# FINANCIAL DEVELOPMENT AND CONFLICT MITIGATION: CAN FINANCE COMBAT CONFLICT?*

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**Abstract**

A typical conflict is a complex phenomenon. It can have multiple roots; social (ethnic and religious differences), political (civil wars), economic (control of natural resources in a contested area). In this paper, we investigate whether a given economic intervention can mitigate domestic conflicts of different types, regardless of their different origins and characteristics. The intervention that we consider is financial development, measured either as an increase in bank credit supply or an increase in the number of bank accounts, in a conflict-affected area. Using a model as well as extensive empirical tests with district-level data from India comprising different types of conflicts over a long sample period (1983-2010), we find consistent evidence that supports our model's prediction that financial development mitigates conflict, and that this negative relationship holds for conflicts of all types. Employment growth and economic expansion due to financial development serves as a beneficial channel from financial development to conflicts. Multiple identification checks establish causality of our findings. The findings suggest that all conflicts share common economic underpinnings, in particular low opportunity costs of conflict participation for the rank file insurgents. Consequently, conflicts of different types respond similarly to a given economic intervention that raises the opportunity costs. Our findings have important policy implications.

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# 1 Introduction and motivation

The subject of the present study is conflict mitigation. The importance of the subject is self-evident. A conflict is typically very costly in terms of loss of life and property, and is destabilizing to society. Over the sample period of our study (1983-2010), in India alone there were 5,548 reported incidents of conflicts, excluding terrorist attacks. The incidents caused 12,926 deaths and 19,612 cases of injuries. Unfortunately, the total cost of property damage in the incidents is not available[1]. The indirect costs of conflicts are even more overwhelming. Among the economic consequences, the effects of displacement due to conflicts (Kondylis, 2010; Di Maio and Nandi, 2013), the negative effects of conflict on human capital including educational attainments (Chamarbagwala and Moran, 2010) and health of children exposed to violence (Arkesh et al, 2012), on risk preference (Callen et al, 2013), time preferences (Voors et al, 2012), and political choices (Bellows and Miguel, 2009) of the affected households, and on firm preference (Abadie and Gardeazabal, 2003; Guidolin and LeFerrara, 2007) have been documented. In an early study, Knight, Loayza, and Villanueva (1996) suggest that civil wars in developing countries result in a 2 percent *permanent* reduction in GDP just from diversion of resources from productive enterprises without taking into account the destructive effects of military operations on infrastructure. Drawing on many sources, Collier et al (2003, Part I) marshal voluminous evidence that enormously costly social and economic legacies of civil wars continue for years, sometimes decades, after the wars come to an end.

[1] Source: Global Terrorism Database

However, studying conflict mitigation is a challenging proposition. Conflicts are typically complex phenomena. They have many roots and causes, ranging from socio-economic conditions including lack of educational and employment opportunities (Collier and Hoeffler, 1998, 2001, 2002), ethnic differences (Esteban and Ray 2008, 2011), religious differences (Mitra and Ray 2013), and economic shocks (Miguel et al 2004).

In the present paper we set ourselves an ambitious agenda and address the following questions. Given that a conflict is typically complex and has multiple dimensions, several of them outside the usual sphere of economics, is it possible to devise and implement an economic strategy to reduce the incidence and intensity of all conflicts regardless of their specific types and characteristics? Can financial development, measured either as an increase in supply of bank credit or in number of bank accounts in a conflict-affected area, be that strategy? Can financial development serve this role within the market framework and without the aid of direct government intervention, given that there is abundant evidence of ineffectiveness of government strategies to resolve conflicts. We note some of the evidence below.

None of the above questions has so far been investigated in the existing literature. Several existing studies find that economic conditions influence the likelihood of specific types of conflicts, including civil wars (Collier and Hoeffer, 1998, 2004; Miguel et al 2004) and religious riots (Bolken and Sergenti, 2010; Mitra and Ray, 2013). However, while the studies make an important contribution by highlighting the role of economic conditions in general, they do not consider all types of conflicts but focus on specific types such as civil wars or ethnic conflicts. But, different types of conflicts may have significant commonalities which make them respond similarly to a given economic intervention. Further, the studies are typically concerned with causation of conflicts rather than mitigation. Accordingly, it is not relevant for them to go to the next level of analysis and identify the particular economic development strategies, such as financial development, that are conducive to conflict mitigation.

Using a general model of conflict designed to understand whether conflicts of different types share common characteristics, as well as extensive empirical tests of the predictions of the model with district-level data from India comprising different types of conflict over a long sample period (1983-2010) resulting in a large number of observations (19,493), we find consistent evidence of a negative association between conflicts and financial development in a district. To verify the robustness of our results we use several alternative measures of conflict as dependent variables in our empirical tests. The variables indicate occurrence (yes/no), frequency, and intensity of conflicts. We also use two common indicators of financial development as the main independent variables in the tests, namely bank credit supply and the number of bank accounts in a district. The rationale for the second measure of financial development arises from its significance as an indicator of financial inclusion in a developing economy. The observed effects are significant statistically as well as economically. Using a particular measure of conflict, we find that an increase of 1 million Indian rupees (INR) in credit supply in a given district in a year appears to result in a fall in the probability of conflict in the district by 9 percent, which is about a third of the total unconditional probability of conflict in the average district-year in our data. The results for two other measures of conflict used in this paper are even stronger. A second major finding is that the results of tests for our entire sample comprising different types of conflict are very similar to the separate test results for the different types of conflicts in our sample, such as ethnic conflicts which are prevalent in north-eastern India, separatist movements in Jammu and Kashmir and Punjab in north India, and political conflicts in central India known alternately as left-wing extremism (LWE) or Maoist insurgency. Further tests indicate that employment growth due to financial development serves as a beneficial channel from financial development to conflicts in our data.

Multiple identification checks establish causality of our findings. First, we check for reverse causality and omitted variable bias for the main independent variable, namely credit supply or number of bank accounts in a district as the case may be, in our test models. We find that reverse causality does not cause a problem in our setting. To correct for the omitted variable bias, we use a proxy variable, per capita consumption expenditure in a district, for the likely omitted variable, namely level of economic activity or GDP of the district for which no data is available. We verify that the proxy variable corrects the bias in our results. For more verification, we use the Debt Recovery Tribunal (DRT) Act, 1993, to identify policy induced exogenous shocks to credit supply. The DRT Act allowed the central government to establish DRTs in different Indian states for speedy recovery of overdue debt owed to financial institutions. The act became effective in 12 states in 1994, and in the remaining 13 states over 1997 - 1999. The timing of the DRTs was completely exogenous to the pre-existing conflict levels in the states (Visaria, 2009; Lilienfeld-Toal et al, 2012). We use the phased introduction of DRTs in Indian states to employ two alternative instruments for credit supply: establishment of DRTs in the first group of states and duration of DRTs in the states since their establishment. We find negative and significant impact of credit supply on conflict with the first instrument, and similar effects with DRT duration until 2008. However, DRT duration appears to lose significance for the period 2008 - 10. It appears that the financial crisis of 2008, which affected both effectiveness of DRTs in recovering overdue debt and conflict levels in the states(through negative effects on employment), confounds the results beyond 2008.

Taken together, the findings offer a special insight into organization of conflicts. Conflicts of different types, including ethnic conflicts, civil wars, and extremist political insurgencies, share a critical common feature that makes all of them respond similarly to economic expansion and employment creation brought about by financial development. Arguably, regardless of the specific type of conflict they are engaged in, rank and file insurgents have low opportunity costs of conflict participation in common. Absence of suitable employment opportunities elsewhere in the economy drives their opportunity costs low. When new jobs materialize as a result of financial development and economic expansion, their opportunity costs rise, inducing some or all of them to exit conflict. Our channel test results support this view. The insight that low opportunity costs are a pre-condition for participation in civil wars is originally due to Collier (2003). What our findings suggest is that it cuts across all forms of conflict and serves as a common thread between them.

The central contributions of the present paper are as follows. First, many conflicts, if not all, that appear to be driven by ostensibly non-economic motivations have economic underpinnings. This observation is similar in spirit to a key finding in Mitra and Ray (2012) who have documented economic motivation for Hindu-Muslim riots in India. However, what differentiates our contribution from theirs is that our results suggest that the economic underpinnings are common to conflicts of different types. They all rest on their rank and file having low opportunity costs of conflict participation. Second, following from the above, a strategy of economic expansion and growth that has the effect of raising the opportunity costs results in mitigation of conflicts of different types. In the present paper financial development is our strategy of choice though, conceivably, other economic strategies that deliver employment creation and growth could work as well. Our choice of financial development as the strategy conflict mitigation is dictated by several factors important for our study, including theoretical and empirical factors. Our model explicitly incorporates a realistic feature of conflict financing, namely that some of the funds provided for legitimate businesses get diverted to conflicts. Bank credit allows us to model this feature seamlessly. The model shows that, in spite of this diversion, an increase in credit supply csuses a decline in conflict. Availability of superior data of financial development has also motivated us to consider this strategy. For our empirical tests, the source of the data for the independent variables of interest, namely credit supply by Indian commercial banks and number of bank accounts which are the two common indicators of financial development, is Basic Statistical Returns (BSR) database of the Reserve Bank of India (RBI). BSR provides this data annually for each district-year in the aggregate as well as separately for different sectors, such as agriculture, industry, professional services etc. The quality and comprehensiveness of BSR data are excellent.

Finally, and importantly, we consider financial development to check whether economic development occurring within the market system, with banks giving credit to businesses, can mitigate conflicts without government intervention. Our findings are affirmative. Until now the policy as well as academic literatures have largely focused on government interventions as the means to conflict mitigation. The two types of options that are in principle open to a government faced with insurgency within its jurisdiction are a military response, which may take various forms such as use of paramilitary forces or launch of counterinsurgency operations, and a negotiated settlement with the insurgents. Sometimes both options are pursued simultaneously. Both approaches have well-documented limitations. All existing evidence indicates that the first option is extremely costly, particularly when it takes the form of civil wars. We have referred to some of the evidence in the opening paragraph of this paper. Further, the existing evidence on the long-term success rate of the military option is ambiguous, even ignoring concerns about causaliy of estimates of the impact of military operations on conflict given that it is difficult to be sure if the operations are in reaction to conflict or the result of a planned government strategy. While Berman, Felter, and Sharipo (2011) and Berman, Felter, Sharipo, and Troland (2013) find that security operations are complementary to provision of aid and were effective in reducing conflict in Iraq, Dube and Naidu (2012) find that American aid-supported paramilitary operations in Colombia is not negatively associated with guerrilla violence. In fact, some existing studies find that counterinsurgency operations lead to increased insurgency among the local people (Benmelech, Berrebi, and Klor, 2010; Kocher, Pepinsky, and Kalyvas, 2011). Within our sample period, the "Salwa-Judam" operation launched by the government of Chhattisgarh state in central India in 2005 is a case in point. The operation is named after a paramilitary force organized by the state government that recruited tribal youths as special police officers to fight Maoist insurgency. However, our data indicates that both the frequency and intensity of conflicts in Chhattisgarh increased following the launch of Salwa-Judam. There were also many allegations of human rights violation associated with the operation, Finally, in 2011 the Supreme Court of India intervened and declared the operation illegal and unconstitutional, forcing its termination.

The second option, a negotiated settlement with the rebels,is unsuitable for any government that fears sending out a signal that violence leads to political gains, especially if there are other potential rebel groups in the country. Even if the government is willing, it may lack the means to credibly commit to the terms of the settlement after the rebels disarm (Collier et al, 2003). Walter (1997, 2002) finds that lack of credible guarantees also dooms prospects of third-party enforcement of peace settlements. On the other side, even within the same group of rebels there may be significant heterogeneity between the members (Esteban and Ray, 2011), ruling out a united approach by the group in negotiations with the government. Besides, The case of ethnic conflicts in north-east India illustrates this problem. Since the beginning of the conflicts soon after Indian independence in 1947, the different governments in office have attempted to work out various settlements with the many insurgent groups operating in the area without any settlement taking hold.

As we have indicated above, our contributions are based on a model as well as empirical tests of the prediction of the model. The model is parsimonious by design but quite broad in its scope It incorporates several innovative but realistic features. In a two-sector economy (industry with certain outcomes and conflict with uncertain outcomes), two parties engage in a conflict over a reward. The reward has a binary distribution: X (to accrue to the winner of the conflict) or zero. To fit conflicts of different types, the reward in the model can potentially have many different forms: political (effective control of a district); economic (control of mineral resources in a contested area); ethnic (displacement of an ethnic group from a contested area). To finance their conflict-related activities, the parties divert part of the bank credit obtained for industrial projects. For either party, the probability of winning the conflict and obtaining the reward increases in the amount of its investment in the conflict and decreases in the investment by the other party. Engaging in conflict is tempting, because X exceeds the certain outcome from the industry with full investment of funds. However, it is also costly. The costs are of two kinds. The warring parties face the opportunity costs of not investing the diverted funds in the industry. The other type of costs are indirect, but can be very substantial. They arise from collateral damage that conflicts entail, including destruction of resources such as manpower and infrastructure, in addition to the planned destruction that the parties cause to each other [2] The indirect costs increase in the total amount of capital invested in the conflict by both parties, and hurt them both as also the rest of the society. Starting from an equilibrium where the marginal costs of the two types of costs combined equal the marginal expected reward from the conflict, we show that an infusion of credit supply reduces investment in the conflict by all parties *regardless* of their respective probabilities of winning if the indirect costs increase

[2] As an example of such costs, about 40 percent of immobile capital in the agriculture, communications,and administrative sectors in Mozambique was destroyed in civil conflicts (Brck, 2001). There are other equally staggering examples.

at an increasing rate. Interestingly, diversion of credit to conflict declines as credit supply increases. A second major prediction of our model is that this negative relationship holds for all types of conflict, because the reward can fit any type. As we have indicated above, both predictions are consistently borne out by the results of our empirical tests.

The data and variables used in the tests are described in detail in section 4 below. The conflict data comes from Global Terrorism Database. As stated above, the source of district-level data of credit supply to different sectors, such as agriculture, industry, professional services etc. by Indian commercial banks and number of bank accounts is the BSR database of the Reserve Bank of India. Since bank finance constitutes a small part of the total agricultural finance in a given year in India, the majority coming from informal sources, and professional services do not have a significant presence in the rural areas where a majority of the conflicts take place, we use industrial credit supply and industrial credit accounts in our tests. Industrial credit constitutes the largest sector, accounting for almost 44 percent of the total bank credit supply in the average district-year. We also use an array of control variables that have been shown in other studies to influence conflicts. Additionally, we use a few other controls that we consider important for our investigations. The control variables and the corresponding data sources are of four types: (1) worker participation rate, literacy rate, urbanisation, population density, scheduled tribe population in Indian districts (source Indian population census 1991, 2001, and 2011), (2) monthly per capita consumption expenditure, consumption expenditure inequality and unemployment in Indian districts (source five rounds of survey conducted by National Sample Survey Organisation, India),(3) area covered under forests and net state domestic product (source IndiaStat), and (4) district roads, national and state highways (source *Pradhan Mantri Gram Sadhak Yojana* website).

The paper proceeds in the following manner. Section 2 below presents a review of the relevant literature. Section 3 presents our model. The data and the variables used in our empirical investigations are discussed in section 4. Section 5 presents the basic test results and identification checks. The results of tests of both predictions of our model are presented in section 6 The results reported in section 7 indicate that employment serves as a channel from credit supply to conflict. Section 8 discusses the special case of credit to the mining industry in mineral-rich states in India. Section 9 presents several robustness test results. We present our conclusions in section 10.

# 2 Relevant Literature

Much of the existing literature on conflicts has been concerned with causation of conflicts, with a focus on identifying the specific determinants of conflicts. The part of the literature that has focused on conflict mitigation is mostly limited to the impact of government interventions on conflict, including provision of aid (Berman,, Shapiro, and Felter, 2011; Crost,Felter and Johnston, 2013), setting up institutions aimed at conflict resolution (Blattman, Hartman, and Blair, 2013), security provision (Berman, Felter, Shapiro and Troland, 2013; Berman, Felter and Shapiro, 2011), and counter insurgency operations (Kocher, Pepinsky and Kalyvas, 2011). Most studies in this part consider a specific case of conflict in a given country, and come up with findings that appear to suggest that the effects of government policies are heterogeneous and sensitive to the specific circumstances of the cases concerned. For example, Berman et al (2013) find a negative relationship between inflow of foreign aid and attacks against coalition forces and the government in different regions of Iraq, while Crost et al (2013) find no effect of a community development project on conflict in the Philippines.

Importantly for our purpose, this literature has not considered the impact of economic interventions on conflict within a market framework, which is the focus of our paper. However, in a broader context, the existing studies that have looked at economic causes of conflict have implications for conflict mitigation as well. Collier (2003)suggests that low opportunity costs of insurgency in poorer countries, in the form of foregone income and farm output, contributes to civil wars in poorer countries. Miguel et al (2004) use annual variation in income per capita due to rainfall variation in 41 African countries, (arguably, rainfall-dependent agrarian countries) to identify the causal impact of temporary economic shocks on civil wars. Other economic shocks that have been considered include variation in prices of export commodities (Bazzi and Blattman, 2013) and droughts and floods (Bai and Kung, 2011). The findings of the studies suggest that improvement in economic conditions should reduce conflict. In the present paper we use exogenous changes in bank credit supply to causally establish that employment growth and economic expansion driven by financial development reduces conflict of all types, not just civil wars. Though the improvements that we consider are longer-term improvements, it should be noted that increased credit should also soften the impact of temporary income shocks. In other words, softening temporary economic shocks is a beneficial channel in our framework, along with employment growth and other longer-term economic effects.

At a broader level, our paper bridges a gap in the existing literature. There is a sizable literature by now that connects conflict causation with economic outcomes, and another sizable literature that connects economic outcomes with financial development. Levine, 2005, provides a survey of the latter literature. However, the existing literature has not yet considered the possible connections between conflicts and financial markets.

# 3 Theoretical framework

## 3.1 The setting

In this section we present a theoretical framework for the impact of bank credit supply on conflict. There are two sectors in the model: Industry and Conflict. There are two parties or groups, i and j. The groups are homogeneous. Our parsimonious model has too few group characteristics to allow for heterogeneity among the members of a group. The groups may engage in both sectors.

Capital invested in industry and conflict sectors by group i are denoted by $K_i^I$ and $K_i^c$ respectively. The investments by group j are similarly denoted by $K_j^I$ and $K_j^c$. Group i's output in the industry sector is given by the production function, $f_i(K_i^I)$, where $f_i : [0, \infty) \rightarrow [0, \infty)$ is assumed to be strictly increasing, concave, twice differentiable and Inada condition-satisfying. The production function for Group j, $f_j(K_j^I)$, satisfies similar conditions. Per unit price of the industrial output is 1, so $f_i$ or $f_j$ denotes the value of industrial output.

Groups i and j may also engage in conflict with a view to obtaining a reward characterized by a binary distribution; X or 0. X can have many forms; political (administrative control of a geographic area), economic (control over natural resources in an area), ethnic (displacement of another community from an area), and religious (extermination of a religion in an area). We assume that, regardless of the specific form of X in a given situation, possession of X generates a monetary outcome for the reward holder. Without ambiguity we denote the monetary outcome also as X. The production function in the conflict sector is represented by $F_i$ for group i. The output of conflict sector can be interpreted as outcomes that propel group i toward winning the conflict and capturing X, such as destruction of employable resources (manpower, capital stock etc) of group j. $F_i : [0, \infty] \rightarrow [0, \infty]$ is strictly increasing, weakly concave, twice differentiable and Inada condition-satisfying. The production function for group j, $F_j$, satisfies similar conditions.

For tractability we assume that the groups do not have an initial endowment, though all our results hold if this assumption is relaxed. A financial market exists. Groups i and j can borrow money at an interest rate of $r$ from a bank for industrial activity. The lending institution's objective is to break even on each credit decision. The lender is a passive player in the game between the two parties in the conflict. The lender lends $\overline{K}_i^*$ amount of industrial credit to group i, making sure that his objective to break even is satisfied. Institutional regulations as well as law of the country prevents the lender from lending directly for investment in the violent conflict sector. However, monitoring by the lender is imperfect. Hence, both groups can divert a part of the total credit, $\overline{K_i^*}$ to conflict without the lender's knowledge. Let $K_i^c$ be the amount diverted to conflict by group i. Therefore, the amount left to be invested in industry by group i is $\overline{K}_i^*$- $K_i^c$. Since $f_i(K_i^I)$ is concave, $f_i(\overline{K}_i^* - K_i^c)$ is convex in $K_i^c$.

Conflicts generate two types of costs for the participants. We incorporate both costs explicitly in our model. The first type is opportunity costs of loss of industrial output arising from diversion of funds. Conflicts also generate special costs due to their unique nature. A conflict of necessity involves collateral damage in the form of destruction of life and property (beyond what the parties intend to inflict on each other). The costs due to collateral damage are indirect costs as opposed to direct costs of conflict (such as costs of troops, ammunitions etc.)incurred by the warring parties. The direct costs are paid with diverted funds in our model and represented by the opportunity cost noted above. The indirect costs are experienced not only by the party directly responsible for the collateral damage but also by other parties involved in the conflict (as also the rest of the society). Such costs can be substantial. We assume that the indirect cost function, denoted by $C(K_i^c + K_j^c)$, is strictly increasing in the total amount of capital invested in conflict by both groups. Though collateral damages are an inevitable feature of conflicts, incorporating such costs explicitly is a new contribution to conflict modeling. Since this is an innovative feature, at this stage we decide to consider both concave and convex indirect cost functions, and not pre-suppose a specific functional form. Which of the two functional forms is consistent with data will be known when we proceed to empirical work.

We assume the following two conditions:

I) The probability with which group i wins the prize X is $\frac{F_i(K_i^c)}{F_i(K_i^c)+F_j(K_j^c)}$. Since $F_i$ is concave by assumption, it is easily seen that the probability of winning the conflict by group i is also concave in $K_i^c$. Note that this probability decreases in $F_j(K_j^c)$, the level of capital investment in conflict by group j. This condition encapsulates the idea of conflict in our model.

II) $X > f_i(\overline{K}_i^*)$ and $X > f_j \overline{K}_j^*$. The reward from conflict exceeds the maximum industrial output when the entire credit is invested in industry. Hence engagement in conflict is tempting for both groups.

## 3.2 The game

As the lender is prevented from lending for conflict sector activities, the lender considers only the borrower's output from industry in his lending decision. The lender chooses $\overline{K}_i^*$ such that $f_i(\overline{K}_i^*) \geq \overline{K}_i^*(1+r)$. This condition ensures that the output from industry is sufficient to cover debt repayment. Similarly, the bank lends $\overline{K}_j^*$ to group j such that the output from industry for group j exceeds $\overline{K}_j^*(1+r)$. We assume that if the entire funds are invested in industry, the loans can be repaid and the lender's break even conditions are satisfied.

Group i has the following utility function:

$$U_i(K_i^c, K_j^c) = f_i(\overline{K}_i^* - K_i^c) + \frac{F_i(K_i^c)}{F_i(K_i^c) + F_j(K_j^c)} X - r(\overline{K}_i^*) \tag{1}$$

where $U_i$ is assumed to be concave. However, the indirect cost function must impact group i's utility negatively. Hence, group i maximises the following augmented utility function $\overline{U_i}$

$$\overline{U_i}(K_i^c, K_j^c) = f_i(\overline{K}_i^* - K_i^c) + \frac{F_i(K_i^c)}{F_i(K_i^c) + F_j(K_j^c)} X - r(\overline{K}_i^*) - C(K_i^c + K_j^c) \tag{2}$$

If C is convex, that is if the indirect costs due to conflict increase at an increasing rate, then $\overline{U_i}$ is also concave like $U_i$, because C enters equation 2 above with a negative sign. However, if C is concave then $\overline{U_i}$ is not always concave. We consider the two cases separately below.

#### 3.2.1 Convex indirect cost function

Since in this case, as argued above, $\overline{U_i}$ is concave, and $K_i^c$ belongs to [0,$\overline{K}_i^*$], an equilibrium exists. Further, the first order condition for the equilibrium outcome $K_i^{c*}$ implies that

$$f_i^{'}(\overline{K_i^*} - K_i^{c*}) + C_{K_i^{c*}}(K_i^{c*} + K_j^c) = \frac{F_i^{'}(K_i^{c*}) F_j(K_j^c)}{[F_i(K_i^{c*}) + F_j(K_j^c)]^2} X \tag{3}$$

Note that the left hand side of (3) is increasing in $K_i^c$ whereas the right hand side is decreasing. Hence the equilibrium is unique. The first order condition for group j similarly is

$$f_j'(\overline{K_j^*} - K_j^{c*}) + C_{K_j^{c*}}(K_i^c + K_j^{c*}) = \frac{F_j'(K_j^{c*})F_i(K_i^c)}{[F_i(K_i^c) + F_j(K_j^{c*})]^2}X \tag{4}$$

The main aim of our paper is to estimate the impact of an increase in credit supply on the equilibrium level of investment in conflict

$$\frac{dk_i^{c*}}{d\overline{K}^*} = \frac{f_i''(\overline{K}^* - k_i^c)}{f_i''(\overline{K}^* - K_i^c) - C_{K_i^c}'' + \frac{XF(K_j^c)[(F(K_i^c)+F(K_j^c))F''(K_i^c)-2[F'(K_i^c)]^2]}{([F(K_i^c)+F(K_j^c)]^3)}} \tag{5}$$

If the indirect cost function is convex, the sign of the denominator is negative. It follows from the concavity of $\overline{U_i}$. [3]The numerator in (5) is positive, given our assumption of strictly concave industrial production function (in $K_I^i$). Hence, the sign of $\frac{dk_i^c}{dK_i^*}$ is negative.

The intuition for this result is straightforward. As credit supply goes up, with convex indirect costs it becomes increasingly costly to invest in conflict compared to industry. The rate at which conflict costs increase exceeds the rate of increase in conflict reward, Hence an increase in credit supply reduces investment in conflict. Note that costs here include indirect costs of investment in conflict $C(.)$ as well as opportunity costs of loss of industrial output.

#### 3.2.2 Concave indirect cost function

If the indirect cost function is concave, the function $\overline{U_i}$ is not necessarily concave because the concave cost function enters $\overline{U_i}$ with a negative sign. By differentiating

[3] $\frac{\partial U_i}{\partial K_i^c} < 0$ implies that

$$f_i''(\overline{K_i^*} - K_i^c) - C_{K_i^c}''(K_i^c + K_j^c) + \frac{XF(K_j^c)[F(K_i^c)+F_j(K_j^c)F''(K_i^c)-2F'[(K_i^c)^2]]}{[F(K_i^c)+F(K_j^c)]^3} < 0$$

$\overline{U_i}$ twice, we get the following expression

$$f_i^{''}(.) - C_{K_i^c}^{''}(.) + \frac{XF_j(.)[F_i(.) + F_j(.)F_i^{''}(.) - 2F_i^{'}[(K_{i1}^c)]^2]}{[F_i(.) + F_j(.)]^3} \tag{6}$$

From (6) $\overline{U_i}$ is concave if $\frac{XF_j(.)[F_i(.)+F_j(.)F_i^{''}(.)-2F_i^{'}[(K_i^c)]^2]}{[F_i(.)+F_j(.)]^3} < C_{K_i^c}^{''}(.) - f_i^{''}(.)$. This will happen when the expected reward from conflict increases at a slower rate than the opportunity cost and social cost.

When $\overline{U_i}$ is concave, equilibrium investment $K_i^{c*}$ is given by equation 4 as in the case of a convex indirect cost function. However, a unique equilibrium will now exist only if $f_i^{'}(\overline{K}_i^* - k_i^c) + C^{'}$ increases in $K_i^c$

The magnitude of the impact of credit supply on the level of conflict is given by equation 5 as in the case of the convex indirect cost function. However, now the sign of $\frac{dk_i^c}{d\overline{K}_i^*}$ may be ambiguous. The sign of the numerator is positive as before, but the sign of denominator is ambiguous. The denominator will be negative if expression 6 is negative, that is if the rate of increase in conflict reward is less than the rate of increase in the costs of conflict. Intuitively, this could happen at a high level of investment in conflict where the expected reward of conflict increases slowly. Should it happen, there will exist a threshold level of $K_i^c$ such that, for $K_i^c$ above the threshold level, the rate of increase in conflict reward is less than the rate of increase in costs, and investment in conflict falls. For investment levels below the threshold, both reward and costs of conflict increase in response to increased credit supply, making the net effect ambiguous.

To illustrate the intuition, we present a numerical analysis exercise to obtain the value of critical investment level for which the expression 6 becomes negative. Let us assume the following functional forms for this exercise:

$f_i(K_i^a) = K_i^{\alpha}$, where $\alpha < 1$

$F_i(K_i^c) = \beta + K_i^c$

$C(K_i^c + K_j^c) = log(K_i^c + K_j^c)$

$\frac{dk_i^c}{d\overline{K}} = \frac{\alpha(\alpha-1)[(\overline{K}-K^c)]^{\alpha-2}}{\alpha(\alpha-1)[(\overline{K}-K^c)]^{\alpha-2}+[K^c]^{-2}-X\frac{\beta^2}{[\beta+K^c]^2}}$

Assuming X=100 ,$\alpha = 0.5$,$\beta = 1$ and $\overline{K} = 90$ in period 1. Using python, we solve the above equation to compute the threshold value of $\overline{K}$ above which investment in conflict will fall with an increase in credit supply. Given the above assumed values, the level of investment in conflict above which the sign of $\frac{dk_i^c}{d\overline{K}}$ is negative turns out to be 32.8. Thus the range of capital investment in conflict for which the impact of credit supply on conflict is negative is [32.8,90].

## 3.3 Predictions

From the discussion above, the model offers the following two testable predictions:
I(a) If the indirect cost function of conflict is convex, an increase in credit supply reduces investment in conflict by all parties. Hence, conflict declines.
I(b) On the other hand, if the function is concave, the implications are ambiguous. However, even in this case, the negative relationship between credit supply and conflict may hold for high levels of investment in conflict.

Later in the paper we resort to our data and test results to resolve the issue. Our test results find a negative relationship at all levels of conflict, indicating a convex indirect cost function.
II) The negative relationship between credit supply and conflict (or lack thereof) in the first prediction holds for all types of conflict. This follows from our model specification that the reward of conflict, X, fits all conflict types.

# 4 Data and variables

To test the theoretical predictions of our model in data, we consider incidents of conflict in Indian districts[4] during 1983-2010. Data sources and construction of the variables used in our tests are described below.

Our data on conflict comes from Global Terrorism Database (GTD) which provides district level information on conflicts in India since 1976. Compiled by The National Consortium for the Study of Terrorism and Responses to Terrorism (START), GTD is an open-source database on conflicts and similar events around the world. We choose GTD over South Asian Terrorism Portal, another open data source on conflict, because the latter has data starting much later. GTD includes detailed information about the incidents, including number of people killed, whether there was any property damage, targets of the incidents, perpetrators, weapons used and a brief description of each incident. The type of conflict in each incident is easily inferred from the data. We include all types of conflict in our sample but not terrorist attacks. We exclude terrorist attacks because they are incompatible with our framework discussed in the preceding section of this paper where two or more clearly identified parties actively engage in a conflict. In a typical terrorist attack active participation of a second party, besides the terrorists themselves, is usually not satisfied. Actually, though they may share some common features, the fact that terrorist attacks and conflicts are two different types of violence is widely recognized and has led to a separate literature on terrorist attacks (Blattman and Miguel, 2010).

The unit of the observations in our sample is district year, However, some district years in our sample are repeated because of multiple occurrences of conflicts. As a result, the total number of observations in our sample (19,493) exceeds the

[4]District is a unit of administration in a state/ region in India

total number of district-years in our sample. The sample includes a total of 5,548 reported incidents of conflict, implying that about 72 percent of the district-years in our sample did not experience any conflict. Information about the targets of the incidents is available for 5479 incidents. The following summary provides an idea of the variety of conflicts in our sample. 39 percent of the reported conflicts took place in Jammu, Kasmir and Punjab in north India where civil wars in the form of violent separatist movements were the norm. 31 percent took place in Left Wing Extremism (LWE) states in central India affected by Maoist insurgency. Another 20 percent of the incidents driven by ethnic conflicts took place in north-eastern India. Other types of conflicts, including religious conflicts, accounted for the remaining 10 percent. Figure 1 below shows the geographic distribution of different types of conflicts in India.

Figure 1 here

*Dependent variables in main tests*

We use the data to construct three alternative dependent variables for our main tests. Conflict (G), our main dependent variable takes a value of 1 if there is any reported death, property damage, or both in our sample. According to this definition, 28 percent of the total number of observations in our sample included conflicts, of which about 50 percent included property damage. Conflict(I), a categorical variable, is constructed to indicate the intensity of conflict. It takes a value of zero if there is no conflict, 1 if number of people killed is between 0-5, 2 if the number is between 6 and 25, 3 if number is between 26 and 50 and 4 if number is above 50. Conflict(F) is constructed to represent the total number of incidents of conflict in a given district year. It thus indicates the frequency of conflict in the district year.

*Dependent variables in our channel tests*

To test the channels through which credit supply affects conflicts, we consider reduction in unemployment as a possible channel and use two measures of unemployment, namely general unemployment and strict unemployment, as dependent variables in our tets. The data source for both measures is National Sample Survey (NSS). NSS is a nationally representative large household survey conducted quinquennially in India. We use data from four thick NSS rounds[5]; 43rd (conducted in 1987-88), 55th (conducted in 1999-2000), (61st conducted in 2004-05) and (66th conducted in 2009-10). During our sample period, NSS conducted one more thick round, namely the 50th round in 1993-94. However this round does not have district level identifiers. Hence, in its place we use data from a thin 51st round conducted in 1994-95. Consistent with the standard practice in research with NSS data, we use linear interpolation between two successive rounds to generate variables for the intervening years to be used in our tests.[6]

General unemployment measure is constructed using a question on unemployment in principal line of activity in the NSS questionnaire. General unemployment indicates the percentage of people unemployed in a district in their principal activity. Strict unemployment measure is constructed using a question on unemployment in weekly activity in the NSS questionnaire. Strict unemployment indicates the percentage of people in a district unemployed *all* seven days in a week.

*Main independent variables*

As we have said in the introduction, the source of the data for credit supply by Indian commercial banks and number of bank accounts, which are the two common indicators of financial development, is BSR database of the RBI. BSR provides this data annually for each district-year in our sample period in the aggregate as well as separately for different sectors, such as agriculture, industry, professional services

[5]Thick rounds are conducted quinquennially and have a large sample size whereas thin rounds have a much smaller sample size and are conducted in the years between two successive thick rounds

[6]We use data from the 51st round because, otherwise, the gap would be too long, more than 10 years, between the 43rd and 55th rounds, for our interpolation exercise. For verification, we have run tests excluding the data from the 51st round, and all our predictions still hold though a couple of control variables become insignificant

etc. The main independent variables of interest in our empirical tests are credit supply to the industrial sector (in million INR) as well as the number of credit accounts in this sector. The reason for not considering credit supply to agriculture is that the sector relies much more heavily on informal sources of funding. No reliable and comprehensive data source for informal financing is available. Using only bank credit supply to agriculture would highly underestimate the total credit received by this sector. The reason for not considering the service sector is that the sector is fully developed only in urban districts. Since conflict is somewhat more common in rural districts than urban districts in India (Lakshmi Iyer, 2009), considering the service sector would cause selection problem and bias results in our favour.

BSR provides data on the stock of credit as well as number of accounts in different occupations or sectors in a district in a given year. In order to compute the supply (flow) of industrial credit, we compute the difference in the stock of credit between two consecutive years. If there are some district-years with negative flow of credit, indicating more repayment than new credit,we code them as zero supply of credit. The summary statistics reported in Table II show that average industrial credit supplied in a district-year is INR 1.2 million which is about 44 percent of the total credit supply for the district-year. But the standard deviation of industrial credit is very high, indicating high variability in the supply of industrial credit across district years.

Another independent variable that we consider in our empirical analysis is mining credit. Data on credit to the mining industry is also obtained from the BSR database. Mining industry is one of the four broad categories of industries covered under industry in BSR data.[7] But credit data for the four sub-sectors is available

[7]The four categories are (1) electricity, gas and water, (2) construction, (3) manufacturing and processing and (4) mining and quarrying

only since 1996. Hence, for our tests on the impact of mining credit on conflict the sample is restricted to years 1996-2010. Note that average mining credit in a district year is INR 0.17 million which is about 6 percent of the total credit and 14 percent of industrial credit supply for the district-year.

We also consider the impact of number of bank accounts under industrial credit on conflict. We use the log of the number of accounts in industry as the independent variable in our tests. As reported in Table II, the average number of bank accounts in a district-year is 8,247 in our sample, with a standard deviation of only 1.59. The number of bank accounts in given district changes very slowly from one year to the next, typically in the upward direction. More new accounts are created than closed.

*Control variables*

The control variables include:

1,2)Worker participation and literacy rate: source Indian population census 1991, 2001, 2011

The variables are included because they are likely to increase the opportunity cost of participation in conflicts. There is existing evidence that they are associated with low levels of conflict (Collier and Hoeffler (1998, 2001, 2002)).

3) Urbanisation: source Indian population census 1991, 2001, and 2011

We expect the coefficient of urbanisation to be negative because conflict is more a rural than an urban phenomenon in India (Lakshmi Iyer, 2009)

4) Population density- source Indian population census 1991, 2001, and 2011

We control for population density because higher population density in a geographic area increases competition for local resources, increasing scope for conflict and making the expected association between conflict and population density positive

5) Scheduled tribal population in Indian districts: source Indian population census 1991, 2001, 2011

6) Area covered under forests: source IndiaStat

We include this variable because it has been shown that a high proportion of area under forests leads to high levels of conflict (Fearon and Laitin, 2003). Because difficult terrains are conducive to insurgent activities, we expect the sign of the coefficient to be positive.

7) Net state domestic product: source IndiaStat

Net state domestic product (NSDP) controls for a state's capacity for counter insurgency measures. In India, counterinsurgency operations are a state subject. It may also control for opportunity cost of conflict participation by providing resources for productive non-conflict activities. Both channels suggest a negative association between conflict and NSDP. (Miguel, Sergenti, and Satyanath, 2004)

8) District roads, national and state highways: source Pradhan Mantri Gram Sadhak Yojana website.

The variables national highways and district roads in a district reflect how connected the district is. Since it influences movement by insurgents as well as counter insurgency personnel, the expected sign is ambiguous.

9) Monthly per capita consumption expenditure: source NSS five rounds noted above. Since we have only five rounds of NSS data available, for non-NSS years we linearly interpolate variables computed using NSS data.

We include this variable as a proxy for district level economic activity. Expected association with conflict is negative.

10) Inequality: source National Sample Survey five rounds noted above

Inequality in consumption expenditure is known to be positively associated with conflict (Esteban and Ray).

The definitions and data sources of all variables used in our empirical work are reported in table I below. Table II(a) reports the summary statistics of the variables for the full sample. The statistics indicate that 28.5 percent of the total number of observations in our sample experienced conflict defined as Conflict(G), while 35.5

percent of the district-years in our sample experienced Conflict(F). As we have noted above, the total number of observations exceeds the total number of district-years in our sample. Average industrial credit supplied in a district-year is INR 1.2 million which is about 44 percent of the total credit supply (INR 2.74 million)in the district year. But the standard deviation of industrial credit is high, indicating high variability in the supply of industrial credit across district years. Note that average credit to mining industry in a district year is INR 0.17 million, amounting to about 6 percent of the total credit and 14 percent of industrial credit supply in the average district-year.

**** Tables I and II(a) here

Table II(b) reports similar summary statistics for conflicts in different regions of India. Compared to the rest of the country (indicated as region 4 in the table), separatist insurgency in Jammu, Kashmir, and Punjab (region 1), ethnic conflicts in north-eastern India (region 2), and Maoist insurgency in central India (region 3) give rise to a much higher incidence (0.79, 0.43, 0.19 respectively), frequency (2.14, 0.57, 0.22 respectively) and intensity (0.89, 0.48, 0.21 respectively) of conflicts. The same three measures of conflict are 0.09, 0.10.and 0.9 for the rest of India. At the same time the industrial credit supply in the average district year is significantly less in the three regions (0.78, 0.22, 0.96 million INR respectively) than in the rest of India (2.34 million INR). The numbers are consistent with a pattern of negative relationship between industrial credit supply and conflict. The table also indicates that per capita net state domestic product is lower in the three regions than in the rest of the country.

Table Il(b) here

# 5 Basic results and identification

## 5.1 Basic tests

To start with, we evaluate the impact of credit supply on conflict by estimating the following regression model:

$$Conflict(G)_{d,s,t} = \alpha_d + \gamma_t + \beta Icredit_{d,s,t} + \delta X_{d,s,t} + \epsilon_{d,s,t} \qquad \text{(I)}$$

The dependent variable, $Conflict(G)_{d,s,t}$ is a dummy which takes a value of 1 if there is any report of conflict in district d, state s and time t; 0 otherwise. The independent variable of interest, $Icredit_{d,s,t}$ is the flow of industrial credit in district d, state s and time t. $X_{d,s,t}$ is a vector that includes all district and state-level control variables discussed in the preceding section of this paper, $d$ and $t$ indicate district and time fixed effects respectively.

By prediction 1 of our model, the expected sign of $\beta$, the coefficient of industrial credit supply, is negative.The estimated coefficients of the regression equation are reported in column 1 of table III below. The results show that Conflict(G)(coefficient -0.008, p 0.00) falls as more industrial credit is supplied in a district. We check that one standard deviation increase in the credit supply reduces the likelihood of conflict by 0.10. Given the average conflict level of 0.28 (table II), a reduction by 0.10 amounts to about one third reduction in the average value of conflict. In other words, the economic impact is significant in vindication of prediction 1. The reported coefficients of the control variables, wherever significant, have expected signs, such as worker participation rare, literacy rate, and population density. However, a number of control variables are insignificant.

**** Table III here

We also investigate the impact of industrial credit supply on the intensity as well as frequency of conflicts. The results for $Conflict(I)$ and $Conflict(F)$ are reported in columns 2 and 3 respectively of table III. The results show that industrial credit supply also negatively impacts $Conflict(I)$ and $Conflict(F)$. In fact, the reported coefficients are marginally more negative for $Conflict(I)$ (-0.0086, p 0.00) and significantly more for $Conflict(F)$ (-0.137, p 0.00). In the rest of the paper, to save space we report results for $Conflict(G)$ in all tests though we run the tests with all three conflict variables, because $Conflict(G)$ represents a more general notion of conflict occurrence and also because it gives weaker results in support of our hypothesis than the other two conflict variables.

All regressions include district fixed effects to control for possible district specific omitted variables affecting both conflict and credit supply. The regressions also include time fixed effects to control for macroeconomic shocks affecting conflict. We cluster standard errors at the district level. The total number of observations used in each regression is 7,878 though from table II, the total number of observations for conflict is much higher (19,493). This is due to lack of availability of data for all control variables in all district years.

## 5.2 Addressing endogeneity: Omitted variable bias

The coefficients of industrial credit reported in table III may be inconsistent because of endogeneity issues. Endogeneity could arise due to time varying unobservable variables affecting both conflict and industrial credit supply. One possible omitted variable is the district level economic activity. Financial development has been shown to cause economic growth (Rajan and Zingales). Also, the existing literature on conflict has documented a negative link between per capita income and conflict (see Collier and Hoeffler 2002; Fearon and Laitin 2003; Miguel et al2004). Since our basic test model does not control for district level economic activity for which no organized data is available, our regression estimates for conflict are likely to be biased downward, that is in favor of our hypothesis. To correct this problem we use a proxy for district level economic activity. Since district level GDP data is not available for all district-years in our sample, we use per capita monthly household consumption expenditure[8] in a district. Per capita consumption expenditure has been widely used as a proxy for per capita income in the existing literature. The results are reported in column 1 of table IV below.

***Table IV here

Note that the magnitude of the coefficient of industrial credit supply is less negative (-0.007) than the corresponding coefficient in table III (-0.008), confirming that the latter estimate is indeed biased downward. The sign of the coefficient of per capita monthly consumption expenditure is negative, indicating, as expected, a negative association between economic activity and conflict. We believe that the bias-corrected coefficient of credit supply reflects consistent and causal impact of credit supply on conflict. The coefficients of the other variables are similar to Table III, and are suppressed in this table.

### 5.3 Addressing endogeneity: Reverse causality

It is possible that the level of conflict in a district has an impact on the supply of credit into the district. The environment of fear and instability created by conflicts might effect the lending behaviour of banks, resulting in a reverse causality problem and causing the point estimates in Table III before to be inconsistent.

To correct this problem, we use lagged industrial credit supply as an independent variable in place of current industrial credit supply. While current supply may be endogenous. lagged supply should not be so, since it is unlikely that conflict in a

[8]Computed from NSS rounds as discussed in the section on data and variables

given period could influence credit supply in previous periods. The estimates with lagged industrial credit supply are reported in column 2 of Table IV. Note that the observed coefficient of lagged credit supply is also negative and significant (-0.008, p-value 0.00), and is in fact very similar in magnitude to the coefficient of current credit supply reported in table III before. We conclude that the results reported in Table III were not confounded by reverse causality. The empirical results in Table III and IV provide strong evidence in support of the theoretical prediction of our model of a negative association between credit supply and conflict (Prediction 1). However, even after addressing reverse causality industrial credit supply could still be endogenous. For instance, if banks/financial institutions base their lending decision in a district not only on the current level of conflict but also on the expected conflict level in future. We address this issue in the sub section 5.4 below.

## 5.4 More identification using instrumental variables

We have so far addressed two main sources of endogeneity, namely omitted variable bias and reverse causality, in an effort to identify causal impact of industrial credit supply on conflict. We now present more evidence that our basic test model is well-identified. We identify a clearly exogenous policy-induced shock to industrial credit supply in our sample, and verify that the changes in credit supply cause corresponding changes in conflict consistent with our prediction of negative association between them. The policy change in question is the introduction of Debt Recovery Tribunals (DRTs) in Indian states starting from late 1993. The DRT act, 1993, allowed the central government to establish DRTs for speedy recovery of debts in excess of INR 1 million owed to banks and other financial institutions ((Visaria (2009); LilienfeldToal, Mookherjee and Visaria (2012)). Under this law the central government determines the territorial jurisdictions of DRTs. The state governments are not given any authority to influence this process (Visaria (2009)). Five DRTs were set up in 1994 with jurisdiction over thirteen states (group 1 states) and another five during 1997-1999 with jurisdiction over the remaining sixteen states at the time (group 2 states). The phased introduction of DRTs occurred as a result of legal issues, and was entirely uncorrelated with pre-existing conflict levels in the states. Table V below lists the timing of DRT introduction in group 1 and group 2 states.

***Table V here

We exploit the phased introduction of DRTs to design tests verifying the causal impact of industrial credit supply on conflict. We use two alternative instruments for credit supply; introduction of DRTs in group 1 states and duration of a DRT in a given state in our sample period. The first instrument is intended to capture the differential impact of DRT introduction in group 1 over group 2 states on credit supply starting from 1994 until 1996. We restrict our analysis until 1996 as the group 2 states also get DRTs after 1996. We model the first instrument as the interaction between group 1 states and a post-1994 year dummy (post-94 is 1 for years after 1994 and zero otherwise). Our second instrument, DRT duration, represents the total number of years for which a DRT has been in place in a given state at a given time. Since DRTs were introduced in 1994, and given that our sample ends in 2010, the maximum value of DRT duration variable is 16 and minimum is 0 (for years prior to DRT establishment). It follows that the value of DRT duration for group 1 states is higher than that for group 2 states.

## 5.5 First stage results

Given that DRTs made debt recovery less costly, we expect DRT introduction to have a positive impact on credit supply. Accordingly, the first stage regression results of credit supply on the two instruments are expected to be positive. LilienfeldToal et al (2012) also show that on an average DRTs increased credit supply to the firms in their sample.

For the first instrument, the first stage regression is designed as a difference-in-difference test capturing the differential impact of DRTs for group 1 states over group 2 states. Before running the first stage regression, we first verify the existence of parallel trends between group 1 and group 2 states before 1994. We interact group 1 states with eleven year dummies for 1983-1994. The results, reported in Table VI below, indicate that the coefficients of all interaction terms are insignificant, except in two years (year 8 and year 10) when they are negative. Overall, we find no evidence of a positive pre trend in credit supply in group 1 states before DRT introduction. Note that this particular test uses fewer observations (6026) than the previous tests because it uses a smaller sample period (1983-1996).

***Table VI here

The first stage regression equation to verify the relevance of the first instrument is as follows, where the instrument is represented by $group1 * post94_{s,t}$:

$$Icredit_{d,s,t} = \alpha_s + \gamma_t + \beta group1 * post94_{s,t} + \eta group1_s + \delta X_{d,s,t} + \epsilon_{s,t} \quad \text{(II)}$$

For the second instrument, $DRTduration_{s,t}$, the first stage regression equation is:

$$Icredit_{d,s,t} = \alpha_s + \gamma_t + \beta DRTduration_{s,t} + \delta X_{d,s,t} + \epsilon_{s,t} \quad \text{(III)}$$

We control for state fixed effects, year fixed effects and other control variables represented by the vector $X_{d,s,t}$ in both regressions. The results, reported in columns 1 and 2 of Table VII below, confirm that the first stage results for both instruments are positive and significant (coefficients 1.05 with p-value 7 percent and 0.178 with p-value 1 percent), consistent with our prediction. The results satisfy relevance conditions. [9]

***Table VII here

We also verify that the instruments satisfy exclusion restriction, namely that DRT introduction was not independently correlated with the level of conflicts in states. As we have discussed earlier, the timing of DRT introduction was driven by factors which were completely exogenous to the pre existing levels of conflicts in the states. Further, LilienfeldToal et al (2012) investigate the possibility of state level factors influencing the timing of DRT introduction, and find that the timing of DRTs was not correlated with any economic, political or legal factors in the states. Their findings provide further support to the exogeneity of the instruments. However, the last three years of the sample period, 2008-2010, witnessed a serious financial crisis in many countries, including India. The crisis could have affected both the conflict levels in the states (positively through reduction in the level of economic activity) and functioning of DRTs (negatively through corporate bankruptcies and excessive increase in non-performing loans for financial institutions). This would confound our second stage test results during 2008-2010 Accordingly, we re-estimate our first stage regressions until 2008, and verify that the association between credit supply and DRT duration, reported in column 3 of table VII for the sub sample period 1983-2008, remains strong and significant (coefficient 0.175 with p-value 1 percent). In fact, the reported coefficients of DRT duration in columns 2 and 3 of the table are virtually identical.

[9] In order to check the joint significance of the instrumental variables, F statistic is checked in both cases. Usually, F statistic of 10 or above is considered standard for a strong IV. However, STATA does not report F statistic when the number of clusters is more than the number of parameters. This is so in our case as we cluster our standard errors at year level, resulting in 28 clusters, However if standard errors are not clustered, the reported F is greater than 20, well above the standard threshold.

## 5.6 Second stage results

The results of 2SLS regression of conflict on credit supply where the values of credit supply are predicted from the first stage tests are presented in Table VIII below. Column 1 of the table reports the results when group1*post94 is the instrument. Column 2 has DRT duration as the instrument, We consider DRT duration for the period 1983 - 2008. As discussed above, DRT may not be exogenous to conflict after 2008.

*** Table VIII here

The results reported in columns 1 and 2 confirm the negative relationship between conflict and credit supply. The results permit us to claim that an increase in industrial credit supply causally impacts the likelihood of conflict negatively. Note from the table that the reported credit supply coefficients in columns 1 (0.08) and 2 (0.10) are considerably higher than the corresponding OLS results reported in table III before (0.008). The results indicate that OLS estimates are biased upward against our hypothesis. The IV results in table VIII appear to have corrected this bias. The number of observations in column 1 is smaller because the analysis is done for 1983-1996.

# 6 Tests of model predictions

## 6.1 Does the negative relationship between credit supply and conflict hold at all levels of conflict?

We now proceed to test the predictions of our theoretical model discussed in section 3 before. To recall, prediction I(b) states that, if the indirect cost function is concave, industrial credit supply reduces conflict only when capital invested in conflict crosses a threshold. In other words, only districts above the threshold experience a fall in conflict when industrial credit supply increases. The effect for districts below the threshold is indeterminate. On the other hand, according to prediction I(a), if the indirect cost function is convex, the negative relationship holds at all levels of conflict.

To test this prediction, we compute average conflict level of each district over our sample period. We assign 0 if the district has no report of a conflict in a given year and 1 if it does. By construction, the average number for the district over the entire sample period of 28 years is between 0 (minimum) and 1 (maximum). Thirty percent of the districts register a value of 0. We can choose to designate districts above a certain threshold as conflict prone. We vary the threshold and partition the full sample of districts into two groups with the following proportions: 60/40, 50/50, 40/60, 30/70 and 20/80. In each ratio, the numerator indicates the proportion of districts in the top (that is, conflict prone) group. We do not go below 20 percent for the top group, because at this stage the bottom group will end up having too many districts with elevated conflict records. We then estimate the differential impact of credit supply for the conflict prone and the other districts by interacting conflict prone districts with credit supply. The model for testing this prediction is

$$Conflict(G)_{d,s,t} = \alpha_s + \gamma_t + \beta Icredit_{d,s,t} + \eta Icredit * conflictpronedistrict \tag{IV}$$

$$+ \phi conflictpronedistrict + \delta_1 X_{d,s,t} + \delta_2 Cexpenditure_{d,s,t} + \epsilon_{d,s,t}$$

In all specifications we include state fixed effects to control for time invariant state level unobserved factors that may influence conflict proneness of a district. $\delta X_{d,s,t}$ includes all the control variables used in test model 1. We also control for per capita monthly consumption in a district. The results are reported in Table IX below.

***Table IX here

In Columns 2-6 of table IX we report the differential impact for districts designated as conflict prone according to the following thresholds: 60, 50, 40, 30 and 20 percentile respectively. In all specifications the coefficient of industrial credit reported in the top row of the table is negative and significant. The results provide consistent evidence that industrial credit reduces conflict in the other less conflict prone districts. Note also that the coefficients of the interaction terms are positive and significant in all specifications. In other words, industrial credit supply has a less negative impact on conflict mitigation in conflict prone districts, contradicting prediction 1(b). However, though less negative than the corresponding bottom groups, The top groups register a negative and significant impact of credit supply except when the threshold is 20 percent leaving too few districts in the top group. In this case the effect is insignificant. In other words, the negative relationship between credit supply and conflict appears to hold at practically all levels of conflict We conclude that the results convincingly uphold prediction I(a), and in the process indicate that the indirect cost function is convex.

## 6.2 Does the negative relationship between credit supply and conflict hold for all types of conflict?

From our discussion in the data section before, 39 percent of the reported incidents of conflict in our sample took place in Jammu, Kasmir and Punjab (JKP) in north India where civil wars in the form of violent separatist movements were the norm. 31 percent took place in states central India affected by Left Wing Extremism (LWE) or Maoist insurgency. Another 20 percent driven by ethnic conflicts took place in north-eastern India. The rest of the incidents of conflict, including religious conflicts, accounted for 10 percent of the total.

Prediction II of the model stipulates that the negative relationship between credit supply and conflict holds for all types of conflict. To test this prediction, we test the following regression model:

$$Conflict(G)_{d,s,t} = \alpha_s + \gamma_t + \beta Icredit_{d,s,t} + \phi_1 LWE + \phi_2 NE + \phi_3 JK + \quad \text{(V)}$$

$$\eta_1 Icredit * LWE + \eta_2 Icredit * NE + \eta_3 Icredit * JK + \delta X_{d,s,t} + \epsilon_{d,s,t}$$

The test model includes the same control variables as in model I before.

***Table X here

The three independent variables of interest in the test model are *Icredit*LWE*, *Icredit*NE*, and *Icredit*JK*. The omitted category in the regression is the rest of the sample. For this category, the reported coefficient of *Icredit* is 0.0078 (p-value 0.00), which is remarkably similar to the coefficient for the entire sample in Table IV before. Note that the coefficients of both *Icredit*LWE* and *Icredit*NE* are insignificant. In other words, in the case of LWE and JKP states, industrial credit supply causes a similar decline in conflict as the whole sample. Interestingly, the coefficient of *Icredit*NE* is negative and significant, implying that industrial credit supply has a stronger effect on conflict reduction than the other categories. But for all of them the association between credit supply and conflict is negative and highly significant at 1 percent level. The results strongly vindicate prediction II.

# 7 Mechanism

So far our results have consistently documented a significant negative impact of industrial credit supply on conflict. In this section we explore the channels through which industrial credit is likely to impact conflict. Other studies (see Collier and Hoeffler(1998, 2001, 2002)) have found a negative association between employment and conflict. Accordingly, we check whether industrial credit impacts conflict through employment creation in a district. Increased supply of credit to industry should boost industrial activity which is a major employment generating sector in India.

To test whether employment serves as a channel, we estimate the following two regression equations

$$unemprate_{d,s,t} = \alpha_d + \gamma_t + \beta Icredit_{d,s,t} + \eta \overline{X}_{d,s,t} + \epsilon_{d,s,t} \quad \text{(VI)}$$

$$unemprate_{d,s,t} = \alpha_d + \gamma_t + \beta Icredit_{d,s,t-1} + \eta \overline{X}_{d,s,t} + \epsilon_{d,s,t} \quad \text{(VII)}$$

The two regression models above alternately use current and lagged industrial credit supply as the independent variable of interest, since structural changes like unemployment generally take time to respond to changes in the economy. We do not use both of them in the same regression model because of multicollinearity issues. We also use two notions of unemployment rate as the dependent variable; general unemployment and strict unemployment. As discussed in the data and variables section before, the first notion corresponds to a person being unemployed in her principal line of activity most of the time, while the second notion refers to unemployment all seven days in a week. $\overline{X}_{d,s,t}$ is a vector that includes few control variables that may affect unemployment, such as per capita monthly consumption expenditure (as a proxy for economic activity in a district (which affects both unemployment and industrial credit), literacy rate and population density. The regressions include district and time fixed effects. The results for the channel tests are reported in Table XI below.

***Table XI here

Columns 1 and 2 in the table report the results for general unemployment, while columns 3 and 4 report the results for strict unemployment. The coefficient of industrial credit is negative and significant for general as well as strict unemployment (-0.0048 with p-value 0.00 and -0.0049 with p-value 0.00 respectively), indicating that increased industrial credit leads to a statistically significant decline in unemployment. The results are economically very significant as well. As reported in the summary statistics table (Table II) before, the average unemployment (general and unemployment (strict) rates over the district-years in our sample are 1.57 and 1.50 percent respectively. The observed declines of 0.4 and 0.5 percent in the rates arising from an additional credit supply of 1 million INR amount respectively amounts to 27 and 33 percent of the average rates.

Lagged industrial credit is also negative and significant for strict unemployment (coefficient -0.003, p-value 0.00) and negative but not significant for general unemployment. Overall, the results indicate that industrial credit supply causes an economically significant fall in unemployment, supporting our conjecture that unemployment reduction is a channel through which industrial credit impacts conflict.

Note that the tests in this part use more observations (10,692-10,764) than the tests reported before. This is because they use fewer controls, resulting in fewer missing observations.

## 7.1 Placebo test

Our results above have established that credit supply to industry causes decline in conflict through unemployment reduction. It follows that credit supply to some other sector which does not have the potential of employment generation should not have any impact on conflict. To test this proposition, we perform a placebo test. We test the impact of personal loans on unemployment and also on conflict. If our hypothesis is correct, we will not observe a significant impact of personal loans on either unemployment or conflict. The results of the placebo test are reported in table XII below.

***Table XII here

The BSR database includes data on personal credit extended by commercial banks in India.The coefficients of current and lagged personal loans in column 1 and 2 of the table, though negative, are not significant (p values 0.21 and 0.18 respectively), confirming that personal loans have no impact on unemployment. Therefore, if unemployment reduction is an effective channel to reduce conflict, personal loans should not impact conflict either. The test results reported in column 3, confirm this intuition. The coefficient of personal loans is in fact positive though insignificant (p value 0.20).

# 8 Mining Credit

The industrial credit supply data taken from the BSR database that we use in our analysis comprises credit to four industrial sectors, namely electricity, gas, and water, construction, manufacturing and mining/quarrying. Of the four categories, mining industry has been positively linked to conflict in some states in India (Hoelscher, Miklian, and Vadlamannati, 2012). The explanation offered for this finding is that mining causes land dispossession for many poor people in rural areas. The loss of their livelihood drives them to conflict.

Given this finding, we investigate if and how increased credit supply to the mining industry in India affects conflict, particularly whether the effect is different from other cases discussed above. But this exercise reduces our sample size, because the disaggregated data of industrial credit separately for the four sectors mentioned above is available only since 1996. We estimate the following regression model:

$$Conflict(G)_{d,s,t} = \alpha_d + \gamma_t + \beta Mcredit_{d,s,t} + \delta X_{d,s,t} + \epsilon_{d,s,t} \quad \text{(VIII)}$$

where Mcredit, denoting credit to mining industry, replaces Icredit in test model 1 before. The test results are reported in Table XIII below.

*** Table XIII here

The results for the full sample reported in column 1 of the table do not appear to support the view that credit to the mining industry increases conflict. The coefficient of mining credit is negative, although statistically insignificant (p value 0.65). However, the mining industry in India is concentrated in a limited number of states. In the non-mining states credit to the mining sector is negligible. Hence,the above finding could be the result of a small proportion of mining credit in the total industrial credit (14 percent). Therefore, at the second stage of our investigation, we restrict our sample to eleven states identified as mining states by Ministry of Mines, Government of India. [10] The test results for mining credit in the eleven states are reported in column 2 of Table XIII. In this case the impact of mining credit on conflict is again negative and insignificant, though the significance level is higher (coefficient -0.005, p-value 0.16).

The existing research (Hoelscher et al. 2012) has documented that mining industry is associated with conflict in the states that have both high mineral resources and high Scheduled Caste and Scheduled Tribe (ST) population. In those states land dispossession suffered by these groups due to expansion of the mining indus-

[10]Ministry of mines, Government of India in its report titled "State Wise Mineral Scenario" categorizes the following eleven states to be mineral rich: The eleven states arAndhra Pradesh, Chhattisgarh, Goa, Gujarat, Jharkhand, Karnataka, Madhya Pradesh, Maharshtra, Odisha, Rajasthan and Tamil Nadu.

try contributes to conflict, as inequality between the marginalised population and the richer strata of society widens. Accordingly, we decide to examine the impact of mining credit in those mining states that have also experienced Maoist insurgency which typically features high participation by ST population. Our sample at this stage comprises six Indian states: Andhra Pradesh, Chhattisgarh, Jharkhand, Madhya Pradesh, Maharshtra, and Odisha. The six states represent the intersection of two separate lists of states, namely the eleven mining states mentioned before and nine states separately categorised as affected by Maoist insurgency by the Department of Left Wing Extremism, Ministry of Home Affairs, Government of India.[11]. The test results for the six states are reported in column 3 of Table XIII. The coefficient of mining credit is now negative and significant (coefficient 0.995, p value 0.05).The result implies that increased credit to the mining sector in states affected by Maoist conflict has mitigating effect on conflict, consistent with our results for the total industrial credit supply throughout this paper, but inconsistent with the finding of positive association of mining industry with conflict in states affected by Maoist insurgency noted above. The control variables in the three columns mostly have expected signs.

# 9 Robustness Checks

All our tests so far have used a linear specification, where the dependent variable is a dummy variable. We now verify that results are robust to non linear specification in Probit models. Table XIV below reports the marginal impact at the mean of all covariates from a Probit regression of test model 1 before. Note that our results remain unchanged. The marginal impact of credit supply on the probability of

[11] The nine states are Andhra Pradesh, Chhattisgarh, Jharkhand, Madhya Pradesh, West Bengal, Maharshtra, Odisha, Bihar and Uttar Pradesh

conflict remains negative and significant.

***Table XIV here

The marginal impact of the control variables are also along expected lines and similar to the linear specification results observed before. The impact of worker participation rate and literacy rates is negative and significant, while that of urbanization is negative but not significant. The impact of population density and area under forests is positive and significant consistent with expectations

We perform another robustness check for our results reported in Table IV before with an alternative measure of our main independent variable. We use log of number of accounts in industrial credit in a district-year in place of volume of industrial credit. Similar to credit supply, number of accounts is also an important measure of financial development. An increase in number of accounts in industrial credit usually indicates industrial expansion. As discussed in the section on data and variables before, data on number of accounts in a sector in a district-year is also included in the BSR database published by the RBI. The results are reported in Table XV below.

***Table XV here

The coefficient of number of accounts is negative (-0.017) though weakly significant (p-value 11 percent) In fact, the coefficient is more negative than the coefficient for industrial credit supply in Table IV before (-0.007) However, one standard deviation increase in number of accounts leads to a three percentage point fall in the likelihood of conflict, whereas the corresponding effect for industrial credit supply is much higher (10 percentage points). This is because, as we have noted in the data and variables section before, the variability of number of accounts across district-years is far less than that of credit supply.

The coefficient of per capita consumption expenditure (-0.033, p-value 0.00) is very comparable to the corresponding coefficient in Table IV before (0.038, p-value 0.00). Also similar to Table IV before, the coefficients of the control variables wherever significant, have expected signs.

We conclude that the robustness tests carried out in this section strongly confirm our findings before, especially the negative impact of industrial credit on conflict.

# 10 Concluding Remarks

Using a model as well as extensive empirical tests based on district-level evidence from India over a long sample period (1983-2010), in this paper we have investigated the impact of financial development, measured both as an increase in supply of bank credit and in number of bank accounts in a geographic area, on conflicts in the area. Our tests have used multiple measures of conflict and an exhaustive list of control variables that includes variables shown by other papers to influence conflicts and some additional ones that we consider important for our investigations. The test results overwhelmingly support our models prediction that financial development mitigates conflicts. Further, the negative relationship holds for all types of conflict. The observed effects are significant statistically as well as economically. Interestingly, we find that, the effects are stronger in less conflict-prone districts, making a case for early intervention in those districts. Further tests have indicated that employment growth due to financial development serves as a beneficial channel from financial development to conflict in our data. We have also considered the special case of credit supply to the mining industry in India. Previous research has linked this industry with incidence of conflicts. However, credit supply to mining industries in mineral-rich states appears to have similar conflict-mitigating effects as in other cases, although when we restrict our sample to the six Indian that have high mineral deposits as well as high incidence of conflicts the test results become insignificant.

Overall, our findings make a strong case for more financial development within a market framework as a means to combat conflicts in affected areas. The policy prescriptions suggested by the findings challenge conventional wisdom in the subject. Until now, the governments of most states affected by insurgency have relied on a combination of military interventions and specially funded initiatives, such as community development projects, intended to offer alternative occupations to conflict participants. For the most part, the initiatives have not been successful. Our findings have encouraging implications for the many policy-makers and governments around the world who are currently seized with the daunting task of conflict mitigation within their respective jurisdictions but are without an effective tool to accomplish their mission.

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Figure 1: Geographic distribution of conflict types

Table I: Variable definition and data source

| Variable | Definition | Source |
|---|---|---|
| Conflict(G) | Dummy variable, takes a value of 1 in case of death/property damage; 0 otherwise | Global Terrorism Database |
| Conflict(F) | Total number of conflict incidents in a district year | Constructed using Global Terrorism database |
| Conflict(I) | An index indicating intensity of conflict based on total number of deaths | Constructed using Global Terrorism database |
| Icredit | Bank credit supply to industry in a district year | Basic Statistical Return published by Reserve Bank Of India |
| Naccounts | Log of number of industrial bank accounts in a district year | Basic Statistical Return published by Reserve Bank Of India |
| Mcredit | Bank credit supply to Mining industry in a district year | Basic Statistical Return published by Reserve Bank Of India |
| Personal Loan | Bank credit supply to individuals in a district year | Basic Statistical Return published by Reserve Bank Of India |
| Total bank Credit | Total bank credit supply in a district year | Basic Statistical Return published by Reserve Bank Of India |
| Lagged Industrial Credit | Bank credit supply to industry in a district lagged by one year | Basic Statistical Return published by Reserve Bank Of India |
| Lagged Mining Credit | Bank credit supply to Mining lagged by one year | Basic Statistical Return published by Reserve Bank Of India |

| | | |
|---|---|---|
| Worker participation(%) | Percentage of people employed out of total labour force | Census India |
| Literacy(%) | Percentage of people literate out of total population | Census India |
| Urbanisation | Percentage of population living in urban areas | Census India |
| ST | Proportion of Scheduled tribal population in a district | Census India |
| Forests(%) | Percentage of total area covered by forests in a state | Open Government Database Website |
| NSDP(per capita 1000 INR) | Per capita net state domestic product | India Stat |
| Cexpenditure | Per capita monthly consumption expenditure of a household in a district | National Sample Survey Rounds |
| Unemp(general)(%) | Percentage of people unemployed according to their principal activity | National Sample Survey Rounds |
| Unemp(strict)(%) | Percentage of people unemployed on all the seven days of the week | National Sample Survey Rounds |
| State highways | Total number of state highways in a district | Pradhan Mantri Gram Sadak Yojana website |
| National highways | Total number of national highways in a district | Pradhan Mantri Gram Sadak Yojana website |
| District roads | Total number of district roads in a district | Pradhan Mantri Gram Sadak Yojana website |
| Inequality | Coefficient of variation of per capita monthly consumption expenditure | National Sample Survey Rounds |

Table II (a): Summary statistics for full sample

| **Variable** | **Mean** | **Std. Dev.** | **N** |
|---|---|---|---|
| Conflict(G) | 0.285 | 0.451 | 19493 |
| Conflict(I) | 0.323 | 0.544 | 19258 |
| Conflict(F) | 0.355 | 2.466 | 15157 |
| Icredit(million INR) | 1.216 | 13.352 | 16739 |
| Naccounts | 8.247 | 1.592 | 17588 |
| Mcredit(million INR) | 0.181 | 2.47 | 7154 |
| Total bank credit(million INR) | 2.744 | 27.405 | 16774 |
| Worker Participation(%) | 52.268 | 5.059 | 13926 |
| Literacy(%) | 75.120 | 12.254 | 12256 |
| Urbanisation(%) | 25.293 | 19.408 | 13662 |
| Forests(%) | 21.73 | 20.64 | 19144 |
| NSDP(per capita 1000 INR) | 11.388 | 11.641 | 18306 |
| Cexpenditure(100 INR) | 2.521 | 2.605 | 17568 |
| Inequality | 2.000 | 7.462 | 17528 |
| Unem(General)(%) | 1.574 | 1.3 | 16970 |
| Unem(Strict)(%) | 1.503 | 1.087 | 17135 |

Variable definitions are given in table 1.

Table II (b): Summary statistics types of conflict

| | 1 | | 2 | | 3 | | 4 | |
|---|---|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | mean | sd | mean | sd |
| Conflict(G) | 0.79 | 0.41 | 0.43 | 0.49 | 0.20 | 0.40 | 0.09 | 0.28 |
| Conflict(I) | 0.89 | 0.55 | 0.49 | 0.61 | 0.22 | 0.47 | 0.10 | 0.35 |
| Conflict(F) | 2.14 | 6.08 | 0.57 | 2.64 | 0.22 | 2.15 | 0.09 | 0.76 |
| Icredit(in million Rs.) | 0.78 | 5.41 | 0.22 | 1.06 | 0.96 | 15.13 | 2.34 | 15.68 |
| Naccounts | 8.40 | 1.48 | 6.61 | 1.87 | 8.52 | 1.21 | 8.46 | 1.63 |
| Mcredit(in million Rs.) | 0.63 | 7.32 | 0.04 | 0.17 | 0.11 | 1.20 | 0.22 | 1.46 |
| Total bank credit(in million Rs.) | 1.46 | 8.93 | 0.41 | 1.49 | 2.26 | 30.25 | 5.31 | 33.79 |
| Worker Participation | 51.30 | 3.36 | 50.26 | 4.80 | 51.83 | 4.85 | 54.79 | 5.50 |
| Literacy Rate | 63.43 | 9.25 | 73.90 | 10.70 | 74.26 | 11.94 | 82.04 | 10.25 |
| Urbanisation | 36.51 | 26.50 | 17.12 | 12.17 | 20.89 | 15.18 | 31.30 | 19.69 |
| Forests | 7.50 | 2.43 | 57.92 | 20.34 | 16.87 | 10.79 | 18.56 | 18.28 |
| NSDP(pc in 1000) | 8.42 | 8.57 | 11.37 | 9.80 | 10.45 | 10.34 | 14.87 | 15.09 |
| Cexpenditure(100 INR) | 2.73 | 2.44 | 2.54 | 2.64 | 2.29 | 2.03 | 2.79 | 3.34 |
| Inequality | 0.44 | 0.26 | 0.26 | 0.30 | 0.42 | 0.29 | 0.46 | 0.39 |
| Unem(General) | 1.33 | 0.74 | 1.86 | 1.63 | 1.43 | 1.16 | 1.80 | 1.49 |
| Unem(Strict) | 1.58 | 0.81 | 1.67 | 1.35 | 1.32 | 0.96 | 1.69 | 1.21 |
| Observations | 2786 | | 2696 | | 8815 | | 5196 | |

1 indicates conflicts present in Jammu and Kashmir and Punjab. These regions are mostly plagued with separatist insurgency. 2 denotes conflicts in North East where ethnic conflicts are rampant. 3 denotes conflicts in LWE states where Maoist insurgency is widespread. 4 indicates conflicts in the rest of the country

Table III: Effect of credit supply on conflict

| | (1) Conflict(G) | (2) Conflict(I) | (3) Conflict(F) |
|---|---|---|---|
| Icredit(in million Rs.) | -0.0082*** | -0.0086*** | -0.0137* |
| | (0.000) | (0.000) | (0.072) |
| Urbanisation | -0.0010 | -0.0007 | -0.0099 |
| | (0.492) | (0.632) | (0.128) |
| Worker Participation | -0.0150*** | -0.0161*** | -0.0516*** |
| | (0.001) | (0.001) | (0.001) |
| Literacy Rate | -0.0147*** | -0.0142*** | -0.0604*** |
| | (0.000) | (0.000) | (0.000) |
| Population density | 0.4806*** | 0.5719*** | 3.0604*** |
| | (0.000) | (0.000) | (0.000) |
| Forests | -0.0009 | -0.0006 | -0.0097 |
| | (0.791) | (0.795) | (0.625) |
| Inequality | 0.0514 | 0.0637 | -0.0964 |
| | (0.222) | (0.187) | (0.713) |
| State Highways | 0.0256* | 0.0257* | 0.0554 |
| | (0.098) | (0.066) | (0.265) |
| District Roads | -0.0044 | -0.0028 | -0.0240* |
| | (0.277) | (0.446) | (0.072) |
| National Highways | -0.0297 | -0.0277 | 0.1728** |
| | (0.418) | (0.407) | (0.016) |
| NSDP(pc in 1000) | -0.0074*** | -0.0079*** | -0.0262** |
| | (0.008) | (0.009) | (0.014) |
| Year FE | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes |
| Observations | 7878 | 7878 | 5839 |

$p$-values in parentheses

Dependent variable in column 1, Conflict(G) takes a value of 1 in case of death/property damage; 0 otherwise

Conflict(I) in column 2 indicates intensity of conflict based on total number of deaths

Conflict(F) denotes the frequency of insurgent activities in a given district and in a given year

Independent varibale of interest is Icredit, bank credit supply to industry in a district year

For description of other dependent variables see table 1. Standard errors are clustered at the district level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IV: Addressing omitted variable and reverse causality problem

| | (1) Conflict(G) | (2) Conflict(G) |
|---|---|---|
| Icredit(in million Rs.) | -0.0077*** | |
| | (0.000) | |
| Urbanisation | -0.0002 | 0.0001 |
| | (0.897) | (0.967) |
| Worker Participation | -0.0164*** | -0.0164*** |
| | (0.000) | (0.001) |
| Literacy Rate | -0.0159*** | -0.0158*** |
| | (0.000) | (0.000) |
| Population density | 0.5736*** | 0.6086*** |
| | (0.000) | (0.000) |
| Forests | 0.0029 | 0.0035 |
| | (0.518) | (0.444) |
| Inequality | 0.0923** | 0.0938** |
| | (0.050) | (0.050) |
| Cexpenditure(100 INR) | -0.0385*** | -0.0442*** |
| | (0.003) | (0.001) |
| State Highways | 0.0255* | 0.0278* |
| | (0.096) | (0.078) |
| District Roads | -0.0043 | -0.0049 |
| | (0.284) | (0.240) |
| National Highways | -0.0266 | -0.0266 |
| | (0.514) | (0.481) |
| NSDP(pc in 1000) | -0.0055* | -0.0052* |
| | (0.052) | (0.058) |
| Lagged Icredit | | -0.0084*** |
| | | (0.000) |
| Year FE | Yes | Yes |
| District FE | Yes | Yes |
| Observations | 7878 | 7624 |

$p$-values in parentheses
Results for control variables are suppressed. Dependent variable, Conflict(G) takes a value of 1 in case of death/property damage; 0 otherwise. Independent varibale of interest in column 1, Icredit, is bank credit to industry
Independent varibale of interest in column 2, lagged Icredit, is bank credit to industry lagged by one year
For description of other dependent variables see table 1. Standard errors have been clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table V: Timing of DRT establishment

| DRT location | Date | Jurisdiction |
|---|---|---|
| Kolkata | Apr 27, 1994 | West Bengal, Andaman and Nicobar Islands |
| Delhi | July 5, 1994 | Delhi |
| Jaipur | August 30, 1994 | Rajasthan, Himachal Pradesh, Haryana, Punjab, Chandigarh |
| Bangalore | November 30, 1994 | Karnataka, Andhra Pradesh |
| Ahemdabad | December 21, 1994 | Gujarat, Dadra and Nagar Haveli, Daman and Diu |
| Chennai | November 4, 1996 | Tamil Nadu, Kerala, Pondicherry |
| Guwahati | January 7, 1997 | Assam, Meghalaya, Manipur, Mizoram, Tripura, Arunachal Pradesh, Nagaland |
| Patna | January 24, 1997 | Bihar, Orissa |
| Jabalpur | April 7, 1997 | Madhya Pradesh, Uttar Pradesh |
| Mumbai | July 10,6 1999 | Maharashtra, Goa |

Table VI: Checking parallel trends between group 1 and group 2 states (1983-1993)

| | (1) |
|---|---|
| | Icredit(in million Rs.) |
| Group1*year2 | -0.0260 |
| | (0.430) |
| Group1*year3 | -0.0797 |
| | (0.195) |
| Group1*year4 | -0.1978* |
| | (0.099) |
| Group1*year5 | -0.2980 |
| | (0.219) |
| Group1*year6 | -0.0638 |
| | (0.662) |
| Group1*year7 | -0.0433 |
| | (0.570) |
| Group1*year8 | -0.4459* |
| | (0.051) |
| Group1*year9 | -0.2302 |
| | (0.312) |
| Group1*year10 | -0.3554* |
| | (0.056) |
| Group1*year11 | 0.0000 |
| | (.) |
| Group1*post94 | 0.7940* |
| | (0.085) |
| Year FE | Yes |
| State FE | Yes |
| Observations | 6043 |

*p*-values in parentheses

Results for control variables are suppressed.Dependent variable, Icredit is bank credit to industry in a district year.
Coefficient of interaction of group 1 dummy with different year dummies provide evidence for
parallel trends. Standard errors are clustered at the year level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table VII: Instrumental variable regression: First stage results

| | (1) | (2) | (3) |
|---|---|---|---|
| | Icredit(in million Rs.) | Icredit(in million Rs.) | Icredit(in million Rs.) |
| Group1*post94 | 1.0578$^{*}$ | | |
| | (0.070) | | |
| Cexpenditure(100 INR) | 0.0601$^{*}$ | 0.2806$^{***}$ | 0.1785$^{**}$ |
| | (0.075) | (0.001) | (0.021) |
| DRTduration | | 0.1787$^{***}$ | 0.1754$^{***}$ |
| | | (0.001) | (0.002) |
| Year FE | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes |
| Observations | 4858 | 8752 | 7637 |

*p*-values in parentheses

Results for control variables are suppressed.. Dependent variable, Icredit is bank credit to industry Independent varibale of interest in column 2 is DRT duration which is the number of years for which DRT has been in place, in column 1 it is the interaction of group 1 dummy with post 94 dummy Column 1 has years till 1996, column 3 has years till 2008. Variable cons expenditure denotes the average household consumption expenditure, it has been used as a proxy for district level economic activity. Standard errors are clustered at the year level

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table VIII: Instrumental variable regression: Second stage results

| | (1) Conflict(G) | (2) Conflict(G) |
|---|---|---|
| Icredit(in million Rs.) | -0.0799$^{***}$ | |
| | (0.007) | |
| Cexpenditure(100 INR) | -0.0154$^{**}$ | 0.0070 |
| | (0.021) | (0.510) |
| Icredit(in million Rs.) | | -0.1013$^{**}$ |
| | | (0.034) |
| Year FE | Yes | Yes |
| State FE | Yes | Yes |
| Observations | 5316 | 8126 |

*p*-values in parentheses

Results for control variables are suppressed. Dependent variable, Conflict(G) takes a value of 1 in case of death/property damage; 0 otherwise. Inpependent variable, is industrial credit is credit to industry. Variable cons expenditure denotes the average household consumption expenditure, it has been used as a proxy for district level economic activity. Column 1 has years till 1996, column 3 has years till 2008 which is why number of observations are more in column 3. Standard errors are clustered at the district level

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table IX: Differential impact of credit supply on conflict-prone and other districts

| | (1) Conflict(G) | (2) Conflict(G) | (3) Conflict(G) | (4) Conflict(G) | (5) Conflict(G) |
|---|---|---|---|---|---|
| Icredit(in million Rs.) | -0.0163** | -0.0184*** | -0.0176*** | -0.0087*** | -0.0039** |
| | (0.024) | (0.003) | (0.001) | (0.000) | (0.043) |
| Conflict prone (top 60) | 0.1031*** | | | | |
| | (0.000) | | | | |
| Top60*Icredit | 0.0130* | | | | |
| | (0.073) | | | | |
| Conflict prone (top 50) | | 0.1679*** | | | |
| | | (0.000) | | | |
| Top50*Icredit | | 0.0151** | | | |
| | | (0.018) | | | |
| Conflict prone (top 40) | | | 0.2432*** | | |
| | | | (0.000) | | |
| Top40*Icredit | | | 0.0136** | | |
| | | | (0.014) | | |
| Conflict prone (top 30) | | | | 0.2787*** | |
| | | | | (0.000) | |
| Top30*Icredit | | | | 0.0080** | |
| | | | | (0.014) | |
| Conflict prone (top 20) | | | | | 0.2971*** |
| | | | | | (0.000) |
| Top20*Icredit | | | | | 0.0051* |
| | | | | | (0.086) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 7878 | 7878 | 7878 | 7878 | 7878 |

*p*-values in parentheses

Results for control variables are suppressed.Dependent variable, Conflict(G) takes a value of 1 in case of death/property damage; 0 otherwise. Coefficient of Icredit indicates impact of industrial credit supply in less conflict prone districts. Coefficient of the interaction gives the differential impact of credit supply on more conflict prone and less conflict prone districts. Threshold for categorizing district as conflict prone is 40th, 50th, 60th, 70th and 80th precetile in columns 1-5 respectively

Standard errors are clustered at the district level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table X: Effect of credit supply on different types of conflict

| | (1)<br>Conflict(G) |
|---|---|
| Icredit(in million Rs.) | -0.0078*** |
| | (0.000) |
| LWE | -0.0415 |
| | (0.675) |
| NE | 0.8997 |
| | (0.805) |
| JK | 0.8242 |
| | (0.803) |
| Icredit*LWE | 0.0037 |
| | (0.555) |
| Icredit*NE | -0.0242*** |
| | (0.001) |
| Icredit*JK | -0.0004 |
| | (0.854) |
| Inequality | 0.0922* |
| | (0.050) |
| Cexpenditure(100 INR) | -0.0378*** |
| | (0.003) |
| NSDP(pc in 1000) | -0.0056** |
| | (0.047) |
| Year FE | Yes |
| District FE | Yes |
| Observations | 7878 |

*p*-values in parentheses

Results for control variables are suppressed. Dependent variable in column 1, Conflict(G) takes a value of 1 in case of death/property damage; 0 otherwise. Variable LWE is a dummy variable to indicate LWE affected states. Variable NE is a dummy variable to indicate. North Eastern states. Variable JK is a dummy to indicate states of Jammu Kashmir and Punjab. Independent varibale of interest is Icredit, bank credit supply to industry in a district year. Variables Icredit*LWE, Icredit*NE, Icredit*JK indicate the interaction between Icredit and LWE dummy, Icredit and NE dummy, Icredit and JK dummy respectively.For description of other dependent variables see table 1. Standard errors are clustered at the district level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table XI: Test for unemployment as a channel from industrial credit to conflict

| | (1) Unem(General) | (2) Unem(General) | (3) Unem(Strict) | (4) Unem(Strict) |
|---|---|---|---|---|
| Icredit(in million Rs.) | -0.0048$^{***}$ | | -0.0049$^{***}$ | |
| | (0.001) | | (0.000) | |
| Literacy Rate | -0.0074 | -0.0062 | 0.0031 | 0.0040 |
| | (0.388) | (0.462) | (0.673) | (0.578) |
| Population density | 2.3672$^{***}$ | 1.7799$^{**}$ | -0.0004 | -0.0757 |
| | (0.000) | (0.015) | (0.999) | (0.654) |
| Cexpenditure(100 INR) | -0.0684$^{*}$ | -0.0724$^{*}$ | 0.0236 | 0.0220 |
| | (0.074) | (0.062) | (0.540) | (0.566) |
| Lagged Icredit | | -0.0011 | | -0.0035$^{***}$ |
| | | (0.690) | | (0.004) |
| Year FE | Yes | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes | Yes |
| Observations | 10692 | 10485 | 10764 | 10556 |

*p*-values in parentheses

Dependent variable in column 1 and 2 is general unemployment; defined according to prinicpal activity

Dependent variable in column 3 and 4 is strict unemployment; defined according to weekly activity

Independent variables of interest are industrial credit and lagged industrial credit(lagged by one year)

variable cons expenditure denotes the average household consumption expenditure, it has been used as a proxy for district level economic activity

Standard errors are clustered at the district level

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table XII: Placebo test with personal loans

| | (1)<br>Unem(General) | (2)<br>Unem(General) | (3)<br>Conflict(G) |
|---|---|---|---|
| Personal Loan | -0.0000 | | 0.0000 |
| | (0.209) | | (0.202) |
| Literacy Rate | -0.0080 | -0.0083 | -0.0152*** |
| | (0.350) | (0.330) | (0.000) |
| Population density | 2.1788*** | 0.8667* | 0.6050*** |
| | (0.000) | (0.061) | (0.000) |
| NSDP(pc in 1000) | -0.0022 | -0.0006 | -0.0057** |
| | (0.714) | (0.916) | (0.044) |
| Cexpenditure(100 INR) | -0.0889** | -0.1009** | -0.0413*** |
| | (0.046) | (0.028) | (0.008) |
| Lagged Personal Loan | | -0.0000 | |
| | | (0.179) | |
| Urbanisation | | | -0.0002 |
| | | | (0.875) |
| Worker Participation | | | -0.0156*** |
| | | | (0.001) |
| Forests | | | 0.0028 |
| | | | (0.565) |
| State Highways | | | 0.0242* |
| | | | (0.092) |
| District Roads | | | -0.0033 |
| | | | (0.382) |
| National Highways | | | -0.0246 |
| | | | (0.517) |
| Year FE | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes |
| Observations | 10144 | 9691 | 7570 |

*p*-values in parentheses

Dependent variable in column 1 and 2 is general unemployment; defined according to prinicpal activity

Dependent variable in column 2 is strict unemployment; defined according to weekly activity

Dependent varibale in column 3 is Conflict(G), which takes a value of 1 in case of conflict; 0 otherwise

Independent variable of interest is personal loans. Variable cons expenditure denotes the average household consumption expenditure, it has been used as a proxy for district level economic activity.

Table XIII: Impact of mining credit on conflict

| | (1)<br>Conflict(G) | (2)<br>Conflict(G) | (3)<br>Conflict(G) |
|---|---|---|---|
| Mcredit(in million Rs.) | -0.0024 | -0.0054 | -0.0044* |
| | (0.648) | (0.162) | (0.050) |
| Urbanisation | 0.0007 | -0.0178 | -0.0272 |
| | (0.857) | (0.236) | (0.207) |
| Worker Participation | -0.0079 | -0.0327 | 0.0496 |
| | (0.583) | (0.222) | (0.218) |
| Literacy Rate | -0.0252*** | -0.0240** | 0.0064 |
| | (0.000) | (0.014) | (0.331) |
| Population density | 1.1671*** | 6.0628 | 0.0000 |
| | (0.000) | (0.199) | (.) |
| Forests | 0.0113* | 0.1536 | 0.1110*** |
| | (0.074) | (0.137) | (0.000) |
| Inequality | 0.3185** | 0.1589 | -0.0985 |
| | (0.020) | (0.331) | (0.228) |
| Cexpenditure(100 INR) | -0.0820*** | -0.0708*** | 0.0045 |
| | (0.000) | (0.002) | (0.740) |
| State Highways | 0.0387 | 0.0588** | 0.0285 |
| | (0.162) | (0.013) | (0.253) |
| District Roads | -0.0080 | -0.0123** | 0.0214* |
| | (0.241) | (0.019) | (0.073) |
| National Highways | -0.0252 | 0.0107 | -0.0111 |
| | (0.641) | (0.864) | (0.828) |
| NSDP(pc in 1000) | -0.0027 | -0.0026 | 0.0030 |
| | (0.357) | (0.561) | (0.338) |
| ST share | | | -0.0051 |
| | | | (0.482) |
| Year FE | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes |
| Observations | 3652 | 1654 | 562 |



*p*-values in parentheses

Dependent variable, Conflict(G) takes a value of 1 in case of death/property damage; 0 otherwise

Independent variable of interest is mining which is credit to mining industry

Table XIV: Robustness Check with probit regression

| | (1) |
|---|---|
| | Conflict(G) |
| Icredit(in million Rs.) | -.0040* |
| | ( .093) |
| Urbanisation | .0058*** |
| | (.000) |
| Worker Participation | -.0094** |
| | (.010) |
| Literacy Rate | -.0123*** |
| | (.000) |
| Population density | -.1460*** |
| | (.000) |
| Forests | -.0004 |
| | (.586) |
| Inequality | -.0213 |
| | (.766) |
| Cexpenditure(100 INR) | -.0066 |
| | (.623) |
| State Highways | -.0010 |
| | (.486) |
| District Roads | -.0011*** |
| | (.000) |
| National Highways | .0034 |
| | (.134) |
| NSDP(pc in 1000) | -.0033 |
| | (.228) |
| Year FE | Yes |
| Observations | 7658 |

Dependent variable, Conflict(G) takes a value of 1 if there's conflict; 0 otherwise
Independent variable of interest is industrial credit
variable cons expenditure denotes the average household consumption expenditure, it has been used as a proxy for district level economic activity. This table presents the results for probit specification
standard errors are clustered at the district level

Table XV: Robustness Check with number of credit accounts

| | (1) |
|---|---|
| | Conflict(G) |
| Naccounts | -0.0174 |
| | (0.115) |
| Urbanisation | -0.0006 |
| | (0.676) |
| Worker Participation | -0.0162*** |
| | (0.000) |
| Literacy Rate | -0.0154*** |
| | (0.000) |
| Population density | 0.3981 |
| | (0.107) |
| Forests | -0.0063 |
| | (0.508) |
| Inequality | 0.0876* |
| | (0.058) |
| Cexpenditure(100 INR) | -0.0339*** |
| | (0.004) |
| State Highways | 0.0258* |
| | (0.097) |
| District Roads | -0.0044 |
| | (0.278) |
| National Highways | -0.0234 |
| | (0.573) |
| NSDP(pc in 1000) | -0.0058** |
| | (0.040) |
| Year FE | Yes |
| District FE | Yes |
| Observations | 7961 |



*p*-values in parentheses

Dependent variable, Conflict(G) takes a value of 1 in case of death/property damage; 0 otherwise

Independent variable of interest is noof accounts which is the number of accounts under industry

variable cons expenditure denotes the average household consumption expenditure, it has beenused as a proxy for district level economic activity.

Standard errors have been clustered at the district level