the true extent of riots as the police (who records the occurrence of riots) has not intervened in recent years in riots of small scale and duration. The reliability of the data depends also on the reporting accuracy of each state police bureau. Possible data measurement errors will, however, be systematic across all states and all years and thus unlikely to affect significantly our empirical results.

The Indian federal system provides the main institutional form of conflict management. India is divided into 25 states, each representing roughly one dominant ethno-linguistic group. Although each of these groups is divided into different castes and religions, federalism allows the compartmentalisation of conflict into contained borders and conflict in one state rarely spills on to another [Hardgrave, 1993]. India has also an active police force and the numbers of civil plus armed police have increased in most states in the past three decades (table 1). However, the use of force has, generally, been relatively ineffective in counteracting ethnic and regional violence [Hardgrave, 1993] (Table 2).

India's strong democratic values and political institutions seem to have played a more important role in the diffusion of conflict. In general, problems of ethnic and regional conflict tend to ease in India when political and group leaders deal with them by accommodating demands from different factions and using their bargaining power within the democratic political process [Hardgrave, 1993].

An effective way of assessing the response of the government to welfare demands is to look at the amount spent by the Government of India on social redistributive policies. One variable readily available in India, and in other developing countries, is public expenditure on social services.[17] Despite recent increases (Table 1), public expenditure on social services in India is very small in comparison to other developing countries.[18] Remarkably, such small outlay has proved to have very significant positive impact on India's economic growth in the same period of time [Justino, 2003b].

We have calculated the coefficients of correlation between expenditure on social services and rioting in India (Table 2). This variable is lagged one period in order to comply with the theoretical predictions discussed in section 2. The results exhibit a high correlation between these two variables. This is confirmed by the scatter diagrams depicted in Figure 2 for some years between 1973 and 1999. In the next section, we investigate in further detail the

[17] This variable includes public expenditure on education; medical, public health and family welfare; welfare of scheduled castes, schedule tribes and other backward classes; labour welfare; social security and welfare; and nutrition.
[18] The World Development Report 2000-01 shows that, in 1997, India spent 3.2% of its GNP on education, against an average of 4.1% in other low- and middle-income countries. Between 1990 and 1998, India's public expenditure on health services represented, on average, 0.6% of its GNP, whereas the same percentage for other low- and middle-income countries was 1.9%.

effectiveness of social redistributive policies in containing conflict in India, relatively to the use of police forces.

## 4. Empirical analysis

### 4.1. Basic econometric model

In this section, we use data for a panel of fourteen major Indian states to test the theoretical framework developed in section 2. The states are Andhra Pradesh, Assam, Bihar, Gujarat, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal. The use of panel data allows us to capture the large heterogeneity between all Indian states in terms of social, cultural, religious, economic and even political characteristics. The choice of states for the panel was based on data reliability, which is higher for the larger states. We do not expect that the exclusion of smaller states and Union territories to affect significantly our results.[19]

The theoretical model discussed in section 2 can be easily transformed into an econometric model. If we relax the assumption of unitary rate of change of conflict across time and assume the existence of a normally distributed vector of unknowns uncorrelated with the vectors of independent variables, we can re-formulate equation (1) (section 2) to take into account the panel dimension of the Indian dataset. The resulting expression would be

(3) $$C_{it} = \upsilon_i + \beta_t + \gamma Y_{it-1} + \delta P_{it} + \varepsilon_{it} \,.$$

In the equation above, $\nu_i$ represents the state effects, with $i$ = 1, …, 14. $\beta_t$ are the year effects, with i = 1973, …, 1999.[20] $Y_{it-1}$ is the vector of lagged regressors with $Y = f(C_{t-1}, P_{t-1}, I_{t-1})$, where $C_{t-1}$ represents levels of conflict lagged one period, $P_{t-1}$ is the level of policing used in period *t-1* and $I_{t-1}$ is the lagged level of inequality. $P_{it}$ is, as before,

[19] In 1999, these 14 states represented 93.3% of the total Indian population.

[20] We use six years within that period: 1973-74, 1977-78, 1983, 1987-88, 1993-94 and 1999-2000. These dates correspond to the dates of the large sample National Sample Surveys (NSS), from where we have derived the poverty and inequality variables. We focus on these six years in order to ensure consistency across all variables. Although periodicity is not constant across all periods, the estimators are efficient and unbiased as the econometric models will consider observations for each variable in the same time periods [Greene, 2000].

the use of police in the current period. $\varepsilon_{it}$ is the panel error term. We will name equation (3) the 'inequality model'.

In order to derive explicitly the relationship between redistribution, policing and conflict, we can make further use of the concept of inequality discuss in section 2 and write the equation above as:

(4) $$C_{it} = \alpha_i + \beta_t + \gamma Y_{it-1} + \delta P_{it} + \varepsilon_{it},$$

with $\alpha_i = v_i + \Delta Y_i^R$, where $v_i$ represents, as before, the state effects and $\Delta Y_i^R$ is the level of income of the *rich* in each Indian state. In equation (4), we have $Y = f(C_{t-1}, P_{t-1}, T_{t-1})$, where $T_{t-1}$ is the level of redistribution in the previous period. We call equation (4) the 'redistribution model'.

The two equations above can be estimated using standard panel fixed effects estimation methods.[21] The variables we used to estimate the two models above were those discussed in the previous section. The level of conflict is approximated by the volume of riots per 1000 people. The policing variable is represented by the total number of civil plus armed police per 1000 people, as both types can be called in a situation of civil unrest. The level of inequality is approximated by the level of consumption inequality measured by the Gini coefficient in state *i* in period *t*. Finally, the level of redistribution across Indian states is represented by the logarithmic function of per capita expenditure on social services at 1980-81 constant prices. This variable illustrates the extent of social redistribution in India, as discussed in section 3. Table 3 presents descriptive statistics for these and other variables used in this section.

Civil unrest may of course be also affected by a variety of state- and national-level variables not controlled for in equations (3) and (4) above. We can take into consideration the impact of further control variables on conflict in India if we extend both the 'inequality model' and the 'redistribution model' to include additional control variables. This will also allow us to test

[21] Results from the Breucsh-Pagan test [Breucsh and Pagan, 1980] suggest that we should reject the presence of random effects. The Breusch-Pagan method tests the null hypothesis that Var( $\varepsilon$ )=0. For both equations (3) and (4) we obtained $\chi^2(1) = 8.75$ with Prob > $\chi^2 = 0.0031$.

for further determinants of social conflict in India. The resulting transformed equations are, respectively

(5) $$C_{it} = \upsilon_i + \beta_t + \gamma Y_{it-1} + \delta P_{it} + \eta X_{it} + \varphi N_t + \varepsilon_{it}$$, and

(6) $$C_{it} = \alpha_i + \beta_t + \gamma Y_{it-1} + \delta P_{it} + \eta X_{it} + \varphi N_t + \varepsilon_{it}$$,

where $X_{it}$ is a vector of independent variables that vary across state and time and $N_t$ is a vector of national-level independent variables, invariant across state. As discussed in the introduction to this paper, research on the causes of unrest has suggested that the propensity of societies for engaging in conflict may depend on the extent of poverty in the country and across different population groups [Elbadawi, 1999; Stewart et al., 2001]. $X_{it}$ includes thus the number of people below the consumption poverty across Indian states, lagged by one period. We have also included the current level of redistribution in order to incorporate both long- and short-term responses of conflict to the use of redistributive policies as with the use of police. Civil unrest is, in addition, likely to depend on the level of economic and social development of each state [Collier and Hoeffler, 2000]. In order to control for these possible determinants of conflict, $X_{it}$ includes the level of state income (logarithmic function of per capita net state domestic product at 1980-81 constant prices) and a measure for the level of education in each state (per capita number of individuals enrolled in primary and secondary education).

$N_t$ includes two additional national-level variables. The first is a measure for openness of the Indian economy, given by the all-India ratio of imports and exports over national domestic product (per capita at 1980-81 constant prices). This variable is invariant across the fourteen states. The inclusion of this variable was motivated by the fact that economic liberalisation, which accelerated in India in the early 1990s [Srinivasan, 2001], can be a cause of conflicts as economic reforms may cause some groups to benefit and others to become worse-off [Winters, 2002]. In order to capture the effects of political institutions on conflict [Alesina et al., 1996; Barro, 2000], we have included a second national-level variable representing the result of national elections. This is a binary variable that takes the value 1 if the Indian

National Congress party obtained the majority of the votes in each given year.[22] Table 3 presents descriptive statistics for these variables. Table 4 presents the results for the estimation of models above.[23] We discuss the results in the subsection below. Before that we address one other important issue regarding the estimation of the models discussed here.

### 4.2. Endogeneity

So far we have not addressed concerns over potential endogeneity in the basic model. The models above contain at least one lagged endogenous variable – the lagged volume of riots. Even if this variable is not correlated with $\varepsilon_{it}$, the fixed effects will not be consistent because $t$ is finite [Wooldridge, 2002]. Another possible source of endogeneity results from the theoretical framework of section 2. That framework implied that conflict, redistributive transfers and use of police are determined simultaneously within the decision process of the *rich*. Hence, the models estimated in Table 3 may be inconsistent as the right-hand side regressors are likely to be correlated with the disturbance term.

Arellano and Bond [1991] have suggested an estimation method to correct for the bias introduced in the model by the presence of the lagged endogenous variable. This method allows also for undetermined endogeneity in the other regressors. Arellano and Bond [1991] derive a generalised method of moments (GMM) estimator that uses the first differences of all variables and lags of all variables as instruments. This estimator is consistent and efficient as long as the $X_{it}$ variables are predetermined by at least one period, and there is no second-order autocorrelation in the first-difference of the residuals. The GMM procedure is thus quite useful to estimate a dynamic panel where the regressors may be correlated with the error term due to the inclusion of lagged endogenous regressors, or due to unknown endogeneity in the other regressors.

[22] The Indian National Congress Party has been for a long time one of the largest political parties in India. Founded by Nehru in the 1940s, the Congress Party was in power almost without opposition until 1977. At that time it was beaten in the national elections by the right-wing Bharatiya Janta Party, but recovered its position quickly in 1980. The Bharatiya Janta Party returned to power in the 1990s and has been the ruling party in India since 1996 (Election Commission of India, http://www.eci.gov.in).

[23] The uncorrected model showed signs of heteroskedasticity and serial correlation. In order to deal with these statistical problems, the results for the fixed-effects models are based on robust standard errors estimated using White's variance estimator and clustered at state level.

Given the theoretical specification developed in section 2, endogeneity can also be modelled by estimating simultaneously a system of three equations – where rioting, expenditure on social services and use of police are the dependent variables – using traditional instrumental variable techniques. Baltagi [1995], chapter 7, has adapted the standard two-stage least squares (2SLS) procedure to panel data. Baltagi's method allows the estimation of a single equation from a system of equations whose functional form does not need to be estimated, though an equal number of instruments and endogenous variables must be provided. These include the level of rioting itself. All exogenous variables in the first equation are taken to be additional instruments in the first-stage estimation of the social expenditure and police equations.

We used four additional instrumental variables.[24] These were the membership of labour unions, the number of people in live register, capital and non-capital public expenditure income shares and population levels in each state. Labour unions have played an important role in the establishment of welfare policies in India [Justino, 2003a], and are thus likely to affected the levels of public expenditure on social services. Similarly, this variable will be related to the number of people in live register in each state, as unemployment benefits constitute a significant expenditure item.

Expenditure on social services will be also associated to public expenditure on capital and non-capital items across India, as social services are a component of the capital account. In order to eliminate possible serial correlation we have used the share capital and non-capital expenditure on state income. Finally, levels of population in each state are used as an instrument for state demographic characteristics. These are likely to influence to a large extent the levels of expenditure on social services, the numbers of police and the level of riots in each Indian state. We do not expect the first three instruments to affect the number of police in India,[25] which is expected to depend mostly on the volume of civil unrest plus all other exogenous variables from the first equation.

[24] Variables modeled as endogenous in the 'inequality model' were lagged riots, policing, lagged policing and lagged Gini coefficients. Endogenous variables in the 'redistribution model' are lagged riots, policing, lagged policing, expenditure on social services and lagged expenditure on social services.
[25] In the first-stage estimation, those variables were only statistically significant in the social expenditure model.

The results for both the GMM and the 2SLS estimations of equations (5) and (6) are presented in table 5.[26] The GMM estimator is the more efficient Arellano-Bond two-step estimator given the presence of heteroskedasticity we found in the model. We have estimated Sargan tests for over-identification of restrictions in the GMM models presented in Table 5. These confirm the validity of our results (see Table 5). We also rejected the hypotheses of first- and second-order autocorrelation in all models at less than 5% level of significance (see bottom of Table 5).

### 4.3. <u>Results and discussion</u>

The theoretical framework developed in section 2 was based on three key propositions, which form our main empirical hypothesis: (i) civil unrest tends to self-perpetuate across time, i.e. levels of conflict will not change in time in the absence of factors that either limit or encourage conflict; (ii) high levels of inequality between the *rich* and the *poor* lead to social discontent and, eventually, the breakdown of social cohesion; and (iii) societies respond to a repression threshold, whereby excessive use of force will result in social discontent. In addition, we will test a further hypothesis: (iv) redistributive policies reduce existing conflicts. This hypothesis comprises the main result of section 2. The results for the empirical testing of these hypothesis are given in Tables 4 and 5. Table 4 includes estimations for the basic models, discussed in subsection A. Columns (1) and (2) present, respectively, the results for the initial 'inequality model' and 'redistribution model' (equations 3 and 4 above). The estimators for equations 5 and 6 (the two models plus control variables) are given in columns (3) and (4). Columns (5) and (6) illustrate, respectively, the 'inequality model' and the 'redistribution model' with the inequality and poverty variables disaggregated into rural and urban sectors. These two regressions include control variables. Table 5 compares these initial results with the results obtained when conflict, redistributive policies and policing are modelled within an endogenous framework. The first two columns of table 5 are the same as columns (3) and (4) of table 4, respectively, and are included here to facilitate comparisons of results. Columns (3) and (4) in table 5 present the GMM estimations of the 'inequality model' and the 'redistribution model', respectively, while the 2SLS estimators are given in columns (5) and (6). Table 5 presents only the results of the extended versions of the two models (with controls).

[26] For reasons of space restriction we do not present here the GMM and 2SLS estimations of models (3) and (4). These can be obtained upon request from the author. The 2SLS results presented are the second-stage results only

*Hypothesis 1: Self-perpetuation of civil unrest*. Current levels of rioting are positively affected by the extent of rioting in the past. This effect becomes statistically insignificant in the extended 'inequality model' (columns (3) and (5)) but is statistically significant in all specifications of the 'redistribution model'. This effect remains statistically significant in the endogenous models represented in table 5, with the exception of column (4). These results suggest that forms of social and political conflict may tend to self-perpetuate. This is in line with the existence of 'conflict traps' found in other studies [Azam et al., 2001; Collier, 2000]. In the presence of adequate controls, the danger of this 'trap' may, however, disappear in the longer-term. The coefficient for lagged conflict is in all equations statistically significantly different from (and less than) one, indicating that past levels of conflict will affect current levels of conflict at a progressively lower rate.

*Hypothesis 2: Inequality increases civil unrest*. We have not found any statistically significant relationship between income inequality and the volume of rioting in India. This result could be due to the presence of other types of inequality – access to land, education, health or political inequalities – not captured by the consumption Ginis. The Gini coefficient also does not capture inequalities between population groups, which have been shown to matter for civil conflict [Stewart, 2002; Wilkinson, 2004].[27] We should note also that civil unrest in India is affected by the levels of net state domestic product and the extent of poverty headcounts. It is thus possible that the inequality effects are being captured by stronger state-level income and poverty effects. State income has a positive and statistically significant impact on rioting in India in extended versions of the 'inequality model' in Table 4 (column (5)) and the 'redistribution model' in columns (4) and (6). Higher incomes may be linked to increases in civil unrest if the benefits from economic growth are distributed unevenly across different population groups. This effect has been to some extent hampered by the negative impact of trade openness on civil unrest in India, though this effect is not consistently statistically significant across all model specifications.

Civil unrest is also affected positively by poverty in all models in tables 4 and 5. These results confirm previous findings in the literature reviewed in the introduction to this paper.

as we are only interested in estimating models (5) and (6).

[27] Solving this issue requires individual-level data. We will address this in future research.

Moreover, the magnitude of this effect varies very little across all model specifications. The desegregation of the poverty and inequality measures by rural and urban areas (columns (4) and (6)) suggests that the result is driven mostly by rural poverty.[28] This could be a result of the size of the rural sector across all Indian states. Most Indians live in the rural sector and thus our models are more likely to better capture the impact of events that take place in rural areas than in urban areas.

*Hypothesis 3: Repression threshold*. The coefficients estimated in tables 4 and 5 confirm the presence of a repression threshold in India. In all model specifications, the current use of police has a negative coefficient, whereas the coefficient for lagged policing is positive. These results are in accordance with the predictions of the theoretical model. This repression threshold may be partially due to the heavy-handiness of police intervention at times [Upadhyaya, 2002]. As argued in section 2, excessive use of force is likely to result in resentment and, consequently, in the increase of the potential for further civil conflict. Our empirical results substantiate this hypothesis. The coefficients for lagged and current use of police are jointly significant in the extended versions of the 'redistribution model' in table 4 (columns (4) and (6). The lagged police coefficient becomes statistically insignificant once endogeneity is introduced into the various models. This is probably because India falls within the bounds of a society with a low potential for conflict: the absolute value of the coefficient for the use of police ($\lambda$) on conflict is larger than that of lagged use of police ($\sigma$) in all specifications of the fixed effects model.[29] These results suggest that the use of police is a rather efficient means to reduce civil unrest in India, though its effects are of short duration.

*Hypothesis 4: Redistribution decreases civil unrest*. The results show that conflict in India has been negatively affected by the level of expenditure on social services. In the initial specification of the 'redistribution model', only the current expenditure coefficient is statistically significant (Table 4). Both lagged and current coefficient become statistically significant in the endogenous framework estimated in table 5. The results indicate, as we expected, that higher levels of expenditure on social policies are associated with decreases in

[28] The aggregated inequality and poverty measures were calculated from rural and urban coefficients weighted by rural and urban populations in each state as provided by the Indian Census.
[29] It is not clear what will happen to these coefficients if civil unrest continues its upwards trajectory in India. For instance, our analysis does not include recent violent clashes between police and some population groups and between different religious and caste groups in Maharashtra and Gujarat as the data has not yet been made available.

civil unrest across India. The relationship between redistributive policies and civil conflict is particular significant in the longer-term, as was previously illustrated in Figure 2. The relationship is also particularly important once redistributive policies are modelled as endogenous variables to the occurrence of civil unrest. Our results indicate that failure to address the endogenous nature of this variable may result in the underestimation of the significance of the impact of redistributive policies on social conflict and instability.

These results suggest that the level of redistribution across the various Indian states has been sufficient to avoid scenario 3, predicted by the theoretical model in section 2, where civil unrest would tend to escalate into serious conflict. Whether intentional or not, and despite its small outlay, social redistributive policies have had a significant impact on the prevention and reduction of civil unrest in India, particularly in the medium term, as predicted in the theoretical model of section 2. Social redistributive policies not only address distributional concerns that may drive social discontent, but also contribute towards the reduction of poverty. This has, in turn, been shown to have triggered some episodes of social conflict in India. Policing has had mixed effects on civil unrest in India. While in the short-term it reduces conflict, in the medium term, the continued use of police has either inconsequential effects on social conflict or is associated increases in rioting in India.

### 4.4. <u>Alternative measures of civil unrest</u>

A final question we have addressed is whether our theoretical and empirical frameworks can be used to analyse other forms of political instability. One example is industrial disputes. These have been associated with both gains and losses in terms of social welfare amongst traditionally vulnerable population groups, as well as the whole population, in India [Justino, 2003a]. Trade unions may influence both national and local job practices undertaken by public and private enterprises and lobby for the interests of otherwise disadvantaged groups in the design of national policies [Freeman and Medoff, 1984]. They may also cause social and political uncertainty and, consequently, increased the risk of investment and reduced economic growth [Freeman and Medoff, 1984]. Both effects have been present in various Indian states [Justino, 2003a].

We have brought together data on the volume of strikes and lockouts per 1000 people across the same 14 Indian states between 1973 and 1999. The results for this analysis are given in Table 6. Descriptive statistics for this variable are presented in table 3. The models depicted Table 6 include additional control variables not in the rioting regressions. This is because the replication of the previous models using strikes as the dependent variables exhibited serious biases resulting from the omission of significant variables. In fact, there is no immediate reason to expect industrial disputes and rioting to be explained by common factors. In order to address the biases in our initial regressions, we have included two additional variables in the models in Table 6. The first is the number of workers' unions, which controls for workers' mobilization in India. The second variable is the number of factory workers. This variable impacts significantly on the volume of strikes as these are more likely to take place in the industrial sector.

As with rioting, the volume of strikes and lockouts in India is associated with both the use of police or redistributive policies.[30] Our estimates show that the use of police has, as expected, a negative impact on the onset of strikes and lockouts. They do not, however, support the repression threshold hypothesis. This result is understandable given that the onset of strikes and riots will be likely to have different motivations. Whereas feelings of repression may provide strong motives for individuals to engage in riots, strikes will be specific to labour market decisions. The police is also less likely to resort to more aggressive methods of crowd management in strikes than in riot situations.

Similarly to our previous conclusions, strikes are negatively associated with the level of public expenditure on social services. This result is only statistically significant in the longer-term and validates once more the theoretical predictions discussed in section 2. The use of redistributive policies is thus shown to have had significant impacts on the reduction of socio-political instability in India, not only in terms of the onset of riots but also in restraining labour market disputes.

## 5. Conclusions

[30] Table 6 presents only the GMM estimators in order to save space. The 2SLS results were very similar and can be obtained upon request.

Civil unrest entails important social and private costs [Barron, Kaiser and Pradhan, 2004], and can represent the prelude to more violent conflicts, including civil wars. Yet we have little understanding of what generates civil unrest and what can be done to prevent it. In this paper, we have addressed some of these questions. We analysed means of reducing and preventing civil unrest through the use of either policing or social redistributive policies. We showed both theoretically and empirically, using the example of India, that policing is only at best a short-term instrument in the fight against civil unrest. In the medium-term it may trigger further social discontent and unrest. In the medium-term, social redistributive policies are a more effective tool for reducing conflict. These policies address directly distributional concerns that may cause social discontent. They also contribute towards the socio-economic protection of the most vulnerable groups of the population and the reduction of poverty, which has been shown to impact significantly on the onset of civil unrest in India.

Our empirical results are robust to different model specifications and are particularly significant when the relationship between redistribution, policing and conflict is analysed within an endogenous framework. This is an important contribution of the paper. Although some types of conflict can be treated as external to local economic decisions, local animosities and social divides are likely to be an endogenous cause of civil unrest, as local conflicts may simultaneously be a cause and a consequence of the welfare characteristics of their instigators. Failure to address the endogenous nature of conflict may underestimate the significance of redistribution for the reduction and prevention of civil unrest.

The results of this paper yield important lessons for other countries where social cohesion tends to break frequently but large-scale wars may be avoidable. Some countries in Latin America, such as Brazil, Mexico and Peru, have exhibited a combination of high income inequalities (much higher than India's) and high potential for socio-political conflict [Binswanger, Deininger and Feder, 1995], while other countries have shown signs of deterioration of previously successful social development policies (for instance, former Soviet Union republics). This may result in increases in civil unrest. The implementation of adequate social protection programmes and other social redistributive policies may have an important role to play in the establishment and/or maintenance of stable socio-political environments in those countries.

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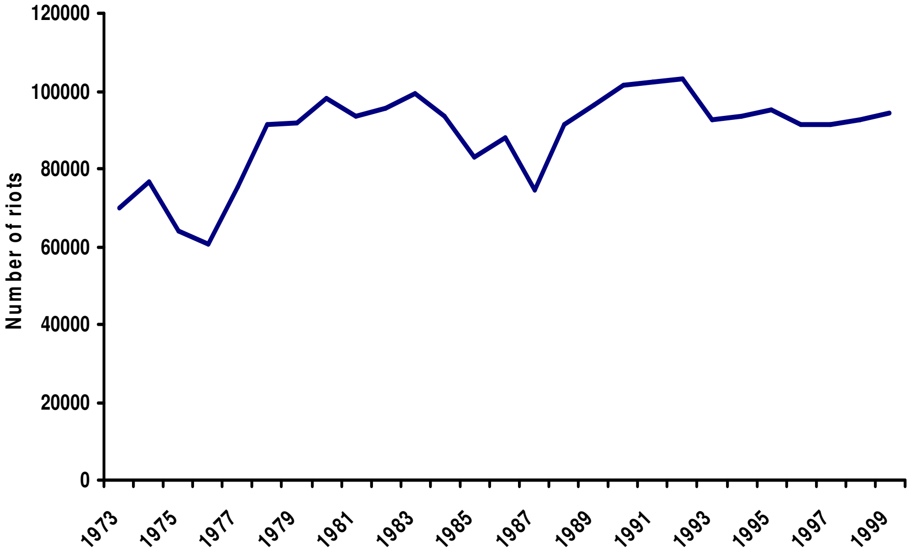
**FIGURE 1: Incidence of Riots in India, 1973 to 1999**




Source: Government of India, *Crime in India* (New Delhi: National Crime Records Bureau, Ministry of Home Affairs, various years).

**TABLE 1: Policing and Social Expenditure in Selected Indian States, 1973 and 1999**

| | Police strength | | Expenditure on social services | |
|---|---|---|---|---|
| | 1973 | 1999 | 1973 | 1999 |
| Andhra Pradesh | 0.98 | 0.99 | 85.7 | 151.8 |
| Assam | 1.66 | 2.03 | 203.7 | 31.6 |
| Bihar | 0.85 | 0.97 | 56.2 | 145.0 |
| Gujarat | 1.54 | 1.28 | 106.6 | 227.8 |
| Karnataka | 1.25 | 0.99 | 153.0 | 194.1 |
| Kerala | 0.96 | 1.18 | 227.0 | 184.0 |
| Madhya Pradesh | 1.33 | 1.24 | 81.4 | 52.2 |
| Maharashtra | 1.49 | 1.52 | 183.2 | 285.5 |
| Orissa | 1.04 | 0.99 | 113.9 | 50.3 |
| Punjab | 1.70 | 3.02 | 137.2 | 66.3 |
| Rajasthan | 1.40 | 1.24 | 105.0 | 129.3 |
| Tamil Nadu | 1.00 | 1.30 | 166.5 | 226.0 |
| Uttar Pradesh | 1.47 | 0.99 | 77.9 | 31.3 |
| West Bengal | 1.44 | 1.99 | 101.6 | 215.3 |
| India | 1.29 | 1.41 | 128.5 | 142.2 |

Source: Data on police from Government of India, *Crime in India* (New Delhi: National Crime Records Bureau, Ministry of Home Affairs, various years). Data on social services expenditure published by the Reserve Bank of India, *Bulletin* (New Delhi, various years).

Notes: Police strength refers to the number of civil plus armed police per 1000 people. Expenditure on social services refers to annual real expenditure per capita at 1980-81 constant prices in rupees.

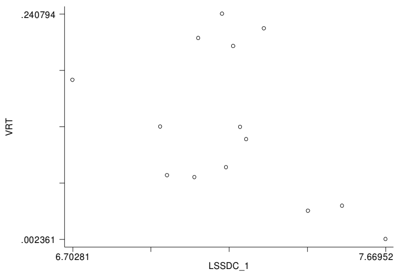
**TABLE 2: Correlation Coefficients for Rioting in India, 1973 to 1999**

| | Lagged expenditure social Services | Police strength | Lagged police strength |
|---|---|---|---|
| Andhra Pradesh | -0.884 | -0.634 | -0.409 |
| Assam | -0.766 | -0.507 | -0.270 |
| Bihar | -0.464 | -0.179 | -0.215 |
| Gujarat | -0.053 | -0.467 | 0.487 |
| Karnataka | 0.556 | -0.173 | -0.295 |
| Kerala | 0.215 | -0.593 | 0.288 |
| Madhya Pradesh | -0.771 | -0.065 | -0.461 |
| Maharashtra | -0.026 | -0.214 | -0.345 |
| Orissa | -0.775 | -0.049 | -0.067 |
| Punjab | -0.413 | -0.543 | -0.746 |
| Rajasthan | -0.001 | -0.883 | -0.039 |
| Tamil Nadu | -0.655 | -0.408 | -0.359 |
| Uttar Pradesh | -0.976 | 0.435 | 0.503 |
| West Bengal | -0.958 | 0.244 | 0.285 |
| India | -0.457 | -0.205 | -0.150 |
| | (0.000) | (0.060) | (0.215) |

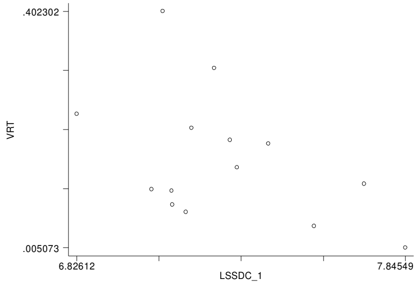
Source: Own calculations from published data from Reserve Bank of India, *Bulletin* (New Delhi, various years) and Government of India, *Crime in India* (New Delhi: National Crime Records Bureau, Ministry of Home Affairs, various years).

Note: Numbers in brackets indicate levels of significance.

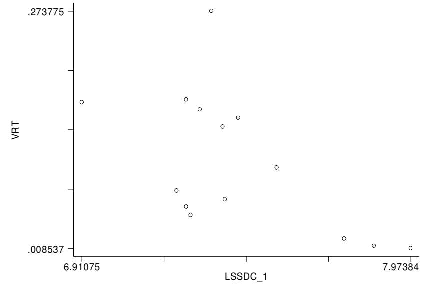
**Figure 2: Correlations Between Volume of Riots and Current Levels of Expenditure on Social Services**



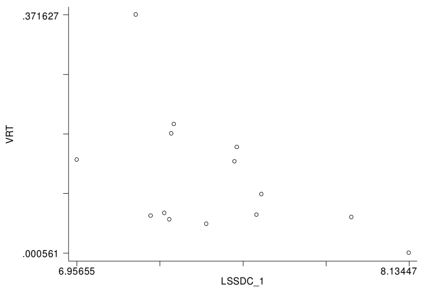

1977 (ρ = -0.470)



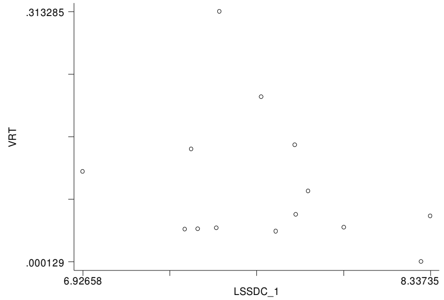

1983 (ρ = -0.465)




1987 (ρ = -0.588)




1993 (ρ = -0.496)




1999 (ρ = -0.312)

**TABLE 3: Descriptive Statistics: Means and Standard Deviations**

| | Andhra Pradesh | Assam | Bihar | Gujarat | Karnataka | Kerala | Madhya Pradesh |
|---|---|---|---|---|---|---|---|
| 1. Volume of riots | 0.060 (0.015) | 0.223 (0.094) | 0.172 (0.041) | 0.035 (0.016) | 0.133 (0.030) | 0.209 (0.026) | 0.063 (0.022) |
| 2. Volume of strikes | (0.404) (0.351) | 0.224 (0.225) | 0.409 (0.459) | 0.250 (0.077) | 0.134 (0.119) | 0.398 (0.348) | 0.247 (0.256) |
| 3. Number of police | 0.946 (0.098) | 1.994 (0.608) | 0.931 (0.105) | 1.544 (0.212) | 1.098 (0.113) | 1.090 (0.242) | 1.373 (0.212) |
| 4. Gini coefficient | 29.722 (2.133) | 28.365 (3.509) | 21.579 (1.571) | 26.654 (2.892) | 29.927 (2.451) | 33.052 (3.073) | 29.865 (3.389) |
| 5. Headcount (%) | 36.561 (13.929) | 38.826 (10.307) | 20.755 (11.007) | 39.837 (15.802) | 42.249 (13.657 | 39.403 (17.940) | 51.289 (10.695) |
| 6. Rural Gini | 28.785 (2.505) | 28.168 (3.992) | 20.238 (1.865) | 25.647 (3.488) | 28.607 (2.897) | 31.755 (3.062) | 28.812 (3.030) |
| 7. Urban Gini | 32.268 (2.088) | 29.938 (2.778) | 30.437 (1.723) | 28.568 (2.146) | 32.877 (2.049) | 36.668 (3.135) | 33.355 (5.855) |
| 8. Rural poverty (%) | 36.020 (16.016) | 40.987 (10.016) | 16.689 (12.589) | 40.543 (16.432) | 43.522 (15.105) | 38.927 (18.429) | 52.367 (11.324) |
| 9. Urban poverty (%) | 38.030 (8.693) | 21.520 (14.291) | 47.623 (9.060) | 38.487 (15.108) | 39.407 (11.133) | 40.730 (17.271) | 47.715 (8.816) |
| 10. Exp social services | 4.130 (0.988) | 3.845 (1.076) | 3.618 (0.116) | 4.316 (0.908) | 4.332 (0.930) | 17.906 (6.287) | 3.762 (0.800) |
| 11. State product | 7.446 (0.274) | 7.257 (0.135) | 6.894 (0.116) | 7.781 (0.338) | 7.568 (0.330) | 7.407 (6.287) | 7.278 (0.230) |
| 12. School enrolments | 0.145 (0.058) | 0.177 (0.0515) | 0.117 (0.032) | 0.134 (0.058) | 0.174 (0.039) | 0.167 (0.072) | 0.140 (0.050) |
| 13. Openness measure | 24.248 (0.895) | 24.248 (0.895) | 24.248 (0.895) | 24.248 (0.895) | 24.248 (0.895) | 24.248 (0.895) | 24.248 (0.895) |
| 14. Congress majority | 0.667 (0.516) | 0.667 (0.516) | 0.667 (0.516) | 0.667 (0.516) | 0.667 (0.516) | 0.667 (0.516) | 0.667 (0.516) |
| | **Maharashtra** | **Orissa** | **Punjab** | **Rajasthan** | **Tamil Nadu** | **Uttar Pradesh** | **West Bengal** |
| 1. Volume of riots | 0.052 (0.034) | 0.067 (0.021) | 0.003 (0.003) | 0.285 (0.060) | 0.135 (0.032) | 0.087 (0.040) | 0.142 (0.069) |
| 2. Volume of strikes | 0.292 (0.282) | 0.568 (0.331) | 0.240 (0.165) | 0.505 (0.426) | 0.363 (0.225) | 0.249 (0.194) | 0.306 (0.176) |
| 3. Number of police | 1.550 (0.100) | 1.086 (0.142) | 2.161 (0.584) | 1.297 (0.092) | 1.108 (0.149) | 1.204 (0.229) | 1.307 (0.240) |
| 4. Gini coefficient | 32.617 (4.267) | 27.138 (2.210) | 29.243 (2.807) | 30.959 (6.909) | 32.291 (1.897) | 28.212 (1.927) | 28.782 (2.192) |
| 5. Headcount (%) | 48.189 (14.132) | 52.094 (8.243) | 19.340 (8.747) | 43.508 (14.926) | 43.863 (12.657) | 21.114 (5.797) | 39.933 (12.849) |
| 6. Rural Gini | 31.105 (6.138) | 26.457 (2.334) | 28.310 (2.592) | 31.165 (8.670) | 30.703 (2.416) | 27.488 (2.526) | 27.015 (3.048) |
| 7. Urban Gini | 35.012 (1.423) | 31.553 (2.123) | 31.468 (4.377) | 30.265 (1.575) | 35.352 (2.800) | 31.135 (2.793) | 33.445 (0.850) |
| 8. Rural poverty (%) | 53.547 (18.523) | 52.315 (8.359) | 19.048 (8.359) | 45.523 (16.232) | 46.235 (15.294) | 14.869 (8.128) | 43.757 (14.571) |
| 9. Urban poverty (%) | 39.698 (8.152) | 50.663 (7.849) | 20.035 (10.979) | 36.712 (11.795) | 39.290 (10.559) | 46.338 (12.329) | 29.843 (9.522) |
| 10. Exp social services | 4.554 (0.971) | 3.947 (0.906) | 4.198 (0.811) | 4.107 (0.879) | 4.410 (1.013) | 3.629 (0.774) | 4.228 (0.907) |
| 11. State product | 7.995 (0.396) | 7.245 (0.141) | 8.064 (0.294) | 7.338 (0.187) | 7.567 (0.362) | 7.257 (0.207) | 7.634 (0.302) |
| 12. School enrolments | 0.172 (0.055) | 0.134 (0.057) | 0.147 (0.048) | 0.125 (0.058) | 0.179 (0.065) | 0.121 (0.050) | 0.149 (0.027) |
| 13. Openness measure | 24.248 (0.895) | 24.248 (0.895) | 24.248 (0.895) | 24.248 (0.895) | 24.248 (0.895) | 24.248 (0.895) | 24.248 (0.895) |
| 14. Congress majority | 0.667 (0.516) | 0.667 (0.516) | 0.667 (0.516) | 0.667 (0.516) | 0.667 (0.516) | 0.667 (0.516) | 0.667 (0.516) |

Note: Standard deviations in brackets.

Source: Own calculations based on data published by the following sources: 1. 3. Government of India (GOI), *Crime in India* (New Delhi: National Crime Records Bureau, Ministry of Home Affairs, various years). 2. GOI, *Annual Report* (New Delhi: Ministry of Labour, various years); GOI, *Indian Labour Year Book* (New Delhi: Ministry of Labour, various years); GOI, *Indian Labour Statistics* (New Delhi: Ministry of Labour, various years). 4. 5. 6. 7. 8. 9. 1973-74 to 1993-94 data from Özler, Datt and Ravallion [1996], World Bank. 1999-2000 headcount indices from Deaton [2001]. 1999-2000 Gini coefficients from National Human Development Report 2001, Planning Commission, GOI. 10. 11. 13. GOI, *National Accounts Statistics* (New Delhi: Central Statistical Organisation, Department of Statistics, Ministry of Planning and Programme Implementation, various years). 12. GOI, *Education in India* (New Delhi: Ministry of Education, various years). 14. GOI, Indian Election Commission.

**TABLE 4: Basic Model**

| | (1)<br>Volume riots<br>FE<br>[inequality model] | (2)<br>Volume riots<br>FE<br>[redistribution model] | (3)<br>Volume riots<br>FE<br>[inequality model]<br>[with controls] | (4)<br>Volume riots<br>FE<br>[redistribution model]<br>[with controls] | (5)<br>Volume riots<br>FE<br>[inequality model]<br>[with controls]<br>[rural/urban] | (6)<br>Volume riots<br>FE<br>[redistribution model]<br>[with controls]<br>[rural/urban] |
|---|---|---|---|---|---|---|
| Lagged riots | 0.380** | 0.390** | 0.320 | 0.342** | 0.300 | 0.334** |
| | (2.29) | (2.55) | (1.58) | (2.14) | (1.56) | (2.23) |
| Use of police | -0.047 | -0.046 | -0.055* | -0.053* | -0.054* | -0.053* |
| | (1.21) | (1.11) | (1.87) | (1.74) | (2.00) | (1.90) |
| Lagged use of police | 0.021 | 0.023 | 0.034 | 0.040* | 0.029 | 0.042** |
| | (0.88) | (0.94) | (1.65) | (2.13) | (1.32) | (2.17) |
| Lagged Gini | -0.000 | | -0.002 | | | |
| | (0.12) | | (0.52) | | | |
| Lagged rural Gini | | | | | -0.002 | |
| | | | | | (0.91) | |
| Lagged urban Gini | | | | | 0.001 | |
| | | | | | (0.73) | |
| Exp social services | | | | -0.003*** | | -0.004* |
| | | | | (4.16) | | (1.81) |
| Lagged exp sservices | | -0.023 | | -0.121 | | -0.121 |
| | | (0.31) | | (1.31) | | (1.18) |
| Lagged headcount | | | 0.003* | 0.003* | | |
| | | | (1.92) | (2.07) | | |
| Lagged rural poverty | | | | | 0.003** | 0.003** |
| | | | | | (2.42) | (2.21) |
| Lagged urban poverty | | | | | -0.001 | 0.001 |
| | | | | | (0.32) | (0.41) |
| Natural log state income | | | 0.103 | 0.153* | 0.112* | 0.154* |
| | | | (1.55) | (1.74) | (1.77) | (1.77) |
| School enrolments | | | -0.122 | -0.094 | -0.099 | -0.093 |
| | | | (1.23) | (0.92) | (1.01) | (0.81) |
| Openness measure | | | -0.031 | 0.006 | -0.034* | 0.010 |
| | | | (1.66) | (0.31) | (1.81) | (0.30) |
| Congress majority | | | -0.009 | 0.033 | 0.006 | 0.037 |
| | | | (0.25) | (1.38) | (0.23) | (1.01) |
| Constant | | 0.221 | | -0.471 | | -0.584 |
| | | (0.41) | | (1.04) | | (0.80) |
| R-squared | 0.959 | 0.885 | 0.966 | 0.913 | 0.968 | 0.916 |

Note: Absolute values of t-statistics in parenthesis. ***, ** and * indicate, respectively, statistically significance at the 1%, 5% and 10% level. State and year effects present in all columns.

**TABLE 5: Endogeneity**

| | (1)<br>Volume riots<br>FE<br>[inequality model] | (2)<br>Volume riots<br>FE<br>[redistribution model] | (3)<br>Volume riots<br>GMM<br>[inequality model] | (4)<br>Volume riots<br>GMM<br>[redistribution model] | (5)<br>Volume riots<br>2SLS<br>[inequality model] | (6)<br>Volume riots<br>2SLS<br>[redistribution model] |
|---|---|---|---|---|---|---|
| Lagged riots | 0.320 | 0.342** | 0.567** | 0.342 | 0.320* | 0.341** |
| | (1.58) | (2.14) | (2.15) | (0.55) | (1.77) | (2.41) |
| Use of police | -0.055* | -0.053* | -0.016 | -0.124** | -0.055** | -0.053** |
| | (1.87) | (1.74) | (0.42) | (1.98) | (2.06) | (1.97) |
| Lagged use of police | 0.034 | 0.040* | 0.0004 | 0.006 | 0.034 | 0.040 |
| | (1.65) | (2.13) | (0.02) | (0.24) | (1.29) | (1.51) |
| Lagged Gini | -0.002 | | 0.001 | | -0.002 | |
| | (0.52) | | (0.80) | | (0.59) | |
| Exp social services | | -0.003*** | | -0.003* | | -0.004*** |
| | | (4.16) | | (1.79) | | (2.93) |
| Lagged exp sservices | | -0.121 | | -0.105** | | -0.121* |
| | | (1.31) | | (2.33) | | (1.86) |
| Lagged headcount | 0.003* | 0.003* | 0.003*** | 0.004*** | 0.003** | 0.003** |
| | (1.92) | (2.07) | (2.96) | (3.51) | (2.16) | (2.45) |
| Natural log state income | 0.103 | 0.153* | 0.126*** | 0.217*** | 0.103* | 0.153** |
| | (1.55) | (1.74) | (2.94) | (4.60) | (1.72) | (2.08) |
| School enrolments | -0.122 | -0.094 | 0.039 | -0.033 | -0.122 | -0.091 |
| | (1.23) | (0.92) | (0.41) | (0.25) | (1.58) | (1.12) |
| Openness measure | -0.031 | 0.006 | -0.019 | -0.428*** | -0.031* | 0.006 |
| | (1.66) | (0.31) | (1.36) | (3.04) | (1.86) | (0.41) |
| Congress majority | -0.009 | 0.033 | (dropped) | (dropped) | 0.005 | -0.006 |
| | (0.25) | (1.38) | | | (0.34) | (0.44) |
| Constant | | -0.471 | | 0.170*** | | -0.247 |
| | | (1.04) | | (3.00) | | (1.21) |
| F-test instruments | | | | | 79.59 | 53.38 |
| (Pr > F) | | | | | (0.000) | (0.000) |
| Sargan test $\chi^2$ | | | 5.14 | 6.63 | | |
| (Pr > $\chi^2$) | | | (0.822) | (0.676) | | |
| First-order autocorrelation | | | 0.88 | -0.58 | | |
| (Pr > z) | | | (0.370) | (0.562) | | |
| Second-order autocorrelation | | | -0.44 | -1.20 | | |
| (Pr > z) | | | (0.658) | (0.232) | | |
| R-squared | 0.966 | 0.913 | | | 0.905 | 0.913 |

Note: Absolute values of z- and t-statistics in parenthesis. ***, ** and * indicate, respectively, statistically significance at the 1%, 5% and 10% level. State and year effects present in all columns.

**TABLE 6: Alternative Dependent Variables**

| | (1)<br>Volume strikes<br>GMM<br>[inequality model] | (2)<br>Volume strikes<br>GMM<br>[redistribution model] |
|---|---|---|
| Lagged strikes | -0.165 | 1.785** |
| | (0.95) | (2.55) |
| Use of police | 0.067 | -0.299 |
| | (0.75) | (1.47) |
| Lagged use of police | 0.060 | -1.029** |
| | (0.45) | (2.23) |
| Lagged inequality | -0.004 | |
| | (0.37) | |
| Lagged headcount | -0.009 | -0.003 |
| | (1.42) | (0.48) |
| Expenditure social services | | 0.006 |
| | | (0.34) |
| Lagged expenditure social services | | -2.125** |
| | | (2.40) |
| State income | 0.687** | 19.324** |
| | (2.16) | (2.50) |
| School enrolments | 4.253* | 41.884** |
| | (1.94) | (2.59) |
| Openness measure | -0.557*** | -17.805** |
| | (3.43) | (2.57) |
| Congress majority | 0.164 | (dropped) |
| | (0.89) | |
| Workers' unions | 0.008 | 0.137** |
| | (0.72) | (2.30) |
| Factory workers | -0.000 | 0.000** |
| | (1.19) | (2.09) |
| Constant | | 5.368** |
| | | (2.50) |
| Sargan test $\chi^2$ overidentifying restrictions | 0.410 | 0.000 |
| (Pr > $\chi^2$) | (1.00) | (1.000) |
| First-order autocorrelation | -0.92 | -0.17 |
| (Pr > z) | (0.359) | (0.861) |
| Second-order autocorrelation | -0.88 | 0.06 |
| (Pr > z) | (0.380) | (0.949) |

Note: Absolute values of z-statistics in parenthesis. ***, ** and * indicate, respectively, statistically significance at the 1%, 5% and 10% levels. State and year effects present in all columns.